RISK MANAGEMENT IN THE ERA OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE

Nicolae ISTUDOR[1], Raluca IGNAT[2], Elena-Mădălina DEACONU[3], Marius CONSTANTIN[4]
[1] Professor PhD, Bucharest University of Economic Studies, AGRIDATA – Center for Research, Innovation, Extension and Technological Transfer, email: nicolae.istudor@ase.ro
[2] Associate Professor PhD, Bucharest University of Economic Studies, AGRIDATA – Center for Research, Innovation, Extension and Technological Transfer, email: raluca.ignat@ase.ro
[3] Assistant Researcher PhDs, Bucharest University of Economic Studies, AGRIDATA – Center for Research, Innovation, Extension and Technological Transfer, email: madalina.deaconu@eam.ase.ro
[4] Assistant Professor PhD, Bucharest University of Economic Studies, AGRIDATA – Center for Research, Innovation, Extension and Technological Transfer, email: marius.constantin@eam.ase.ro

Abstract
In recent years, the agricultural industry has experienced significant advancements through the integration of artificial intelligence (AI). The utilization of artificial neural networks and deep learning algorithms, in conjunction with Internet of Things devices and data analysis methodologies, holds significant potential for revolutionizing risk management approaches and practices in the field of agriculture. As a result, there has been a significant rise in scientific inquiries and published literature exploring the intersection of risk management and artificial intelligence in the agriculture sector. This academic paper examines the potential of AI in the field of risk management in the agriculture industry, as well as its implications for improving productivity, profitability, and sustainability. The utilization of AI technologies has led to significant progress in the domains of precision agriculture, resource management, and decision-making protocols. The findings of this study suggest that the incorporation of AI into risk management strategies in the agricultural industry holds promise for improving resilience and adaptability. Nevertheless, the application of AI holds the potential to improve agricultural practices, hence increasing output and promoting the development of sustainable and efficient food production systems. This article provides a comprehensive overview of the potential applications AI in risk management within the agriculture industry and examines the implications it holds for the future of the sector.

Keywords: *agri-food sector, artificial intelligence, risk management, sustainable development.*
DOI: 10.24818/CAFEE/2023/12/08

