Журнал НЭА, № 3 (64), 2024, с. 12–29

F.T. Aleskerov
HSE Univeristy, V.A. Trapeznikov Institute of Control Sciences, Russian Academy of Sciences, Moscow, Russia

S.D. Dutta
HSE Univeristy, Moscow, Russia

D.S. Egorov
HSE Univeristy, Moscow, Russia

D.S. Tkachev
HSE Univeristy, Moscow, Russia

Networks under deep uncertainty concerning food security[1]

Abstract. We propose new models to find the vulnerable countries in terms of food security. These models are based on network analysis under deep uncertainty. The conditions of deep uncertainty affect the supply and demand of food, namely, carbohydrates of the countries. Under such conditions networks of the carbohydrate supply between countries are constructed. The countries vulnerability in terms of food security were studied by new centrality indices taking into account carbohydrate consumptions of countries and the possibility of group influence of countries to a country. Also, our models show direct and indirect dependence on import of carbohydrates from other countries. The scenario of one of such situations was constructed, and our models for studying this situation were tested. The vulnerable countries are identified in terms of carbohydrate consumption from main crops in different scenarios based on real data using our new models. The developed models can make the food policy of countries more efficient.

Keywords: *deep uncertainty, food insecurity, network analysis, scenario analysis.*

JEL Classification: C65, D85, Q18.

For reference: **Aleskerov F.T., Dutta S.D., Egorov D.S., Tkachev D.S.** (2024). Networks under deep uncertainty concerning food security. *Journal of the New Economic Association*, 3 (64), 12–29 (in English).

DOI: 10.31737/22212264_2024_3_12-29

EDN: UIJYDA

1. Introduction

Global food trade network is a boon for the countries that are not sufficient enough to fulfill the food demand of their population. It plays a vital role for solving the food security problem in global arena, and there is a growing body of research to study food security issue using the network analysis. According to Food and Agriculture Organization (UN) (FAO UN), “Food security represents a situation where all the people, at all time, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs for healthy life”[2]. Food security stands on four pillars: availability, access, utilization and stability based on which the food policies are formulated. The four pillars can be extended to six with an addition of two more dimensions: agency and sustainability (Clapp et al., 2022). The additional dimensions were proposed

[1] This article is an output of a research project “Study of the models and methods of decision-making under conditions of deep uncertainty. Extension and testing of developed methods” implemented as part of the Basic Research Program at the National Research University “Higher School of Economics” (HSE University).

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[2] FAO, 1996. World food summit plan of action (https://www. fao.org/3/w3613e/w3613e00.htm).

Журнал НЭА, № 3 (64), 2024, с. 12–29

by the high level panel of experts on food security and nutrition to take into account the importance of ecosystem in food security. The new technologies, combined with the conventional methods and approaches used for data collection, and analyses can be made more informative for the decision-makers and policy-makers to achieve food security (Mock, Morrow, Papendieck, 2013). Within the four pillars of food security, more emphasis should be given to the nutrient contain of the products traded in the global market rather than the staple grains (Geyik et al., 2021), especially for the developing and least developed countries. This would diversify the network of food trade and reduce the dependency of the importing countries from particular exporting countries.

The problem of food security strongly depends on the possibility of the natural disasters, such as drought, earthquake, flood, etc., which can change the value of production, the quantity of export or import of the products under consideration (Ali et al., 2017; Bandara, Cai, 2014; Mall, Gupta, Sonkar, 2017). These situations highly depend on the factors of deep uncertainty. The problem of hunger in global terms cannot be solved without increasing productivity as well as without the development of science and technologies, new ways of preserving food products, with the advancement in the theory of logistic schemes, and the rational development of agricultural production (Birthal et al., 2014; Rosegrant, Cline, 2003; Serageldin, 1999). An early warning system became an essential tool for the food assistance, planning and providing information to the government and non-governmental organizations (Brown et al., 2007). The Global Information and Early Warning System on Food and Agriculture (GIEWS) maintained by FAO[3], keep the records of food supply and demand across the world to alerts the decision makers at the international and national level. It monitors crops prospects, food situation, and food prices, and thereby prepare reports for the decision makers with comprehensive forward analyses and assessing the impact on food security. A general equilibrium model for agricultural trade policy with a flexible production structure was proposed in (Heerman, 2020). Different models (such as the Alternative and the Benchmark models) were presented in that paper. The advantage of the model from (Heerman, 2020) over the existing models is that it can handle different tariff distributions over the same sector by introducing policy costs and revenue into the model. Moreover, for understanding the complexity and the uncertainty associated with the food security, problem scenario based models were mostly considered by (Godfray, Robinson, 2015; Zanoli, Gambelli, Vairo, 2012). In particular, scenario based studies were mainly focused on food price, food availability and hunger (malnutrition, or undernourishment) (Hasegawa et al., 2014, 2015; Nelson, Shively, 2014). Apart from these models, different models (Anderson, 2022; Hasegawa et al., 2018; Nelson et al., 2013; 2018; Von Lampe et al., 2014; Wiebe et al., 2015) related to climate change, production and price were studied. Those studies shed light on how climate change may impact the global agriculture in the long run, while there was less progress in other dimensions of food security. In (Wu et al., 2011) the socio-economic and climate change scenarios were defined to predict the crop yields (EPIC model), crop area (crop choice decision model) and the GDP (IFPSIM model) for the period of 2000–2020, where the first two factors represented the food availability and stability, while the third reflected the food accessibility and affordability.

In recent years there was a great increase in the study of food and nutrition security. A variety of monitoring systems was implemented to monitor the indicators of food security (access and utilization) in least developed countries (FAO, IFAD, UNICEF, WFP and

[3] FAO, 2023. GIEWS – global information and early warning system on food and agriculture (https://www.fao.org/giews/en/).

Журнал НЭА, № 3 (64), 2024, с. 12–29

WHO, 2017). The Paris climate agreement[4], Sustainable Development Goals[5] fueled developing intrigued in long–run nourishment and sustenance security. Global models such as MAGNET–IMAGE (Stehfest et al., 2014; Woltjer et al., 2014) and GLOBIUM (Havlík et al., 2014) are now used to trade-offs between food, nutrition, inequality and sustainability to evaluate the multi-dimensional multifaceted attributes of global food security (Meijl et al., 2020). Apart from the four dimensions recognized by FAO, an environmental indicator is added to understand the effect of such greenhouse gases (GHG), as CH_4, N_2O and CO_2 on agriculture practices and harvested area.

In this paper we consider methods of the *social network analysis.* The concept of network, in terms of social network analysis, refers to the approach of analyzing complex system as interconnected networks, with nodes and connections representing the various components and relationships between them. This approach enables a more comprehensive and holistic understanding of the system, identifying patterns, dynamics and emergent properties that is not evident through traditional reductionist methods. Moreover, networks can facilitate the development of innovative solutions to real-world problems. Many network models based on graph theory such as social network and bibliometric network (Aleskerov et al., 2016, 2021; Perkins et al., 2018; Skaf et al., 2020) used to study the evolution and trends of the global scientific research articles on food security. (Wang, Dai, 2021) throws light on the feature of global food trade network, from the analysis of 30 years period — from 1992 to 2018.

