

Chapter 5.

SUSTAINABLE AGRICULTURE IN THE DIGITAL AGE: INNOVATIONS IN INSURANCE

Sustainable agriculture acts as a crucial pillar of global development, supporting economic stability and resource conservation. Advances in data collection, remote sensing, and machine learning enabled policymakers to make more informed and timely decisions in sustainable farming systems. Furthermore, data driven approach has opened new opportunities for forecasting agriculture outcomes, and ultimately, for transforming agriculture insurance practices. By leveraging Big Data and advanced analytics, insurers can now more precisely estimate risk, reduce uncertainty, and form instruments tailored to farmers' needs in changing climate.

The chapter aims to examine how digital innovations in agriculture, particularly a machine learning-based insurance model, can deliver effective insurance solutions and enhance climate resilience in developing countries like Serbia. Furthermore, it explores the contribution of agriculture to sustainable development by examining key global trends and underlining agriculture's vulnerability to climate change, particularly in developing countries like Serbia, where rising temperatures threaten GDP and productivity. It also highlights the increasing role of digitalization in modernizing agricultural practices and improving food security. Against this backdrop, the study presents a novel machine learning-based model for calculating agricultural insurance premiums using historical climate and agricultural data. The model integrates climate variability indicators and actuarial principles to calculate expected losses more accurately. Serving as a data-driven decision support tool, it aims to enhance risk assessment and promote sustainable, resilient insurance solutions in Serbia's agricultural sector.

1. THE CONTRIBUTION OF AGRICULTURE TO SUSTAINABLE DEVELOPMENT

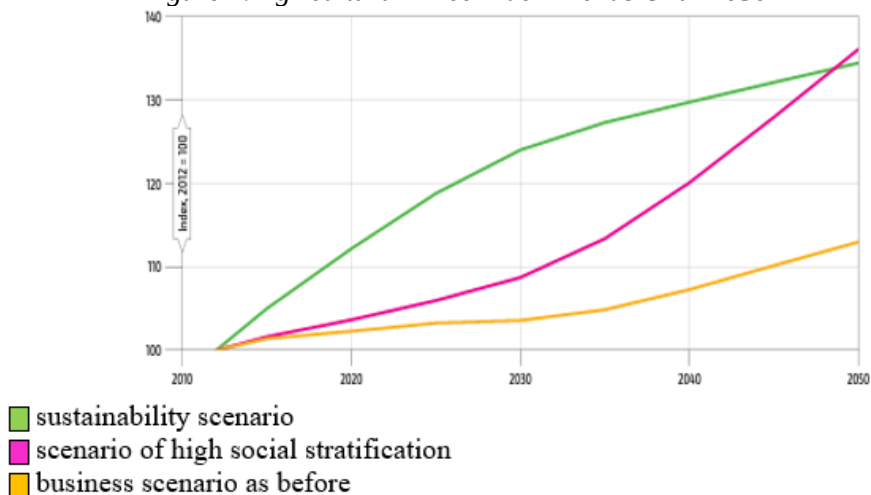
Climate conditions are undergoing significant changes, while intensive agricultural and livestock production continues to provide food for the global population. However, this process can lead to the partial destruction of natural habitats, disruption of biodiversity, and deterioration of water quality, among other environmental concerns. The Sustainable Development Goals (SDGs)

present an opportunity to enhance and promote the advancement of the agricultural sector.

Both crop and livestock production are increasingly exposed to various risks due to the growing frequency of extreme weather events, climate change, and the emergence of new animal diseases. These factors drive the need for agricultural insurance as a mechanism for economic protection against diverse agrarian risks. At the microeconomic level, insurance provides financial security to agricultural producers, ensuring resilience, continuity, and competitiveness while fostering long-term development potential.

The climate crisis exacerbates the global food crisis. An unsustainable food system worsens the issue due to significant losses during transportation and storage, as well as the waste of unused food. Addressing food scarcity in the future requires action in several key areas: raising consumer awareness to discourage food waste, strengthening legal regulations, and implementing more efficient pricing policies that incorporate the environmental costs associated with biodiversity loss. Countries with high living standards should strive for balanced food consumption patterns and the advancement of international food trade to mitigate food deficits.