Introduction

The incorporation of artificial intelligence (AI) across diverse sectors has resulted in a fundamental transformation in our approach to risk management. Within the realm of agriculture, the presence of volatile environmental conditions and uncertain market dynamics has consistently posed significant obstacles. However, the integration of AI holds the promise of fundamentally transforming risk management tactics. Through the utilisation of AI technology, farmers and agricultural enterprises are now able to collect and analyse extensive quantities of data, enabling them to make decisions that are better informed (Purcell & Neubauer, 2023). AI-powered technologies have the capability to make precise predictions regarding weather patterns, evaluate the condition of crops, and forecast swings in the market. This empowers individuals to take pre-emptive measures in order to avoid risks and improve their operations. The implementation of this transformative strategy not only leads to an increase in production and profitability, but also fosters the promotion of sustainability within the agricultural sector. The objective of this study is to examine the present state of risk management in the agricultural industry and emphasise the crucial significance of AI in alleviating and controlling hazards within this domain (Ayoub Shaikh et al., 2022). The agricultural sector is intrinsically characterised by a multitude of risks, including but not limited to natural calamities, pest invasions, and volatile market conditions, all of which pose substantial challenges to the economic sustainability of farmers. Conventional risk management strategies, such as the utilisation of crop insurance and hedging, have demonstrated efficacy in the reduction of certain hazards. Nevertheless, it is frequently observed that these approaches frequently overlook the intricate and uncertain nature of the contemporary agricultural system. AI plays a significant role in this context by using its capacity to analyse extensive datasets, detect trends, and generate precise forecasts. Through the utilisation of AI, farmers are now able to avail themselves of sophisticated tools and technology that have the potential to fundamentally transform their risk management practises. AI has the capability to collect data from diverse sources such as weather patterns, soil conditions, and market trends. By having access to this information, farmers are able to enhance their decision-making process regarding the optimal timing for planting, irrigating, and harvesting crops. This enables them to maximise their agricultural production while decreasing the likelihood of incurring any potential losses. In addition, AI has the potential to assist farmers in identifying initial indications of insect infestations or disease outbreaks, enabling them to promptly respond and mitigate the dissemination of these hazards to their agricultural produce (Wongchai et al., 2022). AI has the capability to evaluate data obtained from many sources such as sensors and satellite imaging. Through this analysis, AI may detect patterns and anomalies that have the potential to signal the existence of pests or diseases. By providing farmers with information about these hazards, AI allows them to execute specific interventions, such as accurate application of pesticides or adoption of crop rotation, in order to reduce the negative impact. In essence, AI provides farmers with the means to enhance their agricultural methodologies, bolster productivity, and make valuable contributions to the development of sustainable and efficient food production systems. As an illustration, AI has the capability to evaluate data acquired from sensors strategically positioned in a given field, so enabling the identification of fluctuations in temperature or moisture levels that could potentially serve as indicators of pest presence or activity (Ganeshkumar et al., 2021). In the case that the artificial intelligence system detects a rapid rise in temperature, it has the capability to promptly notify the farmer on the potential occurrence of an insect infestation (Abbasi et al., 2022). This timely alert empowers the farmer to promptly undertake necessary measures to mitigate any further harm or losses. Moreover, artificial intelligence has the capability to analyse satellite imagery in order to detect regions within a crop that exhibit signs of poor health or abnormal discoloration, which may suggest the existence of a disease. Through the identification and delineation of these particular regions, AI facilitates farmers in directing their interventions with greater precision, resulting in a reduction in the utilisation of pesticides and mitigating their ecological repercussions. In addition, AI has the capability to offer timely suggestions for the most suitable irrigation and fertilisation timetables, taking into account weather patterns and soil conditions (Rejeb et al., 2022). This can effectively enhance agricultural productivity while simultaneously promoting resource conservation. The utilisation of artificial intelligence enables farmers to engage in continuous monitoring and analysis of agricultural data, hence facilitating the adoption of data-driven decision-making processes and the implementation of proactive initiatives aimed at promoting sustainable and efficient farming practises. The advent of AI-based technologies, including precision agriculture, machine learning algorithms, and satellite imaging, has facilitated the ability of farmers to make informed choices based on data. This has resulted in enhanced crop output, efficient allocation of resources, and a reduction in associated risks (Lu et al., 2022). By conducting an analysis of weather patterns and soil data, AI has the capability to furnish farmers with up-to-date and timely information regarding optimal timings for planting, irrigating, and harvesting crops. This technological intervention serves to mitigate the detrimental effects of unfavourable weather conditions on crop yields. In addition, AI can assume a pivotal function in the anticipation and mitigation of possible hazards, as opposed to solely addressing them post-occurrence. As an illustration, artificial intelligence algorithms possess the capability to examine past data pertaining to insect infestations and disease outbreaks. This enables farmers to effectively identify and implement pre-emptive actions aimed at averting the occurrence of such difficulties. Moreover, the utilisation of AI-enabled unmanned aerial vehicles (UAVs) equipped with advanced imaging devices and sensing technologies presents an opportunity to effectively monitor the well-being of crops and identify indications of distress or inadequate nutrient levels. This capability empowers farmers to promptly intervene and administer precise remedies, thereby fostering the growth of robust crops and achieving enhanced agricultural productivity (Zscheischler et al., 2022). Through the constant monitoring and analysis of data, AI has the capability to identify indications of illnesses, pests, or other possible hazards. This enables farmers to adopt preventive measures, thereby mitigating prospective losses. Nevertheless, the incorporation of AI in the agricultural sector also presents inherent risks and obstacles. In order to fully leverage the advantages of AI in risk management, it is imperative to solve various challenges, including technical malfunctions, breaches in data security, and ethical considerations. As an illustration, AI has the potential to be employed in precision agriculture for the purpose of analysing satellite imagery and soil data (Javaid et al., 2023). This analysis enables the determination of the most suitable irrigation and fertilisation requirements for individual crops. This enables agricultural practitioners to optimise their crop production while limiting their water and fertiliser consumption. Moreover, AI may be effectively employed in the domain of livestock management. This is achieved through the analysis of data obtained from sensors attached to animals, which facilitates the identification of indicators related to illness or distress. Consequently, this early detection allows for timely intervention, thereby mitigating the risk of disease transmission within the herd (Sohail et al., 2022).

This study aims to examine the aforementioned difficulties and offer a complete analysis of how AI might augment risk management practises in the agricultural sector. Through the utilisation of AI technology, farmers are able to efficiently evaluate and address potential hazards linked to meteorological conditions, pests, and illnesses. AI-driven models have the capability to analyse both historical and real-time data in order to forecast possible threats and recommend suitable preventive steps. This not only aids farmers in safeguarding their crops and cattle, but also guarantees the implementation of sustainable agricultural methods that are crucial for ensuring long-term food security. The integration of AI into risk management practises has the potential to enhance the resilience and adaptability of the agricultural sector in response to dynamic environmental and economic circumstances.

1. Materials and Methods

Bibliometrics is quantitative form of research which has become a popular instrument for studying research trends (Lund, 2022). This particular conference paper has adopted the bibliometric research method and the study was conducted with the help of VOSviewer 1.16.19, which is a software tool, designed by Ness Jan van Eck and Ludo Waltman. Widely used in bibliometric analysis (Donthu et al., 2021; Petrescu et al., 2022), VOSviewer aids researchers with the construction of networks maps that show the intensity of the connection between the metadata of the publications displayed after querying specific databases. In this formula, the publication metadata represents the ‘raw materials’ required to project, construct and visualize bibliometric networks.

This specific bibliometric analysis was elaborated with metadata of papers extracted from the Web of Science (WoS) database, which provided the necessary requirements needed for elaborating the study of the field of risk management in the era of artificial intelligence in agriculture. Consequently, the WoS database was queried in May 2023 according to the following specifications: TOPIC: ("artificial intelligence") AND TOPIC: (risk) AND TOPIC: (agriculture), with no age filter applied. Only the publications that contain these word structures in their title, abstract or keywords were displayed after running the query. Mixing these three structures in the same query together represents the conceptual foundation for deriving bibliometric research findings based on the scientific publications specific to the topic of risk management in the era of artificial intelligence in agriculture. The WoS query resulted to the identification of 348 publications that contained the "risk management", “food” and "chain" word structures in their title, abstract or keywords.