The evolution of the global food trade network from a unipolar to a multipolar structure enhanced both food availability and nutritional diversity. However, the countries exporting food remained the same while the number of importing countries sprinkled. The increasing dependency on certain countries increased vulnerabilities in terms of food security for some countries. In (Schaffer-Smith et al., 2018) the utility of network analysis in metacoupled systems was explored by examining the nature of global soybean trade for the period of 1986 to 2013 among 217 countries. According to the study, the density of the network increased fivefold with only few countries dominating the trade, which poses serious problems concerning food security. Moreover, the authors found a close connection between the soybean trade and deforestation. Competition network modelling (Dong et al., 2018) examined the wheat trading competition on a global level and formulate targeted policy to promote stability and healthy environment for wheat trading. Clustered wireless sensor network (Bindu, Titus, Dhanya, 2023) to monitor the water flow in irrigation system of agriculture efficiently based on the minimum edge fixed geodetic sets of the connected graph. Famine early warning system network (Krishnamurthy, Choularton, Kareiva, 2020) helps in estimating the factors (weather patterns, price variability) governed by uncertainty to an acceptable rate for making the projection about the future food security. Along with network theory, panel data method (Sun et al., 2022) is used to identify the risk associated with a country using the Herfindahl–Hirschman Index (HHI), and other network indices such as in-degree, out-degree, weighted in-degree, weighted out-degree and betweenness on a global level. That paper also reflects an economic and political risk in correlation with global agricultural trade pattern, and other food trade networks. The authors (Allan et al., 1993; Craven, 2017; Duncan, 2015; Erokhin, 2017; Schiff, Brunger, 2013) extensively studied food security problem with network theory analysis. Particularly, in (Allan et al., 1993) the

[4] UNFCCC, 2016. Report of the Conference of the parties on its twenty-first session, held in Paris from 30 November to 13 December 2015 (https://unfccc.int/resource/docs/2015/cop21/eng/l09.pdf).

[5] Transforming our world: The 2030 agenda for sustainable development. United Nations, 2015 (https://sdgs.un.org/2030agenda).

Журнал НЭА, № 3 (64), 2024, с. 12–29

concept of the virtual water flow was introduced to cope with the water scarcity problems especially in the arid regions. Later, several authors applied network analysis to study the problem of virtual water trade as a global network (Carr et al., 2012; D'Odorico et al., 2012; Shutters, Muneepeerakul, 2012; Suweis et al., 2011; Tamea et al., 2013) to study its impact on agriculture and food supply.

The situation of deep uncertainty is defined by the absence of any statistical evaluations of the situation progress (Bloemen et al., 2019). We use scenario analysis to model the potential outcomes of events affecting exports/imports in the network under deep uncertainty, and consider models of food networks to identify critical countries in case of export/import quantities' change. For instance, a country has reduced its exports because of a drought, then we find the countries which would experience a deficit of food consumption following the decrease in imports from the initial country. Scenario analysis also helps to solve problems of country's economic policy. For instance, the potential replacement of food shortages with supplies from other countries may be considered.

In order to identify countries that are vulnerable in the import/export networks of staple crops, the *per capita consumption deficit* is used, taking into account production levels.The consumption deficit is quantified as the difference between the actual carbohydrate consumption per capita for a given year and the minimum recommended value of carbohydrate consumption per person per year. A negative value indicates a shortage of carbohydrates.

The main aim of this paper is to propose new models to find the vulnerable countries in terms of food security.

We analyze the export/import and production data of basic crops (rice, wheat, maize, sorghum, barley, rye, millet, buckwheat, oats) for 2020. The consumption of grain crops taking into account physiological needs is analyzed. The countries most dependent on imports of grain products were identified in the classic work (Newman, 2003), as well as the new centrality indices (Aleskerov, Yakuba, 2020; Aleskerov, Shvydun, Meshcheryakova, 2022; Aleskerov, Andrievskaya, Permjakova, 2014). Based on the data for 2020, scenario analysis were performed.

2. Methods

2.1. The model of a network

To represent a food network a directed weighted graph is considered. Directed weighted graph G^0 is a pair (V, W^0), where V is the set of vertices, $|V| = n$, W^0 is the set of edges $\{i, j\}, i, j \in V$ with weights w_{ij}^0.

In this article the countries are represented as the vertices, and the weights on the edges represent the export amounts of products from country i to country j. Consider, for instance, a network of four countries (A, B, C, and D) involved in the trade of a specific food product. Country A exports 100 tons of this product to country C ($w_{AC}^0 = 100$), country B exports 50 tons to C ($w_{BC}^0 = 50$). Country C, in turn, exports 200 tons to country D ($w_{CD}^0 = 200$). Let us assume that the production volumes for countries A, B, C, and D are 200 tons, 210 tons, 290 tons, and 40 tons, respectively. This can be represented as a directed weighted graph with weights assigned to its vertices (Figure 1).

Журнал НЭА, № 3 (64), 2024, с. 12–29

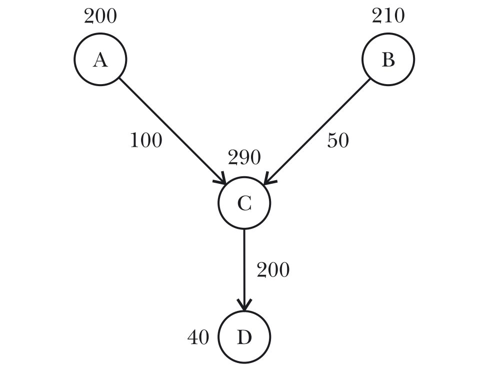

Fig. 1.
An example of network

The per capita value of food consumption for each country i , denoted as FC_i, is defined as:

$$FC_i = (P_i + I_i - E_i) / Pop_i,$$

where P_i is the value of production of product under consideration in the country i; I_i is the value of total import to i; E_i is the value of total export from i; Pop_i is the population of i. It is assumed that the populations of the countries are the following: $Pop_A = 800,\ Pop_B = 1600,\quad Pop_C = 1000,$ $Pop_D = 1600$. Then, the *value of food consumption per capita* for each country is:

$$FC_A = \frac{P_A + I_A - E_A}{Pop_A} = \frac{200+0-100}{800} = 0.125,$$
$$FC_B = \frac{P_B + I_B - E_B}{Pop_B} = \frac{210+0-50}{1600} = 0.1,$$
$$FC_C = \frac{P_C + I_C - E_C}{Pop_C} = \frac{290+150-200}{1000} = 0.24,$$
$$FC_D = \frac{P_D + I_D - E_D}{Pop_D} = \frac{40+200-0}{1600} = 0.15.$$

To identify deficit in food consumption of the product under consideration, the minimum recommended value q is considered. Suppose that the minimum recommended value of consumption of the product in the previous example is 0.06 tons per capita $(q = 0.06)$. If countries A and B stop their export to $C\left(w_{AC}^0 = 0,\ w_{BC}^0 = 0\right)$, then the per capita value of food consumption in C would be 0.09 tons $\left((290+0-200)/1000\right)$. This value exceeds the minimum recommended value of consumption of the product under consideration $(0.09 > 0.06)$, suggesting that C does not depend on imports, its production is sufficient to meet the minimum recommended food consumption. However, if country C stops exporting to D, the value of food consumption in D would be less than the minimum recommended value of consumption $\left((40+0-0)/1600 = 0.025 < 0.06\right)$. This indicates that D is dependent on imports, in other words, country D would face a deficit of food consumption without import. In this way, it is assumed that country i has an influence on country j, if a reduction of export from i to j could lead to a deficit in food consumption in j.