Figure 1. Agricultural Price Index Trends Until 2050

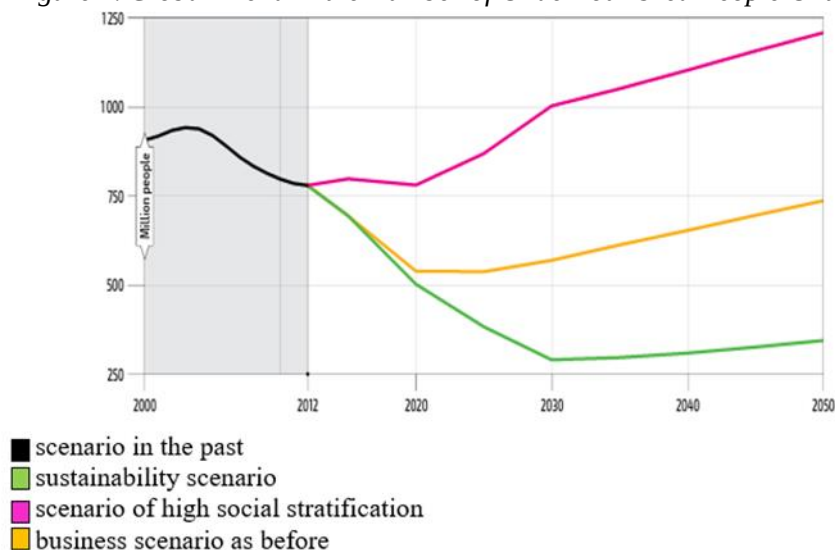


Source: Food and Agriculture Organization of the United Nations (2018). *The future of food and agriculture. Alternative pathways to 2050*. Rome: FAO, p. 100, https://knowledge4policy.ec.europa.eu/publication/future-food-agriculture-alternative-pathways-2050_en

Figure 1 presents the projected agricultural price index, indicating expected changes in agricultural product prices and forecasting market trends for agricultural commodities. The base year for comparison is 2012.

Figure 2 illustrates the dynamics of the global number of undernourished people, showing trends in food insecurity over time. The base year for reference is 2012.

Figure 2. Global Trend in the Number of Undernourished People Until 2050



Source: Food and Agriculture Organization of the United Nations (2018), *op. cit.*, p. 100.

Companies will face a decline in worker productivity as a consequence of heatwaves. Given the pronounced trend of population aging, this issue is expected to become more significant. In 1995, rising temperatures in the agricultural sector resulted in a loss of 0.04% of total working hours, equivalent to 25,200 lost labor hours. Projections indicate that by 2030, the lost working hours will increase to 0.09%, amounting to 56,700 hours. Table 1 presents the decline in labor productivity across various sectors in Serbia.

Due to rising temperatures and declining productivity in enterprises, Serbia's GDP is expected to experience significant changes. Projections indicate a GDP reduction of \$171 million by 2040. Additionally, with a minimum temperature increase of 1°C, Serbia's GDP could decline by \$1.097 billion by the end of the

century. In a more severe scenario, with a 4°C temperature rise, the GDP loss could reach \$6.261 billion.⁸⁸

Table 1. Decline in Productivity (Lost Working Hours) Across Different Sectors in Serbia: A Comparative Analysis for 1995 and 2030

Sector	1995	2030
Agriculture (Shaded) (%)	0.04	0.09
Industry (%)	0.01	0.03
Construction (Shaded) (%)	0.04	0.09
Services (%)	0	0
Total (%)	0.01	0.03
Total (in thousand work hours)	0.4	1

Source: Mitrović & Božanić (2019), op. cit., p. 24.

In alignment with the Paris Agreement, Serbia has adopted the Climate Change Strategy with an Action Plan, establishing a comprehensive national policy framework aimed at reducing greenhouse gas emissions and enhancing climate resilience. Agriculture is among the most vulnerable sectors, facing land degradation, reduced ecosystem productivity, and increased frequency of extreme weather events^{89 90}. These effects disproportionately impact developing countries, which have contributed the least to global emissions.

Intensive agriculture, relying on fossil fuel combustion and extensive legume cultivation, has significantly disrupted the nitrogen cycle, resulting in ecosystem imbalances, eutrophication, and nitrous oxide emissions—a potent greenhouse gas. In response, companies such as Nestlé are adopting regenerative agriculture, engaging over 600,000 farmers to promote sustainable, deforestation-free supply chains and ecosystem restoration⁹¹.

⁸⁸ Mitrović, Đ., & Božanić, D. (2019). *Studija o socio-ekonomskim aspektima klimatskih promena u Republici Srbiji*, p. 25. Retrieved from <https://www.klimatskepromene.rs/dokumenta/studija-o-socio-ekonomskim-aspektima-klimatskih-promena-u-republici-srbiji/>

⁸⁹ Mirković, V., & Lukić, J. (2018). Energy Transition in the EU and Serbia: Strategic Approach to Climate Change. *Economic Perspectives*, 23(3-4), pp. 229-230.

⁹⁰ Mihailović, B. M., Radosavljević, K., Popović, V., & Puškarić, A. (2024). Impact of digital marketing on the performance of companies in the agricultural sector of Serbia. *Ekonomika poljoprivrede*, 71(1), pp. 173-188.

⁹¹ Creating Shared Value Sustainability Report, 2022, p. 5. Nestle company report. 2020. 2020 – annual – review – en, Retrieved from 2024-annual-review-en.pdf (nestle.com)

Emerging trends emphasize the role of digitalization and ICT, biotechnology, and nanotechnology in enhancing productivity and sustainability in agriculture⁹². The Internet of Things (IoT) plays a pivotal role in precision agriculture by enabling remote monitoring of soil, crops, and water usage, thus supporting data-driven decision-making. IoT systems further facilitate livestock management and pest control, both of which are increasingly challenged by climate variability⁹³.