2. Results and Discussion

The first studies published on the topic of risk management in the era of artificial intelligence in agriculture date back in the late 1990s, and, to be more precise, the first articles containing the words "agriculture", "risk" and the word structure "artificial intelligence" in their title, abstract or keywords date back in the year 1994. The paper of Gu et al. (1994) attempted to use artificial intelligence techniques with the purpose of carrying out inferences based on uncertain information related to climatic factors and yield. Of course, as results stand proof in Figure 1, risk management in the era of artificial intelligence in agriculture is a novel field of research, taking into consideration the burst in the development of technology in the beginning of the third millennium. Thus, approximately 9% of the papers in this field were published before 2014 and a significant increase occurred in 2019, continued each year after. The peak was reached in the year 2022 with 102 papers (almost 30% of all the paper corresponding to the "agriculture", "risk", and "artificial intelligence" WoS keywords), proving the ardent interest for this subject. Most papers were indexed under the "Environmental Sciences" WoS category. Naturally, another WoS category of importance under which paper were indexed was the "Computere Science Artificial Intelligence" category, with 63 papers (18.10%), followed by the "Computere Science Information Systems" category with 39 papers (11.20%).

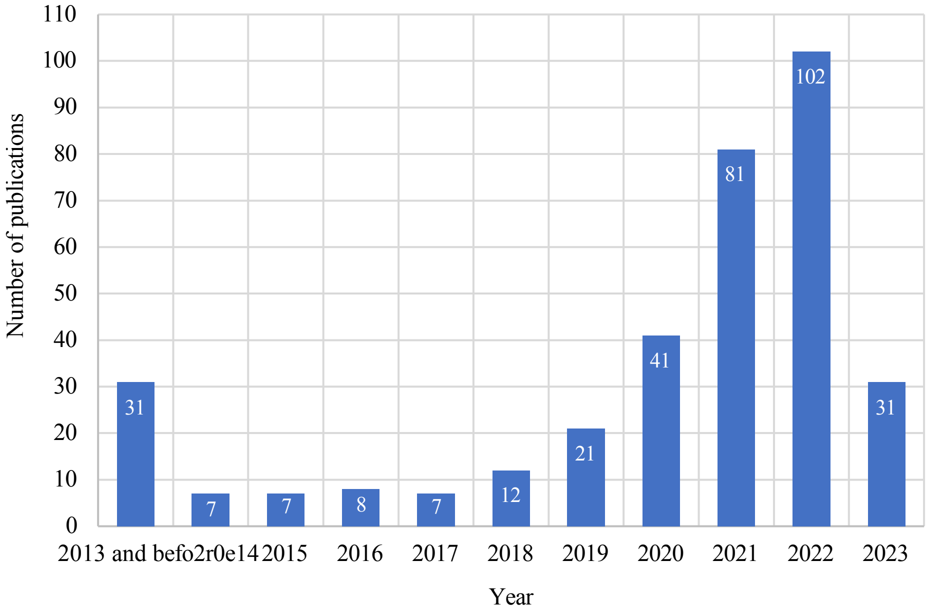

Figure 1. The evolution of the scientific papers published on the topics of agriculture, artificial intelligence, and risk management
Source: Authors' own computation in VOSviewer 1.6.19

The study of the research papers dealing with the topic of risk management in the era of artificial intelligence in the agricultural sector was fundamentally made possible by carrying out a keyword cluster analysis in VOSviewer. Visualizing bibliometric networks and interpreting the results is essential for elaborating a qualitative analysis (van Eck and Waltman, 2014). The construction of Figure 2 was grounded on the VOSviewer-processed metadata corresponding to the 348 scientific publications extracted from the Web of Science database. With the purpose of representing the most insightful information and focus on the most important aspects of the bibliometric analysis, specific VOSviewer filters were applied: (1) type of analysis: co-occurrence, (2) unit of analysis: all keywords, (3) counting method: full counting, (4) minimum number of occurrences of a keyword to be displayed in Figure 2: three occurrences in both cases–out of all the 2,297 keywords, only 179 met the threshold. The red cluster consists of items such as artificial neural network, climate change, ecosystem services, land use, risk management, precipitation, river, soil, and water. Inspired by the structure of the human brain, artificial neural networks (ANNs) are computational models used in programming with the aim of processing complex data and making predictions or classifications, but not limited only to those goals. Models based on ANN have been employed in various fields, including agriculture, climate modeling, hydrology, and land use planning. For example, Dai et al. (2005) used ANNs to collect multitemporal remote sensing data, mix them with socio-economic data, process them together and identify the factors influencing land use changes in the Pearl River Delta Region of southeast China. Hachani et al. (2019) implemented a retrieval algorithm grounded on ANN designed to estimate the soil moisture content in Tunisia for water and risk management purposes, aiming to efficiently schedule agricultural practice and mitigate water wastes. Zhang et al. (2019) used four types of ANNs: multilayer perceptron, generalized feedforward, linear regression and probabilistic neural network to model the upland rice yield function in the case of three West Africa provinces to assess its response to climate change factors. Circling back to the keywords composing the red cluster from Figure 3, climate change is well-connected to risk management in agriculture through a mathematic approach of long-term shifts in weather patterns, including temperature changes, precipitation dynamics, and extreme weather events (Antón et al., 2013; Crane-Droesch et al., 2019; Wheeler & Lobley, 2021).