Thus, we introduce the value of deficit of food consumption per capita δ_i for each country i as $\delta_i = FC_i - q$, where q is the minimum recommended value of consumption of the product under consideration.

It means that the value of the deficit per capita δ_i for i is equal to the difference between the value of food consumption per capita in i and the minimum recommended value of consumption of the product under consideration per capita. In other words, the deficit δ_i is the value of excess of food consumption per capita in i . If the value of deficit of food consumption per capita δ_i is a negative number, then country i has an excess (deficit) in food consumption, $FC_i \geqslant q$ $(FC_i < q)$.

Журнал НЭА, № 3 (64), 2024, с. 12–29

Consider the example of the food network in Figure 1. The value of deficit δ_i or countries is equal to:

$$\delta_A = FC_A - q = 0.125 - 0.06 = 0.065,$$
$$\delta_B = FC_B - q = 0.1 - 0.06 = 0.04,$$
$$\delta_C = FC_C - q = 0.24 - 0.06 = 0.18,$$
$$\delta_D = FC_D - q = 0.15 - 0.06 = 0.09.$$

Each country has an excess in food consumption of the product under consideration. Consider the situation where country C reduces its export. The value of deficit δ_i for C and D will be

$$\delta_C = FC_C - q = 0.29 - 0.06 = 0.23,$$
$$\delta_D = FC_D - q = 0.025 - 0.06 = -0.035.$$

The value of excess in food consumption in C will become higher because of export reduction. Country D will have a deficit in food consumption, there is a need to increase food consumption by 0.035 tons to have the minimum recommended value. One of the main aims for networks analysis is to identify key vertices. There are several classic centrality indices such as Eigenvector centrality, PageRank centrality etc (Newman, 2003). In (Aleskerov, Andrievskaya, Permjakova, 2014) it was argued that classical centrality indices do not take into account parameters of the vertices and group influence of vertices to a vertex. In (Aleskerov, Yakuba, 2020; Aleskerov, Andrievskaya, Permjakova, 2014) new classes of centrality indices in networks were introduced, which take into account properties of vertices and group influence. The quota q and the maximum number k of vertices are defined, which can simultaneously influence a node. In this article new centrality indices are adopted for food network.

In (Aleskerov, Yakuba, 2020) the following centrality indices are considered.

1. In-degree index $C^{0in\text{-}degree}$. The In-degree index is calculated for each $i \in V$ in graph as

$$C^{0in\text{-}degree}(i) = \sum_j w_{ji}^0,$$

where w_{ji}^0 – value of weight of the edge from j to i.

In other words, the In-degree index for node i in the graph G^0 is equal to the sum of weights of edges from other nodes to i. For the food network it is considered w_{ji}^0 / Pop_i instead of w_{ji}^0, where Pop_i is the population of i. So, formally,

$$C^{0in\text{-}degree}(i) = \frac{1}{Pop_i} \sum_j w_{ji}^0.$$

1. The In-degree index $C^{0in\text{-}degree}(i)$ is equal to the total value of import per capita for i.

Consider the network in Figure 1. Assume that the population of country A is 800 $(Pop_A = 800)$, B is 1600, C is 1000, and D is 1600. Country A exports to country C 100 tons of considered product, B exports to C 50 tons. The total value of import per capita for C is 0.15 tons,

$$C^{0in\text{-}degree}(C) = \frac{1}{Pop_C} \sum_j w_{jC}^0 = \frac{w_{AC}^0 + w_{BC}^0}{Pop_i} = \frac{100+50}{1000} = 0.15.$$

Country C exports 200 tons of product to D. The total value of import per capita for D is 0.125 tons,

$$C^{0in\text{-}degree}(D) = \frac{1}{Pop_D} \sum_j w_{jD}^0 = \frac{w_{CD}^0}{Pop_D} = \frac{200}{1600} = 0.125.$$

Журнал НЭА, № 3 (64), 2024, с. 12–29

Countries A and B do not get any import from other countries, i.e.

$$C^{0\,in\text{-}degree}(A)=0,\quad C^{0\,in\text{-}degree}(B)=0.$$

Country D is the most dependent of import by the In-degree index.

2. Bundle index BI^0. It is assumed that the maximum number of nodes in G^0, which can simultaneously influence a node is k. For each node i it is defined a critical group S,

$$S\subseteq V\setminus\{i\},\quad (Pop_i)^{-1}\sum_{j\in S}w_{ji}^0 \geqslant \delta_i.$$

In other words, critical group S is the set of vertices which can simultaneously influence i. It is a group of countries that has an influence on country's i import in food network.

For each country i and its critical group of countries S in food network is defined the value $BI_i^0(S)$:

$$BI_i^0(S)=\begin{cases}1, \text{ if } \ Pop_i^{-1}\sum_{j\in S}w_{ji}^0 \geqslant \delta_i,\\ 0, \text{ otherwise.}\end{cases}$$

In other words, the value $BI_i^0(S)$ is equal to 1 for the critical group S, if the sum of edges' weights from countries to i is not less than δ_i. It means that the group of countries S has an influence on i, if a reduction of its export to i can lead to a deficit in food consumption in i.

The Bundle index BI^0 for each country i is defined as $BI^0(i)=\sum_S BI_i^0(S)$. Consider the network in Figure 1. Assume, that the maximum number of countries which can simultaneously influence a node is 2, i.e., $k=2$. The quantities of deficit for A, B, C and D are 0.065, 0.04, 0.18 and 0.09 respectively. Since the countries A and B have no import, the Bundle index BI^0 for A and B is 0. So, $BI^0(A)=\sum_S BI_A^0(S)=0$, $BI^0(B)=\sum_S BI_B^0(S)=0$.

Country C has 0 critical groups. The value of import per capita from A is less $(0.1<0.18)$, from B is less $(0.05<0.18)$ and from the group $\{A,B\}$ is less $(0.1+0.05<0.18)$ than the quantity of deficit.

Country D has one critical group $\{C\}$. The value of import per capita is higher than the quantity of deficit $(0.125>0.09)$.

