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О необходимости трансформации парадигмы научных исследований по земледелию (сообщение второе)

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Представлен анализ направлений научных исследований по земледелию, связанных с преобладающей современной парадигмой и четвертой сельскохозяйственной революцией. Следующим этапом развития цифровизации сельского хозяйства становится интеллектуальное земледелие, которое подразумевает использование различных технологических инноваций, включая машинное обучение, компьютерное зрение, дистанционное зондирование, геоинформационное моделирование, Интернет вещей. Рассмотрены особенности использования цифровых технологий и методов искусственного интеллекта по блокам систем земледелия, которые целесообразно применять в планировании научных исследований и анализе полученных результатов. Формирование севооборотов осуществляется моделированием их продуктивности с использованием различных подходов искусственного интеллекта на основе временных рядов урожайности культур и данных дистанционного зондирования. Выбор системы основной обработки почвы возможен с помощью предиктивных моделей урожайности возделываемых культур и других базовых параметров ее эффективности с помощью машинного обучения. Разработку рекомендаций по срокам, дозам и способам внесения удобрений осуществляют с помощью моделей на основе искусственного интеллекта. Синхронизацию внесения удобрений со свойствами почв, погодными условиями и возделываемыми культурами регулируют с помощью различных подходов к цифровому управлению. Защиту посевов сельскохозяйственных культур от вредных организмов реализуют в системе прогнозирования их развития на основании данных о погоде, управляющих воздействий и других типов данных. Предиктивные модели урожайности сельскохозяйственных культур в научных исследованиях по земледелию должны решать задачи имитации урожая и управляющих воздействий в камеральных условиях. На основании результатов виртуальных моделей разрабатывают программы и планы полевых исследований с целью валидации этих моделей. Выбор и сопровождение агротехнологий реализуют в системе учета и анализа взаимодействия широкого спектра условий и факторов с помощью проксимального и дистанционного зондирования (мониторинга) с последующим моделированием процессов и объектов для создания системы поддержки принятия решений в виде ЦСУЗ. В целях масштабирования и адаптации инноваций целесообразно использовать возможности гражданской науки и сетевых Web-платформ.

Ключевые слова: парадигма, системы земледелия, машинное обучение, прогнозирование, масштабирование, севооборот, обработка почвы, удобрения, защита растений, агротехнологии

On the need for a paradigm shift in agricultural research (message two)

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Analysis of the agricultural research directions related to the prevailing modern paradigm and the fourth agricultural revolution is presented. The next stage in the development of digitalization of agriculture is smart farming, which involves the use of various technological innovations, including machine learning, computer vision, remote sensing, geo-information modeling, and the Internet of Things. The peculiarities of using digital technologies and methods of artificial intelligence on farming systems blocks are considered, which are expedient to apply in planning scientific research and analyzing the obtained results. Formation of crop rotations is carried out by modeling their productivity using various artificial intelligence approaches based on time series of crop yields and remote sensing data. Selection of the main tillage system is possible with the help of predictive models of cultivated crop yields and other basic parameters of its efficiency with the help of machine learning. The development of recommendations on timing, doses and methods of fertilizer application is carried out with the help of artificial intelligence-based models. Synchronization of fertilizer application with soil properties, weather conditions and cultivated crops is regulated through various digital management approaches. Protection of crops from pests is realized in the system of forecasting their development on the basis of weather data, control actions and other types of data. Predictive models of crop yields in agricultural research should solve the problems of crop simulation and control actions under office-compiled conditions. Based on the results of virtual models, programs and field study plans are developed to validate these models. Selection and support of agro-technologies are implemented in the system of registration and analysis of the interaction of a wide range of conditions and factors by means of proximal and remote sensing (monitoring) with subsequent modeling of the processes and objects for the creation of a decision support system in the form of DFMS (digital farming management system). In order to scale and adapt the innovations, it is advisable to utilize the capabilities of citizen science and Web-based networking platforms.