Cloud computing and Big Data analytics allow for the efficient processing of large datasets to identify sustainability patterns, optimize energy use, and mitigate environmental impacts⁹⁴. Predictive analytics, driven by these technologies, contribute to enhanced production planning and risk reduction⁹⁵. To mitigate climate-related risks, companies are encouraged to implement risk assessment, supply chain diversification, resource optimization, investments in resilient infrastructure, and the promotion of sustainable business models^{96 97}.

As an example of digital innovation, the BioSens Institute developed the DDOR TERRA platform for rapid damage reporting in agriculture. Furthermore, robotics and autonomous systems, such as drones and driverless tractors, are transforming agricultural operations, although adoption barriers remain due to limited technological acceptance among farmers.

2. THE DIGITALIZATION OF AGRICULTURE

In the context of sustainable development, agriculture faces the challenge of how to provide enough food for a growing population while preserving natural resources and the environment. Digitization in agriculture appears as a key tool

⁹² Paraušić, V., & Nikolić Roljević, S. (2021). *The Role of Innovations in the Agricultural Sector in Achieving Serbia's Sustainable Development Goals*. Belgrade: Institute for Agricultural Economics, p. 18.

⁹³ Čelik, P. (2020). *Digital Transformation of Business and Its Security Implications*. Novi Sad: Faculty of Economics and Engineering Management, pp. 95-96.

⁹⁴ Zečević, A., & Radosavljević, K. (2014). Web-based business applications as the support for increased competitiveness in agribusiness. *Ekonomika preduzeća*, 62(7-8), pp. 405-418.

⁹⁵ <http://m.srja.cropprotection.net/news/smart-farming-iot-is-transforming-the-future-42791147.html>

⁹⁶ De Mauro, A., Greco, M., & Grimaldi, M. (2019). Understanding big data through a systematic literature review: the ITMI model. *International Journal of Information Technology & Decision Making*, 18(04), pp. 1433-1461.

⁹⁷ Kostić, M. (2021). *Precision Agriculture*. Novi Sad: University of Novi Sad, Agricultural Faculty, p. 18.

for solving that challenge, as it introduces advanced technologies for more efficient and environmentally responsible production management. Digital transformation of the agricultural sector thus becomes a bridge between the principles of sustainable development and modern technological solutions, including the application of artificial intelligence on farms. Key areas of application of digital technologies in agriculture include precise soil analytics, irrigation optimization and rational application of pesticides and fertilizers. Thanks to sensors, GPS navigation and satellite observation, farmers can monitor soil properties such as moisture, pH value and nutrient content in detail, and make precise sowing and fertilization plans according to the actual crop needs. At the same time, the application of smart irrigation systems based on the Internet of Things (IoT) ensures optimal use of water, so that plants are watered at the right time and with exactly the amount of water they need. This resource optimization reduces waste and increases the resilience of agriculture to drought and climate change. Digital innovations also contribute to a more sustainable use of agrochemicals through a more rational use of pesticides and mineral fertilizers. Drones and digital systems for crop surveillance make it possible to detect pests or plant diseases early and allow for targeted application of protective agents only where necessary, instead of broad preventive application across entire fields. Such an approach not only reduces costs and negative impact on the ecosystem, but also preserves soil quality in the long term. In this way, the digitization of agriculture lays the foundations for sustainable agricultural development, while at the same time opening the door to specific application of artificial intelligence in the following chapters. For the aforementioned reasons, we analyze the specific contribution of the application of advanced technologies in the agricultural sector, with a special focus on precise analytics, optimization of the irrigation process and rational use of pesticides and fertilizers. The review will include current global trends, European practices and Serbian examples, all in order to show how digital transformation contributes to the achievement of sustainable development goals in the agricultural sector.

Precise soil analytics

Precise soil management begins with detailed analytics. It includes monitoring the chemical composition, structure and moisture content of the soil in real time. Networked IoT sensors in the field today record parameters such as moisture, temperature, pH and nutrient content, while AI algorithms turn that data into recommendations for agronomists. That way, farmers get information about when and how much fertilizer to add, or whether the soil is wet enough for seeding, instead of relying on field-wide averages. Studies emphasize that lower

use of fertilizers and higher soil fertility are the key benefits of this approach⁹⁸. By supplementing historical soil data with data on weather conditions, artificial intelligence can predict optimal times for planting and harvesting cultivated crops. In this way, it is possible to predict which climatic conditions and soil moisture bring the least risk of crop failure.

An example of the use of advanced technology in this area is shown in research published in *Nature Food*. Scientists have developed a soil ammonium sensor (called chemPEGS) that, with the help of artificial intelligence algorithms, combines multiple factors such as weather data, pH value, soil conductivity and time since previous fertilization. The goal is to predict the total nitrogen in the soil and establish the optimal time for the next crop feeding⁹⁹. This system helps farmers precisely establish the amount and timing of fertilization, which maximizes nutrient utilization by plants and prevents overfertilization that leads to pollution. Data shows that the excessive use of fertilizers has so far rendered infertile about 12% of the once arable land in the world, and the consumption of nitrogen fertilizers has increased by 600% in the last 50 years³.