The Bundle index for C and D is calculated as

$$BI^0(C)=\sum_S BI_C^0(S)=BI_C^0(\{A,B\})+BI_C^0(\{A\})+BI_C^0(\{B\})=0,$$

$$BI^0(D)=\sum_S BI_D^0(S)=BI_D^0(\{C\})=1.$$

Hence, the country D is the only dependent of the import by the Bundle index.

3. Pivotal index PI^0. The node j is called pivotal for a node i in the critical group S, if

$$\sum_{k\in S}w_{ki}^0 \geqslant \delta_i,\quad \sum_{k\in S\setminus\{j\}}w_{ki}^0<\delta_i.$$

In other words, node j is pivotal for node i in the critical group S, if the sum of edges' weights from the nodes without j is less than the quota.

For food network it is considered w_{ji}^0/Pop_i instead of w_{ji}^0, where Pop_i is the population of i. More formally,

$$(Pop_i)^{-1}\sum_{k\in S}w_{ki}^0 \geqslant \delta_i,\quad (Pop_i)^{-1}\sum_{k\in S\setminus\{j\}}w_{ki}^0<\delta_i.$$

Pivotal index PI^0 for each country is defined as

$$PI^0(i)=\sum_S |S|\,PI_i^0(S),$$

where $PI_i^0(S)$ is the number of Pivotal countries in critical group S. In other words, the

Журнал НЭА, № 3 (64), 2024, с. 12–29

Pivotal index PI^0 for node i is equal to the sum of multiplication of the number of critical nodes in S and its cardinality over all critical groups S for i.

For example, consider the food network in Figure 1. The Pivotal index PI^0 for A, B is 0, i.e.

$$PI^0(A) = \sum_S |S| PI_A^0(S) = 0,$$

$$PI^0(B) = \sum_S |S| PI_B^0(S) = 0.$$

Country C has 0 critical groups. There are no pivotal countries in these critical groups, because the quantity of import per capita is less than the deficit δ_C for them.

$$PI^0(C) = \sum_S |S| PI_C^0(S) = 2 \times PI_C^0((A,B\})+1 \times PI_C^0(\{A\})+1 \times PI_C^0(\{B\}) = 0.$$

Country D has one critical group $\{C\}$. Country C is Pivotal because the quantity of import per capita from C is higher than the deficit δ_D.

$$PI^0(D) = \sum_S |S| PI_D^0(S) = 1 \times PI_D^0(\{C\}) = 1.$$

Country D is the only one which depends on import by the Pivotal index.

4. Total influence index TI^0. The Total influence index TI^0 is defined for each node $i \in V$ as

$$TI^0(i) = \alpha_1 CI^0(i) + \alpha_2 BI^0(i) + \alpha_3 PI^0(i),$$

where $\alpha_1, \alpha_2, \alpha_3 \geqslant 0$, $\alpha_1 + \alpha_2 + \alpha_3 = 1$.

In other words, the Total influence index $TI^0(i)$ is equal to weighted arithmetic mean of the In-degree, Bundle and Pivotal indices. For example, if $\alpha_1 = \alpha_2 = 0.3$; $\alpha_3 = 0.4$, then for the example considered above

$$TI^0(A) = 0,\ TI^0(B) = 0,$$

$$TI^0(C) = 0.3 \times 150 + 0.3 \times 0 + 0.4 \times 0 = 45,$$

$$TI^0(D) = 0.3 \times 200 + 0.3 \times 1 + 0.4 \times 1 = 60 + 0.7 = 60.7.$$

Country D is the most dependent of import by the Total index.

Note that the considered indices (in-degree, Bundle, Pivotal, Total) show the dependence of the countries on import. The in-degree index shows the dependence on import by the value of import per capita. The Bundle and Pivotal indices take into account the amount of deficit (of cabohydrates per capita) of each country and group influence of its exporters'. It means that Bundle and Pivotal indices concern coalitions (grouping) of exporting countries, thus influencing the country in concern by blocking exports to it.

2.2. Cascade reactions

Consider the example of the food network in Figure 1. If countries A and B reduce their exports to country C, the food consumption in country C will decrease by 150 units. To maintain its previous level of food consumption, country C could reduce its exports to country D by 150 units, which would lead to a reduction in food consumption in country D by 150 units. The perturbation in the value of export of A and B leads to a change in the food consumption value in country D. This phenomenon is referred to as the indirect influence of countries A and B on country D of length $d = 2$. To assess indirect influence of j on i of length d, we evaluate

$$P_{jk_{11} \ldots k_{1d-1} i} = \min\left(w_{jk_{11}}^0, \ldots, w_{k_{1d-1} i}^0\right),$$

$$\ldots$$

$$P_{jk_{t1} \ldots k_{td-1} i} = \min\left(w_{jk_{t1}}^0, \ldots, w_{k_{td-1} i}^0\right), w_{ji}^{d-1} = \max\left(P_{jk_{11} \ldots k_{1d-1}}, \ldots, P_{jk_{21} \ldots k_{2d-1} i}\right),$$

Журнал НЭА, № 3 (64), 2024, с. 12–29

where $\min\left(w^0_{jk_{n1}},\ldots,w^0_{k_{nd-1}i}\right)$ is the minimum of values of export from j to i in the supply chain of the length d, $\{k_{11}\ldots k_{1d-1}\}$ is the set of intermediate countries in the supply chain under consideration (Aleskerov, Yakuba, 2020).

The value $\max\left(P_{jk_{11}\ldots k_{1d-1}i},\ldots,P_{jk_{t1}\ldots k_{td-1}i}\right)$ is equal to the maximum value of the minimum values of import across all food supply chains from j to i in the food network. In other words, it is the highest reduction over all possible variants of decreasing export from j to i.

Then we construct the directed weighted graph $G^{d-1}(V^{d-1},W^{d-1})$; V is the set of vertices; $|V|=n$, W^{d-1} is the set of edges $\{i,j\},\ i,j\in V$ with weights w^{d-1}_{ji}. The graph G^{d-1} represents an indirect influence of length d in food network G^0.

Centrality indices ($C^{d-1in\text{-}degree}$, BI^{d-1}, PI^{d-1}, TI^{d-1}) for the network G^{d-1} are calculated in the same way as for G^0. The In-degree index $C^{d-1in\text{-}degree}$ is defined as

$$C^{d-1in\text{-}degree}(i)=\left(Pop_i\right)^{-1}\sum\nolimits_j w^{d-1}_{ji},$$

the Bundle index BI^{d-1} – as

$$BI_i^{d-1}(S)=\begin{cases}1,\text{if } \left(Pop_i\right)^{-1}\sum\limits_{j\in S} w^{d-1}_{ji}\geqslant\delta_i,\\ 0,\ \text{otherwise.}\end{cases}\quad BI^{d-1}(i)=\sum\nolimits_S BI_i^{d-1}(S),$$

the Pivotal index PI^{d-1} – as $PI^{d-1}(i)=\sum\nolimits_S |S|\,PI_i^{d-1}(S)$, and the Total influence index PI^{d-1} as $TI^{d-1}(i)=\alpha_1 CI^{d-1}(i)+\alpha_2 BI^{d-1}(i)+\alpha_3 PI^{d-1}(i)$.