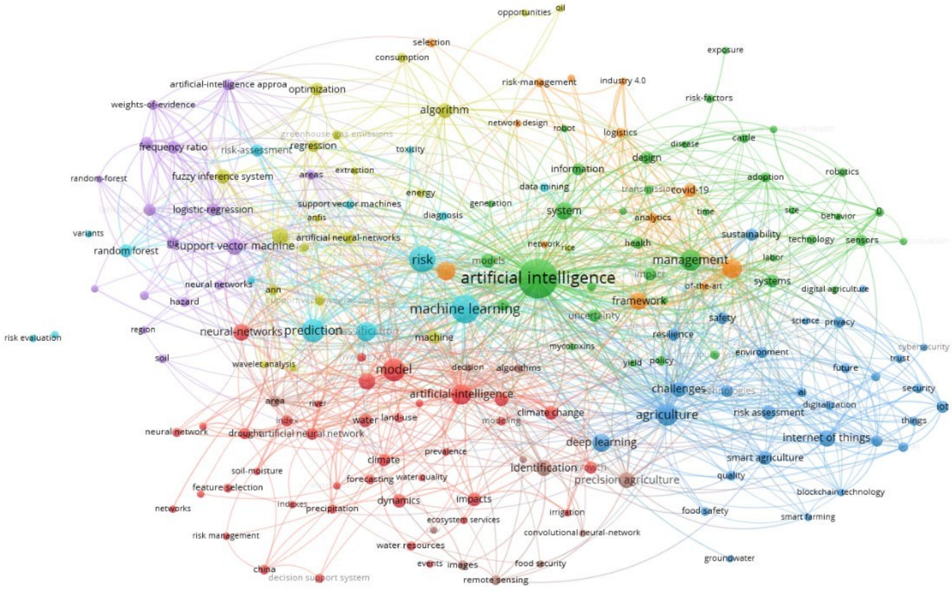

Figure 2. Cluster analysis–network visualization

Source: Authors' own computation in VOSviewer 1.6.19

In this context, ANNs can be utilized as an intelligent tool to analyze climate data, define trends, and establish models that contribute to predicting future climate scenarios and mitigate the negative impacts of climate change (Bhattarai et al., 2022). Adding the "ecosystem services" keyword structure into the equation, this concept refers to the benefits such as clean air, pollination, clean water (Negrei et al., 2022; Patarlageanu et al., 2022); benefits that humans capitalize on from natural ecosystems. However, climate change can significantly impact ecosystem services in unfavorable manners, negatively affecting biodiversity, food production systems, and the availability of resources (Marx et al., 2019). In this regard, based on data, ANNs can assist in predicting the interactions between climate change and ecosystem services, providing actual insight for the formulation of conservation strategies (Morshed et al., 2022). Thus, since climate change introduced new risks and uncertainties, ANNs have become a real aid in risk assessment and management through the capability of forecasting, hinting at future scenarios, and establishing prediction models (Kunreuther, 2020). This type of AI use in agriculture and its corresponding risk management approaches help policymakers to efficiently develop strategies for the agricultural sector (Adli et al., 2023; Amini et al., 2021; Wong et al., 2022).

The blue cluster is composed of items such as agriculture, internet of things, cybersecurity, deep learning, risk assessment, digitalization, food safety, and smart agriculture. The relationship between these items highlights the advancement, progress and sustainability of modern agricultural practices in the context of digitalization (Burlacu et al., 2021) and in the era of artificial intelligence (Misra et al., 2022). With the help of structural funds for the rapid development of technology (Popescu et al., 2019), the emergence and imminence of the Internet of Things (IoT) is no surprise. IoT refers to the network of interconnected devices that are in a loop of collecting and exchanging data. In the case of the agricultural sector, IoT devices, which include drones, sensors, smart machinery, and other similar devices; they can provide real-time information on agricultural-specific parameters such as soil moisture, humidity, temperature, crop health, and livestock conditions (Dutta & Mitra, 2021; Saha et al., 2018). Collected and processed data enables decision makers to take more informed decisions and improve resource management techniques. The relationship between agriculture, IoT, and AI is transformative and has the potential to revolutionize the agricultural sector (Bhat & Huang, 2021). IoT-devices generate vast amounts of relevant agricultural data, which can be integrated in AI algorithms to gather precious agronomic and economic insights. Additionally, since AI-powered analytics detect patterns based on IoT-device collected data, decision-makers are provided with actionable recommendations for optimizing crop management and resource allocation plans (Sah Tyagi et al., 2021). The integration of IoT and AI in the agricultural sector has led to the birth of precision agriculture (Sharma et al., 2021). With the aid of IoT sensors and AI algorithms, monitoring and the management of agricultural fields is possible at a granular level. AI has proven to be a must for the analysis of the data from sensors, satellite imagery, and even historical records–this contributes, for example, to making more precise recommendations regarding the pest control process, irrigation scheduling, fertilization activities, and crop rotation for increased agronomic and economic efficiency (Muhamediyeva et al., 2023). AI, combined with IoT data, enables the development of decision support systems for farmers and these systems process the IoT real-time-collected data. Data are compared with historical trends and integrated in predictive models to provide customized recommendations and propose actual actions, such as, for example, the optimal time for crop planting, harvesting, or selling crops and, in this manner, decision support systems empower decision-makers to undertake decisions scientifically-grounded that maximize productivity and, in the end, profitability. Regarding the sustainability aspect, the integration of IoT and AI in agriculture ensures sustainable farming practice by making best-use of the IoT-device-collected data in AI algorithms that minimize water usage, boosts energy efficiency, reduce chemical inputs, and maximize the agricultural production function (Goralski & Tan, 2020; Hassoun et al., 2022; Mhlanga, 2021). This mix of technologies enables farmers and/or stakeholders to adopt precision agriculture techniques in their day-to-day activities, as well as practicing risk management, thus reducing negative environmental impacts, simultaneously with maintaining or increasing productivity (Linaza et al., 2021).

