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Risk Mitigation in Agriculture in Support of COVID-19 Crisis Management

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Abstract: The main focus of this article is the problem of exacerbating agricultural risks in the context of the COVID-19 crisis, which started against the background of the novel coronavirus (COVID-19) pandemic. The motivation for conducting the research presented in this article was the desire to increase the resilience of agricultural companies to economic crises. This paper is aimed at studying the Russian experience of changing the production and financial risks of agricultural companies during the COVID-19 crisis, substantiating the important role of innovations in reducing these risks, and determining the prospects for risk management in agriculture based on innovations to increase its crisis resilience. Using the structural equation modelling (SEM) method, we modelled the contribution of innovations to the risk management of agriculture during the COVID-19 crisis. The advantages of the SEM method, compared to other conventional methods (e.g., independent correlation analysis or independent regression analysis), include the increased depth of analysis, its systemic character, and the consideration of multilateral connections between the indicators. Using the case-study method, a "smart" vertical farm framework is being developed, the risks of which are resistant to crises through the use of datasets and machine learning. The originality of this article lies in rethinking the risks of agriculture from the standpoint of "smart" technologies as a new risk factor and a way to increase resilience to crises. The theoretical significance of the results obtained is that they make it possible to systematically study the changes in the risks of agriculture in the context of the COVID-19 crisis, while outlining the prospects for increasing resilience to crises based on optimising the use of "smart" technologies. The practical significance of the article is related to the fact that the authors' conclusions and applied recommendations on the use of datasets and machine learning by agricultural companies can improve the efficiency of agricultural risk management and ensure successful COVID-19 crisis management by agricultural companies.

Keywords: agricultural risks; datasets; machine learning; COVID-19 crisis management; risk management of agricultural companies

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1. Introduction

The risks of agriculture are complex and require a special approach to their study. Firstly, they include financial risks, similar to other sectors of the economy (Panagiotou and Tseriki 2022). Financial risks are linked with the changes in the market (e.g., changes in input/output prices in production) and are manifested in the changes in the financial results of business activity (i.e., profits/losses). Entrepreneurial risks in agriculture represent a deterioration in the financial and economic performance of agricultural companies, the main manifestation of which is a decrease in the net financial result (i.e., decrease in profits, increase in losses) (Bai and Jia 2022; Polukhin and Panarina 2022).

Secondly, there are production risks, associated with reduced food production (Welsh et al. 2022). In this case, agricultural risks pose a threat to food security and, therefore, acquire economic significance (Franken et al. 2022; Liu 2022). Food forms the main, lower tier of Maslow's pyramid of needs; therefore, meeting the need for it is critically important for individuals and society (Van Lenthe et al. 2015).

It is also advisable to consider the production risks of agriculture from the perspective of international trade (Zhang et al. 2022a). Unlike other commodities, domestic agricultural production cannot fully replace imports (Panagiotou and Tseriki 2022). Because of this, guided by the principle of the international division of labour, and specialising in the non-food sector, the countries of the world experience increased agricultural production risks in terms of food shortages (Sun et al. 2022).

It should also be taken into account that the establishment of agricultural production requires compliance with a number of serious conditions: the availability of fertile soil suitable for agriculture, a favourable climate, the availability of water supply and fertilisers, etc. (Popkova et al. 2022). Because of this, many countries cannot fully satisfy their domestic demand for agricultural products and must depend on imports. Therefore, the reduction in agricultural production in exporting countries increases the production risks of agriculture in terms of reducing the supply of food available on world markets (i.e., deficits and rising food prices) (Popkova 2022).

The COVID-19 crisis is a serious challenge for the modern economy and entrepreneurship, causing a situation of uncertainty and increasing overall business risks to a critical level (Litvinova 2022; Yelikbayev and Andronova 2022). At the same time, industrial markets reacted differently to the COVID-19 crisis (Inshakova et al. 2021). So, despite the overall decline in GDP—or at least a significant slowdown in economic growth (varying among countries around the world)—some sectors (for example, transport, due to the suspension of international transport links and domestic social distancing regimes) demonstrated a decline, while others (for example, healthcare—medical services, equipment, and pharmaceuticals) showed an increase (Dorczak et al. 2021; Yankovskaya et al. 2022).

Taking into account the noted differences in the consequences of the COVID-19 crisis, its interpretation from the standpoint of risk can provide the most complete and reliable picture of it in the economy and entrepreneurship. The risks of agriculture also deserve special attention due to their specificity, and due to the priority of agriculture as a sector of the economy—associated with low natural rent and good environmental characteristics (for example, compared to industry), as well as playing a major role in ensuring food security.

The purpose of this article is to study the impact of the COVID-19 crisis on the risks in agriculture and to determine the prospects for improving the resilience of agricultural companies to crises based on innovations, using the example of Russia. To achieve this goal, the following research tasks are sequentially resolved in this article: analysis of changes in the risks of agriculture in the context of the COVID-19 crisis; modelling the contribution of innovations (i.e., R&D costs) to agricultural risk management during the COVID-19 crisis; and development of a framework for a "smart" vertical farm, the risks of which are resistant to crises through the use of datasets and machine learning.

Agriculture is a sector that is unique due to the fact that it has not suffered any negative effects from COVID-19. On the contrary, it has grown. Therefore, it is particularly important to study the successful experience of agricultural companies in the sphere of managing the risks of the COVID-19 pandemic and crisis. The main question of this research was what allowed agricultural companies to achieve high resilience to the risks of the COVID-19 pandemic and crisis. This paper tests the hypothesis that this risk resilience is based on innovations. The originality of this article lies in rethinking the risks of agriculture from the standpoint of innovations and, in particular, "smart" technologies as a new risk factor and a way to increase resilience to crises.

The empirical framework of this research is the statistics on food production volume (using the example of grain), with the balanced financial results of agrarian companies and agricultural R&D costs in regions of Russia in 2019–2020. The relevance of this research is due to its revelation of the production risks that are connected with the reduction in food production volume (using the example of grain), as well as financial risks, which are manifested in the deterioration of the financial and economic indicators of agricultural companies' activities (i.e., decrease in the balanced financial result).

The need to study these risks is due to the fact that they inevitably grow under the conditions of economic crises and hinder the sustainable development of agricultural entrepreneurship. The world grain market is destabilised in 2022–2023, and to restore its balance it is necessary to study the experience of managing the risks of agricultural entrepreneurship under the conditions of previous crises, of which the COVID-19 crisis is the most relevant. The experience of Russia is particularly useful and notable, since Russia is one of the largest grain producers and exporters in the world.

This paper's novelty is in its opening a new (regional) aspect of the research of agriculture risks and describing the poorly studied and leading experience of Russia in risk management in grain production. Due to this new regional aspect, this paper's contribution to the literature consists in determining the specifics of production and financial risks and the management of these risks given the climatic, geographical (regions belong to federal districts, with a clear division into southern and northern regions), and socioeconomic (new classification of regions by the level and rate of development) features of agricultural regions.

2. Theory

2.1. Literature Review and Gap Analysis

The conceptual framework of this research is the concept of the agrarian economy. According to this concept, the basis of food systems is agricultural entrepreneurship, which—under the conditions of the market economy—is a flexible market subject that faces risks and implements innovations (Bene et al. 2021). This article draws on the risk theory of agriculture, which has been deeply developed and widely represented in the available research literature.

Each of the identified types of agricultural risk depends on the relevant factors. Production risks depend on natural and climatic factors (Sohail et al. 2022). Deteriorating and unpredictable climate change, soil depletion, and shrinking agricultural land reduce the agricultural production capacity, as well as productivity, exacerbating the problem of food security (Ahmed et al. 2022; Zhang et al. 2022b).

Sales risks are influenced by market factors, including the crisis. The nature of these risks comes down to the ability of agricultural companies to profitably sell the entire volume of agricultural products that they produce on the market (Adhikari and Khanal 2022). This opportunity is determined by market conditions: the level and nature of competition among food producers, the degree of monopolisation at other stages of the value chain in the agro-industrial complex, solvent demand (which is especially important for natural/organic agricultural products), and government regulation of food prices (Bai and Jia 2022; Bai et al. 2022).

Innovations and, in particular, "smart" technologies make a huge contribution to reducing the risks of agriculture. Production risks are reduced by improving the resource provision of the AI-based horizontal farm: precision farming with automated irrigation, dosed fertiliser delivery to each plant, automated harvesting, etc. (Nayal et al. 2022). Sales risks are mitigated by intelligent AI-based sales decision support (Pena et al. 2022).

There are also arguments in the literature that agricultural risks have increased in the face of the COVID-19 crisis. Production risks have increased due to the increase in the cost of raw materials and equipment for agriculture (Prasad et al. 2022). Financial risks have increased due to the disruption of value chains, reduced effective demand, and government regulation of food prices (Gascón and Mamani 2022; Kuleh et al. 2022).

According to the features described in the existing literature, it is proposed to manage each type of risk in agriculture separately. Industrial risk management involves making agriculture more climate-resilient (Howland and Francois Le Coq 2022; Jones and Leibowicz

2022). Agricultural financial risk management involves strengthening the market position of agricultural companies (Ricome and Reynaud 2022; Wang et al. 2022).

The review of the literature presented a high degree of elaboration on the problem at hand. Along with this, an in-depth content analysis of scientific literature revealed two research gaps: The first gap is related to the lack of knowledge of the impact of the COVID-19 crisis on the risks in agriculture. The available literature is dominated by theoretical studies, while empirical experience remains underdeveloped. The existing literature is represented by scattered studies reflecting the experience of individual countries, while the experience of other (i.e., most) countries remains insufficiently studied—in particular, the experience of Russia.

The second gap lies in the lack of scientific research on the prospects for managing risks in agriculture based on "smart" technologies to increase resilience to crises. The existing literature offers scientific and methodological recommendations and applied solutions to reduce the risks of agriculture, but it does not guarantee their resilience to crises, and the role of "smart" technologies in this process is insufficiently researched. The resulting separate management causes inconsistency in the risk management of agriculture.

For example, improving the climate resilience of agriculture through "smart" technologies reduces production risks. However, it often increases financial risks due to the inability of agricultural companies to recoup the high capital costs of technological modernisation, because of their inability to influence market prices in the highly competitive environment (Tong et al. 2019; Yang et al. 2022a). In another example, agrarian companies often reduce their financial risks through artificial scarcity—through monopolistic collusion, causing a rush for food and, consequently, an increase in prices (Kakraliya et al. 2022; Yang et al. 2022b).

These examples point to the serious shortcomings of isolated agricultural risk management, and to the need for an alternative (i.e., new) approach to risk management. This article seeks to fill both identified gaps through a systematic study of the changing risks of agriculture in the context of the COVID-19 crisis and the prospects for increasing resilience to crises based on the optimisation of the use of "smart" technologies, based on a detailed study of the experience of Russia.

2.2. Research Questions and Hypotheses

The identified gaps in the literature determined the formulation of the following two research questions (RQ) in this article:

RQ1: How have the risks of agriculture changed during the COVID-19 crisis?

