POTENTIAL IMPACT OF ARTIFICIAL INTELLIGENCE APPLICATIONS ON AGRICULTURAL PRODUCTIVITY

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ПОТЕНЦИАЛНО ВЪЗДЕЙСТВИЕ НА ПРИЛАГАНЕТО НА ИЗКУСТВЕН ИНТЕЛЕКТ ВЪРХУ СЕЛСКОСТОПАНСКАТА ПРОДУКТИВНОСТ

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Abstract

Development of Artificial Intelligence (AI) methods and their applications are becoming important drivers of innovations which significantly affect all areas of economic activities including agriculture. The aim of the paper is to examine how AI solutions applied in agriculture can influence not only production practices, but the sector Total Factor Productivity (TFP). First, types of AI systems and areas of their use in agriculture and related activities are presented. Second, an attempt is made to indicate effects of such technological changes for agricultural TFP worldwide.

Key words: Artificial Intelligence, Technological Change, Agricultural Productivity

JEL codes: O33, O47, Q16

Introduction

Artificial Intelligence (AI) is one of the most striking technology developments which has recently inspired thinking about potential innovations in various sectors of the economy. This includes agriculture where opportunities for innovative development based on implementations of AI solutions are numerous (Bannerje et al., 2018, Eli-Chukwu, 2019). AI while itself discussed broadly both in literature and on business forums, seems to be underestimated by agricultural economists and even more by the agricultural extension service and farmers themselves. Thus, strengthening awareness among all stakeholder groups regarding possible uses of AI methods in agricultural production and benefits of adopting them is important to understand properly this process of unavoidable technological changes we have been recently facing.

Artificial Intelligence (AI) cannot be clearly and concisely defined as a scientific term, nevertheless is well enough rooted as a subject matter for discussion and anal-

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ysis both in theory and practice (Russell and Norvig, 2020). The term AI has become used since 1955 when John McCarthy and team of researchers established scientific foundation for its meaning and understanding (McCarthy et al., 1955). Over the next decades understanding of AI evolved along with the programming and computer technology advancements. AI systems both real and hypothetical can be categorized into three types (O'Carroll, 2017):

- narrow intelligence (ANI), also called weak AI, having limited range of abilities;
- general intelligence (AGI) which can be considered equivalent to human capabilities;
- superintelligence (ASI) being more capable than a human.

While there are a lot of examples of successfully implemented ANI solutions, potential developments of AGI and ASI are more a matter of speculative imagination or futuristic visions. For the purpose of clarifying our considerations we adopt a definition presented by O'Carroll (2017) who described it as a "branch of computer science that endeavours to replicate or simulate human intelligence in a machine, so machines can perform tasks that typically require human intelligence" including planning, learning, reasoning, problem solving, and decision making.

The aim of the paper is to examine how AI solutions applied in agriculture can influence not only production practices, but the sector Total Factor Productivity (TFP). Considering potentially widespread adoption of AI solutions in agriculture it seems to be plausible to hypothesize that effects of such technological changes should be positive for agricultural TFP worldwide. This issue is discussed theoretically using macroeconomic production function and the Solow residual framework. Also, based on the Global AI Innovation Index Report country rankings and agricultural TFP data series indices provided by the United States Department of Agriculture we look for an empirical evidence supporting the proposed hypothesis.

A brief overview of AI applications in agriculture

Various types of AI systems have been used in agriculture since relatively long time ago. The rule based expert systems were extensively used in the 1980s and early 1990s. Next, artificial neural network and fuzzy logic based systems have become dominant solutions. At present, hybrid systems such as neuro-fuzzy or image processing coupled with artificial neural networks are more and more frequently applied. AI solutions impended in agriculture are often of a hybrid nature. In other words, more than just one method or technique is employed in the systems developed encompassing a combination of decision making process and automatization of work to be performed.

Examples of AI applications in agriculture are numerous. They are used in such activities as general crop management, pest management, disease management, weed management, agricultural product monitoring and storage control, soil and irrigation management, and yield prediction. Current AI applications represent advanced tools which enable implementation of precision agriculture at low cost (Bannerje et al., 2018). They are more automated and accurate systems acting in real time. Apart from supporting farm production AI methods and techniques are applied in other related activities. Examples include agricultural price forecasting, marketing and electronic trading by farmers using special applications allowing implementation a quick go-to-market strategy (Figiel, 2019, Khandelwal and Chavhan, 2019).

