# Innovative Technology in the Agricultural Sectors: Opportunities for green jobs or exacerbation of rural youth unemployment?

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***Abstract:*** *Review of recent investment and development trends in innovative agricultural technology reveal the following observations: 1) Low-skill, labour-intensive green jobs in agriculture may face even worse competition with the decreasing deployment cost of existing and innovative technology; while 2) the few existing high-skill work in agriculture are prone to being significantly reduced, or replaced by the innovative technology; and that 3) the newly created high-skill work are mostly out of reach for the under-skilled rural youth. The volume of investment in agricultural technology – including those that are potentially labour-displacing – has increased by 45-folds in the past 9 years. These findings and their implications for the agricultural labour market and rural youth employment are contextualized in the old and new challenges in rural development. This paper proposes policy interventions to minimize the disruptive impact of (exogenous) technology in local agricultural labour markets: closing the data gap in agricultural labour market; along with ensuring public and open access to key means of production such as agricultural big data, land, and natural resources. Linking skills development with decent, green jobs opportunities for the rural youth is essential, with emphasis on public employment programmes in contexts where markets have failed to create jobs and businesses. On a macroeconomic level, it is suggested that a clear vision of the roles and goals of the agricultural sectors within the specific contexts of the national economy should lay the foundation on which the policy coherence of the future of work in agriculture can be developed.*

***Keywords:*** *Green jobs, future of work, agtech, rural youth employment, automation, artificial intelligence, rural development*

## Introduction

### The Green Hype: Green Jobs in the Green Economy for Green Growth

Greening the economy, or low-carbon growth, is estimated to bring US$ 26 trillion to the global economy by 2030, inclusive of rural economies and the agricultural sectors (Global Commission on the Economy and Climate, 2018). In terms of labour market impacts, the transition to the Green Economy is expected to affect 1.5 billion people by 2030, which is 50% of the global labour force (ILO and UNEP, 2012). Against this backdrop, green innovations introduced in the rural areas and the agricultural sectors are expected to create green jobs.

As a type of decent work with focus on environmental preservation and restoration, green jobs[2] are loosely defined as "… decent employment opportunities, [which] enhance resource efficiency and build low-carbon sustainable societies" which emphasize sustainability across environmental, social, economic spheres. In particular, green jobs in agriculture can yield 52-59% increase in employment by 2050, compared to today's level. This in turn will increase the primary sector's contribution to the global GDP by 20% compared to conventional practices, by 2050 (FAO, 2012). Green jobs in other prominent sectors in transition to the Green Economy – namely, the provision of rural infrastructures such as

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transportation, construction, energy, and waste management – also are promising fields of employment and enterprise development for youth, as global investment in infrastructure is estimated to reach 57 billion USD by 2030.[3]
These promising figures have made green jobs attractive solutions to pressing global economic issues, such as the persisting under and unemployment rates (192 million unemployed and 1.4 billion vulnerable employment) (ILO, 2018); ageing agricultural population due to rural youths' aversion to agriculture; hollowing out of rural populations with rapid urbanizations; and the exploitation of natural resources beyond its replenishing capacities, by the business-as-usual modes of economic activities. Therefore, at a glance, green jobs are welcomed news across all economic, social, and environmental frontiers, especially to address rural youth employment and related issues. Green jobs in agricultural sectors in particular are viewed as the 'point of attraction' that will bring youth back to agriculture.

## Innovative Technology and Green Jobs

One of the key attractions that green job offer to the youth is that (some of) green jobs utilize innovative technology, thereby offering new types of jobs that are different from the traditional jobs in agricultural sectors that are often associated with having inferior work conditions, are hazardous, and underpaid.[4]
A bulk of green jobs forecasted in agricultural sectors are not necessarily laden with the use of high-technology. However, the types of green jobs that involve innovative technology require high enough skills to make productive use of them, and therefore, are associated with decent wage, and safe work conditions. It is therefore of paramount importance that the prospective youths have the necessary skills to acquire these high-skill green jobs.
At the same time, innovative technology involved in these high-skill green jobs include the so-called labour-displacing technology such as automation and the use of artificial intelligence (AIs), which have received much spotlight from labour economists and policy stakeholders to labour unions and lay workers, due to their potentially 'disruptive impact' on the labour market, and the organization of work itself. At the center of the discussion is whether the advancing technology will contribute more to new job creation or result in increased unemployment.
Recent reports from international organizations which delve into this issue in the context of future of work, namely, World Bank's *Changing Nature of Work* (2018) and ILO's *Future of Work Research Paper Series* (for example, see Ernst, Merola, and Samaan, 2018), seem to provide carefully optimistic outlook towards the outcome of the new trends in technology. Both acknowledge the possible exacerbation of income inequality due to the uneven distribution of productivity gains from technology. However, the assumption that the skilled labour is rewarded through wage premium so that they may increase productivity by utilizing technology (capital-skill complementarity) which predicates skilled labour force (skills-biased technological change), are preserved intact throughout the main arguments of both reports[5]. In this vein, the two reports emphasize the need to develop the necessary skills of the future labour force, so that they can keep pace with and utilize the innovative technology. Interestingly, both direct towards portability of the skills,[6] as the utility of sector-specific skills are difficult to predict at this point.