To correctly understand this issue, it should be noted that the COVID-19 crisis is an unfavourable general business climate in the economy in a certain period (the crisis peaked in 2020). There is no doubt that the impact of the COVID-19 crisis on the risks in agriculture was negative. At the same time, in addition to the COVID-19 crisis in 2020, the risks of agriculture were influenced by many other factors. An example of this is the factor of state regulation—increased state support for agriculture to help it in the context of the COVID-19 crisis, as a priority sector of the economy, could potentially prevent an increase or even reduce the risks of agriculture in 2020 (Sánchez et al. 2022).

The totality and nature of the influence of factors on the risks in agriculture differ between countries, making it advisable to study the experience of each country separately. Russia's experience is noteworthy for several reasons. The country has a progressive, dynamic economy that is clearly showing the impact of the COVID-19 crisis. According to the International Monetary Fund (2022), the economic growth rate in Russia decreased from 2.033% in 2019 to −2.951% in 2020. At the same time, the COVID-19 crisis has not had a critical impact on the Russian economy, allowing for various consequences for agricultural risks (they have not necessarily increased and, therefore, need to be studied). Positive economic growth has already been achieved in 2021, more than doubling the pre-crisis level of 4.690%.

The experience of Russia is also interesting because it has a largely agrarian economy. According to World Bank (2022) estimates, the share of agriculture in the structure of Russia's GDP in 2020 was quite large (more than in many other developed and dynamically developing post-industrial economies) and amounted to 3.7%—an increase compared to the 3.3% in 2010. The experience of Russian agriculture in the context of the COVID-19 crisis has been little studied from the standpoint of entrepreneurial risks. Therefore, to answer t RQ1, we took into account the aforementioned general recession of the Russian economy in 2020, and we also relied on the literature of Manian et al. (2022) and Štreimikienė et al. (2022)—which presents international experience—to put forward the H_1 hypothesis about the risks of agriculture that have increased in Russia in the context of the COVID-19 crisis.

The choice of financial and production risks in this research is explained by the fact that, according to the works of Melekhova et al. (2022) and Wegren (2021), agricultural business is most exposed to these risks in the context of the COVID-19 pandemic and crisis. Assumptions regarding an increase in production risk are explained by the agricultural businesses facing coronavirus limitations because of the lockdown, which could have led to a reduction in the level of loading and production capacity. Financial risks could grow due to the increase in expenditures for fighting the viral threat with fixed prices, which could have led to a decrease in profits—and even losses.

RQ2: Do innovations facilitate better management of agricultural risks, to increase its resilience to the risks of crises?

For the correct understanding of this issue, it should be noted that the foundations of risk management in agriculture are laid down in the works of Capitanio (2022) and of Jones and Leibowicz (2022), studied in sufficient detail, and they are well known. However, the existing management approach can only mitigate—not completely neutralise—the negative impact of the economic crisis on the risks in agriculture. In this regard, it is important to develop a new, alternative approach. Building on the works of Menaga and Vasantha (2022), Qureshi et al. (2022), and Rani et al. (2022), this article puts forward the H_2 hypothesis: that "smart" technologies can increase the resilience of agricultural risks to crises.

In this regard, the experience of Russia as a country with a well-formed digital economy is also interesting. R&D costs in the analysed companies include "smart" technologies—in particular, AI and machine learning. According to the National Research University "Higher School of Economics" (2022), in Russia, 17.2% of agricultural companies used big data collection, processing, and analysis technologies in their activities; 11.6% of agricultural companies in 2020 actively used the Internet of things (IoT); 2.2 % used artificial intelligence (AI); and 4.1% used industrial robots/automated lines.

Therefore, 2.2–35.1% (17.2 + 11.6 + 2.2 + 4.1) of companies from the sample use "smart" technologies in their activity. More precise information on the sample is provided by its creator: automation and digitalisation are used only in 10–13% of enterprises in the sphere of precision farming, and in 15–20% of enterprises in the sphere of precision livestock farming. The main motive of digitalisation is the optimisation of costs. Innovations are implemented mainly in large agro holdings, which have a better technical base and financial risk resilience (Expert 2022).

Answers to the set RQs can be found in this paper with the help of econometric modelling of the systemic interconnection between the balanced financial results (i.e., profit minus loss) of agricultural companies in 2019–2020 and the yield of grain and legumes (weight after processing, in farms of all categories) in 2020, along with R&D costs for agricultural sciences in 2019. The research covers all regions of Russia.

3. Materials and Methods

The main estimation method used to obtain the main results in this paper was structural equation modelling (SEM). The advantages of SEM compared to other conventional methods (e.g., independent correlation analysis or independent regression analysis) are the increased depth of analysis, its systemic character, and the consideration of multilateral connections between the indicators (Crăciun et al. 2023).

The weaknesses of other methods that could have been applied in this research are as follows: (1) insufficient depth of analysis—superficial reflection of only generalised connections between the indicators, with the impossibility of determining the regularities of change in certain indicators under the influence of the change in other indicators (weakness of correlation analysis) (Tseytlin and Grebneva 2022); (2) fragmented results of the analysis—the presence of only one dependent variable, while factor variables can influence several dependent variables at the same time, but each case is considered in isolation, due to which the general picture remains unclear (weakness of regression analysis) (Park and Yi 2023); (3) analysis limited by unilateral connections of the indicators—only the influence of the factor variable on the dependent variable is reflected, but possible reverse influence, through which variables exchange places—i.e., the resulting variable becomes the factor variable, and vice versa—is ignored (weakness of regression analysis) (Pimentel et al. 2023).

The above drawbacks reduce the precision of the results, make them fragmentary, and complicate their interpretation, causing inaccuracies and errors in their treatment. SEM overcomes these disadvantages and allows, first, a quantitative description—with high precision—of the regularities of change in some indicators under the influence of the change in other indicators (Singh et al. 2023) and, second, systemic reflection of the entire totality of connections among the large set of indicators (Yu et al. 2023).

Third, SEM demonstrates multilateral connections among the indicators, which in some cases may be resulting variables, and in other cases factor variables (Syafriana et al. 2023). Due to the above advantages of SEM, using it as the basis for this research methodology guarantees the receipt of the most comprehensive, correct, and precise results, as well as their correct qualitative treatment and scientific interpretation (Yuan et al. 2023). In this article, the study is carried out according to the following structural and logical scheme (Table 1):

Table 1. Structural and logical scheme of the study.

Research Question	Research Objective	Research Method	Essence of the Research
RQ1: How have the risks of agriculture changed during the COVID-19 crisis?	Risk analysis of agriculture during the COVID-19 crisis	Horizontal analysis method	Analysis of changes in the volume of production and the net financial results of agricultural companies in the regions of Russia in 2020 compared to 2019
RQ2: Do innovations facilitate better management of agricultural risks, to increase resilience to the risks of a crisis?	Modelling the contribution of smart technologies to agricultural risk management during the COVID-19 crisis	Structural equation modelling (SEM) method	Modelling systemic links between the costs of agricultural R&D in 2019 and the production and balanced financial results of agricultural companies in Russian regions in 2020
	Development of a framework for a "smart" vertical farm, the risks of which are resistant to crises through the use of datasets and machine learning	Case-study method	Description of the case experience of organising the work of a "smart" vertical farm of ISC * and CSDTL * based on datasets and machine learning, reflecting its advantages in the form of increased risk resistance of this farm to crises—in particular, the COVID-19 crisis

* ISC—Institute of Scientific Communications: a research institute in Volgograd (Russia), one of the main areas of which is the agrarian economy and agriculture. * CSDTL—Consortium for Sustainable Development and Technology Leadership: a consortium that brings together a number of universities and research institutes (Russia), one of the main areas of which is the agrarian economy and agriculture. Source: developed and compiled by the authors

As shown in Table 1, to answer RQ1, the first task of this study was to analyse the risks of agriculture in the context of the COVID-19 crisis. The methodology for solving this problem was based on a theoretical understanding of risks as deterioration in the economic performance of agricultural companies. Two key types of risk faced by agricultural companies were taken into account: Firstly, financial risks, manifested in the deterioration of the financial and economic performance of agricultural companies, and the decrease in the net financial result (i.e., decreased profits, increased losses).

Secondly, production risks are associated with a reduction in the volume of food production (e.g., grain). Using the horizontal analysis method, the changes in the yield of grain and legumes (weight after processing, in farms of all categories) and the changes in the balanced financial results of agricultural companies in the regions of Russia in 2020 compared to 2019 were determined. Negative growth indicates the presence of risks in agriculture during the COVID-19 crisis.

The method of analysis of variance was used to discover trends in the annual variation in the production of grain and the balance of agricultural companies. The method of correlation analysis was used to determine the connections between the innovation performance in agriculture before the pandemic (2018–2019), during the acute phase of the pandemic (2020), and after the end of the acute phase of the pandemic (2021). The methods of analysis of variance and correlation analysis were used as part of a preliminary analysis to obtain important information for the subsequent application of the main method of this research: structural equation modelling (SEM).

The balanced financial result (i.e., profit minus loss) of agricultural companies (unit: million RUB in the Appendix A) reflects the average profit/losses of companies in each region. The research was performed at the meso level (the level of Russian regions) in the context of categories of regions designated by the Institute of Scientific Communications (2022) in the dataset "Interactive statistics and intellectual analytics of the balance of the Russian regional economy based on big data and blockchain—2022": (1) Rockets: leading and quickly developing regions; (2) Racers: regions with a large potential for development; (3) Parachutists: progressive regions with slow development; (4) Turtles: lagging regions.

This allows consideration of the specifics of risk management based on innovations and the differences in the risk resilience of agricultural companies that are predetermined by the meso-economic environment, i.e., the level and rate of the region's socioeconomic development. To take into account the influence of natural and climatic factors on the risk management of agrarian companies with the help of innovations, we analysed the model in the context of federal districts, which are based on geographical factors.

To answer RQ2, the second objective of this study was to model the contribution of smart technology to agricultural risk management during the COVID-19 crisis. Using the structural equation modelling (SEM) method, systemic relationships were modelled between the costs of agricultural R&D in 2019 and in 2020, and between the production and balanced financial results of agricultural companies in the regions of Russia in 2020.

The SEM method was used for the same purposes (RQ_2) in previous works by Luu et al. (2019) and Sohail and Chen (2022). The choice of SEM can be explained by its high precision and its ability to obtain the most explicit results, which describe not only unilateral but also bilateral (which cannot be discovered with the help of regression analysis) links between indicators.

The economic point is the systemic relationship between the risks of agricultural companies, and it takes into account the delayed effects of these risks. As a key risk factor for agricultural companies, the costs of research and development (R&D) in agricultural sciences must be taken into account. According to Rosstat (Federal State Statistics Service) (2023), R&D costs are not necessarily the implementation of smart technologies, but the implementation of any innovations. Dependencies between indicators are determined using the regression analysis method, and the so-called SEM errors are determined using the variation analysis method as a measure of the spread of indicator values. The research model is written as follows:

$$\begin{cases} Balance20 = a_1 + b_1 RD19 + b_2 RD20 + b_3 RProduction20; \\ Production20 = a_2 + b_4 RD20 + b_5 Balance19, \end{cases} \tag{1}$$

where Balance19 is the balanced financial result (profit minus loss) of agricultural companies in 2019 (million RUB);

Balance20 is the balanced financial result (profit minus loss) of agricultural companies in 2020 (million RUB);

Production20 is the yield of grain and legumes (weight after processing, in farms of all categories) in 2020 (centners per hectare of harvested area);

R&D19 is the cost of R&D in agricultural sciences in 2019 (million RUB);

R&D20 is the cost of R&D in agricultural sciences in 2020 (million RUB).