The European Union's projects and institutions actively research and apply the approach of precise soil analysis. A number of digital agronomy platforms have been developed to help farmers make the most optimal decisions. The BioSense Institute in Serbia applies various technologies in agriculture. They have developed an advanced system for autonomous soil sampling and analysis called Agrobot Lala¹⁰⁰. It is an automated system that moves over cultivated areas and takes soil samples. The goal is to measure nitrate content in real time with the help of ion-selective probes¹⁰¹.

Each sample is analyzed individually depending on the geographical location, which is a big shift compared to traditional systems that take into account the

⁹⁸ Sharma, A., Sharma, A., Tselykh, A., Bozhenyuk, A., Choudhury, T., Alomar, M. A., & Sánchez-Chero, M. (2023). Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture. *Open Life Sciences*, 18(1), 20220713.

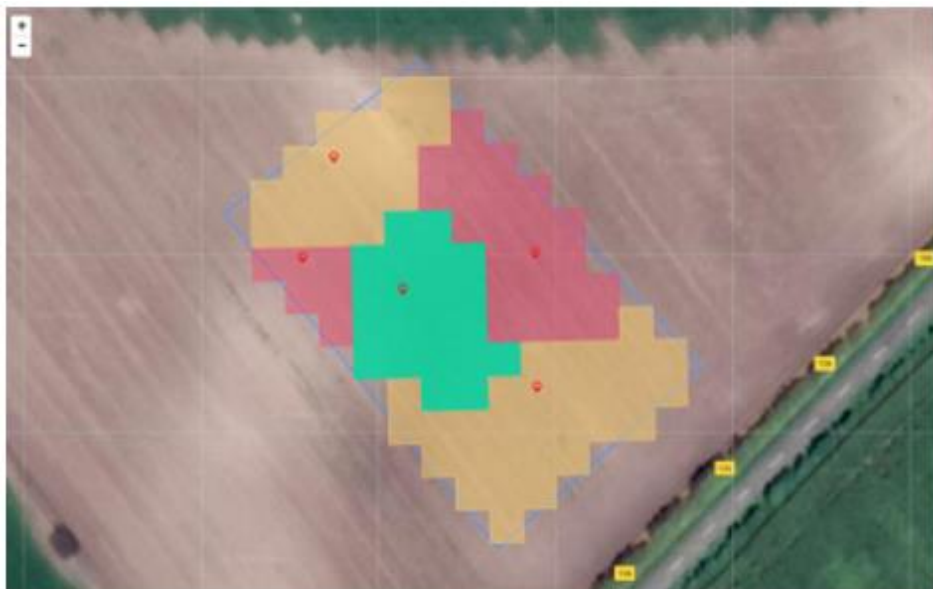
⁹⁹ Imperial College London (2021). Low-cost AI soil sensors could help farmers curb fertilizer use. *Phys.org*. Retrieved March 19, 2025, from <https://phys.org/news/2021-12-low-cost-ai-soil-sensors-farmers.html>

¹⁰⁰ Agrobot for in-field soil analysis. (n.d.). *BioSense Institute*. Retrieved March 28, 2025, from <https://biosens.rs/en/themes/agrobot-2>

¹⁰¹ Kitić, G., Krklješ, D., Panić, M., Petes, C., Birgermajer, S., & Crnojević, V. (2022). Agrobot Lala—an autonomous robotic system for real-time, in-field soil sampling, and analysis of nitrates. *Sensors*, 22(11), 4207.

average multi-site sample. The result of such a detailed analysis are precise fertility maps based on which the user can apply fertilizer in a targeted manner, as Figure 3 shows. This system optimizes the soil fertilization process and enables sustainable production.

Figure 3. Sampling zones and points generated by Robot Lala



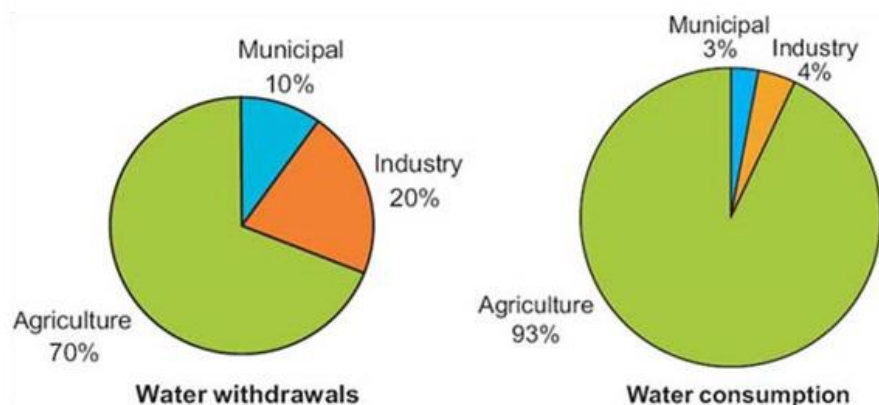
Source: Kitić et al. (2022), op. cit., p. 4.