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[3] Infrastructure productivity: How to save $1 trillion a year https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/infrastructure-productivity
[4] See ILO's "Improving working and living conditions for agricultural families programme (WIND)".
[5] To clarify, ILO's research paper claims that provided the work utilizing social and emotional skills (over technological skills, such as development of AIs) are available, the users (not developers) of AI technology are not necessarily affected by the skills-biased technological change in their segment of the labour market.
[6] See section *5.1 Skills and occupational mobility* of the above ILO Future of Work Research Paper Series, and chapter *3. Building human capital* of the World Development Report.

**Why the agricultural and rural economies require sector-specific analysis**

This paper first reviews the current state of development and investment trends in the agtech. Then, its impacts are estimated against the distributed skills level of existing and forecasted jobs in agricultural sectors. There are different ways to group the types of the agtech that are already available or are under development. As the purpose of this paper is to examine the impact of agtech on agricultural labour market, it would be ideal to distinguish them by their relation to labour: labour-replacing (saving), or labour-augmenting. However, it is difficult to uphold a dichotomous distinction between the two relations. Existing literature in academia, especially in the discipline of economics, have used panel dataset mostly from developed countries to trace the changing contribution of labour and capital in the long-term growth, through which productivity is derived as a proxy to estimate the contribution of technology. Simplifying the impact of technology to the residual of capital or labour contributions has led to complications in explaining observed phenomena such as the different contributions of technology to productivity and income inequality throughout longer periods. To address these issues, jobs are further specified by their tasks (Acemoglu and Restrepo, 2018b, 2018a; Autor and Salomons, 2018; Acemoglu and Autor, 2011), in order to provide a more robust description of relationship between technology and labour, and capital. That is, impact of technology is not simply seen as *whether or not* but as a degree, via tasks, to which jobs can be displaced or augmented. However, immediate application of such task-based approach to assess the impact of technology is not feasible for analyses of jobs in agricultural sectors, mainly because even the most basic data on agricultural labour – such as hours worked, number of workers per jobs, enterprises, and their sizes, etc. – are difficult to obtain, let alone tracked to yield a quality panel data that allows for reliable calculation of the resulting productivity growth. Due to the informal and seasonal characteristics of the agricultural labour, most of the data on agriculture are not disaggregated, and difficult to record[7].

To address these challenges albeit partially, an overview of the top invested agtech and their propensity to either displace or augment agricultural labour are extrapolated based on the analyses of their task functions within the job. Then, the impact of the diffusion and deployment of these agtech to the existing and forecasted jobs in agriculture, with specific focus on the green jobs, will be estimated by superimposing the capacity of the technology to significantly change or replace the jobs, to the skill levels needed and the tasks involved in carrying out these jobs.

## Observations on the Agricultural Technology and its Impact on Jobs in the Agricultural Sectors

### Agtech Development and Investment Trends

*Global investment in agtech on a steep rise*

The global investment in agtech is on a steep rise: the total amount of investment has increased by 42-times in the past 9 years (2010-2018). In the same period – although the percentage of agricultural sectors within the global VC investment market currently marks relatively small share of 6.7% – it has multiplied by more than 8-times.