Circling back to keywords from the blue cluster, the relationship between risk management, deep learning, food security, and smart agriculture is worthy of discussion–this nexus is dynamic and symbiotic. In the context of smart agriculture, deep learning plays a crucial role in risk management practices because it resorts to analyzing large amounts of data from various sources, including historical climate records, soil composition, crop-specific agronomic indicators, and many more (Pham et al., 2021). Moreover, deep learning algorithms contribute to identifying correlations in data, enabling decision-makers to minimize risks and maximize positive outcomes, including yields. Powered by AI in some cases, deep learning algorithms can enhance food security levels, a pressing global concern. With the aid from these modern technological innovations, the ability to anticipate and respond to risks effectively ensures a favorable level of food security (How et al., 2020).

The purple cluster is composed of words such as neural networks, random forest, logistic regression, support vector machine, frequency ratio, weights-of-evidence, artificial intelligence approaches, geographic information systems (GIS), spatial prediction, and other similar words. This cluster focuses on the mathematical techniques and modeling approaches of AI to process data and make predictions based on patterns within the data. In the context of risk management, these techniques are used to address the probability and severity of risks in different areas of the agricultural activities. Frequency ratio and weights-of-evidence are statistical techniques used in spatial and risk management analyses to determine the correlation between a specific events or phenomenon and other independent variables. Therefore this implies determining the likelihood or probability of an event occurring in relation to specific factors, such as land use, terrain characteristics, and/or other environmental conditions (Ullah & Zhang, 2020). If mixing the power of machine learning algorithms with GIS data, spatial prediction techniques can be used to label high risk areas and inform decision-makers in a timely manner.
Table 1 was designed as a ranking of the most frequently-identified keywords in the analyzed publications that contained the "risk management", “food” and "chain" word structures in their title, abstract or keywords. Since AI is at the core of this conference paper, it is no surprise to find this concept on the first place in the ranking, followed by "machine learning". These items are immediately followed by the word "risk", another important component of analysis in this paper. AI encompasses machine learning, deep learning neural networks, which resort to big data analysis to build predictive models. In agriculture, these models enable risk assessment, prediction, and efficient management; they enhance performance and aid the decision-making process.

Table 1. Top twenty most used words identified in the metadata (title, abstract or keywords) of the analyzed papers

No.	Keyword	Occurrences	Percentage of total occurrences (Top-20)	No.	Keyword	Occurrences	Percentage of total occurrences (Top-20)
1	artificial intelligence	76	17.12%	11	performance	17	3.83%
2	machine learning	39	8.78%	12	deep learning	16	3.60%
3	risk	34	7.66%	13	framework	15	3.38%
4	prediction	26	5.86%	14	system	15	3.38%
5	model	25	5.63%	15	internet of things	14	3.15%
6	agriculture	23	5.18%	16	support vector machine	14	3.15%
7	management	21	4.73%	17	climate-change	13	2.93%
8	artificial-intelligence	20	4.50%	18	neural-network	13	2.93%
9	big data	19	4.28%	19	neural-networks	13	2.93%
10	classification	19	4.28%	20	identification	12	2.70%

Source: Authors' own computation of the Web of Science-extracted metadata

Robotics and artificial intelligence are part of the green cluster from Figure 2 and their linkage represents an ardent topic that requires discussion. The incorporation of robots and artificial intelligence inside the green cluster has elicited significant enthusiasm and discourse. While there are proponents who assert that these advanced technologies have the potential to bring about a paradigm shift in sustainability endeavors and facilitate the adoption of more efficient and environmentally conscious practices, there are other individuals who harbor apprehensions regarding the potential adverse consequences. Engaging in comprehensive deliberations and carefully evaluating the advantages and drawbacks are necessary in order to ensure the effective utilization of robotics and artificial intelligence (AI) in fostering an environmentally sustainable future.

Conclusions

The integration of AI into risk management processes within the agriculture business holds significant potential for augmenting decision-making processes, minimising risks, and promoting sustainability. AI-powered systems possess the ability to evaluate extensive and intricate datasets with the purpose of producing precise predictions concerning weather patterns, agricultural conditions, and market trends. This technology empowers agricultural practitioners by providing them with the ability to implement proactive measures to mitigate hazards and improve their operational efficiency. The utilisation of AI has promise in aiding the prompt detection of pests and diseases, hence enabling timely intervention and minimising the detrimental impact on agricultural productivity. AI is of paramount importance in enhancing decision-making processes and promoting the development of efficient and sustainable food production systems by offering timely insights and recommendations. However, it is crucial to recognise and address numerous challenges that arise in the application of AI for risk management, encompassing technical malfunctions, data security breaches, and ethical quandaries. In order to fully capitalise on the benefits presented by artificial intelligence in this particular field, it is imperative to address these challenges in a proficient manner. The incorporation of AI into the agricultural sector has the potential to enhance resilience and adaptability in the face of dynamic environmental and economic conditions.