Keywords: paradigm, farming systems, machine learning, forecasting, scaling, crop rotation, tillage, fertilizers, plant protection, agricultural technologies

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The focus of research on farming systems in the world science within the framework of the "fourth agricultural revolution" is increasingly shifting towards the application of artificial intelligence methods and digital technologies to assess sustainable development, stable food supply, adaptation to possible climate change, taking into account emerging technological, socio-economic and demographic challenges. Smart farming is the next stage in the development of digitalization of agriculture (after precision farming). In intelligent farming the priority belongs to information analysis with the help of machine learning, predictive analytics and knowledge formalization (conceptualization, ontologization, knowledge bases), including the use of precision farming technologies to create decision support systems (DSS) [1, 2].

According to some authors, smart farming is agriculture 5.0, also called digital agriculture. The integration of artificial intelligence and other modern digital technologies into agriculture represents a significant paradigm shift in this industry. The paradigm transformation is driven by the convergence of various technological innovations, including machine learning, computer vision, remote sensing, geographic information modeling, the Internet of Things, predictive analytics, and others. Together, these technologies are changing the way agriculture is practiced, enabling more efficient resource management, increasing productivity and contributing to sustainable development [3, 4].

Therefore, it is appropriate to consider some aspects of application of artificial intelligence methods and modern digital technologies used in the world science and practice in order to transform the paradigm of scientific research on agriculture and to include them in the programs of research works to meet the world level.

It is known that changes in the type of crops cultivated in a single field over several consecutive growing seasons help to mobilize nutrients in the soil, interrupt disease cycles and limit the spread of weeds and pests. In this regard, crop rotation provides an opportunity to reduce the use of pesticides necessary to protect crops from pests, as well as fertilizers to obtain higher yields. The choice of cultivated crop types, varieties and their distribution over plots on a given planning horizon are the basis for the management of the farming system, and these tasks are realized through crop rotations. These decisions concentrate all the complexity associated with the formatting of the farming system at the level of a particular land use.

Since in adaptive-landscape farming the emphasis is on adaptation to natural and production conditions of land use, crop rotations should not be dogmatic, with a "frozen" scheme of implementation. In this regard, it is advisable to consider crop rotations in at least three variants (alternatives):

– cyclic with fixed length;
– cyclic with variable length;
– less structured cyclic with highly variable lengths.

The specific feature of the implementation of this approach to crop rotations is the possibility of annual adjustments of the crop sowing plan depending on the changing context. For the development and subsequent mastering of flexible crop rotations, it is advisable to model them using various mathematical formalizations.

Two categories of approaches to crop rotation modeling are currently being developed: a theoretical knowledge-based approach and a data-driven machine learning approach. In the first approach, there are methods that model crop rotation as an optimization problem whose solution can be found using linear programming[1],

[1] *Sviridov V.I.* Methodological and methodical aspects of designing the optimal structure of sowing areas in the conditions of transition to adaptive-landscape farming // Bulletin of the Kursk State Agrarian University, 2018, N 2, pp. 4–10.

the CropRota tool[2] or network flow modeling[3]. There are also methods based on agronomic rules (knowledge), such as ROTAT[4] and ROTOR[5]. The main disadvantage of these methods is their inability to adapt to changing conditions, since any change in the model requires the formulation of new rules.

Several approaches can be cited as examples belonging to the second category. For example, the AI4CROPR tool, which determines possible crop yield potential before sowing and generates crop rotation matrices using past normalized difference vegetation index (NDVI) data from remote sensing, clustering and artificial intelligence [5]. Using recurrent neural network (RNN) in the Seq2Seq architecture to predict the most likely scenarios of rotations that will be used in the field in subsequent growing seasons, according to historical crop cultivation data [6]. A system for designing diversified crop rotations based on a set of sustainability indicators that combines a rotation generator model (ROTAT), Pareto-based decision-making tools and a multi-criteria characterization process [7]. Optimization of crop rotations using Parrondo's paradox (paradox is used in game theory and is characterized as a combination of losing strategies that wins). The approach uses the diversity of crop types and environmental uncertainties to improve crop rotations. They calculate optimal probabilities of growing crops in a randomized sequence and propose their deterministic rotation in combination with fertilizer application [8]. Using a six-stage Markov chain-based methodology that predicts the most likely crops to be cultivated in year $n + 1$. Intelligent process analysis and direct flow graphs (DFGs) help to model and visualize the results [9]. Examples could be continued, but we will limit ourselves to the ones given. Mastering of the promising approaches to crop rotation modeling should be considered as a basic element of DSS and integrated with technologies of digital farming systems management.