The research model (1) aims to demonstrate the impact of R&D and the net financial result of 2019–2020 on the volume of production and, as a result, the net financial results of agricultural companies in 2020. The reliability of the regression models was tested using Fisher's F-test and correlation coefficients (Sureiman and Mangera 2020). To test the regression model, we also performed Student's *t*-test (Marcoulides and Yuan 2016). Only reliable regression results were included in the SEM model.

The study sample included all regions of Russia, because sufficiently detailed statistics have been collected to study agricultural risks at the regional level. The data source was Rosstat (Federal State Statistics Service) (2023). The empirical basis for this study is given in Appendix A.1. A list of the main agricultural companies in Russia and a description of their activities based on the materials of Expert (2022) are given in Appendix A.2.

According to Rosstat (Federal State Statistics Service) (2023), there are 102,900 agricultural companies in Russia. Therefore, the 50 companies of the sample account for 0.05% of agricultural entrepreneurship in Russia. At the same time, the sample includes the 50 largest agricultural companies in Russia, which are leaders in the food markets, and to which other market players look up. This allows the extension of the studied experience of the top 50 companies to the agricultural entrepreneurship of Russia on the whole. The data on agricultural companies were taken from the dataset of Expert (2022).

As part of the third task of this study, a "smart" vertical farm framework was developed, the risks of which are resistant to crises through the use of datasets and machine learning. With the help of the case-study method, the case experience of organising the work of a "smart" vertical farm by the Institute of Scientific Communications (ISC) and the Consortium for Sustainable Development and Technology Leadership (CSDTL)—based on datasets and machine learning—is described, reflecting its advantages in the form of increased risk resistance of this farm to crises (in particular, the COVID-19 crisis).

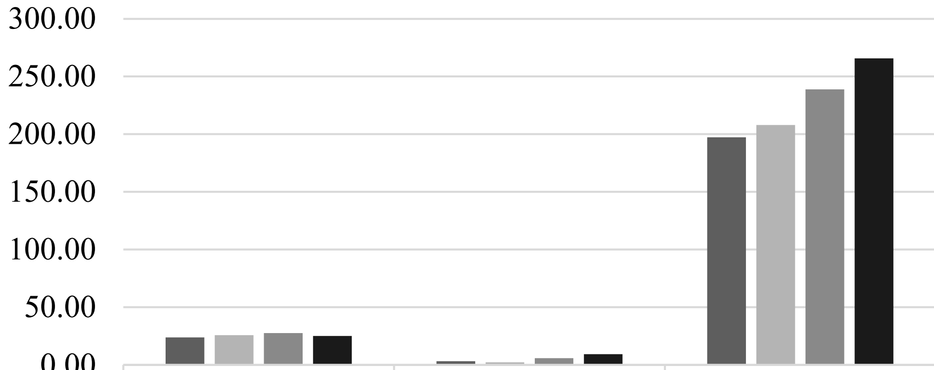
4. Results

4.1. Risk Analysis of Agriculture during the COVID-19 Crisis

To search for an answer to RQ1 within the first task of this research, we performed an analysis of the risks to agriculture during the COVID-19 crisis. The methods of horizontal analysis and analysis of variance, based on the data from Table A1, were used to determine the changes in the yield of grain and legumes (weight after processing, in farms of all categories), the changes in the balanced financial results of agricultural companies, and the changes in agricultural R&D costs in regions of Russia in 2018–2021 (Figures 1–3).

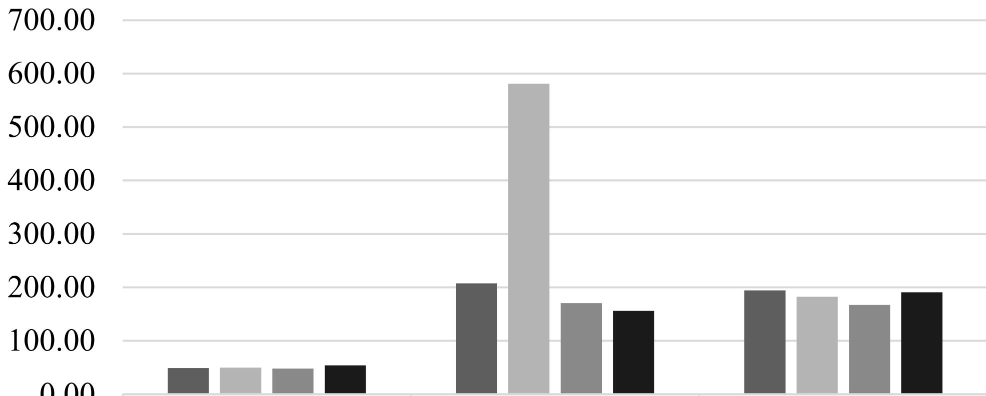
According to Figure 1, agricultural companies in Russia, on the whole, faced financial and production risks during the COVID-19 crisis, but the effect of these risks was delayed in time. Thus, at the level of agricultural entrepreneurship on the whole, the yield of grain and legumes (weight after processing, in farms of all categories) in 2020 (27.63 centners per hectare of harvested area) grew by 7.16% compared to 2019 (25.78 centners per hectare of harvested area).

According to Figure 2, the growth in the yield of grain and legumes in 2020 decreased compared to the pre-pandemic growth in 2019 (7.16%). In 2021, the delayed effect of the pandemic manifested: a reduction in the yield of grain and legumes by 9.12%. Variation in the yield of grain and legumes also grew in 2021 (54%) compared to 2018–2020 (48–49%).



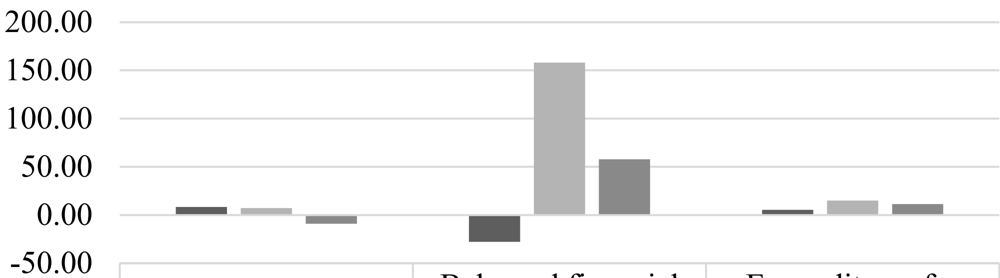
	Yield of grain and legumes	Balanced financial result of agricultural companies	Expenditures for R&D in agricultural sciences
Arithmetic mean in 2018	23.79	3.15	197.31
Arithmetic mean in 2019	25.78	2.27	207.88
Arithmetic mean in 2020	27.63	5.87	238.81
Arithmetic mean in 2021	25.11	9.25	265.63

Figure 1. Arithmetic mean of agricultural risks during the COVID-19 crisis in Russia in 2018–2021. Source: developed and compiled by the authors.



	Yield of grain and legumes	Balanced financial result of agricultural companies	Expenditures for R&D in agricultural sciences
Variation in 2018, %	48.94	207.53	194.34
Variation in 2019, %	49.81	580.93	182.79
Variation in 2020, %	48.20	170.47	167.14
Variation in 2021, %	54.00	156.20	190.87

Figure 2. Analysis of variance of agricultural risks during the COVID-19 crisis in Russia in 2018–2021. Source: developed and compiled by the authors.



	Yield of grain and legumes	Balanced financial result of agricultural companies	Expenditures for R&D in agricultural sciences
Growth in 2019, %	8.37	-27.82	5.35
Growth in 2020, %	7.16	158.03	14.88
Growth in 2021, %	-9.12	57.79	11.23

Figure 3. Trend analysis of agricultural risks during the COVID-19 crisis in Russia in 2018–2021. Source: developed and compiled by the authors.

According to Figure 3, the balanced financial result of agricultural companies in 2020 (RUB 5865.2 million) grew by 158.03% compared to 2019 (RUB 2273.1 million). In 2021, the growth of the balance of agricultural companies reduced to 57.79%, which was much lower than its growth in 2020 (+158.03%), although before the pandemic this growth was negative (−27.82% in 2019). Therefore, the balance of agricultural companies was determined not only by the pandemic in 2020–2021, but also by the influence of other factors that, perhaps, were more significant.

However, certain agricultural companies faced agricultural risks under the conditions of the COVID-19 crisis. Out of 75 objects of the sample, the reduction in the yield of grain and legumes (weight after processing, in farms of all categories) in 2020 compared to 2019 took place in 12 (16%) objects, and deterioration of financial and economic indicators of agricultural companies' activity (i.e., reduction in profit; increased losses) was observed in 30 (40%) objects.

Expenditures for agricultural R&D in 2020 (14.88%) and 2021 (11.23%) were doubled compared to the pre-pandemic level (the growth in 2019, compared to 2018, was 5.35%). To determine how the role of innovations changed before and after the COVID-19 pandemic, a correlation analysis of the connections between the risks to agriculture and innovations (i.e., costs of R&D in agricultural sciences) in Russia in 2018–2021 was performed, as shown in Figure 4 (based on the data from Table A1).

As shown in Figure 4, the connection (correlation) between the yield of grain/legumes and innovations (i.e., costs of R&D in agricultural sciences) before the pandemic was 0.16 in 2018 and 0.13 in 2019, but during the pandemic it increased to 0.19 in 2020, and in 2021 it returned to the highest pre-pandemic level of 0.16.

The connection between the balanced financial result of agricultural companies and innovations (i.e., costs of R&D in agricultural sciences) before the pandemic was 0.23 in 2018; in 2019, it was negative (−0.04). During the pandemic, it reached 0.43 in 2020 and decreased in 2021, remaining at a much higher level compared to the pre-pandemic level (0.25).

The results obtained show that no serious risks to agriculture appeared during the COVID-19 crisis; thus, this crisis did not create a threat to Russia's food security. However, certain agricultural companies faced risks; thus, there is a need for risk management. The financial and production risks faced by agricultural companies in Russia grew substantially after the end of the acute phase of the pandemic (2021), compared to the acute phase of the pandemic (2020) and, in particular, to the pre-pandemic level (in 2018–2019). This is a sign of the delayed effect of the risks caused by COVID-19 in agriculture and the necessity of strategic risk management.