The main objective of this research article was to conduct a comprehensive examination of the risk management factors related to the integration of AI in the agricultural sector. The data presented in the outcomes and analysis part demonstrates a substantial rise in scholarly investigations pertaining to this subject matter, with a noteworthy upsurge anticipated to transpire in 2022. The primary aim of this study was to investigate the application of artificial neural networks in the analysis of climate data and the generation of future projections. Moreover, the analysis prioritised the integration of environmental services and the evaluation of their susceptibility to climate change. Furthermore, the primary aim of this study was to evaluate the potential ramifications of climate change on ecosystem services, including various dimensions including water availability, crop productivity, and biodiversity. The research encompassed an analysis of ecosystem services in order to achieve a holistic comprehension of the potential consequences of climate change on both human welfare and ecological systems. Through the examination of extensive datasets obtained from Internet of Things devices, including soil moisture sensors and weather stations, AI algorithms demonstrate the capacity to deliver timely and valuable observations pertaining to crop health, water utilisation efficiency, and pest control management. In conclusion, the results of this study indicate that the incorporation of AI exhibits considerable promise in augmenting risk management within the agricultural sector, hence facilitating the progression of sustainable farming methodologies. Furthermore, the research findings indicate that the integration of AI-based risk management technologies holds significant promise for enhancing the efficiency of decision-making procedures and minimising potential risks within the realm of agricultural operations. These tools facilitate the analysis of extensive datasets by farmers, enabling them to generate precise forecasts regarding agricultural productivity, occurrences of diseases, and meteorological trends. Through the utilisation of AI, farmers have the opportunity to implement preemptive approaches in order to prevent potential risks and enhance the allocation of resources. This ultimately results in higher levels of productivity and profitability. Furthermore, the incorporation of AI into the field of risk management presents the potential to effectively mitigate environmental consequences. The research findings underscore the advantages of AI in the agricultural sector, demonstrating its ability to exert a substantial and favourable impact, hence enhancing its long-term sustainability. The utilisation of artificial intelligence enables agricultural practitioners to make well-informed decisions by effectively analysing extensive datasets, leading to enhanced resource allocation and significant financial benefits. Moreover, the domain of AI holds potential in its capacity to augment customised agricultural practises, specifically designed to cater to the unique requirements of different crops. As a result, this can potentially result in increased agricultural productivity and improved physiological health of plants. The potential for integrating AI into the agricultural sector is evident, as it has the capacity to revolutionise traditional farming practises and usher in a new era marked by enhanced operational efficiency, ecological sustainability, and economic prosperity for farmers. AI technology is equipped with advanced algorithms and data analysis capabilities, which empower it to enhance numerous processes within the agriculture sector. Therefore, this technology possesses the capacity to augment productivity and improve cost-effectiveness. Moreover, the application of AI can play a crucial role in promoting ecological sustainability by aiding in the optimisation of resource utilisation and the mitigation of environmental impacts linked to agricultural practises. As a result, this can lead to long-term benefits for both agricultural practitioners and the ecology. In addition, the application of AI can result in significant economic benefits for agricultural professionals by offering valuable insights and recommendations related to improved crop management, risk assessment, and market forecasting. The integration of AI inside the agriculture industry exhibits considerable potential in shaping the course of this vital sector. It is crucial for pertinent stakeholders to actively embrace and leverage this technology in order to sustain a competitive advantage within the ever-expanding agricultural sector.

Acknowledgement
This paper is a result of the research project entitled "Research on Identifying the Carbon Footprint of Farms in the Context of the European Green Deal and Digitization" ADER Code 19.1.2 ("*Cercetări privind identificarea amprentei de carbon a fermelor în contextul Pactului Ecologic European și digitalizării*" / cod ADER 19.1.2). This paper was co-financed by The Bucharest University of Economic Studies during the PhD program.

References

1. Abbasi, R., Martinez, P., & Ahmad, R. (2022). The digitization of agricultural industry – a systematic literature review on agriculture 4.0. *Smart Agricultural Technology*, *2*, 100042. https://doi.org/10.1016/j.atech.2022.100042
2. Adli, H. K., Remli, M. A., Wan Salihin Wong, K. N. S., Ismail, N. A., González-Briones, A., Corchado, J. M., & Mohamad, M. S. (2023). Recent Advancements and Challenges of AIoT Application in Smart Agriculture: A Review. *Sensors*, *23*(7), Article 7. https://doi.org/10.3390/s23073752