Consider the example of food network in Figure 1. The values of indirect influence of the length 2 from A and B to D are

$$P_{ACD}=\min\left(w^0_{AC},w^0_{CD}\right)=100,\ w^1_{AD}=\max\left(P_{ACD}\right)=100,$$

$$P_{BCD}=\min\left(w^0_{BC},w^0_{CD}\right)=50,\ w^1_{BD}=\max\left(P_{BCD}\right)=50.$$

In other words, if country A stops the export to C, then the value of food consumption in country C will decrease. Country C can decrease the export to D by 100 tons to compensate the value of food consumption. It can be said that country A has an indirect export to D equal to 100 tons. It is similarly for an indirect export from B to D.

The graph G^1 with = {A, B, C, D}, W^1 = = {w^1_{AD}, w^1_{BD}} is shown in Figure 2. It shows indirect connections of the graph G^0.

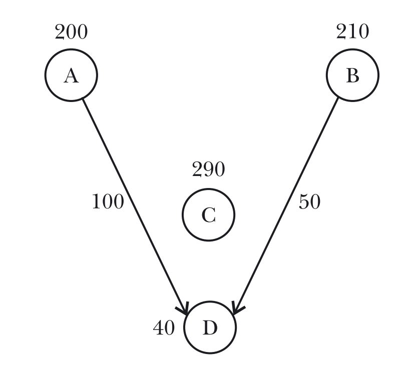

Fig. 2.
The graph of indirect influence

The values of the centrality indices (CI^1, BI^1, PI^1, TI^1) with parameters from the previous examples (k = 2, δ_A = 0.065, δ_B = 0.04, δ_C = 0.18, δ_D = 0.09) are:

$$CI^1(A)=0,\ CI^1(B)=0, CI^1(C)=0,\ CI^1(D)\approx 0.09,$$
$$BI^1(A)=0,\ BI^1(B)=0, BI^1(C)=0,\ BI^1(D)=1,$$
$$PI^1(A)=0,\ PI^1(B)=0, PI^1(C)=0,\ PI^1(D)=4,$$
$$TI^1(A)=0,\ TI^1(B)=0, TI^1(C)=0,\ TI^1(D)\approx 1.93.$$

Журнал НЭА, № 3 (64), 2024, с. 12–29

2.3. Data for Basic Crops

We analyze the export/ import and production data of basic crops (rice, wheat, maize, sorghum, barley, rye, millet, buckwheat and oats) for the year 2018–2020. The import, export, and production data was collected from Food and Agriculture Organization (FAO) and UN Comtrade[6]. The main problem of data was a mismatching in the reporting of import and export values by the countries under consideration. For example, in 2019 data of (wheat, rice, maize, millet, sorghum and rye) from FAO, out of 7078 reported, the equal reported values for import and export were 1461 (20.64%) and the different reported values were 5617 (79.36%). Among the different reported values, the number of missed values (either not reported in import or in export) were 654 (11.64%) in import and 1719 (30.60%) in export. We use methods from (Meshcheryakova, 2020) to correct discrepancies in bilateral trade data.

Carbohydrates

Food contains various nutritious — such as carbohydrates, protein, fats, vitamins and minerals. Carbohydrates provide energy to the body. According to the World Health Organization (WHO), Food and Agriculture Organization (FAO), the percentage of carbohydrates taken daily should be 55–75% calories per person, total fats — 15–30% calories, protein — 10–15% calories, fruits and vegetables greater than 400 grams per day. Carbohydrates play a major role to provide energy to the brain and body without which the body may not function properly. As carbohydrates have 4 calories per grams of consumption then each person should consume 220–320 grams of carbohydrates[7]. The recommended dietary allowance (RDA) suggests the minimum intake for all adults is 130 grams per day (European Food Safety Authority (EFSA), 2017). The main problem of hunger in the world despite producing large volume of food grains is due to the fact that people still cannot have an access to adequate calories or nutrient rich foods (Ravallion, 1987; Sen, 1982). The minimum calories required for an adult is 2000 per day.

The calories contain in various food grains (not cooked) are given in Table 1.

The values of export/import and production of basic crops in 2020 are converted to the values in tons of carbohydrates. For example, 1000 kilograms (1 ton) of wheat contain 725.7 kilograms of carbohydrates (0.7257 tons). For example, Afghanistan exported 327 tons of millet and 2 tons of wheat to Pakistan in 2018. It corresponds to more than 238 and 1 tons of carbohydrates, respectively. We assume that the export from Afghanistan to Pakistan is 239 (238+1) tons of carbohydrates represented by 327 tons of millet and 2 tons of wheat. Based on the total values of export/import in carbohydrates the food network is constructed for 2020.

Table 1.

Quantity of carbohydrates (grams) in 100 grams of crops

Crops	Rice	Wheat	Maize	Barley	Millet	Sorghum	Rye	Oat	Buckwheat
Quantity	79.95	72.57	76.85	73.48	72.85	74.63	69.76	66.27	71.5

Source: Fatsecret, 2023. Whole grain wheat flour. Food database and calorie counter (https://www.fatsecret.com/calories-nutrition/usda/whole-grain-wheat-flour).

---

6 UN Comtrade Database. 2023. Available at: https://comtrade.un.org/data; FAO (2023a). FAOSTAT. Available at: https://www.fao.org/faostat/en/#data

7 Food and Nutrition Information Center (FNIC). National Agricultural Library. USDA, 2023. Available at: https://www.nal.usda.gov/programs/fnic

Журнал НЭА, № 3 (64), 2024, с. 12–29

3. Results and discussion

3.1. Scenario analysis

We use scenario analysis to model the food network under deep uncertainty. Scenario analysis is considered as a process of modeling changes in product flows regardless of the reasons for this process. The main aim is to find the most vulnerable countries when some countries are not able to export or import products for various reasons.

For example, according to information on the official UNICEF website[8], the flood in Pakistan in 2022 led to almost 10 million children suffering from hunger.

We consider the scenario of the flood in Pakistan based on the food network of 2020. It is assumed that production and export will be stopped in Pakistan after the flood. In other words, $P_{Pakistan}=0$, $E_{Pakistan}=0$. The classic (PageRank, In-degree CI^0) and new (Bundle BI^0, Pivotal PI^0) centrality indices are evaluated in the food network before and after the flood to find the most vulnerable countries. The deficit of carbohydrates consumption per capita is calculated to find countries with food insecurity before and after the flood. It is assumed that the maximum number of countries which can simultaneously influence on one country is five ($k=5$). The minimum recommended value of carbohydrates consumption per capita per year is fixed at 47.45 kg (USDA, 2024), $q=47.45$.

3.2. Classic (PageRank, In-degree $C^{in\text{-}degree}$) and new (Bundle BI, Pivotal PI) centrality indices

The list of TOP-5 countries with their centrality indices before and after the flood for direct influence ($d=1$) is presented in Tables 2–3 respectively. The full list of countries' centrality indices can be downloaded by the link[9].

Table 2.