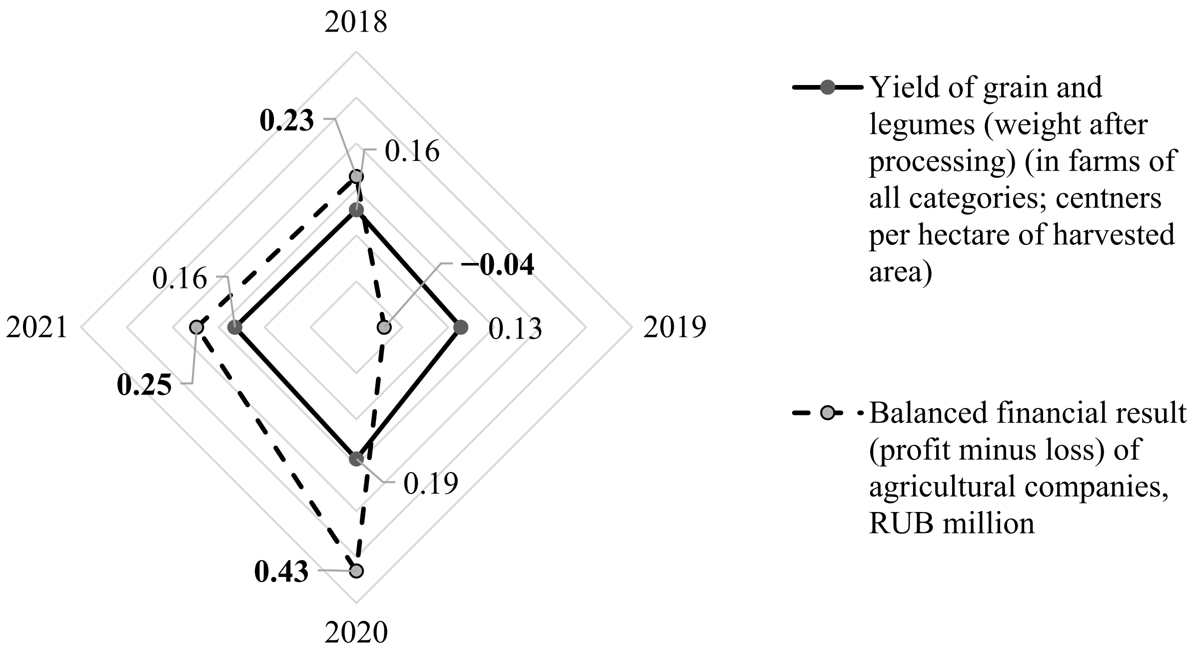


Figure 4. Correlation analysis of the connections between the risks to agriculture and innovations in Russia in 2018–2021. Source: developed and created by the authors.

The quick (i.e., doubled) growth in the innovative activity of agricultural companies in Russia allowed for a substantial reduction in COVID-19 risks. As a result, the connections between innovations and the production (by 46% in 2020 compared to 2019: from 0.13 to 0.19) and financial (by 87% in 2020 compared to 2018: from 0.23 to 0.43) risks of agricultural companies grew significantly. Thus, innovations should be set on the basis of risk management in agriculture during the pandemic.

4.2. Modelling the Contribution of Smart Technologies to Agricultural Risk Management during the COVID-19 Crisis

To answer RQ2, the second task of this study was to model the contribution of smart technologies to agricultural risk management during the COVID-19 crisis. The relationships between the yield of grain and legumes (weight after processing, in farms of all categories), the segregated financial results of agricultural companies, and the volume of R&D costs in agriculture were determined by the research model (1) and empirical data from Table 1 using the regression analysis method:

$$\begin{cases} Balance20 = -2671.2945 - 79.6784RD19 + 84.2098RD20 + \\ \qquad +180.6058RProduction20; \\ Production20 = 25.6342 + 0.0067RD20 + 0.0002Balance19, \end{cases} \tag{2}$$

The system of Equation (2) refines the research model (1) and indicates that the costs of R&D in agricultural sciences act as a key risk factor for agricultural companies. Thus, an increase in the volume of costs of R&D in agricultural sciences in 2020 by RUB 1 million led to an increase in the yield of grain and legumes (weight after processing, in farms of all categories) in 2020 by 0.0067 centners per hectare of harvested area.

An increase in the costs of R&D in agricultural sciences in 2020 by RUB 1 million led to an increase in the balanced financial result (i.e., profit minus loss) of agricultural companies in 2020, by RUB 84.2098 million. An increase in the balanced financial results (profit minus loss) of agricultural companies in 2019 by RUB 1 million led to an increase in the yield of grain and legumes (weight after processing, in farms of all categories) in 2020, by 0.0002 centners per hectare of harvested area.

An increase in the yield of grain and legumes (weight after processing, in farms of all categories) in 2020 by 1 centner per hectare of harvested area led to an increase in the balanced financial result (profit minus loss) of agricultural companies in 2020, by RUB 180.6058 million. The results obtained demonstrate a close systemic interconnection between the considered indicators. Innovations have a quick effect on the production of grain, but a delayed (long-term, manifesting after a year) effect on the balance of agricultural companies.

To check the reliability of the regression models obtained in the system of Equation (2), let us turn to the detailed regression statistics and the results of the dispersion analysis (Tables 2 and 3).

As shown in Table 2, the multiple correlation was 0.7804, and R^2 was 0.6091. Therefore, 60.91% of the change in the balanced financial result (profit minus loss) of agricultural companies in 2020 is explained by the changes in the costs of agricultural R&D in 2019 and the yield of grain and legumes (weight after processing, in farms of all categories) in 2020. The obtained value of significance F (1.77×10^{-14}) demonstrates that the considered regression model must be correct at the level of significance of $\alpha = 0.01$. For 75 observations and three factor variables ($k_1 = 3$; $k_2 = 75 - 3 - 1 = 71$), F-table was 4.0701. F-observed was 36.8721, exceeding F-table (the F-test was passed).

T-table at a 0.01 level of significance and 74 degrees of freedom was 2.6439. The observed t-Stat for all independent variables exceeded this value modulo, equalling 7.3553 for R&D19, 8.1080 for R&D20, and 3.1120 for Production20. This means that the regression model is significant at the 0.01 level of significance.

The independent variable R&D19 did not demonstrate a positive contribution to the balance of agricultural companies in Russia in 2020 (the regression coefficients acquired a negative value: −79.6784). Therefore, the delayed/long-term effect of R&D was not discovered, although we could see the short-term effect of R&D conducted in 2020.

Table 2. Regression statistics and factor analysis of variance of the balance of agricultural companies in Russia in 2020.

Regression statistics						
Multiple R	0.7804					
R-squared	0.6091					
Adjusted R-squared	0.5925					
Standard error	6382.1391					
Observations	75					
	ANOVA					
	df	SS	MS	F	Significance F	
Regression	3	4,505,592,433	1,501,864,144	36.8721	1.77×10^{-14}	
Residual	71	2,891,950,680	40,731,699.7130			
Total	74	7,397,543,113				
	Coefficients	Standard Error	t-Stat	*p*-Value	Lower 95%	Upper 95%
Y-intercept	−2671.2945	1720.8633	−1.5523	0.1250	−6102.5985	760.0095
R&D19	−79.6784	10.8327	−7.3553	2.6×10^{-10}	−101.2782	−58.0785
R&D20	84.2098	10.3861	8.1080	1.1×10^{-11}	63.5006	104.9190
Production20	180.6058	58.0357	3.1120	0.00268	64.8859	296.3257

Source: compiled by the authors.

The *p*-value for the constant a_1 (2671.2945) was 0.1250. Thus, a_1 is different from zero. The *p*-value for the independent variable R&D20 was 1.1×10^{-11}, while that for the independent variable Production20 was 0.0024; therefore, both factor variables had a statistically significant impact on the balance of agricultural companies in Russia in 2020. This allows us to conclude that the balance of agricultural companies in Russia in 2020 was determined by the following: (1) yield of grain and legumes (weight after processing, in farms of all categories) in 2020, and (2) costs of R&D in agricultural sciences in 2020.

Table 3. Regression statistics and factor analysis of variance of the yield of grain and legumes in Russia in 2020.

Regression Statistics						
Multiple R	0.2514					
R-squared	0.0632					
Adjusted R-squared	0.0372					
Standard error	13.0653					
Observations	75					
	ANOVA					
	df	SS	MS	F	Significance F	
Regression	2	829.2160	414.6080	2.4288	0.0953	
Residual	72	12,290.6259	170.7031			
Total	74	13,119.8419				
	Coefficients	Standard Error	t-Stat	*p*-Value	Lower 95%	Upper 95%
Y-intercept	25.6342	1.7941	14.2881	0.0000	22.0578	29.2107
R&D20	0.0067	0.0038	1.7575	0.0831	−0.0009	0.0143
Balance19	0.0002	0.0001	1.4782	0.1437	−0.0001	0.0004

Source: compiled by the authors.

As shown in Table 3, the multiple correlation was 0.2514, and R^2 was 0.0632. Therefore, 25.14% of the change in the yield of grain and legumes (weight after processing, in farms of all categories) in 2020 was explained by the change in the costs of agricultural R&D in 2020 and the balanced financial result (profit minus loss) of agricultural companies in 2019. This relatively small value is a sign of lower predictability of the dependent variable Production20 on independent variables (i.e., R&D20, Balance19).

Both factor variables were statistically significant; their *p*-values were 0.0831 and 0.1437, respectively, both of which were $<\alpha$ (0.15). The obtained value of significance F (0.0953) shows that the considered regression model must be correct at the level of significance $\alpha = 0.15$. For 75 observations and three factor variables ($k_1 = 2$; $k_2 = 75 - 2 - 1 = 72$), F-table was 1.9480; F-observed was 2.4288, exceeding F-table (the F-test was passed). T-table at the level of significance of 0.15, at 74 degrees of freedom, was 1.4546. The observed t-Stat for all independent variables exceeded this value, equalling 1.7575 for R&D20 and 1.4782 for Balance19. This means that the regression model is reliable at the 0.15 level of significance.

Based on the system of Equation (2), using the SEM method, the authors modelled systemic relationships between the costs of agricultural R&D in 2019–2020 and the production and balanced financial results of agricultural companies in the regions of Russia in 2020 (Figure 5).

The SEM model in Figure 5 reflects the systemic relationships among risks faced by agricultural companies and takes into account the delayed effects of these risks. The model also shows that the spread of all considered indicators was huge in the context of the COVID-19 crisis, increasing the agricultural risks. The key to reducing them is to increase spending on agricultural R&D.

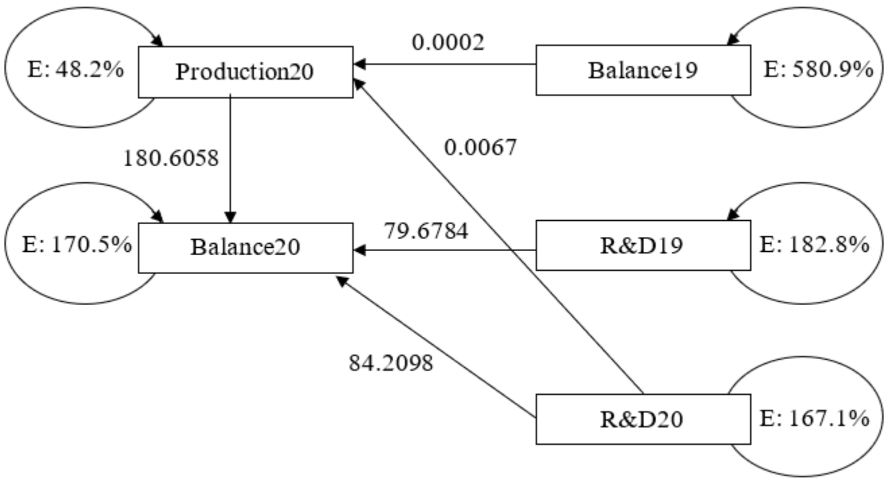


Figure 5. SEM model of systemic relationships of agricultural R&D costs in 2019–2020 with production and net financial results of agricultural companies in Russian regions in 2020. Source: developed and compiled by the authors.