3. Amini, M., Salimi, S., Yousefinejad, F., Tarokh, M. J., & Haybatollahi, S. M. (2021). The implication of business intelligence in risk management: A case study in agricultural insurance. *Journal of Data, Information and Management*, *3*(2), 155–166. https://doi.org/10.1007/s42488-021-00050-6
4. Antón, J., Cattaneo, A., Kimura, S., & Lankoski, J. (2013). Agricultural risk management policies under climate uncertainty. *Global Environmental Change*, *23*(6), 1726–1736. https://doi.org/10.1016/j.gloenvcha.2013.08.007
5. Ayoub Shaikh, T., Rasool, T., & Rasheed Lone, F. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*, *198*, 107119. https://doi.org/10.1016/j.compag.2022.107119
6. Bhat, S. A., & Huang, N.-F. (2021). Big Data and AI Revolution in Precision Agriculture: Survey and Challenges. *IEEE Access*, *9*, 110209–110222. https://doi.org/10.1109/ACCESS.2021.3102227
7. Bhattarai, R., Bhattarai, U., Pandey, V. P., & Bhattarai, P. K. (2022). An artificial neural network-hydrodynamic coupled modeling approach to assess the impacts of floods under changing climate in the East Rapti Watershed, Nepal. *Journal of Flood Risk Management*, *15*(4), e12852. https://doi.org/10.1111/jfr3.12852
8. Burlacu, S., Negescu, M. D. O., Patarlageanu, S. R., & Vasilescu, R. A. (2021). Digital globalization and its impact on economic and social life. *SHS Web of Conferences*, *129*, 06003. https://doi.org/10.1051/shsconf/202112906003
9. Crane-Droesch, B. A., Marshall, E., Rosch, S., Riddle, A., Cooper, J., & Wallander, S. (2019). Climate change and agricultural risk management into the 21st century. *Economic Research Report - Economic Research Service, USDA*, *No.266*. https://www.cabdirect.org/cabdirect/abstract/20193419848
10. Dai, E., Wu, S., Shi, W., Cheung, C., & Shaker, A. (2005). Modeling Change-Pattern-Value Dynamics on Land Use: An Integrated GIS and Artificial Neural Networks Approach. *Environmental Management*, *36*(4), 576–591. https://doi.org/10.1007/s00267-004-0165-z
11. Dutta, P. K., & Mitra, S. (2021). Application of Agricultural Drones and IoT to Understand Food Supply Chain during Post COVID-19. În *Agricultural Informatics* (pp. 67–87). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119769231.ch4
12. Ganeshkumar, C., Jena, S. K., Sivakumar, A., & Nambirajan, T. (2021). Artificial intelligence in agricultural value chain: Review and future directions. *Journal of Agribusiness in Developing and Emerging Economies*, *13*(3), 379–398. https://doi.org/10.1108/JADEE-07-2020-0140
13. Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. *The International Journal of Management Education*, *18*(1), 100330. https://doi.org/10.1016/j.ijme.2019.100330
14. Hachani, A., Ouessar, M., Paloscia, S., Santi, E., & Pettinato, S. (2019). Soil moisture retrieval from Sentinel-1 acquisitions in an arid environment in Tunisia: Application of Artificial Neural Networks techniques. *International Journal of Remote Sensing*, *40*(24), 9159–9180. https://doi.org/10.1080/01431161.2019.1629503
15. Hassoun, A., Prieto, M. A., Carpena, M., Bouzembrak, Y., Marvin, H. J. P., Pallarés, N., Barba, F. J., Punia Bangar, S., Chaudhary, V., Ibrahim, S., & Bono, G. (2022). Exploring the role of green and Industry 4.0 technologies in achieving sustainable development goals in food sectors. *Food Research International*, *162*, 112068. https://doi.org/10.1016/j.foodres.2022.112068

16. How, M.-L., Chan, Y. J., & Cheah, S.-M. (2020). Predictive Insights for Improving the Resilience of Global Food Security Using Artificial Intelligence. *Sustainability*, *12*(15), Article 15. https://doi.org/10.3390/su12156272
17. Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem*, *2*(1), 15–30. https://doi.org/10.1016/j.aac.2022.10.001
18. Kunreuther, H. (2020). Risk Management Solutions for Climate Change–Induced Disasters. *Risk Analysis*, *40*(S1), 2263–2271. https://doi.org/10.1111/risa.13616
19. Linaza, M. T., Posada, J., Bund, J., Eisert, P., Quartulli, M., Döllner, J., Pagani, A., G. Olaizola, I., Barriguinha, A., Moysiadis, T., & Lucat, L. (2021). Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture. *Agronomy*, *11*(6), Article 6. https://doi.org/10.3390/agronomy11061227
20. Lu, Y., Chen, D., Olaniyi, E., & Huang, Y. (2022). Generative adversarial networks (GANs) for image augmentation in agriculture: A systematic review. *Computers and Electronics in Agriculture*, *200*, 107208. https://doi.org/10.1016/j.compag.2022.107208
21. Marx, A., Erhard, M., Thober, S., Kumar, R., Schäfer, D., Samaniego, L., & Zink, M. (2019). Climate Change as Driver for Ecosystem Services Risk and Opportunities. În M. Schröter, A. Bonn, S. Klotz, R. Seppelt, & C. Baessler (Ed.), *Atlas of Ecosystem Services: Drivers, Risks, and Societal Responses* (pp. 173–178). Springer International Publishing. https://doi.org/10.1007/978-3-319-96229-0_27
22. Mhlanga, D. (2021). Artificial Intelligence in the Industry 4.0, and Its Impact on Poverty, Innovation, Infrastructure Development, and the Sustainable Development Goals: Lessons from Emerging Economies? *Sustainability*, *13*(11), Article 11. https://doi.org/10.3390/su13115788
23. Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2022). IoT, Big Data, and Artificial Intelligence in Agriculture and Food Industry. *IEEE Internet of Things Journal*, *9*(9), 6305–6324. https://doi.org/10.1109/JIOT.2020.2998584
24. Morshed, S. R., Fattah, Md. A., Haque, Md. N., & Morshed, S. Y. (2022). Future ecosystem service value modeling with land cover dynamics by using machine learning based Artificial Neural Network model for Jashore city, Bangladesh. *Physics and Chemistry of the Earth, Parts A/B/C*, *126*, 103021. https://doi.org/10.1016/j.pce.2021.103021
25. Muhamediyeva, D. T., Rahmonova, M., & Shaazizova, M. E. (2023). Application of artificial intelligence technologies to select the optimal cotton crop root scheme. *International Conference on Digital Transformation: Informatics, Economics, and Education (DTIEE2023)*, *12637*, 240–244. https://doi.org/10.1117/12.2680673
26. Negrei, C., Istudor, N., & Petrescu, I.-E. (2022). The economy of material flow cycling in anthropized and anthropogenic systems. *Proceedings of the International Conference on Business Excellence*, *16*(1), 367–380. https://doi.org/10.2478/picbe-2022-0036
27. Patarlageanu, S. R., Dinu, M., Diaconu, A., & Negescu, M. D. O. (2022). Ecological agriculture and its role in sustainable development. *Proceedings of the International Conference on Business Excellence*, *16*(1), 390–399. https://doi.org/10.2478/picbe-2022-0038
28. Pham, B. T., Luu, C., Dao, D. V., Phong, T. V., Nguyen, H. D., Le, H. V., von Meding, J., & Prakash, I. (2021). Flood risk assessment using deep learning integrated with multi-criteria decision analysis. *Knowledge-Based Systems*, *219*, 106899. https://doi.org/10.1016/j.knosys.2021.106899