Basic tillage is the most energy-intensive technological method. Its justified application is the most significant way to regulate the costs of technogenic means. Long-term field studies in different soil and climatic conditions of Western Siberia have shown that optimization of tillage consists in its differentiation depending on these conditions, including weather variability and the level of intensification[6]. Thus, on heavy soils with heavy granulometric composition and waterlogged soils after harvesting grain crops fall tillage (plowing, deep no-tillage loosening) is required. Shallow tillage of slope lands with compacted layer of the lower part of the arable layer does not provide erosion resistance. No-tillage and shallow flat-cutting tillage reduce accumulation of mobile nitrogen compounds in the root layer, which is a negative effect as crops move away from fallow in the crop rotation. Deep tillage, especially moldboard tillage, in conditions of deficit moisture leads to large losses of soil moisture. Black earth soils of medium loamy granulometric composition under normal autumn moistening have favorable composition of arable layer and do not require additional deep loosening[7].

The above is the basic provisions for the selection and application of basic tillage systems,

[2]*Schönhart M., Schmid E., Schneider U.A.* CropRota – A crop rotation model to support integrated land use assessments // European Journal of Agronomy, 2011, vol. 34, N 4, pp. 263–277. DOI: 10.1016/j.eja.2011.02.004.

[3]*Detlefsen N.K., Jensen A.L.* Modelling optimal crop sequences using network flows // Agricultural Systems, 2007, vol. 94, N 2, pp. 566–572. DOI: 10.1016/j.agsy.2007.02.002.

[4]*Dogliotti S., Rossing W.A.H., van Ittersum M.K.* ROTAT, a tool for systematically generating crop rotations // European Journal of Agronomy, 2003, vol. 19, N 2, pp. 239–250. DOI: 10.1016/S1161-0301(02)00047-3.

[5]*Bachinger J., Zander P.* ROTOR, a tool for generating and evaluating crop rotations for organic farming systems // European Journal of Agronomy, 2007, vol. 26, N 2, pp. 130–143. DOI: 10.1016/j.eja.2006.09.002.

[6]*Ecologization of soil tillage in Western Siberia* / Vlasenko A.N., Filimonov Yu.P., Kalichkin V.K., Iodko L.N., Usolkin V.T. / Siberian Branch of the Russian Academy of Agricultural Sciences, SibNIIZhim, Novosibirsk, 2003, 268 p.

[7]*Vlasenko A.N., Kalichkin V.K., Filimonov Y.P., Iodko L.N.* Ecologization of soil tillage and energy saving in the conditions of the South of Western Siberia // Siberian Herald of Agricultural Science, 2002, N 1-2, pp. 3–11.

but more than 20 years have passed since then. During this time, crop cultivation technologies, tools and aggregates for tillage and sowing have changed, and there is a desire to minimize tillage to direct seeding (No-Till technology). The attitude to No-Till has been transformed from doubts about its feasibility in Siberian conditions to full approval. Thus, according to the results of field experiments conducted in 2008-2013 on leached medium loamy chernozem in the forest-steppe of the Novosibirsk region in three-field crop rotations, it was concluded that No-Till is fully competitive in comparison with conventional tillage technology (deep moldboard loosening), while the yield of spring wheat was higher by 0.2 t/ha on average[8].

