DETERMINING THE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL PRODUCTION USING ARTIFICIAL INTELLIGENCE (CASE STUDY OF WHEAT AND COTTON)

Imomov Bekzod Marat ugli
PhD student, Bukhara state technical university
Qosimov Fazliddin Tolibovich
Bukhara State Technical University Academic Lyceum,
Teacher of the Department of "Physics and Mathematics"

Received: 28.08.2025
Revised: 29.08.2025
Accepted: 30.08.2025
Keywords:
climate change, crop, crop yields, ai, machine learning, cotton, wheat, climatic factor, effects, analytics, agriculture

Abstract
This article explores and analyzes in detail the main problem of the impact of climate change on crop yields, reveals the transformational potential of AI as a solution, critically assesses the key challenges of its implementation (economic, social and technical) and offers specific, practical recommendations for conducting the study, with a particular focus on the regional context of Uzbekistan.

Introduction. The Imperative of a Climate-Smart Agricultural System. The world faces a complex combination of challenges, including a rapidly growing population, intensifying urbanization and cropland degradation.[1] These factors create a growing burden on the agricultural sector, which is simultaneously struggling with the systemic threats of climate change. In this context, the topic of the research dedicated to the use of artificial intelligence (AI) to determine the impact of climate change on agricultural production is not just relevant, but vital. short-term risks to food production.[2,3] AI's ability to analyze vast and complex data sets and generate actionable insights makes it a key element of modern agricultural innovation.

Bidirectional Impacts of Climate Change on Crop Yields: Global and regional overview. The latest comprehensive analysis from 2025 shows that even with adaptation by farmers, rising global temperatures will reduce the world's ability to produce food from most major crops. Projections indicate that under high emissions, global yields of staple crops, expressed in calories, will be 24% lower by 2100 than without climate change.[5]

The most important finding is that in the short term, by 2050, global crop yields are estimated to decline by 8%, regardless of the trajectory of future emissions. This is because the carbon dioxide emissions accumulated in the atmosphere persist for hundreds of years, trapping heat and causing damage. This

moves the research from a long-term and hypothetical to an immediate crisis response project. This adds a significant layer of relevance and social relevance, as the research aims to mitigate the effects that have already occurred and will affect the food sector security in the coming decades.

Physiological and phenological effects on wheat (*Triticum aestivum*): High temperatures pose a serious threat to wheat production, especially during the reproductive development stage. Heat stress shortens the life expectancy of the crop, damages the components of photosynthesis and reduces the rate of grain filling. Temperatures in excess of 31°C may result in pollen sterility and a significant reduction in the number and weight of grains.[6]

The impact goes beyond quantitative yields. Heat stress can alter the biochemical composition of grains, leading to an increase in total protein content, but a decrease in essential amino acids and impaired glutenin synthesis. This makes the problem a matter not only of agronomy, but also of food security and public health. Intelligent models trained to predict not only yields but also quality indicators can provide a more holistic and meaningful solution for farmers and policymakers.[7]

Climate impact on cotton (*Gossypium hirsutum*): Cotton production is uniquely affected by climate change due to the interaction of two opposing factors. As a plant cotton benefits from an increased concentration of atmospheric CO_2, which can lead to a "fertilizer effect" and increase biomass and yields. However, this positive effect is often offset by the negative effects of rising temperatures. Higher temperatures increase the need for water, especially during the development of flowers and bolls. They also contribute to the growth of pest and disease populations, which can reduce yields by 40-50% and increase the need for pesticide use.[8]

The conflicting effects of CO_2 and temperature on cotton pose a difficult challenge for modelling. A simple AI model can be misled by the positive effects of CO_2 and fail to predict the true, net negative impacts. This requires a more sophisticated, multivariate modeling approach that can separate and weigh these competing forces. Research addressing this question could make a new contribution by developing an AI architecture specifically tailored to deal with these conflicting physiological factors.[9,10]

Culture	Climatic factor	Physiological effects
Wheat	Heat stress	Shortening of the growing season, damage to photosynthesis, sterility of pollen, reduction in the number and weight of grains.
Wheat	Heat stress	Changes in the composition of grain (increase in protein, decrease in essential amino acids, impaired glutenin synthesis).
Cotton	Increased CO_2	Increase photosynthesis, increase in yield.
Cotton	Fever	Increased need for water, growth in pest and disease populations, reduced yields.