[7] See http://www.fao.org/rural-employment/work-areas/data-and-knowledge

| Areas \ Year | 2010 | ... | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|
| Soil, crop, agricultural tech and biotech | n/d | | 314 | 168 | 719 | 696 | 1,500 |
| Farm management, Farm equipment, Robotics, Internet of things, Indoor agriculture, Mechanization | n/d | | 548 (23.2%) | 781 (17.0%) | 719 (22.3%) | 1,325 (13.1%) | 1,909 (11.3%) |
| Agtech total investment | 400 | | 2,360 | 4,600 | 3,230 | 10,100 | 16,900 |
| Percentage share of agtech investment in global venture capital investment market | 0.8%* | | 2.7%* | 3.3%** | 2.5%** | 6.5%** | 6.7%** |

***Table 1. Investment Trends in the Agricultural Technology (agtech).*** *Unit: million US dollars. *Statista Global venture capital investment 2008-2014* **KPMG *Venture Pulse* 2015, 2016, 2017, 2018; *Sources:* AgFunder *Agrifood tech funding report: Year Review* 2014, 2015, 2016, 2017, 2018

The investment trend in the AI and ML industry per se provides a more realistic impact prospective of these technology in agriculture. This is because some key AI and ML technologies which are applicable to agriculture – such as image and pattern recognition, problem identification through cloud server-linked data analyses, etc. – can be developed by corporations that do not necessarily identify themselves as agtech companies, and can spill over across sectors. The estimated amount of VC investment into AI startups differ by source, but they range from over 5 billion USD – which is 350% increase in 2017 compared to 2013 (Shoham *et al.* 2018) – while some estimate up to 9.8 billion USD[8].

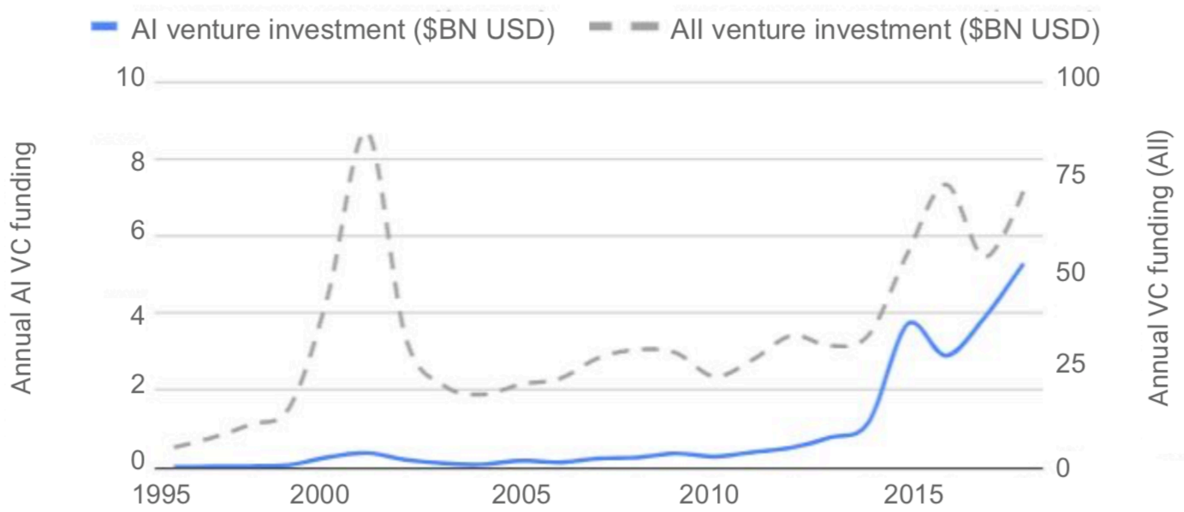


***Figure 1. Annual VC funding of AI startups (U.S., 1995 – 2017).*** *Source: Sand Hill Econometrics, cited from (Shoham et al., 2018).*

*'Data-enabled agriculture' and consolidation*

According to a joint report by the Boston Consulting Group and AgFunder (Walker *et al.* 2016), the recent top 7 investment priorities for over 50 key agribusiness executives were: big data and analytics; food security and traceability; biologics; optimization hardware; sensors and connectivity; new-crop

[8] Jean Baptiste Su. "Venture Capital Funding for Artificial Intelligence Startups Hit Record High In 2018". Forbes. February 12, 2019. https://www.forbes.com/sites/jeanbaptiste/2019/02/12/venture-capital-funding-for-artificial-intelligence-startups-hit-record-high-in-2018/#2ef6fbdf41f7.

technologies; and autonomous equipment. Among these, the category 'data-enabled agriculture'[9] was among the top five priority for 75% of the respondents, while the category 'automation and robotics'[10] was also equally important to 45% of the respondents.