However, it seems premature to consider that the problem of choosing tillage alternatives is unequivocally solved. For example, a global meta-analysis of 678 studies with 6005 paired observations representing 50 crops and 63 countries showed that yields under no-tillage matched those under conventional tillage only for oilseeds, cotton and legumes. Among cereals, the negative impact of no-tillage was lowest for wheat (-2.6%) and highest for rice (-7.5%) and corn (–7.6%). Application of No-Till technology had a positive effect in rainfed conditions in arid climates, with crop yields often equal to or higher than those under conventional tillage. Yields in the first 1–2 years after the introduction of zero tillage decreased for all crops except oilseeds and cotton, but equaled the yields under conventional tillage in 3–10 years, except for corn and wheat in humid climates. In general, without nitrogen fertilizer application, yields under no-tillage decreased by 12%[9].

For various reasons, no-till technology is not widespread. For example, in the U.S., the use of this technology varies from about 70% of areas under soybean to only 40% of areas under cotton. This is explained by the fact that the transition from conventional tillage to No-Till leads to weed proliferation and subsequent dependence on herbicides, so that savings on fuel, time and labor can be offset by increased herbicide costs [10]. In addition, the implementation of this technology usually results in deficiency of mineral nitrogen in the soil, soil compaction, reduced water permeability, and increased surface runoff on slopes.

Large-scale field research on the systems of basic tillage in different crop rotations is hardly possible at present due to limited human and financial support of agricultural science. In this regard, it is necessary to use the possibilities of artificial intelligence and digital technologies.

There are practically no scientific works on modeling of soil tillage system selection. Studies mainly concern modeling of interaction between working tools and soil during its cultivation. However, a multi-objective decision-making procedure based on fuzzy logic FLoDSS can be given as an example. This program accepts fuzzy input data and generates conclusions in order to help agronomists in planning tillage operations[10]. In our opinion, the choice of the main tillage system can be modeled by predicting the yield of cultivated crops using machine learning, taking tillage as the most important attribute (predictor). It is also possible to integrate predictive models of crop yields with modeling of soil density as one of the indicators of its agro-ecological state for the selection of tillage alternatives [11]. In addition, it is necessary to use time series of data accumulated in past stationary studies, to create knowledge bases with the help of artificial intelligence methods and to form logical rules for selecting the main tillage technique.

[8] *Vlasenko A.N., Vlasenko N.G.* Possibilities of ecologization of technologies in agriculture of Siberia // Achievements of Science and Technology of AIC, 2015, vol. 29, N 9, pp. 21–24.

[9] *Pittelkow C.M., Linquist B.A., Lundya M.E., Liang X., van Groenigenc K.J., Lee J., van Gestel N., Six J., Venterea R.T., van Kessel C.* When does no-till yield more? A global meta-analysis // Field crops research, 2015, vol. 183, pp. 156–168. DOI: 10.1016/j.fcr.2015.07.020.

[10] *Thangavadivelu S., Colvin T.S.* Fuzzy-logic-based decision support system for scheduling tillage operations // Engineering Applications of Artificial Intelligence, 1997, vol. 10, N 5, pp. 463–472. DOI: 10.1016/S0952-1976(97)00023-7..

The role of fertilizers in increasing crop yields and sustainability of crop production can hardly be overestimated. The approach to nutrient management in the soil-plant-atmosphere-management system is based on the 4R concept, which means using the right forms of fertilizers at the right dose, at the right time and in the best way. Synchronization of fertilizer application with soil properties, weather conditions and crops can be achieved through various modelling and numerical control approaches [12].

Currently, fertilizer recommendation models fall into three categories: mathematical; knowledge-based; and artificial intelligence-based. Mathematical models use equations that estimate the fertilizer application rate based on input variables such as planned yield, required amount of nutrients and their uptake by the crop, and fertilizer use efficiency [13]. However, it is not easy to obtain the input variables required for mathematical models and it is difficult to apply them on large geographical scales.