To take into account the specifics of risk management based on innovations and the differences in the risk resilience of agricultural companies, predetermined by the meso-economic environment (i.e., the level and rate of the region's socioeconomic development), the model (Figure 2) was analysed in the context of the categories of regions designated by the Institute of Scientific Communications (2022) in the dataset "Interactive statistics and intellectual analytics of the balance of the Russian regional economy based on big data and blockchain—2022". The results obtained are given in Table 4.

Table 4. Analysis of the model by region, categorised by the level and rate of socioeconomic development.

Categories of Regions by the Level and Rate of Socioeconomic Development	Correlation of R&D in 2019 with Production in 2020	Correlation of R&D in 2019 with Balance in 2020
Rockets: leading and quickly developing regions	−0.1041	0.1384
Racers: regions with large potential for development	0.4428	−0.5048
Parachutists: progressive regions with slow development	0.9915	0.5895
Turtles: lagging regions	0.6161	0.5090

Source: authors.

The results from Table 4 show that in "parachutist" regions (progressive regions with slow development), R&D's correlation with the production (0.9915) and balanced financial result of agricultural companies (0.5895) is particularly high. In "turtle" regions, R&D's correlation with the production (0.6161) and balanced financial result of agricultural companies' activity is also high (0.5090).

However, in the "rocket" and "racer" regions, the contribution of innovations to risk management is far less visible. This allows us to conclude that innovations increase the risk resilience of agricultural companies only in the case of a stable meso-economic environment. Rapid socioeconomic development of a region reduces the useful effect of innovations for the risk management of agricultural companies.

To take into account the influence of natural and climatic factors on the risk management of agricultural companies with the help of innovations, we analysed the model at the level of federal districts, which are based on geographical factors (Table 5).

Table 5. Analysis of the model at the level of federal districts of the Russian Federation.

Categories of Regions by the Level and Rate of Socioeconomic Development	Correlation between R&D in 2019 and Production in 2020	Correlation between R&D in 2019 and Balance in 2020
CFD—Central Federal District;	−0.0815	−0.0185
NWFD—Northwestern Federal District;	−0.4581	−0.1482
SFD—Southern Federal District;	0.8206	0.8062
NCFD—North Caucasus Federal District;	0.7575	0.8557
VFD—Volga Federal District;	0.2037	0.1955
UFD—Ural Federal District;	−0.7837	0.6037
SFD—Siberian Federal District;	0.7428	0.6107
FFD—Far Eastern Federal District.	−0.0255	−0.1014

Source: authors.

The results from Table 5 show that in regions with the most favourable natural and climatic conditions for agriculture and a developed agricultural economy, the contribution of innovations to risk management is most vivid. In regions of the Southern Federal District (SFD), the correlation between R&D and production (0.8206) and between R&D and the balanced financial results of agricultural companies' activity (0.8062) is very high.

In regions of the North Caucasus Federal District (NCFD), R&D's correlation with production (0.7575) and the balanced financial result of agricultural companies' activity (0.8557) is also high. In regions of the Siberian Federal District (SFD), R&D's correlation with production (0.7428) and the balanced financial result of agricultural companies' activity is also high (0.6107). In other regions, the useful effect of innovations for the risk management of agricultural companies is moderate or zero.

Thus, the performed detailed analysis of the model reveals two conditions for increasing the risk resilience of agricultural companies through risk management based on innovations: The first condition is a favourable meso-economic environment, i.e., a moderate or low level of regional socioeconomic development. The second condition is favourable natural and climatic conditions for agriculture in the region.

4.3. Development of a Framework for a "Smart" Vertical Farm, the Risks of Which Are Resistant to Crises through the Use of Datasets and Machine Learning

As part of the third task of this study, a "smart" vertical farm framework was developed, the risks of which are resistant to crises through the use of datasets and machine learning. Using the case-study method, the authors considered the practical experience of organising the work of a "smart" vertical farm by the Institute of Scientific Communications (ISC) and the Consortium for Sustainable Development and Technology Leadership (CSDTL) based on datasets and machine learning, reflecting its advantages in the form of increased risk resistance of this farm to crises—in particular, the COVID-19 crisis.

The ISC's "Smart" vertical farm is a scientific experimental platform. It is located in the Volgograd region of Russia (Southern Federal District). For three years, numerous experiments were carried out in this farm on the cultivation of various species and seeds of plants. The main attention was focused on the cultivation of cucumbers and tomatoes, as the most significant types of agricultural products for the region under consideration.

Numerous experiments have shown that hydroponics is vastly superior to the outdoor and indoor growing of tomatoes and cucumbers. Therefore, the ISC has developed its hydroponic installation "Continuous Flow System", as well as unique three-component fertilisers for growing plants in hydroponic "Mineral Solution" and the technology for the optimal use of these fertilisers at all stages of plant cultivation. Continuous automated phytomonitoring has been established, which controls the growth and productivity of plants, as well as environmental parameters (air humidity and temperature, watering plants, lighting, etc.), using the author's "Photon" touch sensors.

Data from phytomonitoring are collected in datasets. Thanks to the use of machine learning technology for the processing and analysis of dataset materials, more and more optimal environmental parameters and plant-care technologies (irrigation, fertilisers, etc.) are constantly being selected. The varieties of tomatoes and cucumbers that take root most successfully and give the greatest yields have already been selected, and multiple year-round yields have also been achieved. The ISC's "smart" vertical farm is resilient to climate and economic risks and crises through the use of datasets and machine learning.

The implications of the results obtained lie in their demonstrating the unique and leading experience of Russia in the management of production and financial risks to agricultural entrepreneurship in the segment of grain production in the agrarian economy. This allowed us to form a systemic view of these risks, which is particularly useful for managing the production and financial risks of agricultural companies during crises. In particular, the experience of COVID-19 is useful for improving risk management, in the interests of stabilisation of the world grain market in 2022–2023.

The new regional aspect described here allows us to increase the effectiveness of the management of production and financial risks in agriculture, given the climatic, geographical, and socioeconomic features of regions' development. At the same time, a critical view of the obtained results shows that the unique experience of Russia's regions cannot be extended to regions of other countries. Hence, this paper sets the basis for subsequent scientific studies of the regional features of agricultural risk management, which should elaborate on the national experience and country specifics.

5. Discussion

This article contributes to the literature through the development of scientific provisions of the theory of risks in agriculture. The article clarifies the essence and nature of the impact of the COVID-19 crisis on the risks faced by agricultural companies (using the example of Russia in 2020), while also outlining the prospects for reducing the risks in agriculture, in support of COVID-19 crisis management. A comparative analysis of the new scientific results obtained in this article with the existing literature is presented in Table 6.

As shown in Table 6, unlike Adhikari and Khanal (2022), Ahmed et al. (2022), Bai and Jia (2022), Bai et al. (2022), Sohail et al. (2022), and Zhang et al. (2022b), we proved that the risks of agriculture are closely interrelated and determined by technological factors. Agricultural R&D makes it possible to systematically manage and reduce the production and financial risks of agricultural companies.

Unlike Nayal et al. (2022) and Pena et al. (2022), we substantiated—using the example of a "smart" vertical farm of ISC—that the contribution of "smart" technologies to reducing risks in agriculture is complex. This contribution lies in the system automation of the production and distribution processes of a "smart" vertical farm based on datasets and machine learning, which are preferable for agricultural risk management compared to artificial intelligence.

Unlike Gascón and Mamani (2022), Kuleh et al. (2022), and Prasad et al. (2022), we proved that changes in the risks of agriculture in the context of the COVID-19 crisis are driven by technology and innovation. Agricultural risks in Russia have increased only in such economic systems and agricultural companies that are too automated, while "smart" technologies make it possible to achieve crisis resilience. Based on this, unlike Howland and Francois Le Coq (2022), Jones and Leibowicz (2022), Ricome and Reynaud (2022), and Wang et al. (2022), we substantiated the need for systematic risk management in agriculture based on "smart" technologies.

The financial and production risks faced by agricultural companies in Russia increased significantly after the end of the acute phase of the pandemic (2021) compared to the acute phase of the pandemic (2020) and, in particular, the pre-pandemic level (in 2018–2019). The growth rate of the yield of grain crops in Russia in 2019 was 8.37%, and it decreased to 7.16% in 2020, before becoming negative in 2021 (−9.12%). The growth of the balanced financial result of agricultural companies in 2018 was 156.20%, and in 2021 it was 57.79%.

This was the argument for the scientific substantiation of the existence of the delayed effects of COVID-19 risks in agriculture and the necessity for strategic risk management.

Table 6. Comparative analysis of the new scientific results obtained in this article with the existing literature.

Area of Comparison	Existing Literature			New Scientific Results Obtained in the Article
	Postulates		Sources	
Determinants of agricultural risks	Production risks	Natural and climatic factors	Ahmed et al. (2022), Sohail et al. (2022), Zhang et al. (2022b)	Technological factors
	Financial risks	Market factors (including crisis)	Adhikari and Khanal (2022), Bai and Jia (2022), Bai et al. (2022)	
The contribution of "smart" technologies to reduce the risks of agriculture	Production risks	AI-based horizontal farm resource improvement	Nayal et al. (2022)	System automation of production and distribution processes of a "smart" vertical farm based on datasets and machine learning
	Financial risks	Intelligent sales decision support based on AI	Pena et al. (2022)	
Changing risks in agriculture during the COVID-19 crisis	Production risks	Increased due to the growth of the cost of raw, materials, equipment for agriculture	Prasad et al. (2022)	Increased only in those economic systems and only in those agricultural companies that are to a small extent automated, while "smart" technologies make it possible to achieve crisis resilience
	Financial risks	Increased due to the disruption of value chains, a decrease in effective demand, and government regulation of food prices	Gascón and Mamani (2022), Kuleh et al. (2022)	
Agricultural risk management	Production risks	Increasing the climate resilience of agriculture	Howland and Francois Le Coq (2022), Jones and Leibowicz (2022)	Systemic risk management in agriculture based on "smart" technologies
	Financial risks	Strengthening the market positions of agricultural companies	Ricome and Reynaud (2022), Wang et al. (2022)	

Source: developed and compiled by the authors.

The quick growth (i.e., double—the annual growth of costs of R&D in agricultural sciences in 2019 was 5.35%, growing to 14.88% in 2020) of the innovative activity of agricultural companies in Russia allowed for a significant reduction in the COVID-19 risks. As a result, the connection between innovations and the production (by 46% in 2020 compared to 2019: from 0.13 to 0,19) and financial (by 87% in 2020 compared to 2018: from 0.23 to 0.43) risks of agricultural companies grew significantly. Thus, it is expedient to set innovations on the basis of risk management in agriculture during the pandemic.

6. Conclusions

The main goal of our research was achieved—we studied the Russian experience of change in the production and financial risks faced by agricultural companies during the COVID-19 crisis, proved the significant contribution of innovations to reducing these risks, and discovered the prospects for risk management in agriculture based on innovations to increase crisis resilience of agricultural companies. The article answered RQ1. The analysis of the risks of agriculture in the context of the COVID-19 crisis showed that in Russia in 2020, instead of the expected reduction, there was a general growth.