This priority on is also reflected in the larger agro companies' recent acquisition of digital agriculture start-ups[11], such as FarmShots (satellite imagery company), Granular (digital enterprise resource planning platform), and the Climate Corporation (digital software tool, which was acquired by Monsanto 930 million USD), to name a few.

**The Impact of the Agtech on the Existing and Forecasted Jobs in the Agricultural Sectors**

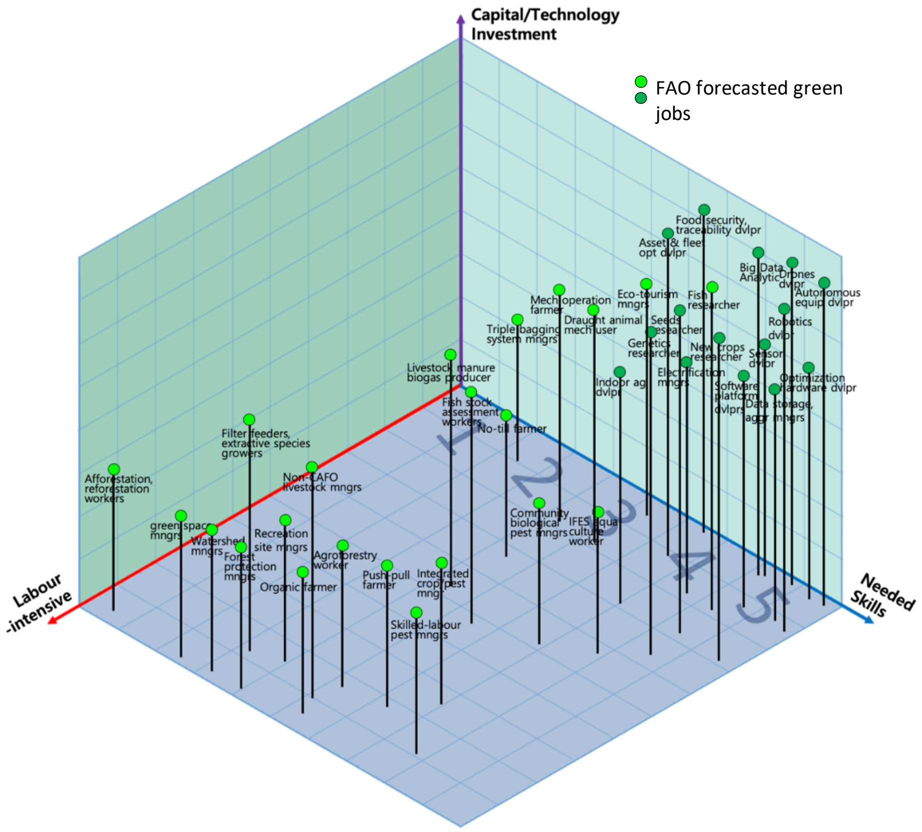


***Figure 2. Green Jobs Forecast in the Agricultural Sectors.*** *Data source: Green Jobs for a Revitalized Food and Agriculture Sector (FAO 2012); Lessons from the Frontlines of the Agtech Revolution (Walker et al., 2016). For a complete list of the jobs and their skills profile, see annex 1.*

In order to make an evidence-based estimate on the extent of the impact of these technologies while there is dearth of data on the employment composition of the agricultural sector, we now look into the

[9] 'Data-enabled agriculture' category includes: big data analytics, optimization hardware, sensors and connectivity, data storage and aggregation, and software platforms.
[10] 'Automation and robotics' category includes: autonomous equipment, robotics, drones, and electrification.
[11] Barclay Rogers. "What's Next for Agtech?" AgFunderNews. September 4, 2018. https://agfundernews.com/whats-next-for-agtech.html.

landscape of the currently existing jobs and forecasted jobs. First, in order to assess the impact of the innovative technology on green jobs in agriculture, mapping of the forecasted green jobs are drawn from the FAO report *Green Jobs for Revitalized Food and Agriculture Sector* (2012), which presents one of the first attempts to estimate the number and scope of green jobs created from adapting green practices in agricultural sectors. The green jobs mentioned in the report, along with their labour intensity, and the necessary skill levels needed, are illustrated along with the amount of capital and technology investment needed to operate the enterprises which creates outputs.[12] The graph is further supplanted from the estimated 'new jobs' created from the increasing investment in agtech – that is, the high-skill jobs that are created as result of the capital investment in the innovative technology. The data on the profile of these jobs are drawn from the aforementioned assessment report on the agtech investment trends, *Lessons from the Frontlines of the Agtech Revolution* (Walker *et al.*, 2016)[13]. Therefore, the first graph Figure 2) is an indicative mapping of the factors of production per agricultural enterprise pertaining to the particular green job. That is, the intensity of employment created, and the capital and technology investment needed, per enterprise which creates the green job, are shown. From both sources, in order to avoid mixing of jobs across other sectors, and for the sake of simplicity, only the jobs in the upstream stages (production) of the agricultural value chains were included.