Knowledge-based models are another common type and represent a representative method. With these models, agrochemical and other knowledge is compiled into explicit rules and stored in a database. After matching the rules in the database according to the input data, an appropriate fertilizer application plan is recommended. Although this method is explained quite explicitly, but these rules cannot express some implicit knowledge, which leads to the loss of some information. In addition, knowledge-based models are less capable of using large amounts of data and do not allow automated construction of a knowledge model by generalizing data. Therefore, it is difficult to obtain and formalize knowledge without human assistance, which is their technical “bottleneck” [14].

In recent years, with an increase in computing power, models based on artificial intelligence have been developed. Compared to the other two methods, these models are more efficient, providing modeling through the input of readily available field information. However, many intelligent systems related to fertilizer recommendations use artificial neural networks, resulting in a lack of transparency and explanatory power in the recommendation process [15]. To overcome these negative features of modeling, explainable artificial intelligence is currently being developed. One of the approaches of the latter can be considered the use of knowledge graph technology. Unlike traditional ontology, a knowledge graph can generate complex semantic information with fine granularity and structure. In terms of applications, knowledge graph is an advanced technology for dealing with heterogeneous and cross-domain datasets to solve emerging issues and can effectively extract semantic knowledge [16].

The ability to anticipate the development of pests, assess the possible risks of yield loss and promptly make informed decisions is an integral part of an integrated plant protection system. For this purpose, various approaches are used, including machine learning. In particular, on the materials of time series of long-term field experiments (1996–2018) conducted in the forest-steppe of the Novosibirsk region, we identified the attributes that determine the degree of weediness of crops and assessed their contribution to the predictive model. Using the CART algorithm of decision tree construction, a model of crop weediness forecasting was developed and logical rules of weed development depending on control actions and agrometeorological conditions were formulated, and the coefficient of determination (R2) of the forecasting model was equal to 0.8 [17]. The previous study [18] showed the possibility of applying Bayesian confidence network and multinomial logistic regression to predict the degree of weed infestation of agricultural land. The predictive results of both models coincided in 79% of the cases.

Prediction of plant diseases is currently carried out by building three types of models:

– weather-based;

– image-based;

– based on different types of data from different sources.

The following machine learning algorithms are used: SVM (support vector method), LDA (linear discriminant analysis), QDA (quadratic discriminant analysis), CCT (compact classification tree), MLR (multilinear regression), KNN (k-nearest neighbor), DT (decision tree), RF (random forest), MLP (multilayer perseptron), BN (Bayesian network), HMM (hidden Markov model), ANN (artificial neural network), CNN (convolutional neural network), BPN (back propagation neural network), etc. It is claimed that the application of machine learning algorithms can predict the onset of disease at the presymptomatic stage or early stage of the disease [19]. The PlantVillage dataset, which consists of 54,309 images, is used to train models for plant disease identification and disease severity assessment [20].

Crop yield forecasting models in scientific research on farming, as already mentioned, should solve the problems of planning (simulation) of yield and control actions in desk conditions before going into the field. Great success in predicting yields has been achieved with the help of machine learning. The applied algorithms are approximately the same as for plant disease forecasting, with some variations. The input variables also vary, but mainly soil and weather data as well as control inputs are taken into account. The forecasts are made 1–2 months in advance of harvesting, and some works show the possibility of forecasting at the beginning of sowing. The accuracy of forecasts varies depending on the applied algorithms and the number of the features included in the model. The coefficient of determination (R^2) usually amounts to 0,8–0,9.

In order to predict crop yields taking into account the influence of various elements of agricultural technology (crop rotation, tillage methods, fertilizer doses, degree of crop protection from pests), it is necessary to use the data time series of long-term field experiments and analyze them with the help of artificial intelligence methods. For example, for this purpose we used a feed-forward neural network (FFNN). As predictors we determined qualitative factors (system of basic tillage, preceding crop, application of man-made means, crop placement in crop rotation) and meteorological indicators (average decadal air temperatures and precipitation amounts) that determine spring wheat yield for 2001–2018 in the forest-steppe of the Novosibirsk region. The construction of three models was carried out, which allows the forecast of crop yield for the future growing season depending on the given parameters. The coefficients of determination of the models (R^2) were 0.90; 0.92 and 0.93, the average absolute error varied within the range of 0,05 ± 0,03 [21].