In Russia, in the context of the COVID-19 crisis, there was a deterioration of agricultural risks—they increased only in certain economic systems. The identified key role of technology and innovation in managing agricultural risks suggests that they increased only in those agricultural companies that are automated, while "smart" technologies make it possible to achieve crisis resistance.

The results of modelling the contribution of "smart" technologies to agricultural risk management during the COVID-19 crisis proved the existence of close systemic links between the costs of agricultural R&D in 2019–2020 and the production (quick effect, manifesting in the same year) and balanced financial results (delayed effect, manifested in one year) of agricultural companies in the regions of Russia in 2020. The developed framework of a "smart" vertical farm proves that in order to increase the resilience of agricultural companies to crises, it is advisable to manage the risks of agriculture using datasets and machine learning.

The theoretical significance of the results obtained lies in the fact that they make it possible to systematically study the changes in the risks of agriculture in the context of the COVID-19 crisis, while outlining the prospects for increasing resilience to crises by optimising the use of "smart" technologies, based on a detailed study of the experience of Russia. With the help of these results, the article presents a new view on the risks of agriculture, from the standpoint of "smart" technologies—which, as proven in this article, are a key risk factor and a way to increase the resilience of agricultural companies to crises.

The practical significance of this article is related to the fact that the authors' conclusions and applied recommendations on the use of datasets and machine learning by agricultural companies can improve the efficiency of agricultural risk management and ensure successful COVID-19 crisis management by agricultural companies. The case study described in this article—organising the operation of a "smart" vertical farm based on datasets and machine learning—can be useful for agricultural companies in Russia and other countries, and it will also allow for more flexible and systematic management of agricultural risks.

The social implications of this research lie in the fact that the authors' recommendations provide comprehensive practical implementation of SDG2 (by ensuring food security while reducing production risks) and SDG8 (by supporting the growth of the agricultural economy while increasing agricultural companies' resilience to crises). The article also provides practical recommendations for the implementation of SDG13 and SDG9 (Sustainable Development Goals) in the activities of agricultural companies while increasing the resilience of agriculture to the adverse effects of climate and the market (crises) through modernisation based on "smart" technologies.

The results of the performed research show the unique experience of the risk management of agricultural companies, the success of which is based—as proven in this paper—on innovations. Nevertheless, it remains unclear whether this successful experience of risk management could be extended to other sectors of the economy—this is a limitation of the results obtained. Further studies should elaborate on the prospects and develop practical recommendations to increase the risk resilience of companies in other sectors of the economy based on innovations.

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Appendix A

Appendix A.1

Table A1. Costs of agricultural R&D in 2019; yield of grain and legumes and balanced financial result of agricultural companies in regions of Russia in 2019–2020.

Region	Federal District *	Type of Region **	Yield of Grain and Legumes (Weight after Processing, in Farms of All Categories) (Centners per Hectare of Harvested Area)				Balanced Financial Result (Profit Minus Loss) of Agricultural Companies (Million RUB)				Costs of R&D in Agricultural Sciences (Million RUB)			
			2018	**2019**	**2020**	**2021**	**2018**	**2019**	**2020**	**2021**	**2018**	**2019**	**2020**	**2021**
Belgorod Region	CFD	P	46.1	48.7	53.2	45.2	35,634	32,242	39,239	59,929	275	224.0	345.6	358.9
Bryansk Region	CFD	T	46.5	44.9	50.4	49.9	−8996	7353	4045	12,442	94	98.4	116.9	118.3
Vladimir Region	CFD	T	21.2	22.5	30.2	22.4	714	1162	1201	1734	709.1	739.1	934.5	1084.9
Voronezh Region	CFD	P	32.9	35.0	39.1	30.9	12,114	12,437	30,971	38,015	547.8	668.0	837.8	853.3
Ivanovo Region	CFD	T	18.7	20.2	24.0	17.1	58	445	389	503	27.5	58.1	114.5	0
Kaluga Region	CFD	T	25.1	29.2	29.1	23.0	952	−3095	−2098	−8610	135.8	130.8	99.8	138.7
Kostroma Region	CFD	T	13.2	16.2	16.8	13.7	289	265	306	649	38.1	27.6	38.1	45.2
Kursk Region	CFD	T	46.8	51.5	56.2	45.0	19,765	12,888	11,604	43,296	139.7	152.3	147.7	148.2
Lipetsk Region	CFD	P	39.7	42.8	51.3	36.9	17,160	14,889	27,521	42,752	192.9	191.9	273.1	177.9
Moscow Region	CFD	RO	27.3	26.5	33.0	27.8	4335	−762	3293	−1181	3039.6	2902.5	2761.2	3635.1
Orel Region	CFD	T	36.7	41.3	45.4	42.3	4700	9091	19,262	24,278	164.9	258.8	336.1	353.4
Ryazan Region	CFD	T	28.6	32.8	41.3	32.0	2236	2830	5759	7535	264.8	243.2	251.5	296.8
Smolensk Region	CFD	T	23.9	25.9	23.5	19.9	177	77	−283	310	18.1	61.4	56.3	76.5
Tambov Region	CFD	T	33.6	31.8	44.6	35.0	10,654	9848	21,722	38,651	365.1	276.7	400.3	425.4
Tver Region	CFD	T	12.3	17.9	15.4	15.4	2536	1695	−1412	1217	151.7	141.7	148.9	140.3
Tula Region	CFD	T	32.1	34.6	40.6	35.8	557	3023	4467	7391	23.5	30.9	30.7	0
Yaroslavl Region	CFD	T	17.7	21.2	19.6	13.6	1622	2081	3275	1886	36.6	40.7	88.9	91.6
Republic of Karelia	NWFD	T	0.0	0.0	0.0	0.0	1636	3369	3203	3536	55.9	49.7	32.4	0
Komi Republic	NWFD	RA	0.0	0.0	0.0	0.0	411	349	431	−71	84.5	81.5	69.9	63.4
Arkhangelsk Region	NWFD	RA	18.7	17.6	20.9	13.2	6196	6559	4259	19,038	86.3	83.3	82.9	110.2

Table A1. *Cont.*

Region	Federal District *	Type of Region **	Yield of Grain and Legumes (Weight after Processing, in Farms of All Categories) (Centners per Hectare of Harvested Area)				Balanced Financial Result (Profit Minus Loss) of Agricultural Companies (Million RUB)				Costs of R&D in Agricultural Sciences (Million RUB)			
			2018	2019	2020	2021	2018	2019	2020	2021	2018	2019	2020	2021
Vologda Region	NWFD	RA	15.9	23.5	17.0	0.0	2973	2917	2988	6324	60.1	70.9	90.4	100.2
Kaliningrad Region	NWFD	T	38.8	51.8	52.6	48.4	4943	5338	8712	9424	17.6	17.6	18.9	19.7
Leningrad Region	NWFD	RO	31.3	37.0	38.8	32.9	5393	6415	5788	11,147	71.3	79.2	73.8	0
Novgorod Region	NWFD	T	20.1	29.4	29.5	27.3	−134	853	−191	−732	15.3	15.9	15.4	0
Pskov Region	NWFD	T	18.2	36.9	35.8	30.2	3359	5863	4596	6600	30.7	30.6	36.9	36
Republic of Adygeya	SFD	T	38.4	43.5	51.2	46.4	552	−40	573	447	63.5	81.9	77.6	81
Republic of Kalmykia	SFD	T	22.9	23.3	22.1	22.6	222	225	98	−178	23.7	24.0	23.8	24
Republic of Crimea	SFD	T	15.0	26.6	16.4	25.1	456	1310	2087	1524	237.4	267.6	373.1	411.7
Krasnodar Territory	SFD	P	52.9	56.5	48.1	57.5	27,464	26,022	40,387	59,670	1192.4	1355.8	1664.7	2019.6
Astrakhan Region	SFD	T	27.1	30.9	31.2	37.2	141	26	384	553	105.3	144.6	125.4	144
Volgograd Region	SFD	T	19.3	21.3	25.5	22.7	4047	4042	11,134	10,903	310.7	330.3	528.2	591
Rostov Region	SFD	T	31.9	34.1	34.5	38.0	−4315	−98,458	52,064	31,994	547.2	639.3	1001.2	1010.0
Republic of Daghestan	NCFD	T	25.3	26.0	27.3	27.5	264	154	253	631	115.8	134.1	172.6	188.3
Republic of Ingushetia	NCFD	T	23.0	19.8	23.6	31.2	5	−54	326	−634	32.1	33.9	34	0
Kabardino-Balkarian Republic	NCFD	T	54.1	54.8	56.7	57.6	240	169	147	205	104	115.3	124.3	148.7
Karachayevo-Chircassian Republic	NCFD	T	46.4	50.5	37.8	45.4	451	102	347	762	2.2	0.6	0	0
Republic of North Ossetia—Alania	NCFD	T	55.4	65.3	61.3	61.3	−60	51	82	−129	37.5	60.3	145.8	75.7
Chechen Republic	NCFD	T	24.7	18.2	25.3	24.2	−5	−127	−1233	89	75.1	142.8	90.1	57.2
Stavropol Territory	NCFD	T	36.6	33.7	26.1	37.4	16,495	10,094	7013	29,480	385.1	414.0	450.1	595
Republic of Bashkortostan	VFD	T	18.6	19.8	22.0	14.0	−662	−491	4678	7491	96.8	76.8	91.4	76.9

Table A1. *Cont.*

Region	Federal District *	Type of Region **	Yield of Grain and Legumes (Weight after Processing, in Farms of All Categories) (Centners per Hectare of Harvested Area)				Balanced Financial Result (Profit Minus Loss) of Agricultural Companies (Million RUB)				Costs of R&D in Agricultural Sciences (Million RUB)			
			2018	2019	2020	2021	2018	2019	2020	2021	2018	2019	2020	2021
Republic of Mari El	VFD	T	18.6	19.9	23.6	14.8	676	2	−487	2618	19.4	19.1	17.8	18.9
Republic of Mordovia	VFD	T	26.2	27.8	34.0	23.5	5434	4567	9257	16,118	21.3	20.4	24	0
Republic of Tatarstan	VFD	RO	24.8	28.6	33.5	14.9	2090	5074	5566	5665	565.6	574.0	630.3	759
Udmurtian Republic	VFD	T	18.2	21.3	20.2	15.8	2716	2815	3345	4061	39.3	39.9	44.7	48
Chuvash Republic	VFD	T	23.7	27.0	32.2	19.1	745	−221	−622	−3876	24.8	18.9	23.8	0
Perm Territory	VFD	T	15.8	14.7	15.4	12.1	641	8	1825	834	81.1	131.2	122.6	107.7
Kirov Region	VFD	T	19.1	21.7	21.3	16.9	3498	2719	3160	4464	164.3	181.1	213.7	237.3
Nizhny Novgorod Region	VFD	T	21.2	22.3	28.0	20.7	969	1574	1981	3877	77.5	64.0	68.7	72.1
Orenburg Region	VFD	T	8.8	8.9	13.5	8.0	−493	−54	539	896	233.8	230.0	180.2	255.6
Penza Region	VFD	T	25.4	24.8	38.4	26.5	−1587	2555	9462	13,348	51.3	50.9	58.8	66.1
Samara Region	VFD	T	17.5	17.7	26.1	17.4	1775	997	4799	8254	151.1	172.3	180.2	165.4
Saratov Region	VFD	T	15.1	14.7	23.8	17.3	−363	1907	5846	6377	433.9	504.2	504	637.5
Ulyanovsk Region	VFD	T	19.8	19.1	31.1	18.0	−201	−187	479	1490	127.8	100.2	173	186.7
Kurgan Region	UFD	T	16.2	16.9	13.5	11.1	298	481	878	1001	85.1	80.7	80.9	82.6
Sverldlovsk Region	UFD	T	19.4	22.3	20.9	16.7	3578	2831	3352	4590	277.5	308.8	329.3	380
Tyumen Region	UFD	RO	20.0	22.4	19.9	16.3	2350	3205	3265	3526	115.1	136.6	140	169.1
Chelyabinsk Region	UFD	P	13.4	13.0	8.6	9.2	3526	1343	2612	−1739	101.7	71.7	86.6	104.1
Republic of Altay	SFD	T	9.5	13.9	15.3	16.5	−46	−41	−45	−2	27.8	14.9	28	29.5
Republic of Tyva	SFD	T	13.5	19.4	13.6	12.7	9	−8	1	3	12.4	10.7	11.9	0
Republic of Khakassia	SFD	T	12.3	19.4	21.0	19.0	92	−66	303	338	27.8	23.2	23.8	0