This 3-axes graph separates capital intensity from labour intensity, based on the conceptualization which graduates from the previous framework that views the impact of automation as production factor-augmenting; here, instead, the impact can be illustrated along the more fine-grained spectrum of measuring productivity effect and displacement effect of technology (Acemoglu and Restrepo, 2018b). Under this new framework, technological change is understood as endogenous: that technological advances and its actual deployment depends on profitability which would be determined by the available supply of skilled or unskilled labour (Acemoglu and Autor, 2011). Also, the departure from the previous framework which assumes skills-biased technological change (for example, see Goldin and Katz, 2007) to be valid is particularly important in the context of understanding skills premium in the agricultural sectors of the developing economies. This is because there are no empirical observations attesting to the advancing technology increasing the demand for more skilled workers in agricultural sectors.

The forecasted green jobs spanned across a diverse range of low-, mid-, and high-skills, which can be labour-intensive or labour-saving. For example, farmers practicing Skilled-Labour Pest Management are to possess relatively high skills (zones 4 – 5) while performing labour-intensive work, and therefore the enterprise would yield high potential for employment-intensive work. Eco-tourism managers, on the other hand, may require lesser skills (zone 3) but result in lesser employment intensity due to limited number of viable opportunities for ecotourism in the rural areas, especially in developing countries where tourism is not developed. Organic farm workers would require minimal skills (zone 1) but per enterprise show high employment intensity.

From the above distribution of low to high skill green jobs in agricultural sectors, it is possible to speculate that the introduction of the highly invested technology will result in the diminished returns for skilled-agricultural workers' expertise. Returning to the example of Skilled-Labour Pest Management Farmers, and farmers using similar practices (Integrated Crop-Pest Management, Push-Pull Farming),

[12] The indicative level of investment (low, middle, high) needed for the operation of such enterprises are based on the budget review of FAO projects directly and indirectly supporting the creation of these enterprises, as according to the project documents in the Field Programme Management Information System (FPMIS).
[13] Among the top 27 invested agtech, the following were excluded as their scope of application is beyond the upstream stages of agricultural production: Biologics; New chemicals; Crop storage; Packaging and shelf life; Processing, Biofuels and bioenergy; Biomaterials; Biochemicals; Alternative foods; Technology-enabled sharing; E-commerce; Farming as a service.

the introduction of weeding robots[14] equipped with machine learning capacity and linked to cloud-based database can quickly demise the human expertise which are the result of the farmers' years of experience. In enterprises that utilize such technology, there would be little incentive for creating a low-capital, high-skill green job such as Skilled-Labour Pest Management Farmer. Similarly, the low-skill green jobs such as Afforestation and Reforestation Workers will retain their jobs as long as the deployment cost of automated tree nursery systems remain higher than the wages of these workers, which undermines the chances of receiving decent wage in such jobs.