We have developed the Crop Yield Analysis & Forecast (CYAF) program to analyze the results of the field experiments and forecast crop yields using various machine learning algorithms. Input data for the program can be the results of the field experiments of any site with an unlimited number of fixed factors and conditions, the values of which can be measured on both qualitative and quantitative scales. Complexity of using data analysis methods, combination of parametric and non-parametric approaches provide high enough accuracy of crop yield forecasting [22].

Recently, in order to predict crop yields, the number of studies on the application of remote sensing data in the form of various vegetation indices (VI) as additional attributes has increased. In particular, the following indices are used: NDVI, EVI (Enhanced Vegetation Index), NIRv (Near Infrared Reflectance of Vegetation), SAVI (Soil Adjusted Vegetation Index), LAI (Leaf Area Index), GAI (Green Area Index), DM (Total Aboveground Dry Matter Content), NDWI (Normalized Difference Moisture Index), LST (Land Surface Temperature) and other indexes. These indices are calculated from spectral reflectance measurements that are detected by several transmission systems such as satellites, unmanned aerial vehicles (UAVs) and handheld devices. In general, the advantages of spectral remote sensing are speed, non-destructiveness and scalability. However, the usability of vegetation indices for yield prediction is limited by the fact that most of their calibrations are only valid for specific crops and their growth periods [23].

UAVs are also widely used for yield forecasting. For example, the use of UAVs and computer vision has made possible 3D reconstructions for orthomosaic photos and 3D photogrammetric point clouds using Structure from Motion (SfM). SfM is a computer vision method that incorporates multi-view stereo images for object matching, 3D structure acquisition, and estimation of camera position and orientation. The SfM approach has been shown to estimate structural information about crops, such as crown size, plant height and leaf shape [24]. These data are then used to model the allometric relationship between yield and biomass accumulation during different periods of crop vegetation.

As part of the development of the paradigm of research on farming, it is also advisable to form an understanding of the need to analyze the effectiveness of crop agrotechnologies and agronomic management in specific conditions of land use. The agronomic research issues should evolve - from taking into account individual factors - to the study of interaction between their wide range of factors. For these purposes, it is necessary to apply more widely the possibilities of monitoring.

Integration of monitoring data by modern digital technologies of natural objects and crops with geoinformation modeling and artificial intelligence will make it possible to create an automated digital agriculture management system (DAMS).

DAMS is a rule-based and knowledge-based DSS that integrates:

– *in situ* monitoring and remote sensing technologies for crops and natural objects;

– Intelligent analysis of monitoring results and long-term field experiments using machine learning algorithms;

– formation of farming system archetypes and their scaling up;

– modeling of spatial objects and land classification using GIS, etc. [25].

Adaptation to natural-climatic conditions and production resources requires field specialists to adjust their crop cultivation technologies over time (most often annually) and minimize risks. In this regard, in order to make optimal management decisions, a specialist (agronomist) must have a high level of qualification to competently and in a short period of time to carry out time-consuming operations to collect and analyze data. The result of the production process directly depends on the degree of qualification of the agronomist, who must possess not only agro-technological knowledge, but also the ability to process heterogeneous streams of information. At the same time, the volume of agronomic knowledge is large, and the conditions for their realization vary significantly. A specialist engaged directly in production, finds it difficult to fully assess them and, consequently, to develop an acceptable strategy and tactics of “economic behavior” depending on the current and predicted situation. Designing and implementation of scientifically based adaptive agro-technology of a particular crop and variety on a particular field with its geomorphological, soil, hydrological and other natural features is actually an objectively difficult task. In this regard, in order to improve the efficiency of production activities and to make informed management decisions, it is advisable to use digital technologies in the performance of each process.