Table 1. Key physiological mechanisms of climate stress on wheat and cotton[11]

The Transformational Potential of Artificial Intelligence: Advanced AI models, including deep learning algorithms such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, are revolutionizing crop yield forecasting. CNNs successfully analyze spatial data from drones and satellites, while LSTMs efficiently work with historical time series (weather, soil conditions). Hybrid models that combine both approaches now provide more accurate and holistic predictions.[12]

The effectiveness of these models depends on the availability of robust, multimodal datasets that are collected through satellite imagery (e.g., MODIS), soil sensors, weather forecasts, and historical crop data.[3] Public datasets for machine learning can be found on platforms such as Kaggle and the United States Department of Agriculture (USDA) directory.[14] The observed shift to hybrid models (CNN-LSTM) indicates a shift in agricultural AI from simple pattern recognition to a more comprehensive understanding of spatio-temporal dynamics. The thesis can make significant methodological contributions by proposing an architecture for merging data from various sources to create a more robust and accurate predictive tool.

AI for precision farming and resource optimization: AI is moving agronomy from forecasting to action. AI systems analyze real-time data to optimize the use of critical resources such as water, fertilizers, and pesticides. Not only does this increase yields (by 15-20%, according to a 2024 study), but it also significantly reduces costs (by 25-30%) and carbon dioxide emissions. AI also integrates seamlessly with robotics to automate time-consuming tasks such as planting, weeding, and harvesting. These autonomous systems can operate in extreme weather conditions and reduce dependence on fossil fuels, improving both efficiency and sustainability of agriculture. For example, robots developed by a Canadian company are equipped with AI and Internet of Things (IoT) sensors to monitor plant health and diseases in real-time.

The role of AI in this context is not to replace farmers, but to empower them. Describing AI as a "personal agronomist" providing "practical solutions" suggests the creation of a collaborative system in which humans remain the key link. This rethinks the purpose of the research: it should not just be a purely technical solution, but also a socio-technical one. but also on the ease of use and the ability to gain the trust of the end user – the farmer.

Enable transparency with explainable AI (XAI): The complexity of deep learning models can turn them into "black boxes" whose solutions are difficult to interpret.[13] Explainable AI (XAI) solves this problem by providing transparent and understandable information about how a model arrives at a particular prediction. Methods such as SHAP and LIME quantify the contribution of each variable (e.g., soil moisture, temperature) to the forecast, providing a crucial understanding of the underlying factors affecting yields.[12]

The value of XAI goes beyond building user trust; It serves as a powerful tool for scientific discovery. By identifying the most influential variables in yield forecasts, XAI can help agronomists discover previously unknown or underestimated factors that influence crop variability. For the research, this transforms research from a simple application of AI into a project that generates new knowledge and contributes directly to agricultural science.

Overcoming the challenges of AI in agriculture: The most significant obstacle to AI adoption is the high upfront costs of equipment, including sensors, drones, and AI-enabled machines.[17] This disproportionately affects small and medium-sized farmers, widening the gap between large commercial enterprises and small family farms.[18] This economic problem is not just logistical, but systemic, linked to inequalities in agriculture. A research that offers costly solutions may be technically sound but socially irrelevant for most farmers, especially in countries such as Uzbekistan where smallholder farmers are prevalent business models, such as data-sharing cooperatives or subscription services, to democratize access to AI technologies.

Over-reliance on technology can also lead to a "dilution of practical knowledge" and skills gaps for a new generation of farmers who may become dependent on AI without a basic understanding of agronomy and soil health.[18]

Another common problem in this area is the lack of extensive and high-quality datasets for training models, which increases the risk of overfitting and reduces practical efficiency.[13] The problem of data scarcity is inextricably linked to the issue of data privacy. The reluctance of farmers to share sensitive data about their activities due to concerns about privacy directly contributes to the lack of data needed to train reliable AI models. This creates a vicious cycle. A research can solve this problem by offering a framework for safe and reliable data exchange or by exploring a federated learning approach in which models are trained locally without centralizing sensitive data. As farms become increasingly dependent on cloud platforms, data collection and storage pose significant risks related to privacy, security, and data ownership.

Uzbek Context: Local Relevance for this research: The Government of Uzbekistan has officially recognized the importance of this topic. The Presidential Decree of October 2024 approved the "Strategy for the Development of Artificial Intelligence Technologies until 2030" in order to turn the country into a regional "IT HUB".[22] This provides a solid state basis for conducting the study. "National Research University Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" (TIIAME NRU) is a key local institution specializing in agricultural mechanization, water resources management, and it offers a new academic program "Software and AI for Agriculture".[23] This institution is an ideal platform for cooperation. This circumstance allows us to consider the research not only as an academic exercise, but also as a direct contribution to the implementation of the national strategic priority. This can significantly increase funding opportunities, institutional support and the overall impact of the project, providing a unique advantage.