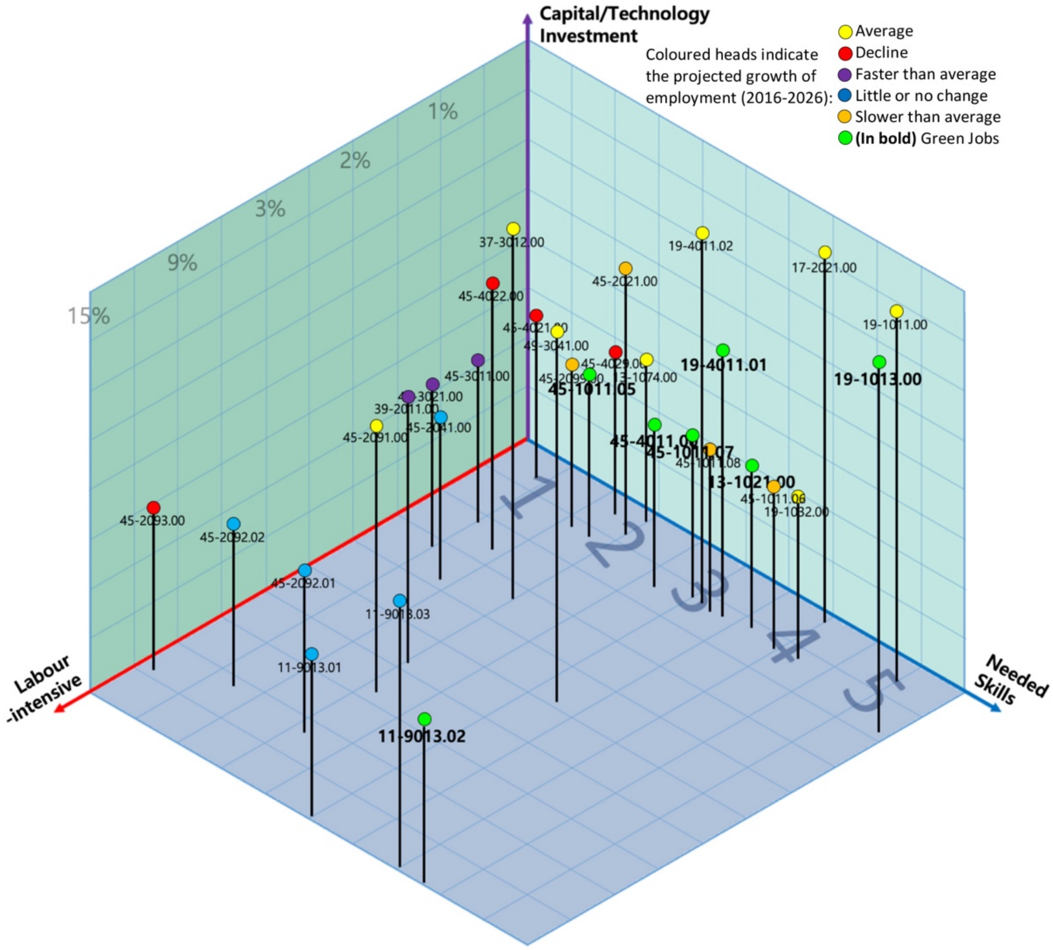


***Figure 3. Current Jobs and Their Growth Forecast in Agricultural Sectors, United States.*** *Data source: Occupational Information Network (O*Net). For a complete list of the jobs and their skills profile, see annex 2. Note 1: Numbers below the dots (which indicate the job codes), and skill level numbers are in accordance to O* NET Job Zone categories. Specific Vocational Preparation (SVP) values are not weighted. Note 2: Growth forecast for the green jobs are as following: 19-4011.01, 19-1013.00: Average; 11-9013.02: Little or no change; 45-1011.07, 45-1011.05: Slower than average; 13-1021.00, 45-4011.00: Decline.*

[14] Which are already commercially available. For example, see https://www.naio-technologies.com/en/agricultural-equipment/large-scale-vegetable-weeding-robot/, https://robohub.org/robotic-weeding-and-harvesting/, https://www.cnbc.com/2018/06/04/weed-killing-ai-robot.html.

Another noteworthy point is that even the very few jobs created in the high skill zones (4 – 5) may be subject to displacement. For example, those who develop and manage the automation and AI technology may be spared of immediate displacement, as there will continue to be a demand for the management of technology at least throughout the foreseeable future. However, for the high-skill jobs with tasks that capitalize on the decision-making, optimization processes and research capacity – such as New Crops Researcher, Seeds Researcher, Fish Researcher, Genetics Researcher, Indoor Agriculture Developer – a bulk of their tasks could be reduced by AIs that are already known to excel in both data gathering for prediction, and combining it with optimization algorithms to produce decisions (combinatorial optimization. See [Wilder, Dilkina, and Tambe 2018]). Some expect that in the short to immediate term, these transformations will largely contend with industrial sectors, and generally occur within developed economies (Manyika, Chui *et al.* 2017; Manyika, Lund *et al.*, 2017). In the long run and in case of agtech, however, one may expect that these jobs could be displaced to a point of no merits in premium wage, if these AI technologies become embedded in the autonomous equipment, as is the current development trend.