Optimization of irrigation

Water is a key resource in agriculture. However, traditional irrigation systems very often lead to its excessive use. Globally, agriculture uses about 70% of available drinking water¹⁰², and excess water can lead to soil erosion and leaching. Therefore, optimization with the help of artificial intelligence can be a significant solution to the problem of suboptimal soil irrigation. Figure 4 shows FAO data on shares of water withdrawal and consumption by sector. Water withdrawal refers to the amount of water taken from natural sources, regardless of whether or not the water will be returned. On the other hand, consumption represents the permanent loss of water that is lost or retained in the system.

¹⁰² <https://www.fao.org/4/y5582e/y5582e04.htm>

Figure 4. Share of global water withdrawals and consumption by sector



Source: Food and Agriculture Organization of the United Nations (2004). *The role of water in agricultural development*. Rome: FAO, <https://www.fao.org/4/y5582e/y5582e04.htm>

AI systems enable precise management of soil irrigation based on weather data and overall soil condition. For example, predictive analytics and machine learning models can adjust watering schedules based on soil moisture, weather forecast and crop development stage. Also, developed sensor networks can take into account additional information about a specific crop or soil type so that irrigation can be automatically started or stopped in order to maintain the optimal level of moisture.

Research shows that the application of AI tools in the irrigation process leads to significantly more efficient use of water in the irrigation process. Analysis of studies has shown that systems based on artificial intelligence achieve an average increase in water use efficiency of 30 to 40% compared to traditional methods¹⁰³. The same study states that under controlled conditions, water consumption was reduced by about 88% thanks to an artificial intelligence system that maintained soil moisture levels. Also, these systems minimize the degree of soil degradation caused by inadequate irrigation.

In Europe, special focus is on precision irrigation. Many European farms are already using sensor networks and satellite monitoring. An example is the

¹⁰³ Oğuztürk, E., Murat, C., Yurtseven, M., & Oğuztürk, T. (2025). The effects of AI-supported autonomous irrigation systems on water efficiency and plant quality: A case study of *Geranium psilostemon* Ledeb. *Plants*, 14(5), 770.

AgriBIT project. A large number of services have been developed that integrate satellite data and sensors in order to effectively monitor crop status and soil moisture in real time through a mobile application¹⁰⁴. Such systems can bring flexibility when planning irrigation. In Serbia, irrigation is insufficiently developed and it is estimated that only 8.3% of arable land is irrigated. However, this may mean that there is huge room for improvement in this field. BioSense institute initiatives have included satellite detection of irrigation problems. The cooperation of the European Union and FAO resulted in the installation of automatic meteorological stations for moisture monitoring in Serbia. It is expected that the wider application of such technologies will contribute to the development of agriculture at the level of the entire country.

Correct dosing of pesticides and fertilizers

The application of pesticides and mineral fertilizers is an area where precision agriculture brings direct environmental benefits. The traditional spraying approach often involves the application of preparations over the entire soil surface, which leads to wastage and irrational consumption of fertilizers¹⁰⁵. Artificial intelligence tools have the potential to change this with the help of computer vision and machine learning. Drones or machines equipped with cameras recognize weeds, pests or signs of crop disease, so chemicals are applied only where they are really needed. For example, modern “spot-spraying” sprayers use high-resolution cameras and AI algorithms that can recognize each weed between crop rows in a fraction of a second and activate the spray directly above the spotted weed, instead of continuously spraying the entire field. This can drastically reduce the amount of herbicide used. Field tests on soybeans in Iowa (USA) showed savings of 76% in the use of herbicides on average (from 43% to even 91% per individual field), without losing the effectiveness of weed control¹⁰⁶. Similarly, experts report that AI targeted spraying systems have helped farmers reduce overall pesticide use by up to 90% in some cases¹⁰⁷. Such a significant reduction in chemicals not only reduces costs for farmers, but also has great environmental significance such as reducing water and soil pollution,

¹⁰⁴ <https://cordis.europa.eu/article/id/454267-improving-europe-s-precision-agriculture-with-ai>

¹⁰⁵ Richards, A. (2024). The Environmental Impact of Precision Spraying: Reducing Chemical Use and Protecting Ecosystems. *AgTechLogic*. Retrieved March 15, 2025, from <https://agtechlogic.com/the-environmental-impact-of-precision-spraying-reducing-chemical-use-and-protecting-ecosystems/>

¹⁰⁶ <https://growiwm.org/herbicide-savings-from-precision-spraying-technology/>

¹⁰⁷ <https://agresearch.okstate.edu/news/articles/2024/scientists-use-ai-to-reduce-ag-costs-and-labor.html>

saving beneficial insects (pollinators, pest predators) and slowing down the emergence of harmful organisms.

Scientific literature confirms these trends. The European Parliament's analysis states that precision methods can lead to a 20-30% reduction in pesticide use, as well as up to 50-80% less pesticide-treated area (owing to targeted application instead of treating every hectare)¹⁰⁸. This protects ecosystems and biodiversity on and around agricultural land. Fewer chemicals in the fields means preservation of the population of bees and other pollinators, as well as richer microbiological life in the soil itself. In addition, precise variable fertilization (with the help of VRT (variable rate technology) allows mineral fertilizers to be applied only where soil analyses show a nutrient deficit, thereby reducing the total amount of nitrogen and phosphorus input.