TOP-5 countries by the centrality indices before the flood with direct influence

	PageRank	In-degree $C^{0\,in\text{-}degree}$	Bundle BI^0	Pivotal PI^0
1	Israel	Saint Lucia	Democratic Republic of Congo	Congo
2	State of Palestine	Netherlands	Montenegro	Mauritius
3	Qatar	Israel	Congo	Latvia
4	Oman	British Virgin Islands	State of Palestine	Malta
5	Benin	Belgium	Burundi	Cabo Verde

Table 3.

TOP-5 countries by the centrality indices after the flood with direct influence

	PageRank	In-degree $C^{0\,in\text{-}degree}$	Bundle BI^0	Pivotal PI^0
1	Israel	Saint Lucia	Democratic Republic of Congo	Congo
2	State of Palestine	Netherlands	Montenegro	Mauritius
3	Qatar	Israel	Pakistan	Latvia
4	Oman	British Virgin Islands	Congo	Malta
5	Benin	Belgium	State of Palestine	Cabo Verde

[8] Devastating floods in Pakistan (https://www. unicef.org/emergencies/devastating-floods-pakistan-2022).

[9] https://www.hse.ru/en/DeCAn/networks_under_deep _uncertainty_food_security

Журнал НЭА, № 3 (64), 2024, с. 12–29

Table 4.

TOP-5 countries by the centrality indices before the flood with indirect influence

In-degree $C^{1\,in\text{-}degree}$		Bundle BI^1	Pivotal PI^1
1	Iran	Democratic Republic of Congo	Congo
2	Japan	Montenegro	Mauritius
3	Philippines	Bahamas	Grenada
4	Netherlands	Burundi	Barbados
5	Saudi Arabia	State of Palestine	Maldives

Table 5.

TOP-5 countries by the centrality indices after the flood with indirect influence

In-degree $C^{1\,in\text{-}degree}$		Bundle BI^1	Pivotal PI^1
1	Iran	Pakistan	Mauritius
2	Japan	Democratic Republic of Congo	Congo
3	Philippines	Montenegro	Grenada
4	Netherlands	Bahamas	Barbados
5	Saudi Arabia	Burundi	Maldives

Note that Pakistan is on the third place by the Bundle index after the flood. It means that Pakistan is more dependent on import after the flood than before by the Bundle index.

The list of the TOP-5 countries by the centrality indices before and after the flood for indirect influence ($d = 2$) is presented in Tables 4 and 5 respectively.

The list of countries with deficit in food consumption is presented in Table 6. The values of deficit before and after the flood are presented in the second and the third columns respectively.

Table 6.

The quantity of deficit before and after the flood, kg of carbohydrates per capita

Country	Quantity of deficit before the flood	Quantity of deficit after the flood
Burundi	**−11.27**	**−11.32**
Vanuatu	−18.00	−18.00
Dominica	**−29.06**	**−29.06**
Democratic Republic of Congo	**−12.30**	**−12.39**
Pakistan	**92.58**	**−38.14**
Palestine	−16.80	−16.83
Papua New Guinea	−10.79	−10.79
São Tomé and Príncipe	−6.92	−6.92
Solomon Islands	−4.93	−4.93

Журнал НЭА, № 3 (64), 2024, с. 12–29

Table 6. End

Country	Quantity of deficit before the flood	Quantity of deficit after the flood
Somalia	−12.49	−12.49
Comoros	**44.44**	**−8.60**
Central African Republic	−25.24	−25.24
Montenegro	**−7.43**	**−7.91**

Countries with changing in deficit after the flood are highlighted in bold.

It is clear that Pakistan and Comoros have a deficit of food consumption after the flood. It means that food security in Pakistan depends on its production, in Comoros it depends on the import from Pakistan. The value of Bundle and Pivotal indices for Comoros is higher than 0 before and after the flood.

Consider one more scenario. Suppose Russia increases export to Pakistan by 10% of Russia's total exports. The quantity of deficit after the increase in Russian export to Pakistan would be −23.9 kg of carbohydrates per capita, i.e., $\delta_{Pakistan} = -23.9$. It is important to note that the initial shortage of carbohydrates after the flood in this scenario is crucially reduced to a significant value of 14 kg per capita.

3.3. Policy implications

In the situation of disasters there is a need for fast detection of the problems. The policy of countries and the entire community should be aimed at obtaining tools for rapid response. In this research, we have constructed the new model to detect problems of basic crops consumption in the conditions under deep uncertainty. Scenario analysis is used in this model to respond properly to different types of disasters. Scenario analysis is considered as a process of modeling changes in food flows regardless of the causes of the process. We offer a tool for food policy instead of a specific policy.

The results of our model could be used as an early warning system (see "early warnings"') for the onset of a shortage of carbohydrates and could help identifying the most vulnerable countries. It may be useful for effective response, for reallocation of trade flows between countries. For example, it is shown that the supply of grain crops from Russia to Pakistan in case of flood scenario leads to reduction in the shortage of carbohydrates by 14 kg based on our model.

Also, we introduce a new methodology to analyze situations after (Sokolov, Chulok, 2012; Rij, 2012). The example of analyzing the flood consequences is considered above for scenario of the flood in Pakistan.

Thus, with the help of our model an analysis of various scenarios can help countries to manage appropriate policies and come to efficient solutions. In particular, it can be used as an early warning system by specialists in different spheres.

4. Conclusion

We introduced a new methodology to analyze consequences after situations under deep uncertianty. The new model for studying networks under deep uncertainty was proposed. Then we proposed the new model to identify vulnerable countries in food networks. This model can be used concerning disasters events. Unexpected situations

Журнал НЭА, № 3 (64), 2024, с. 12–29

have been constructed and analysed. The food network based on the data of 2020 was constructed and analysed. We evaluated the consequences of the flood in Pakistan and of increasing export to Pakistan from Russia, and identified most vulnerable countries and countries with deficit in food consumption. Other scenarios can be considered as well.

REFERENCES / ЛИТЕРАТУРА

Aleskerov F.T., Andrievskaya I., Permjakova E. (2014). Key borrowers detected by the intensities of their short-range interactions. *Higher School of Economics Research Paper, WP BRP 33/FE* (in English).

Aleskerov F.T., Badgaeva D.N., Pislyakov V.V., Sterligov I.A., Shvydun S.V. (2016). An importance of Russian and international economic journals: A network approach. *Journal of the New Economic Association*, 2 (30), 193–205 (in Russian). [**Алескеров Ф.Т., Бадгаева Д.Н., Писляков В.В., Стерлигов И.А., Швыдун С.В.** (2016). Значимость основных российских и международных экономических журналов: сетевой анализ // *Журнал Новой экономической ассоциации*. № 2 (30). С. 193–205.]

Aleskerov F.T., Kazachinskaya A.I., Karabekyan D.S., Semina A.S., Yakuba V.I. (2021). Economic journals of Russia, their characteristics and network analysis. *Journal of the New Economic Association*, 2 (50), 170–182 (in Russian). [**Алескеров Ф.Т., Казачинская А.И., Карабекян Д.С., Семина А.С., Якуба В.И.** (2021). Экономические журналы России, их характеристики и сетевой анализ // *Журнал Новой экономической ассоциации*. № 2 (50). С. 70–182.]