29. Popescu, L. M., Dinu, M., Petrescu, I. & Maerean, C. B. (2019). Structural Funds and EU's Convergence. *Quality – Access to Success*, *20*(Supplement 2), 507–510.
30. Purcell, W., & Neubauer, T. (2023). Digital Twins in Agriculture: A State-of-the-art review. *Smart Agricultural Technology*, *3*, 100094. https://doi.org/10.1016/j.atech.2022.100094
31. Rejeb, A., Abdollahi, A., Rejeb, K., & Treiblmaier, H. (2022). Drones in agriculture: A review and bibliometric analysis. *Computers and Electronics in Agriculture*, *198*, 107017. https://doi.org/10.1016/j.compag.2022.107017
32. Sah Tyagi, S. K., Mukherjee, A., Pokhrel, S. R., & Hiran, K. K. (2021). An Intelligent and Optimal Resource Allocation Approach in Sensor Networks for Smart Agri-IoT. *IEEE Sensors Journal*, *21*(16), 17439–17446. https://doi.org/10.1109/JSEN.2020.3020889
33. Saha, A. K., Saha, J., Ray, R., Sircar, S., Dutta, S., Chattopadhyay, S. P., & Saha, H. N. (2018). IOT-based drone for improvement of crop quality in agricultural field. *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, 612–615. https://doi.org/10.1109/CCWC.2018.8301662
34. Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2021). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*, *9*, 4843–4873. https://doi.org/10.1109/ACCESS.2020.3048415
35. Sohail, M. T., Mustafa, S., Ali, M. M., & Riaz, S. (2022). Agricultural Communities' Risk Assessment and the Effects of Climate Change: A Pathway toward Green Productivity and Sustainable Development. *Frontiers in Environmental Science*, *10*. https://www.frontiersin.org/articles/10.3389/fenvs.2022.948016
36. Ullah, K., & Zhang, J. (2020). GIS-based flood hazard mapping using relative frequency ratio method: A case study of Panjkora River Basin, eastern Hindu Kush, Pakistan. *PLOS ONE*, *15*(3), e0229153. https://doi.org/10.1371/journal.pone.0229153
37. Wheeler, R., & Lobley, M. (2021). Managing extreme weather and climate change in UK agriculture: Impacts, attitudes and action among farmers and stakeholders. *Climate Risk Management*, *32*, 100313. https://doi.org/10.1016/j.crm.2021.100313
38. Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., Lin, B., & Dwivedi, Y. K. (2022). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *0*(0), 1–21. https://doi.org/10.1080/00207543.2022.2063089
39. Wongchai, A., Shukla, S. K., Ahmed, M. A., Sakthi, U., Jagdish, M., & kumar, R. (2022). Artificial intelligence—enabled soft sensor and internet of things for sustainable agriculture using ensemble deep learning architecture. *Computers and Electrical Engineering*, *102*, 108128. https://doi.org/10.1016/j.compeleceng.2022.108128
40. Zhang, L., Traore, S., Ge, J., Li, Y., Wang, S., Zhu, G., Cui, Y., & Fipps, G. (2019). Using boosted tree regression and artificial neural networks to forecast upland rice yield under climate change in Sahel. *Computers and Electronics in Agriculture*, *166*, 105031. https://doi.org/10.1016/j.compag.2019.105031
41. Zscheischler, J., Brunsch, R., Rogga, S., & Scholz, R. W. (2022). Perceived risks and vulnerabilities of employing digitalization and digital data in agriculture – Socially robust orientations from a transdisciplinary process. *Journal of Cleaner Production*, *358*, 132034. https://doi.org/10.1016/j.jclepro.2022.132034