In Europe, these techniques are the focus of sustainable agriculture strategies. Through the "Farm to Fork" strategy, the EU set the goal of reducing the use of chemical pesticides by 50% by 2030¹⁰⁹. Achieving that ambitious goal relies heavily on the wider application of precision spraying and integrated pest management (IPM). Examples of good practice already exist: European producers and researchers have developed systems that combine satellite imagery for the early detection of diseases and pest attacks with drones that carry out targeted spraying only on vulnerable parts of plots.

Serbia follows these trends as well. Larger farms have started using drones to spray orchards and GPS-guided sprayers with sector control (turning off nozzles on already treated zones). However, experts point out that the adoption of precision agriculture in Serbia is only in its infancy among small farms, mainly due to costs and lack of information¹¹⁰. Projects such as the EU H2020 DRAGON educate farmers on the cost-effectiveness of precision methods and have demonstrated successful case studies, from space-based crop monitoring to pest risk assessment models¹¹¹.

¹⁰⁸ <https://croplifeeurope.eu/farmers-toolbox/digital-and-precision-agriculture/>

¹⁰⁹ European Commission (2023). Using Less Chemical Pesticides: European Commission Publishes Toolbox of Good Practices. *News Article*, Retrieved March 27, 2025, from https://agriculture.ec.europa.eu/media/news/using-less-chemical-pesticides-european-commission-publishes-toolbox-good-practices-2023-02-28_en

¹¹⁰ <https://www.acdivoca.org/2024/02/making-agriculture-smarter-in-serbia-through-precision-farming/>

¹¹¹ <https://cordis.europa.eu/article/id/435491-lighting-a-beacon-for-precision-farming-knowledge-in-serbia>

However, despite all the advantages that artificial intelligence and digitization bring, risks in agriculture cannot be completely eliminated. Extreme climatic events, plant diseases and other unforeseen circumstances can still significantly threaten yields, regardless of the level of technology application. That is why, in addition to technological solutions, the development of modern insurance systems in agriculture plays a key role in ensuring the long-term stability and safety of food production.

3. INNOVATIONS IN AGRICULTURE INSURANCE

Agriculture production has proved to be highly risky venture. The uncertainty of future prices and yields impedes farmers' long-term capital planning and short-term production resolutions. As probability of default is relatively high, financial institutions are unwilling to approve loans to farmers, ultimately reducing farm profits in the long term. Due to the substantial systematic component present in a portfolio of agriculture risks, insurance markets are often unable to conduct affordable risk management mechanism for agriculture production. As a result, many governments subsidize insurance companies and/or farmers in form of price-support programs, tax breaks, subsidized reinsurances, etc. However, government programs seldom provide expected results and come at a high social cost.¹¹²

In the face of extreme weather events and climate change, the implementation of advanced technologies and tools has transfigured the agriculture insurance sector, enabling more precise, effective and efficient resolutions for both insurers and producers. Artificial Intelligence (AI) and blockchain-based contracts have proved to enhance insurance premium pricing, loss prediction and farmers' adjustment to climate challenges. AI analyzes extensive datasets on weather patterns, crop health, market trends for real-time policy customization, while blockchain eases automated claims processing through smart contracts, reducing costs and improving transparency.¹¹³ Companies such as Etherisc and Limonade have incorporated parametric insurance, offering automatic compensation calculated on predefined events rather than traditional damage assessments.

Furthermore, digital platforms and mobile technology have broadened access to agriculture insurance by facilitating claims filing process and policy management. Digital transformation improves customer experience and

¹¹² Miranda, M., & Vedenov, D. V. (2001). Innovations in agricultural and natural disaster insurance. *American Journal of Agricultural Economics*, 83(3), p. 653.

¹¹³ Venturini, R. E. (2025). Revolution in agricultural insurance: the integration of AI and blockchain for a more efficient and resilient sector. *Revista Sistemática*, 15(3), p. 192.

operational efficiency, while mobile apps enable farmers to purchase insurance, receive payouts, and report losses.¹¹⁴

Drone technology has significantly improved agricultural insurance assessments by improving accuracy, efficiency, and cost-effectiveness. Equipped with advanced sensors, drones capture high-resolution images that allow insurers to assess crop health, estimate yields, and evaluate damage with precision. Their ability to rapidly cover large farmland areas accelerates claims processing and reduces reliance on subjective manual inspections, which is especially crucial after natural disasters. Additionally, drones help mitigate fraud and improve risk management, leading to more accurate insurance policies tailored to farmers' needs. By fostering transparency and ensuring fair compensation, drone technology strengthens trust between farmers and insurers, ultimately benefiting the agricultural sector.¹¹⁵

Finally, innovations in agricultural insurance are progressively integrating conservation practices such as no-till and mini-till technologies to enhance risk mitigation and optimize claim management. A 2019 analysis of prevent-plant crop insurance claims across six Midwestern states showed that fields utilizing cover crops and no-till methods were 24% less likely to be classified as “prevent plant” and receive insurance payouts compared to conventionally managed fields. This finding underscores the potential of conservation agriculture to buffer against adverse weather conditions, thereby reducing both the incidence and magnitude of insurance claims.¹¹⁶