In the above graph, an actual mapping of the current jobs in agricultural sectors of the United States and their forecasted growth are shown. The configuration of the layout is different on this 3-axes graph because now the labour-intensity figures reflect the actual percentage share of employment per job. Conveniently, the projected growth of each job is available, which allows us to also see which jobs are on the diminish possibly due to advancing technology and globalization.

Some key observations from the above overall distribution of employment percentage share are as following: Jobs with declining growth are low-skill work, and among those includes the land and aquatic animal farm workers which share a sizeable portion (job code 45-2093.00; 11.69%) of employment. From this data alone, however, we cannot assume that this low-skill work displacement is due to technology because it could as well be the result of globalization (outsourcing) of the low-skill work. It would be worthwhile to follow up whether crop and tree nursery farmworkers requiring similar levels of skill (job codes 45-2092.01, 45-2092.02; composite 21.98%) will also be on the decline in the coming years, and whether these jobs have been outsources, or their tasks (or jobs) replaced by technology.

According to the O*Net data, the highest percentage of green jobs are forecasted in high-skill work (11-9013.02: Farmers, Ranchers, and Other Agricultural Managers; composite 44.87%), which requires extensive information processing and decision-making skills. Some of the top technological skills needed for the job group include analytical or scientific software for precision agriculture; software for accounting, database user interface and query, enterprise resource planning, and industrial control. Sector-specific knowledge needed includes understanding of the food production and processing techniques, machines, and equipment; knowledge on administrative and management of business and natural resources; engineering and application of technology; and on public safety and security.

The key tasks comprising the work activities of the above managerial job are making decisions and solving problems; organizing, planning, and prioritizing work; operating vehicles, mechanized devices, or equipment; developing objectives and strategies; and monitoring and controlling resources. Against the backdrop of commercially available innovative agtech and their investment trends, these tasks also are subject to significant replacement by automation and AI technology in agriculture. In contrast to other jobs in the high skill zones (4 – 5) from the previous graph which consisted of jobs with tasks that develop and perform maintenance of such technology, this sizeable and attractive green job group may be affected more by the displacement effect than the productivity effect. It is difficult to assume, therefore, that this green job group will (continue to) yield the near-half of the employment percentage share in the agricultural sectors.

O*NET's definition of green jobs is not further elaborated than that they are jobs which are affected by the changes caused by the green economy[15] and therefore does not provide exhaustive list of all feasible green jobs within the agricultural sector. It is however worrisome that four out of the seven forecasted green job groups are showing either slower than average rate of growth (2), or even decline (2).

### Findings

Observations from the above layout of existing and forecasted work in agricultural sectors, and the possible impact of advancing agtech can be summarized as below three findings:

A. Low-skill work which seemingly fails to attract rural youth in developing economies, is diminishing in the United States. In a developed economy such as the United States, this could either be due to globalization or labour-saving technology. However, in developing countries where further relocation of labour is not an option, the only thing suppressing the replacement of the low skill labour with existing (and possibly, new) technology is the deployment cost efficiency which at the moment is lower than that of the wage for labour.
B. Among the existing high-skill, labour-intensive work which is already very scarce in agricultural sectors, many are prone to being replaced or diminished in size by the new agtech. This means that the segment of labour force for whom skills-biased technological change and the consequential wage premium for high-skilled labour remain valid will only be limited to the few whose main tasks are the development and maintenance of these technology.
C. As for the new, high-skill jobs created that are difficult to assume a greater labour displacement effect, which benefit from the wage premium provided by skills-biased technological change, their tasks are composed of developing and maintaining (not necessarily using) the technology.

To understand what above findings would entail for the agricultural sectors and particularly to rural youth in developing economies, the implications are presented by contextualizing these findings in the broader background of the new and recurring challenges in rural development.

## Implications of the Observed Trends to Rural Youth Employment

### Impact on the agricultural labour market in general

Agriculture currently employs 26.5% of the global labour force (and 68% of employment in low-income economies [World Bank, 2018]), while it is estimated that half of world population and 75% of the world's poor reside in rural areas. At the same time, there are claims that to meet the food demands of the increasing global population, agriculture must increase its production by 50% by 2050 (FAO, 2017). Could this demand for increased production allow room for increased demand of skilled labour, which will contribute towards rural poverty reduction?