REFERENCES:

1. “Atrof-muhitni muhofazasi, iqlim o'zgarishi, degradatsiyaga uchragan tuproqlar unumdorligini oshirishda innovatsion texnolog - Mirzo Ulug'bek nomidagi O'zbekiston Milliy universiteti, accessed September 1, 2025, https://nuu.uz/wp-content/uploads/2025/04/Atrof_muhitni_muhofazasi_iqlim_o%E2%80%98zgarishi_degradatsiyaga_mavzusidagi.pdf
2. Qishloq xo'jaligida robotlarning o'rni - AGRO.UZ, accessed September 1, 2025, https://www.agro.uz/qishloq-xo-jaligida-robotlarning-o-rni/
3. The Future of Food: Sustainability and Climate Impacts of AI, Vertical ..., accessed September 1, 2025, https://freefutures.org/the-future-of-food-sustainability-and-climate-impacts-of-ai-vertical-and-robotic-farming/
4. Making AI an ally for sustainable agriculture in the face of climate change, accessed September 1, 2025, https://journals.openedition.org/factsreports/7898
5. Climate change cuts global crop yields, even when farmers adapt ..., accessed September 1, 2025, https://sustainability.stanford.edu/news/climate-change-cuts-global-crop-yields-even-when-farmers-adapt
6. Effects of Heat Stress on Growth, Physiology of Plants, Yield and Grain Quality of Different Spring Wheat (Triticum aestivum L.) Genotypes - MDPI, accessed September 1, 2025, https://www.mdpi.com/2071-1050/13/5/2972
7. Heat stress in wheat: a global challenge to feed billions in the current era of the changing climate - Frontiers, accessed September 1, 2025, https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2023.1203721/full
8. (PDF) Climate Change and Cotton Production - ResearchGate, accessed September 1, 2025, https://www.researchgate.net/publication/361416659_Climate_Change_and_Cotton_Production
9. The Influence of Climate Change on Global Crop Productivity - PMC, accessed September 1, 2025, https://pmc.ncbi.nlm.nih.gov/articles/PMC3510102/
10. Cotton and Climate Change - USDA, accessed September 1, 2025, https://www.usda.gov/sites/default/files/documents/S21_Hughes-Climate-Change-USDA-V4.pdf
11. The impact of climate change on the cotton industry | Copernicus, accessed September 1, 2025, https://climate.copernicus.eu/impact-climate-change-cotton-industry

12. Next-gen agriculture: integrating AI and XAI for precision ... - Frontiers, accessed September 1, 2025, https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2024.1451607/full
13. Deep learning for crop yield prediction: a systematic literature review, accessed September 1, 2025, https://www.tandfonline.com/doi/full/10.1080/01140671.2022.2032213
14. List of datasets for machine-learning research -September 1, 2025, https://en.wikipedia.org/wiki/List_of_datasets_for_machine-learning_research
15. Department of Agriculture - 6 - Dataset - Catalog - Data.gov, accessed September 1, 2025, https://catalog.data.gov/dataset/?tags=machine-learning&organization=usda-gov
16. freefutures.org, accessed September 1, 2025, https://freefutures.org/the-future-of-food-sustainability-and-climate-impacts-of-ai-vertical-and-robotic-farming/#:~:text=AI%20Farming&text=Another%20study%2C%20in%20Nature%20Sustainability,conventional%20and%20traditional%20farming%20practices.
17. AI in agriculture: pros, cons and how to stay ahead - BPM, accessed September 1, 2025, https://www.bpm.com/insights/ai-in-agriculture/
18. Disadvantages of AI in Agriculture: Key Challenges to Consider - Software House, accessed September 1, 2025, https://softwarehouse.au/blog/what-are-the-disadvantages-of-ai-in-agriculture/
19. Agricultural research and innovation leading global response to climate change - The University of Western Australia, accessed September 1, 2025, https://www.uwa.edu.au/news/article/2025/july/agricultural-research-and-innovation-leading-global-response-to-climate-change
20. AI-LEAF Institute | College of Science and Engineering, accessed September 1, 2025, https://cse.umn.edu/aileaf
21. AI Institute is a leader in climate-smart agriculture | University of Minnesota, accessed September 1, 2025, https://twin-cities.umn.edu/news-events/ai-climate-institute
22. Sun'iy intellekt, accessed September 1, 2025, https://gov.uz/oz/digital/activity_page/sun-iy-intellekt
23. "Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University - Study In Uzbekistan, accessed September 1, 2025, https://studyin-uzbekistan.uz/universities/88