A Data-Driven Approach to Premium Calculation

The evolution of agricultural insurance has been profoundly influenced by advances in Big Data analytics, machine learning, and climate modelling. Recent literature highlights the increasing importance of data-driven risk assessment, particularly in the context of climate uncertainty and yield variability. Traditional methods of premium calculation often fail to capture the spatial and temporal

¹¹⁴ World Bank Group (2022). *Disruptive innovations boost uptake of agriculture insurance solutions in Kenya*. Retrieved March 19, 2025, from <https://www.worldbank.org/en/news/feature/2022/06/15/disruptive-innovations-boost-uptake-of-agriculture-insurance-solutions-in-kenya>

¹¹⁵ <https://husfarm.com/article/the-impact-of-drones-on-enhancing-agricultural-insurance-assessments>

¹¹⁶ Environmental Defence Fund (2023). *Cover crops reduce insurance claims and lower costs for taxpayers*. Retrieved March 19, 2025, from <https://business.edf.org/insights/cover-crop-insurance-claims>

complexities of climate risk, leading to inefficiencies in pricing and risk allocation. This study builds on recent advancements by proposing a precision-based insurance model tailored to the Serbian agricultural sector, focusing on wheat, corn, and soy cultivation.

By integrating machine learning, climate analytics, and actuarial modelling, this research offers an innovative framework for agricultural insurance, improving pricing accuracy and risk assessment. The proposed model serves as a data-driven decision support tool for insurers, facilitating more sustainable and resilient agricultural insurance policies in Serbia. Historical data from wide variety of climate, agriculture and market information serve as a fuel to novel approach of insurance companies' business model.

The proposed insurance premium calculation model is structured around the fundamental actuarial principle that premium is composed of expected loss and a risk adjustment factor multiplied with standard deviation of consecutive dry days. Formally, the premium is expressed as:

$$\text{Premium} = E(L) + \lambda * \sigma_{\text{CDD}}$$

Where $E(L)$ represents the expected loss, λ is the risk load factor, and σ_{CDD} denotes the standard deviation of consecutive dry days, serving as a measure of climate variability and systemic risk. This approach is consistent with the Sharpe ratio method, where the risk margin is proportional to the standard deviation of the insurer's cost.¹¹⁷

Expected loss is mathematically defined as:

$$E(L) = P(D) \times (Y_f - Y_o) \times P_f$$

Where $P(D)$ represents the probability of drought, Y_f is the expected yield, Y_o is the observed yield, and P_f is the market price of the respective crop.¹¹⁸

The primary objective of this research is to accurately estimate the expected loss by leveraging Big Data sources, including the Digital Atlas of Serbia and the Statistical Office of the Republic of Serbia.

¹¹⁷ Leblois, A., & Quirion, P. (2013). Agricultural insurances based on meteorological indices: realizations, methods and research challenges. *Meteorological Applications*, 20(1), pp. 1-9.

¹¹⁸ Kleshchenko, A. D., Lebedeva, V. M., Goncharova, T. A. et al. (2016). Estimation of drought-related yield loss using the dynamic statistical model of crop productivity forecasting. *Russian Meteorology and Hydrology*, 41, pp. 299-306.

At the core of this model is the integration of agricultural and climate Big Data to enhance the accuracy of premium calculations. The proposed methodology utilizes historical climate data from the Digital Atlas of Serbia, specifically focusing on wheat, corn, and soybean cultivation. The dataset encompasses two key climatic indicators—the aridity index and vegetation period—for the Čurug region, one of Serbia’s most fertile agricultural areas, covering the period from 1950 to 2020.

Aridity index (AI) has proved as critical indicator for assessing and predicting drought, for it distinguishes type of climate in respect of water availability. Furthermore, AI considers climatic data of precipitation (P), evapotranspiration (PET) and air temperature (T):¹¹⁹

$$AI = \left(\frac{P}{PET} \right)$$

where P is the monthly precipitation and PET is the monthly potential evapotranspiration. Typically, values below 0.5 indicate dry conditions.

According to the United Nations Environment Programme (UNEP)¹²⁰ classification criteria of climate risk, drought severity is classified into four categories: extreme, moderate, mild, and no drought, based on AI. Table 2 shows defined criteria.

Table 2. Drought Classification Criteria

Category	Aridity Index
Severe Drought	Less or equal than 0.2
Moderate Drought	Less or equal than 0.35
Mild Drought	Less or equal than 0.5
No Drought	else

Source: Budyko, M. I. (1958). *The Heat Balance of the Earth's Surface*. Soviet Geography, 2(4).