AI applications in agriculture constitute a quickly growing market. In 2019 its overall size accounted for almost 1.1 billion U.S. dollars and is expected to grow to more than 3.8 billion U.S. dollars by 2024. AI systems are deployed mainly in field farming, although livestock and indoor farming are considerable segments of the market (Fig. 1).

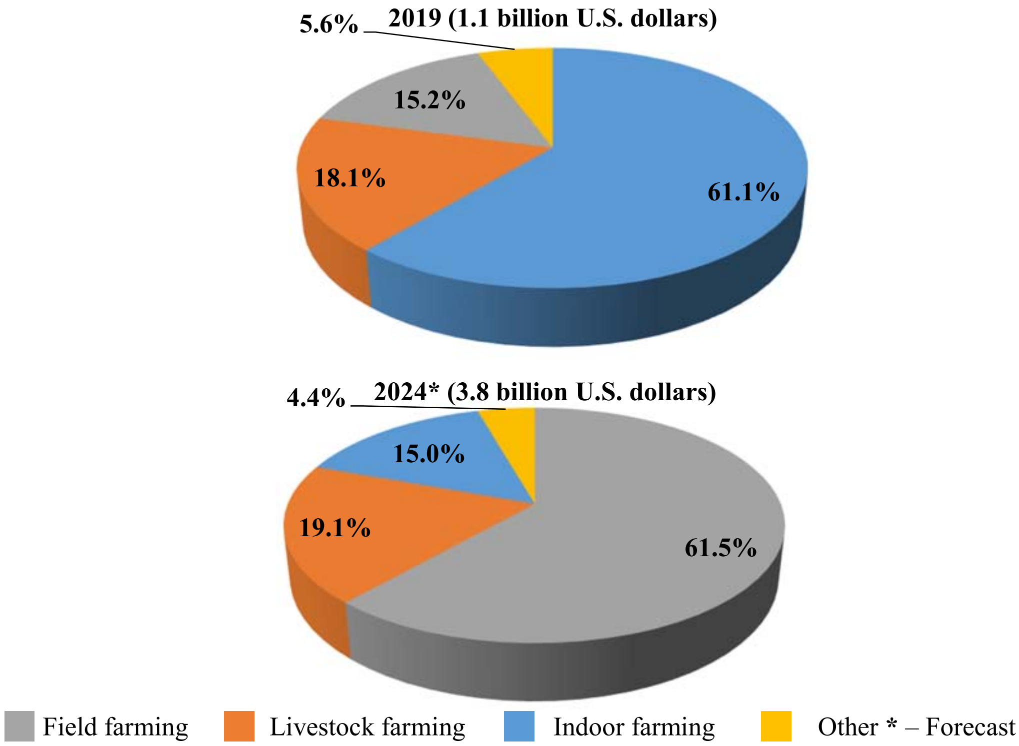

*Figure 1. Structure of the global AI market in agriculture by farming type in 2019 and 2024**

Source: https://www.statista.com/statistics/1174399/global-ai-in-agriculture-market-by-farming-type/ (Date: 2022.04.04).

Theoretical framework for capturing AI impact on agricultural TFP

Agriculture belongs to economic sectors in which work performed by people can be quite easily robotized and many tasks requiring human intelligence can be completed using AI solutions (Kaplan, 2016). Agriculture being inevitably exposed to implementation of such technologies will experience both labor substitution and higher labor productivity effects. Widespread implementation of various AI solutions in agriculture can be viewed as a technical change and analyzed using macroeconomic production function and total factor productivity (TFP) theoretical framework.

First, let consider the textbook Solow model (Solow, 1957):

$$Y(t) = [K(t)]^{\alpha}[A(t)L(t)]^{1-\alpha} \tag{1}$$

$$SR(t) = \frac{\frac{\partial Y}{\partial t}}{Y} - \left(\alpha\frac{\frac{\partial K}{\partial t}}{K} + (1-\alpha)\frac{\frac{\partial L}{\partial t}}{L}\right) \tag{2}$$

where:

$Y(t)$ – output (the GDP in year *t*);

$K(t)$ – capital in year *t*;

$A(t)$ – multifactor productivity in year *t* (technical change or shifts in production function);

$L(t)$ – in year *t*;

$SR(t)$ – Solow residual;

α – equation parameter;

$\frac{\partial Y}{\partial t}, \frac{\partial K}{\partial t}, \frac{\partial L}{\partial t}$ – time derivatives of Y, K, and L, respectively.