Table A1. *Cont.*

Region	Federal District *	Type of Region **	Yield of Grain and Legumes (Weight after Processing, in Farms of All Categories) (Centners per Hectare of Harvested Area)				Balanced Financial Result (Profit Minus Loss) of Agricultural Companies (Million RUB)				Costs of R&D in Agricultural Sciences (Million RUB)			
			2018	**2019**	**2020**	**2021**	**2018**	**2019**	**2020**	**2021**	**2018**	**2019**	**2020**	**2021**
Altay Territory	SFD	T	15.6	14.6	12.6	17.3	5081	4450	11,684	17,823	131.6	258.7	283.3	265.6
Krasnoyarsk Territory	SFD	T	20.5	23.9	28.8	28.4	1659	4442	7694	11,445	191	195.8	286.8	302.5
Irkutsk Region	SFD	RO	19.9	18.7	20.7	22.4	2242	1999	2907	5216	91.7	78.0	89.6	100.4
Kemerovo Region	SFD	T	18.7	20.1	22.4	25.8	434	−338	1496	3208	149.3	156.0	84	0
Novosibirsk Region	SFD	T	18.2	17.2	17.8	22.6	2865	3859	4823	9274	440.6	448.5	444.6	504.9
Omsk Region	SFD	T	16.7	15.8	15.3	14.7	2102	2718	3098	3668	227.7	265.0	420.7	643.2
Tomsk Region	SFD	T	21.6	21.2	25.2	24.4	3117	4739	3303	5668	52.3	51.0	54	58.7
Republic of Buryatia	SFD	T	12.6	14.1	14.6	18.7	415	538	429	591	66.4	58.8	54.6	63.9
Republic of Sakha (Yakutia)	FFD	RO	10.6	10.4	10.2	9.6	−237	48	153	102	191.8	202.8	208.3	213.9
Trans-Baikal Territory	FFD	RO	14.9	13.1	13.5	15.7	−18	−20	−318	−4	70.7	43.4	39.9	40.1
Kamchatka Territory	FFD	RA	24.6	16.1	25.0	45.3	14,630	17,753	16,354	40,024	40.8	42.9	44.9	0
Primorye Territory	FFD	T	39.1	39.4	35.2	45.4	3112	16,599	8139	35,103	170.3	168.6	208.3	221
Khabarovsk Territory	FFD	RA	19.3	17.9	19.4	20.0	−637	1101	3875	14,964	154.3	154.1	176.6	203.4
Amur Region	FFD	T	18.7	18.1	21.0	23.6	1106	1816	3353	6375	206.7	218.3	268.4	288.2
Jewish Autonomous Region	FFD	T	17.6	13.6	18.9	16.6	42	119	−2	−53	0	0.0	0	0

* CFD—Central Federal District; NWFD—Northwestern Federal District; SFD—Southern Federal District; NCFD—North Caucasus Federal District; VFD—Volga Federal District; UFD—Ural Federal District; SFD—Siberian Federal District; FFD—Far Eastern Federal District. ** Rockets: leading and quickly developing regions; Racers: regions with a large potential for development; Parachutists: progressive regions with slow development; Turtles: lagging regions. Source: compiled by the authors based on materials from Rosstat (Federal State Statistics Service) (2023).

Appendix A.2

Table A2. List of the main agricultural companies in Russia, and characteristics of their activities.

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
1 (1)	Group of companies “Sodruzhestvo”	Processing of oil-bearing crops	287,000	42.08	No data	2950	Kaliningrad region	—	Kaliningrad, Omsk, Amur regions
2 (2)	Group of companies “Rusagro”	Production of sugar, pork, oil, and fat products; cultivation of agricultural crops	158,971	15.05	24,297	19,300	Moscow	Russkiy Sakhar, Brownie, Chaikofsky, Mon Caf?, Tyopliye Traditsii, Moskovsky Provansal, Ya lublu gotovit, EZHK, Mechta Khosiaiki, Stolichnaya, Schedroye leto, Rossiyanka, Benefitto, Saratovskiy, Zhar-pechka, Milie, Syrnaya kultura, Buterbrodnoe utro, Slovo Myasnika	Presence in 80 regions of Russia
3 (3)	Group of companies “Efko”	Production of refined vegetable oils and fats	145,000	18.85	18,000	17,000	Voronezh region	Sloboda, Altero	Voronezh, Belgorod, Moscow, Sverdlovsk, Krasnodar regions, CIS countries
4 (5)	Agroholding “Miratorg”	Livestock and crop production and processing	139,245	16.87	28,054	38,277	Moscow	Miratorg, Gurmama	Voronezh, Belgorod, Bryansk, Kursk, Kaliningrad, and Moscow regions, Moscow, St. Petersburg. Export to 30 countries of the world

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
5 (4)	Group “Cherkizovo”	Breeding of pigs and poultry, processing and production of meat products and animal feed	128,803	7.24	15,145	31,100	Moscow	Cherkizovo, Petelinka Kurinoe Tsartvo, PAVA-PAVA, Cherkizovo Premium, Domashnya Kurochka, Mosselprom Dajajti, Imperiya Vkusa, Myasnaya Gubernia, PIT product, Latifa, Fileya, Samson Family dinner, Grilmania, Samson, Altai Broiler	Bryansk, Lipetsk, Kaliningrad, Kursk, Moscow, Orel, Penza, Rostov, Samara, Tambov, Tula, Ulyanovsk regions, St. Petersburg, Moscow
6 (10)	JSC “Aston Foods and Food Ingredients”	Production of foodstuffs, oils, grains, and food ingredients	115,768	73.35	4484	1921	Rostov region	Aston, Zateya, Volshebniy Krai, Svetlitsa	Rostov and Ryazan regions
7 (6)	Group of companies “Danone”	Production of milk, milk drinks, juices, water, and other food products	110,742	1.15	903	2800	Moscow	Activia, Actimel, Actual’, Alpro, Bebelac, Bio Balance, Danissimo, Danone, Prostokvashino, Petmol, Rastishka, Tyoma, Frendiki, Nutrilon, Malyutka	Vladimir, Vologda, Kurgan, Lipetsk, Samara, Sverdlovsk, Tyumen regions, the Republics of Tatarstan and Mordovia, Krasnodar, Krasnoyarsk regions, Moscow, St. Petersburg
8 (13)	Group of companies “Agropromkom-plektatsiya”*	Crop production, animal husbandry, and feed production	99,224	25.85	No data	10,000	Tver region	Blizhnie Gorki, Dmitrogorsky produkt, Iskrenne Vash, Provence Bakery	Ryazan, Tver, Kursk, Moscow regions, Moscow

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
9 (7)	JSC WBD (PepsiCo)	Beverage and food production	98,982	−1.31	3076	9455	Moscow	Love Juice, Domik v Derevne, Agousha, Chudo, Imunele, J7, Mazhitel, Veselyi Molochnik, Kuban Burenka, Rodniki Rossii, 100% Gold, Frugurt, Chudo Yagoda	Moscow, Krasnodar, Volgograd, Voronezh, Irkutsk, Kirov, Samara, Saratov, Sverdlovsk Tyumen regions, the Republic of Tatarstan, and other regions
10 (8)	Ltd "Cargill", Ltd. "Provimi"	Production of starch and starch products; production of sugars and sugar syrups; animal feed	97,493	19.99	1950	1625	Tula region	—	Voronezh, Moscow, Rostov, Tula, Krasnodar regions, Moscow
11 (11)	GAP "Resource"	Production of food products from poultry meat; cultivation of grain and oilseed crops	81,765	33.53	No data	19,000	Moscow	Blagoyar, Nasha Ptichka, URUSSA, An-Noor	Stavropol and Krasnodar, Rostov, Tambov, and Orenburg regions, the Republics of Adygea, Kabardino-Balkaria, and Karachay-Cherkessia
12 (9)	Group of companies "Agro-Belogorye"*	Animal husbandry, meat processing, plant growing, and fodder production	68,426	−13	No data	10,000	Belgorod region	Dalnie Dali, Grill Menu Myasnoe Zastolie	Belgorod region
13 (12)	"Norebo Holding"	Fishing and seafood	65,945	9	No data	3000	Murmansk region	Borealis, Seroglazka	Leningrad, Moscow, Murmansk, Kamchatka regions, St. Petersburg

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
14 (14)	"Velikoluksky agro-industrial holding"*	Breeding and rearing of stock of pigs; meat processing	61,632	7	No data	14,500	Pskov region	Velikoluksky Myasokombinat	Republic of Karelia, Astrakhan, Bryansk, Vologda, Volgograd, Kaliningrad, Leningrad, Moscow, Novgorod, Pskov, Rostov, Ryazan, Smolensk, Tver regions, St. Petersburg
15 (26)	Group of companies "Yug Rusi"	Production of vegetable oils, mayonnaises and sauces, flour, and canned food	60,588	17.99	197	14,600	Rostov region	Zolotaya Semechka, Avedov, Zlato, Milora, YUG RUSI Ryzhikovoe, Sto Retseptov, Anninskoye, Razdolye, Provençal, Vkusnaya Pochta, Krasnodarskiy, Healthy nutrition	Rostov, Voronezh, Volgograd, Krasnodar regions
16 (15)	Firm "Agrocomplex named after N. I. Tkachev"*	Crop production combined with animal husbandry (mixed agriculture)	57,278	7.67	2673	21,235	Krasnodar region	Agrocomplex, Nikolaevskie Syrovarni, Ptitsa Kubani, Mramornaya Govyadina	Krasnodar region
17 (17)	Agroholding "KOMOS Group"*	Pig breeding, poultry farming, meat and milk processing, and feed production	52,345	5.32	1427	13,600	Udmurt Republic	Selo Zelenoye, Molochnaya Rechka, Kezskiy Syrzavod, Glazovptica, Kungur Myasokombinat, Toptyzhka, Vostoc, Platoshino, Dobromyasov, Angelato, Villa Romana, Fitness time, Minions, Immunolact, Varvara Krasa, Danar, Izhmoloko, Suharev-moloko, Dlya Vsei Semyi, To be, Izhevskoye, Sozvezdie, GOST, Favorit, Udmurtryiba, Rybatskie Baiki	Udmurt Republic, Perm region, Republic of Bashkortostan, Republic of Tatarstan