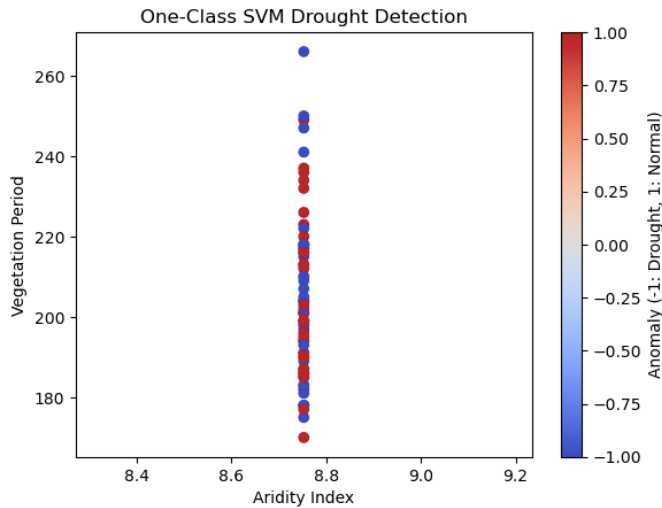
Upon analyzing the 70-year dataset of the most fertile agricultural region in Serbia, no recorded instances of drought were observed based on the United Nations Environment Programme (UNEP) classification. The Aridity Index (AI) values remained consistently above the threshold defining drought conditions, leading to a dataset where the column Drought contained only a single class: "No Drought." Given the absence of variation in drought classifications in Čurug

¹¹⁹ Thornthwaite, C. W. (1948). An approach toward a rational classification of climate. *Geographical Review*, 38(1), pp. 55-94.

¹²⁰ <https://www.unep.org>

region example, traditional supervised learning techniques, which rely on multiple class labels for training, were not applicable in the context.

Figure 5. One-Class SVM Drought Detection



Source: Author's calculations.

To address this challenge, an unsupervised anomaly detection approach was employed using the One-Class Support Vector Machine (One-Class SVM). One-Class SVM is a robust machine learning algorithm specifically designed for outlier detection in scenarios where only one class is well-represented in the data. It constructs a decision boundary around the majority class (in this case, normal conditions) and identifies deviations from this learned distribution as potential anomalies.¹²¹

The model was trained on two key climatic indicators: the Aridity Index and Vegetation Period, both of which play a crucial role in drought assessment. The trained One-Class SVM model assigned each data point to either the normal climatic condition class (1) or an anomalous (potential drought-like) class (-1). The resulting classification was visualized in Figure 5 (shown above), where the red-colored points represent data instances flagged as anomalies by the model. These instances, despite not meeting traditional drought classification criteria, highlight periods where climatic conditions exhibited slight deviations from the typical pattern observed over the seven-decade period.

¹²¹ Yin, S., Zhu, X., & Jing, C. (2014). Fault detection based on a robust one class support vector machine. *Neurocomputing*, 145, pp. 263-268.

Finally, the study integrates historical yield and price data of wheat, soybean, and corn with the Extreme Gradient Boosting (XGBoost) machine learning algorithm to enhance the accuracy of both yield and price forecasts, thereby improving the precision of agricultural insurance premium calculations. XGBoost constructs an ensemble of decision trees that iteratively correct prediction errors while incorporating regularization techniques to mitigate overfitting.¹²²

The dataset spans from 2005 to 2022, enabling the model to capture long-term yield variability and price-related influences. To account for temporal dependencies, lag features representing the previous year's yield values are introduced, allowing the model to learn patterns in yield fluctuations.

The dataset is standardized using StandardScaler to ensure numerical stability, while a train-test split method used data from 2005 to 2021 for model training and 2022 for validation. Separate XGBoost regression models are trained for each crop, utilizing a squared error loss function and hyperparameters optimized for predictive performance. Future yield and price predictions for the period 2024–2026 are generated iteratively, where the predicted values serve as inputs for subsequent years, enabling multi-year forecasting. Table 3 presents the predicted prices and yields for wheat, soybean, and corn.

Table 3. Predicted Prices and Yields for Wheat, Corn and Soy

Year	Wheat Yield	Wheat Price	Corn Yield	Corn Price	Soy Yield	Soy Price
2024	4.0998	17.5487	6.3984	16.0269	2.4001	43.6402
2025	3.4084	16.5514	6.2987	14.5077	2.1028	35.4479
2026	4.2973	17.8297	5.9001	14.3909	2.4001	34.7039

Source: Author’s calculations

By integrating historical data with machine learning techniques, this approach enhances the accuracy of price, yield, and drought probability forecasts, leading to improved risk assessment in agricultural insurance. The incorporation of conservation practices, such as no-till and mini-till technologies, further strengthens risk mitigation by reducing insurance claims associated with adverse weather conditions. Additionally, emerging technologies like drones, IoT, and blockchain provide innovative solutions for real-time monitoring, data transparency, and automated insurance processing, and eventually trust between insurers and farmers. These advancements collectively optimize insurance

¹²² Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 785-794.

pricing strategies, ensuring more precise policy design and fairer compensation mechanisms. Ultimately, the convergence of data-driven models and technological innovations transforms agricultural insurance into a more resilient and adaptive system.

The complete implementation of each machine learning model used in this study is available on GitHub at:

<https://github.com/bradickristina/agri-insurance.git>.