Second, let refer to the Solow model augmented with a human capital term, what can be written as follows (Mankiw et al., 1992):

$$Y(t) = [K(t)]^{\alpha}[H(t)]^{\beta}[A(t)L(t)]^{1-\alpha-\beta} \tag{3}$$

$$SR(t) = \frac{\frac{\partial Y}{\partial t}}{Y} - \left(\alpha\frac{\frac{\partial K}{\partial t}}{K} + \beta\frac{\frac{\partial H}{\partial t}}{H} + (1-\alpha-\beta)\frac{\frac{\partial L}{\partial t}}{L}\right) \tag{4}$$

where:

$H(t)$ – stock of human capital in year *t*;

β – additional equation parameter;

other terms – the same as in (1) and (2).

Inclusion of $H(t)$ in equations (3) and (4) means that the effect of changes in human capital is transferred from the Solow residual to capital accumulation, thus, mathematically the residual is smaller in the textbook Solow model. Hypothetical implications of widespread use of AI for agricultural Total Factor Productivity (TFP) can be viewed as expected changes (positive or negative) in the model terms. Considering the nature of AI applications in agriculture it seems plausible to surmise that their impact on all terms in equation 4 but labor term will be positive. Such deductive reasoning comes from meta-analysis of observed and discussed in literature influences of AI development and its applications on agricultural production practices (Bannerje et al., 2018, Eli-Chukwu, 2019, Chu et al., 2019, Elugbadebo and Johnson, 2020, Jha et al., 2019, Khandelwal and Chavhan, 2019, Moallem et al., 2017, Unay et al., 2011)

Diminishing role of physical labor in agricultural production has been observed everywhere in the world and AI development will additionally strengthen this is trend due to substitution effect, therefore, it will have a negative influence on the labor term. The other model terms are supposed to be influenced positively due to productivity effect, investments in physical capital, and accumulation of human capital resulting from education. A general mechanism of AI positive impacts on agriculture is diagrammatically presented in Figure 2.

AI applications help optimize use of inputs, both agricultural (seeds, feed, etc.) and nonagricultural (fertilizers, chemicals such as herbicides and pesticides, and energy), consequently leading to more efficient use of resources (labor, land, water) and higher factor productivity due to the increased yields. Also, the role of AI solutions in monitoring negative externalities (water pollution, gas emissions) and protection of the natural environment cannot be omitted as an important contribution to foster sustainable growth of agricultural production (Geli et al., 2019).

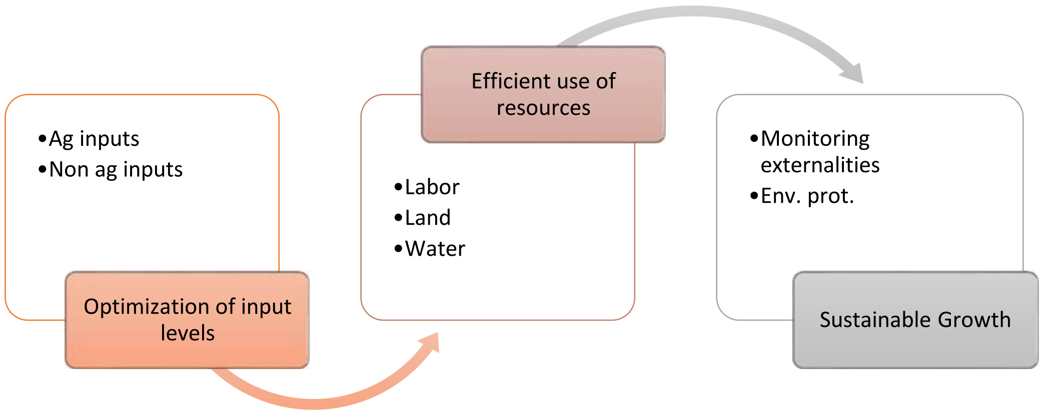

Figure 2. Benefits of using AI solutions in agricultural production

Source: own elaboration.