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
18 (16)	Agro-industrial holding “BEZRK-Belgrankorm”	Animal husbandry combined with crop production; production of poultry, pork, beef, and sausages	50,548	0.76	5122	5597	Belgorod region	Yasnie Zori, Utka Yasnozorenskaya	Belgorod, Novgorod regions
19 (18)	LTD “Prodimex”	Production of sugar, grain, and sunflower seeds	48,579	7.67	285	17,000	Moscow	—	Republic of Bashkortostan, Belgorod, Voronezh Kursk, Penza regions,
20 (23)	JSK “Agrosila”*	Cultivation of grain, technical and fodder crops, production of feed and oils, livestock production, poultry farming, and purchase	46,500	21	600	8700	Republic of Tatarstan	Zainskiy Sahar, Chelny-broiler, Prosto moloko, Vkysnie traditsii, Sochnaya Gamma, Delicur, Chicken han	Republic of Tatarstan, Republic of Bashkortostan, Yekaterinburg
21 (23)	IPC “Atyashevo”*	Production of sausage products and meat delicacies	45,677	81	No data	4721	Republic of Mordovia	Atyashevo, Dauriya	Republic of Mordovia, Ulyanovsk region
22 (33)	Group of companies AST	Production, storage, and processing of cereals; horticulture	44,676	97.9	859	No data	Moscow	—	Kaluga, Lipetsk, Moscow, Volgograd, Saratov, Voronezh, Altai, and Krasnodar regions, Chechen Republic

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
23 (22)	JSC NMGK	Production of margarine and foodstuffs	44,620	26.38	839	3790	Nizhny Novgorod region	Ryaba, Sdobri, Nezhny, Astoria, Khozyayushka, Slivochnik, Toplenaya, Stepanovna, Kremlevskoe, Postnoye, Slivochnik, Delicato, Retsepty chistoty, Moy malysh, Mylo Suvenirnoye, Vanda, Monpari Provence, Dushistoye oblako, Glitserinovoye, Svetloyar, Podsolnechnoye, Originalnoye, UNIPAV	Nizhny Novgorod, Samara, Orenburg, Uryupinsk, Sorochinsk, Volgograd, Orenburg, Samara, and Saratov regions, Republic of Bashkortostan
24 (19)	OJSC "Ostankino Meat Processing Plant"	Pig breeding; production of meat processing products and semi-finished products	44,345	6.19	1227	4103	Moscow	Papa mozhet, Ostankino, Slivochnye, Sosiska ru	Moscow and Moscow region, Smolensk region
25 (31)	"Econiva—AIC Holding"*	Animal husbandry combined with crop production	39,840	34.79	205	12,049	Voronezh region	Econiva	Voronezh, Kursk, Novosibirsk, Kaluga, Ryazan, Moscow, Tyumen, Orenburg, Leningrad, Samara, Altai regions, Republics of Tatarstan and Bashkortostan
26 (21)	"PRODO" Group	Poultry farming, pig breeding and processing, and grain production	38,000	0	No data	12,000	Moscow	Troekurovo, Klinsky, Omsky bacon, Rokoko, Nasha Ryaba, Rosa na trave, Yasnaya gorka, Umka, Chukchum, Cherny Kaban, Khalif, UMKK, Yarkoe utro, Nazionalny standart, Permsky myasokombinat	Kaluga, Moscow, Novosibirsk, Omsk, Tyumen, Perm regions, Republic of Bashkortostan

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
27 (20)	JSK "PRIOSKOLE"	Poultry farming	35,952	−7.21	559	16,000	Belgorod region	Prioskole, Al Safa, Coco Pullet, Fly de lunch, Slavnaya marka, Odnazhdy v derevne, Kurinye delicatesy, Kolbasnye delicatesy	Belgorod region
28 (30)	JSK "Sibagro"	Agriculture, pig breeding, and food production	34,071	21.09	7769	9015	Tomsk region	Sibagro, Myasnaya tema	Tomsk, Sverdlovsk, Kemerovo, Tyumen regions,
29 (—)	Group of companies "Concern Pokrovsky"	Sugar production; meat processing	34,000	31.2	5500	7900	Rostov region	Kanevskoy, Solntsem Sogrety	Krasnodar, Stavropol, Astrakhan, Volgograd, Nizhny Novgorod, Rostov regions, Chechen Republic
30 (29)	Agro-holding "Horoshee Delo" Sphere group*	Production and processing of agricultural products	33,579	33.54	1268	6500	Republic of Mordovia	Horoshee delo	Republic of Mordovia, Ulyanovsk region
31 (25)	Agro-holding "Steppe" with PJSFC "Sistema"	Crop production, dairy farming, intensive horticulture, and trading of agricultural products	32,800	15.2	3900	6150	Rostov region	Steppe	Krasnodar, Stavropol, Rostov regions
32 (38)	Group of companies "Renna"*	Production of canned milk, whole milk products, and ice cream from natural cream	32,600	13	170	5000	Moscow	Korovka iz Korenovki, Alekseevskoe, Oblaka iz moloka, Ruslada, Gustiyar, Korenovskoe, Risovashka, Milkimony, Chizby, Kubanskie tvorozhniki	Krasnodar region

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
33 (32)	LLC "Blago"	Vegetable oil production	30,100	28.2	No data	No data	St. Petersburg	Almador, Freya, Blago PRO, Dary Kubani	Altai, Krasnodar, Voronezh, Omsk regions
34 (35)	JSC "Molvest"	Dairy product production	28,700	12.5	286	5000	Voronezh region	Vkusnoteevo, Molvest, Fruate, Nezhny vozrast, Ivan Poddybny, Vilzhskie prostory, Kubanskiy hutorok, Felicita	Moscow, St. Petersburg, Volgograd, Kursk, Lipetsk, Rostov, Samara, Saratov, Ulyanovsk, Krasnodar regions, Republic of Crimea
35 (27)	Group of companies "Damate"	Agricultural production (cultivation and processing of turkey; production and processing of milk)	26,390	0.34	No data	9000	Penza region	Indilite, Ozerka, Molkom	Penza, Tyumen, Rostov, Stavropol regions
36 (24)	Agro-holding "Kopitaniya"*	Agro-industrial holding of a full cycle, from crop production to the production and sale of meat products	25,700	−18.24	No data	4000	Moscow	Lavla, Ilovliskie tsyplyata, ZMK	Moscow, Tver, Saratov, and Volgograd regions
37 (37)	Holding "Avangard-agro"	Agricultural production	23,146	11.9	11874	4700	Moscow	Avangard-agro	Voronezh, Orel, Kursk, Tula, Lipetsk, Belgorod regions, Moscow
38 (36)	JSFEC "Exima"	Meat processing and preservation	23,110	11.33	2450	6500	Moscow	Mikoyan, Okhotny ryad, Pivchiki, Snexi, Russkiy fermer	Moscow, Moscow, Kaluga, Vladimir regions

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
39 (28)	JSC "Russian Fish Company"	Catch and sale of fish and seafood	23,000	−7.94	812	2000	Moscow	Russian Fish Company	St. Petersburg, Murmansk, Arkhangelsk regions, Primorsky krai
40 (—)	Group of companies "Foodland"	Dairy production	22,430	10	No data	2000	Moscow	Radost vkusa, VardeVaal, Excelsior, Lvinoe serdtse, Korol' severa, GoldenGot, Veselyy Rodzher, Dontaler, Lyubimyy khutorok, Monarkh, Produkty is Elani, HeidiHeidi, La Paulina, Lattesso, Mlekara, Shabats, Ricrem, Meggle, Bonfesto, CooKing, Rama, Pyshka, Mamontovskaya syrovarnya, Basni o syre, Novogrudskie dary, Syrnaya volost, Savushkin product	Volgograd, Saratov regions
41 (44)	JSC "Makfa"	Production of flour from grain, vegetable crops, and ready-made flour mixtures and dough for baking	20,802	16.47	2300	2000	Moscow	Makfa, Smak, Grand di Pasta, Grand di Oliva, Mishkinskiy Product	Sverdlovsk, Chelyabinsk, Kurgan regions, Altai, Stavropol regions
42 (—)	Group of companies "Agroeco"	Crop production, feed production, animal husbandry, and meat processing	20,769	42.2	3913	3614	Voronezh region	Agroeco	Voronezh, Tula regions
43 (40)	LLC Poultry Farm "Aka-shevskaya"	Poultry breeding and processing	20,724	2.22	1991	5822	Mari El Republic	Akashevo, Tsarevoslobodskie kolbasy, Prostomyasovo, Znatny perekus, Akashevskaya	Mari El Republic

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
44 (39)	Poultry farm "Severnaya"	Poultry farming	20,104	−2.71	2035	1400	Leningrad region	Severnaya	Leningrad region
45 (46)	Group of companies "Yanta" (main assets—Irkutsk oil and fat plant, Angarsk poultry farm)*	Production of high-quality food products, raw materials for the food and processing industry, and agricultural feed	20,070	15.34	No data	No data	Irkutsk region	Baikalskoe, Vilkin, Salatny provence, Favorite cup, Standart professionalnoy kucshni, Lugovoe, Angarskaya kurochka	Primorsky Krai, Irkutsk, Amur regions
46 (42)	Agro-holding "Trio"*	Sugar production, dairy farming, and crop production	19,459	5.3	No data	No data	Lipetsk region	No data	Lipetsk region
47 (41)	"Aladushkin Group"*	Production of flour from cereals, vegetable crops, and ready-made flour mixtures and dough for baking; cereals, granules, and other products from cereals; production of prepared feed	18,099	−3.33	No data	950	St. Petersburg	Yasno solnyshko, Muka predportovaya, Kudesnitsa, Aladushkin, Hleburg, FarmerGood, Gornitsa	St. Petersburg, Leningrad, Samara, Tyumen regions
48 (43)	"Okeanrybflot"	Fishing and seafood	17,382	−5.08	2741	2331	Kamchatka krai	Okeanrybflot	Moscow, St. Petersburg, Astrakhan, Murmansk regions, Kamchatka, Primorsky krai

Table A2. *Cont.*

Ranking Position in 2020 (2019)	Company	Specialisation	Revenue in 2020 (Million RUB)	Change (%)	Net Profit in 2020 (Million RUB)	Average Number of Employees (Persons)	Registration Region	Trade Marks	Regions of Presence
49 (—)	Holding company “Ak Bars”*	Animal husbandry, crop production, poultry farming, and grain processing; production of milk, eggs, sugar, and bakery products	16,859	22.48	No data	10,000	Republic of Tatarstan	Tsyplenok pod solntsem, Gosudarev, Ambar, Pestrechinka, Kuriny gurman, Kyrinye istorii, Ak Bars	Republic of Tatarstan, Chuvashia
50 (—)	Agro-holding “Zvenigov”	Animal husbandry and crop production; processing	16,344	9.44	640	2675	Mari El Republic	Zvenigov	Mari El Republic
-	Total	-	2,828,182	16.7	153,569	408,380	-	-	-

Source: Compiled by the authors based on Expert (2022).

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