Aleskerov F., Shvydun S., Meshcheryakova N. (2022). New centrality measures in networks: How to take into account the parameters of the nodes and group influence of nodes to nodes. New York: CRC Press (in English).

Aleskerov F., **Yakuba V.** (2020). Matrix-vector approach to construct generalized centrality indices in networks. *SSRN Electronic Journal.* Available at: https://ssrn.com/abstract=3597948 (in English).

Ali S., Liu Y., Ishaq M., Shah T., Abdullah, Ilyas A., Din I.U. (2017). Climate change and its impact on the yield of major food crops: Evidence from Pakistan. *Foods*, 6 (6), 39.

Allan J. A. (1993). Fortunately there are substitutes for water otherwise our hydro-political futures would be impossible. *Priorities for Water Resources Allocation and Management*, 13 (4), 26.

Anderson K. (2022). Trade-related food policies in a more volatile climate and trade environment. *Food Policy*, 109, 102253.

Bandara J.S., Cai Y. (2014). The impact of climate change on food crop productivity, food prices and food security in South Asia. *Economic Analysis and Policy*, 44 (4), 451–465.

Bindu L., Titus P., Dhanya D. (2023). Clustered wireless sensor network in precision agriculture via graph theory. *Intelligent Automation & Soft Computing*, 36 (2). DOI: 10.32604/iasc.2023.030591

Birthal P.S., Khan T., Negi D.S., Agarwal S. (2014). Impact of climate change on yields of major food crops in India: Implications for food security. *Agricultural Economics Research Review*, 27 (2), 145–155.

Bloemen P.J., Hammer F., Vlist M.J. van der, Grinwis P., Alphen J. van (2019). DMDU into practice: Adaptive delta management in the Netherlands. In: *Decision making under deep*

Журнал НЭА, № 3 (64), 2024, с. 12–29

uncertainty: From theory to practice. N.Y.: Springer International Publishing, 321–351. DOI: 10.1007/978-3-030-05252-2_14

Brown M.E., Funk C.C., Galu G., Choularton R. (2007). Earlier famine warning possible using remote sensing and models. *Eos, Transactions American Geophysical Union*, 88 (39), 381–382.

Carr J.A., D'Odorico P., Laio F., Ridolfi L. (2012). On the temporal variability of the virtual water network. *Geophysical Research Letters*, 39 (6), L06404.

Clapp J., Moseley W.G., Burlingame B., Termine P. (2022). The case for a six-dimensional food security framework. *Food Policy*, 106, 102164.

Craven L.K. (2017). System effects: A hybrid methodology for exploring the determinants of food in security. *Annals of the American Association of Geographers*, 107 (5), 1011–1027.

D'Odorico P., Carr J., Laio F., Ridolfi L. (2012). Spatial organization and drivers of the virtual water trade: A community-structure analysis. *Environmental Research Letters*, 7 (3), 034007.

Dong C., Yin Q., Lane K.J., Yan Z., Shi T., Liu Y., Bell M.L. (2018). Competition and transmission evolution of global food trade: A case study of wheat. *Physica A: Statistical Mechanics and its Applications*, 509, 998–1008.

Duncan J. (2015). *Global food security governance: Civil society engagement in the reformed Committee on World Food Security.* London: Routledge.

Erokhin V. (2017). *Establishing food security and alternatives to international trade in emerging economies.* IGI Global. DOI: 10.4018/978-1-5225-2733-6

European Food Safety Authority (EFSA) (2017). *Dietary reference values for nutrients summary report* (tech. rep.). Wiley Online Library. DOI: 10.2903/sp.efsa.2017.e15121

FAO, IFAD, UNICEF, WFP and WHO (2017). *The state of food security and nutrition in the world 2017: Building resilience for peace and food security.* Rome: FAO.

Geyik O., Hadjikakou M., Karapinar B., Bryan B.A. (2021). Does global food trade close the dietary nutrient gap for the world's poorest nations? *Global Food Security*, 28, 1–13.

Godfray H.C.J., Robinson S. (2015). Contrasting approaches to projecting long-run global food security. *Oxford Review of Economic Policy*, 31 (1), 26–44.

Hasegawa T., Fujimori S., Havlík P., Valin H., Bodirsky B.L., Doelman J.C. et al. (2018). Risk of increased food insecurity under stringent global climate change mitigation policy. *Nature Climate Change*, 8 (8), 699–703.

Hasegawa T., Fujimori S., Shin Y., Takahashi K., Masui T., Tanaka A. (2014). Climate change impact and adaptation assessment on food consumption utilizing a new scenario framework. *Environmental Science & Technology*, 48 (1), 438–445.

Hasegawa T., Fujimori S., Takahashi K., Masui T. (2015). Scenarios for the risk of hunger in the twenty-first century using shared socioeconomic pathways. *Environmental Research Letters*, 10 (1), 014010.

Havlík P., Valin H., Herrero M., Obersteiner M., Schmid E., Rufino M.C. et al. (2014). Climate change mitigation through livestock system transitions. *Proceedings of the National Academy of Sciences*, 111 (10), 3709–3714.

Heerman K.E. (2020). Technology, ecology and agricultural trade. *Journal of International Economics*, 123, 103280.

Журнал НЭА,
№ 3 (64), 2024,
с. 12–29

Krishnamurthy P.K., Choularton R.J., Kareiva P. (2020). Dealing with uncertainty in famine predictions: How complex events affect food security early warning skill in the Greater Horn of Africa. *Global Food Security*, 26, 100374.

Mall R.K., Gupta A., Sonkar G. (2017). Effect of climate change on agricultural crops. In: *Current developments in biotechnology and bioengineering*. Amsterdam: Elsevier, 23–46. DOI: 10.1016/B978-0-444-63661-4.00002-5

Meijl H. van, Shutes L., Valin H., Stehfest E., Dijk M. van, Kuiper M. et al. (2020). Modelling alternative futures of global food security: Insights from FOODSECURE. *Global Food Security*, 25, 100358.

Meshcheryakova N. (2020). Network analysis of bilateral trade data under asymmetry. In: *2020 IEEE / ACM international conference on advances in social networks analysis and mining* (*ASONAM*). M. Atzmüller, M. Coscia, R. Missaoui (eds.), 379–383. Moscow: HSE University. DOI: 10.1109/ASONAM49781.2020.9381408 (in English).

Mock N., Morrow N., Papendieck A. (2013). From complexity to food security decision-support: Novel methods of assessment and their role in enhancing the timeliness and relevance of food and nutrition security information. *Global Food Security*, 2 (1), 41–49.

Nelson G., Ahammad H., Deryng D., Elliott J., Fujimori S., Havlík P. et al. (2013). Assessing uncertainty along the climate-crop-economy modeling chain. *Proceedings of the National Academy of Sciences USA*, 111 (9), 3274–3279.