However, it should be noted that there are both objective and subjective problems with linking scientific data (innovation implementation) to the decision-making process, which can be formulated in the following categories:

– science often emerges from theory that does not always take into account the needs of decision makers;

– individuals differ in how they understand and interpret scientific information for cognitive reasons as well as because of different interests, goals, and prior knowledge;

– decision makers often have “local knowledge” based on experiences that challenge the findings of scientists;

– scientific information is developed and presented to influence, not just to inform, so decision-makers understandably challenge or distrust it [26].

One of the options for increasing confidence in scientific results may be the use of citizen science methodology [27]. The essence of this methodology is that the research involves direct participation of local specialists. It is believed that combining the formal studies of research institutions and the informal knowledge of agronomists can increase efficiency by suggesting more appropriate solutions at the local level. This can be achieved by outsourcing certain tasks to participants and converging the individual steps of research and adaptation. This approach hopes to not only provide adequate information for further analysis, but also to involve specialists in a broad discussion of the results. The implementation of participatory citizen science approaches can make the development of agro-technologies not only more efficient, but also increase the ecological and economic sustainability of the developed innovations.

For the realization of innovations in the world science, the study of various effects at scale has been recently developed [28, 29]. Scaling has become an increasingly popular research area for sustainable development and is one of the most important challenges facing the scientific community. Scaling is concerned with the adaptation, assimilation and use of innovations in wider communities of producers or spatial sites. This approach is usually perceived as the result of deliberate efforts that lead to certain outcomes for society, such as maintaining food availability, job creation and economic growth. In this sense, scaling up is associated with positive change, and high targets have become indicators for those who fund, implement and evaluate scientific results. The growing popularity of the field has contributed to the perception that scaling up is something that can be done and should be pursued in achieving the sustainable agriculture goals.

Also, for the purpose of mastering innovations in agriculture in developed countries in the information respect use various network structures [30]. For example, multi-stakeholder Web-based networking platforms enhance collaboration, training, knowledge and experience sharing, and influence the interaction between agricultural producers, researchers and other actors. It is argued that networked platforms enhance the cognitive potential of innovations and contribute to their scalability.

CONCLUSIONS

1. Intelligent farming is currently the main paradigm of rational use of land resources, increasing biodiversity, reducing the negative impact on the environment, increasing crop productivity and payback of non-renewable resources. It is possible to realize this paradigm through the integration of modern digital technologies and artificial intelligence methods.

2. Crop rotations, being the basis of intrafarm agriculture system, should be flexible and considered in alternative variants: cyclic with fixed length, cyclic with variable length and less structured cyclic with highly variable length. Formation of crop rotations can be carried out by modeling their productivity using various artificial intelligence approaches based on time series of crop yields and remotely sensed data.

3. Selection of the main tillage system is possible with the help of predictive models of cultivated crop yield and other basic parameters of its efficiency with the help of machine learning, taking tillage as the most important trait.

4. Nutrient management in crops and the development of recommendations on the timing, doses and methods of fertilizer application can be carried out using models based on artificial intelligence. Synchronization of fertilizer application with soil properties, weather conditions and crops is managed through various digital management approaches.

5. Protection of crops from pests is realized in the system of forecasting their development on the basis of weather data, control actions, images of plant leaves or other types of data with the use of machine learning algorithms.

6. Crop yield forecasting models in scientific research on agriculture should solve the problems of planning (simulation) of crop yield and control actions in the cameral conditions before going to the field. Based on the results of virtual models, programs and plans of field studies are developed for validation purposes.

7. Selection and support of agro-technologies are realized in the system of taking into account the interaction of a wide range of conditions and factors with the help of proximal and remote sensing (monitoring). Integration of monitoring data by modern digital technologies of natural objects and crops with geoinformation modeling and artificial intelligence makes it possible to create a decision support system and implement it in the form of a DAMS.

8. In order to scale and adapt innovations, it is advisable to utilize citizen science and Web-based networking platforms.

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