Countries AI development levels and agricultural TFP

Countries differ regarding the AI development level. Taking into account such criteria as: AI infrastructure, AI research and development, and AI industrial application, the 10 top-ranking countries are the U.S., China, South Korea, Canada, Germany, UK, Singapore, Israel, Japan, and France. The scores countries achieved in this ranking, presented in The 2020 Global AI Innovation Index Report, co-drafted by the Institute of Scientific and Technical Information of China and the Peking University, are shown in Figure 3. The United States is a unquestionable leader of the ranking with China coming second. These two countries are ahead of the other surveyed countries with scores 47 and 12% above the average for the TOP 10, respectively (see the horizontal line).

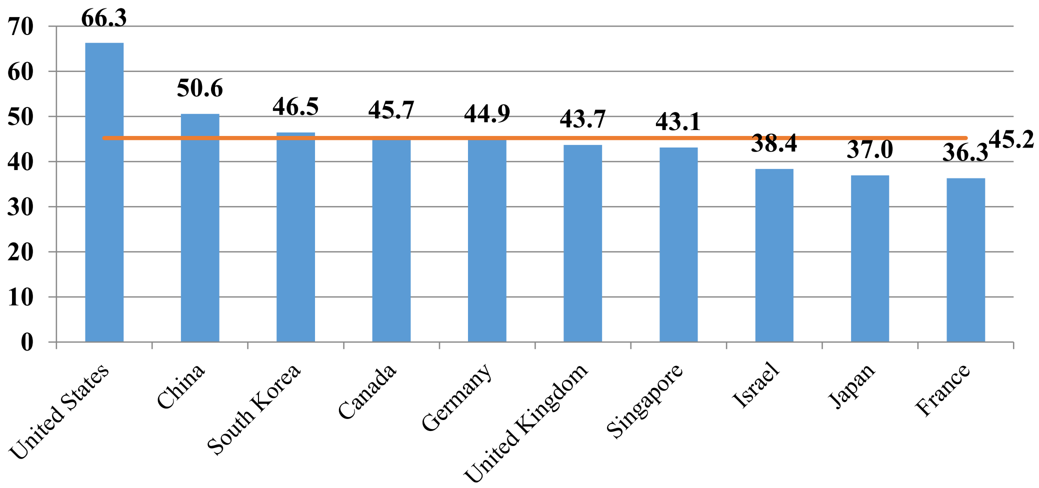

Figure 3.

Source: https://www.chinadaily.com.cn/a/202108/23/WS6122d245a310efa1bd66a545.html (Date: 2022-06-07).

Impact of the AI applications on economic growth is multidimensional and complex. Intuitively, knowing that widespread use of AI methods becomes reality, it seems to be obvious to expect positive effects of such technological change. However, the issue is that AI applications influence basically all areas of human activities, hence, separating pure productivity effects of AI uses without methodological reservations is sort of impossible. In cross-country analysis one of the problems is a global diffusion of innovations among sectors and countries. Nevertheless, it needs to be noticed that the United States and China are the two largest world agricultural producers while Germany, Japan, and France are among the TOP 10 agricultural producing countries. More importantly, values of the index of Agricultural Total Factor Productivity (TFP) calculated for the period 2016 – 2019 indicate a significant agricultural TFP growth in all that countries. For each country every year the index value (year 2015=100) was higher than 100 with average value for the whole set of the panel observations (4x5) equal to 104.2. This implies that agricultural sectors of these countries experienced noticeable productivity growth during the period considered. Whether it is just a coincidence, or indirect evidence showing the positive impact of AI on agricultural TFP should be considered as an open question.

Conclusion

The recent AI based technological advancements and solutions can greatly improve efficiency of farming practices regarding control of crop diseases, pest and weed management, and irrigation and water management. It can be stated that applications of AI in agriculture lead to both substitution and more efficient use of the labor remaining in agriculture. Also, physical asset and land and water resources can be used more efficiently. This is why higher agricultural TFP can be achieved. In fact, there appears to be a connectedness between the advancement level of AI industries in countries belonging to the TOP 10 in this area and their agricultural TFP dynamics observed over the last few years. Incidentally, five of these countries (China, the United States, Germany, Japan, and France) are in the group of TOP 10 largest agricultural producers in the world. This simple observation cannot be ignored considering the share of these countries in the global agricultural production. However, an in-depth analysis is required to provide convincing empirical evidence on the positive connectedness between country AI development level and its agricultural TFP.

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