Nelson G., Bogard J., Lividini K., Arsenault J., Riley M., Sulser T.B. et al. (2018). Income growth and climate change effects on global nutrition security to mid-century. *Nature Sustainability*, 1 (12), 773–781.

Nelson G.C., Shively G.E. (2014). Modeling climate change and agriculture: An introduction to the special number. *Agricultural Economics*, 45 (1), 1–2.

Newman M.E. (2003). The structure and function of complex networks. *SIAM Review*, 45 (2), 167–256.

Perkins J.M., Nyakato V.N., Kakuhikire B., Tsai A.C., Subramanian S., Bangsberg D.R., Christakis N.A. (2018). Food insecurity, social networks and symptoms of depression among men and women in rural Uganda: A cross-sectional, population-based study. *Public Health Nutrition*, 21 (5), 838–848.

Ravallion M. (1987). *Markets and famines*. Oxford: Oxford University Press.

Rij V. van (2012). New emerging issues and wild cards as future shakers and shapers. *Foresight*, 6, 60–73.

Rosegrant M.W., Cline S.A. (2003). Global food security: Challenges and policies. *Science*, 302 (5652), 1917–1919.

Schaffer-Smith D., Tomscha S.A., Jarvis K.J., Maguire D.Y., Treglia M.L., Liu J. (2018). Network analysis as a tool for quantifying the dynamics of metacoupled systems. *Ecology and Society*, 23 (4). DOI: 10.5751/ES-10460-230403

Schiff R., Brunger F. (2013). Northern food networks: Building collaborative efforts for food security in remote Canadian aboriginal communities. *Journal of Agriculture, Food Systems, and Community Development*, 3 (3), 31–45.

Sen A. (1982). *Poverty and famines: An essay on entitlement and deprivation*. Oxford: Oxford University Press.

Serageldin I. (1999). Biotechnology and food security in the 21st century. *Science*, 285, 387–389.

Журнал НЭА, № 3 (64), 2024, с. 12–29

Shutters S.T., Muneepeerakul R. (2012). Agricultural trade networks and patterns of economic development. *PloS One*, 7 (7), e39756. DOI: 10.1371/journal.pone.0039756

Skaf L., Buonocore E., Dumontet S., Capone R., Franzese P.P. (2020). Applying network analysis to explore the global scientific literature on food security. *Ecological Informatics*, 56, 101062.

Sokolov A., **Chulok A.** (2012). Russian science and technology foresight – 2030: Key features and first results. *Foresight*, 6, 12–25.

Stehfest E., Vuuren D. van, Bouwman L., Kram T. et al. (2014). *Integrated assessment of global environmental change with IMAGE3.0: Model description and policy applications.* Netherlands Environmental Assessment Agency (PBL). Available at: https://www.pbl.nl/sites/default/files/downloads/pbl-2014-integrated_assessment_of_global_environmental_change_with_image30_735.pdf

Sun Q., Hou M., Shi S., Cui L., Xi Z. (2022). The influence of country risks on the international agricultural trade patterns based on network analysis and panel data method. *Agriculture*, 12 (3), 361.

Suweis S., Konar M., Dalin C., Hanasaki N., Rinaldo A., Rodriguez-Iturbe I. (2011). Structure and controls of the global virtual water trade network. *Geophysical Research Letters*, 38 (10). DOI: 10.1029/2011GL046837

Tamea S., Allamano P., Carr J., Claps P., Laio F., Ridolfi L. (2013). Local and global perspectives on the virtual water trade. *Hydrology and Earth System Sciences*, 17 (3), 1205–1215.

U.S. Department of agriculture (USDA) (2024). *Food and Nutrition Information Center (FNIC).* Available at: https://www.nal.usda.gov/programs/fnic

Von Lampe M., Willenbockel D., Ahammad H., Blanc E., Cai Y., Calvin K. et al. (2014). Why do global long-term scenarios for agriculture differ? An overview of the AgMIP global economic model intercomparison. *Agricultural Economics*, 45 (1), 3–20.

Wang J., Dai C. (2021). Evolution of global food trade patterns and its implications for food security based on complex network analysis. *Foods*, 10 (11), 2657.

Wiebe K., Lotze-Campen H., Sands R., Tabeau A., Mensbrugghe D. van der, Biewald A. et al. (2015). Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic and emissions scenarios. *Environmental Research Letters*, 10 (8), 085010.

Woltjer G.B., Kuiper M., Kavallari A., Meijl H. van, Powell J., Rutten M. et al. (2014). *The MAGNET model: Module description.* Tech. rep. LEI Wageningen UR.

Wu W., Tang H., Yang P., You L., Zhou Q., Chen Z. et al. (2011). Scenario-based assessment of future food security. *Journal of Geographical Sciences*, 21, 3–17.

Zanoli R., Gambelli D., Vairo D. (2012). Scenarios of the organic food market in Europe. *Food Policy*, 37 (1), 41–57.

Поступила в редакцию 09.04.2024

Received 09.04.2024

Журнал НЭА,
№ 3 (64), 2024,
с. 12–29

Ф.Т. Алескеров
НИУ «Высшая школа экономики», Институт проблем управления
им. В.А. Трапезникова РАН, Москва

С.Д. Дутта
НИУ «Высшая школа экономики», Москва

Д.С. Егоров
НИУ «Высшая школа экономики», Москва

Д.С. Ткачев
НИУ «Высшая школа экономики», Москва

Сетевой анализ проблем продовольственной безопасности в условиях глубокой неопределенности

Аннотация. Мы предлагаем новые модели поиска уязвимых стран с точки зрения продовольственной безопасности. Данные модели основаны на сетевом анализе в условиях глубокой неопределенности. Условия глубокой неопределенности серьезно влияют на спрос и предложение продовольствия, в том числе углеводов, в различных странах. В таких условиях нами построены сети поставок углеводов между странами. Уязвимость стран с точки зрения продовольственной безопасности определена с помощью новых индексов центральности, учитывающих потребление углеводов и возможность группового влияния экспортеров на рассматриваемую страну. Помимо этого, наши модели определяют прямую и косвенную зависимость конкретной страны от импорта углеводов из других стран. Нами построен сценарий одной из подобных ситуаций и применены наши модели для её исследования. Уязвимые страны определялись нами через потребление углеводов из основных зерновых культур в различных сценариях на основе реальных данных с использованием наших новых моделей. Разработанные модели способны сделать продовольственную политику стран более эффективной.

Ключевые слова: *глубокая неопределенность, продовольственная безопасность, сетевой анализ, сценарный анализ.*

Классификация JEL: C65, D85, Q18.

Для цитирования: **Aleskerov F.T., Dutta S.D., Egorov D.S., Tkachev D.S.** (2024). Networks under deep uncertainty concerning food security // *Журнал Новой экономической ассоциации.* № 3 (64). С. 12–29 (на англ. яз.).

DOI: 10.31737/22212264_2024_3_12-29

EDN: UIJYDA