*The cost effectiveness of 'Decent Work' vs. technology*

Two critical factors prohibit the assumption that increased demand for production will lead to an increased demand for skilled labour in agricultural sectors. First, the low productivity in agricultural sectors have been identified as the culprits of both the 'food shortage' and low-replenishing rate of labour market entrants in the sector (for example, see Restuccia, Yang, and Zhu, 2008; Adamopoulos and Restuccia, 2018; Hajra and Ghosh, 2018). Attempts to address this productivity deficit mainly consist of efforts to increase conventional mechanization (FAO and African Union Commission, 2018) in

[15] See https://www.onetonline.org/find/green.

developing countries and providing entrepreneurial skills development of farmers. Neither of these streams of effort directly contribute to equipping the labour force with the necessary skills needed to obtain the little remaining high-skill jobs we have reviewed. Secondly, in the current context of the stand-off for market share between the smallholder (such as family farming) and industrial (multinational, globalized, and vertically integrated) agricultural production, there is no coherent policy framework for increasing production. This means that the volume of production may increase locally, and in employment-intensive manner, or simply by increasing the output per investment – productivity. In the latter case, supply of skilled labour is not a requirement, considering the recent development trends in agricultural technology.

Above needs to be considered in tandem with the fact that agricultural sectors is believed to have one of the highest potentials for automation.[16] The rapid, capital-led introduction of mechanization, automation technology, and machine-learning robot technology will have impact on both the already-thin demand for high-skill labour, and overwhelmingly prevalent demand for low-skill labour in agricultural sectors. The middle- and high-skills requiring, cognitive work in agricultural sectors faces competition with the use of machine learning, which can adapt and improve its activities without being programmed. The low-skill require manual labour – which traditionally attracts entry-level labour force to agricultural sectors – face competition with increased automation.

However, human labour will only be replaced by machine labour if the development and deployment cost of machines is lower than the cost of human labour (Acemoglu and Restrepo, 2018c). This implies that – contrary to the concerns in the context of advanced sectors in developed economies – *how low the human wage can go down* will determine the rate of diffusion of the advanced technology in under-developed rural economies. Considering that jobs in agricultural sectors are already prone to negligence of labour and social rights, already regarded the most dangerous industry, and already yields only thin margin of profit, the competition between human and automated labour force to drive down production costs is bound to have negative consequences on wage.

It is not only the physical labour power that competes against technology, but also the knowledge and expertise in agriculture. For example, in agroecology high skilled farmers use low input methods and sustainable practices which allows them to avoid the common problems found in conventional farming such as chemical runoffs and residues, use of harmful pesticides, degradation or overuse of nutrients, etc. Whatever (extra) efforts – which could be both physical or technical – were put into avoiding these problematic by-products are rewarded with the price premium, be it for the organic, fair, and environmentally-friendly processes and outcomes. With the use of data-enabled agricultural techniques that may reduce the need for the cognitive decision-making process, or robotic facilities that can reduce the labour power involved in environmentally friendly practices, even these knowledge-intensive green jobs in agriculture cannot remain shielded from the impact of innovative technology.

It is estimated that by 2020, about 1.33 billion people will be earning their living in agriculture, while 450 million of them are wage earners. As the principles of decent work calls for productive and fair income, employers in agriculture will soon be faced with a choice between investing in 1) workers, ideally providing them with decent work, or in 2) technology and machinery, whose deployment costs are dropping and may shortly meet those of the wage of workers. If market logic and cost-effectiveness are

[16] See *Where Machines Could Replace Humans – and Where they Can't Yet.* According to this data, 50% of the assessed work in agricultural sectors (equivalent to 328.9 million workers) has the potential to be automated. https://public.tableau.com/profile/mckinsey.analytics#!/vizhome/InternationalAutomation/WhereMachinesCanReplaceHumans.

the only logic at this microeonomic decision level, the rational choice for an individual employer would opt for the latter.

**Impact on rural youth employment**

The multifaceted social and economic implications of youth unemployment have led policy stakeholders to try to engage the 'surplus' youth labour supply to the sectors where there is deficit of labour: namely, the ageing agricultural sectors suffering from low-productivity. For this, many have attempted to "make agriculture attractive to youth" by changing the young people attitudes (thus the 'mindset approach') towards agriculture – that it is fun, attractive, and lucrative. These attempts include promotional activities ranging from showcasing success stories of young farmers at national and international venues[17]; campaigns to appraise young farmer 'champions'; and to the extensive use of social networks to spur connection and networking among the young farmers[18]. These awareness-changing efforts are sometimes (but not often) linked with short-term skills training opportunities, in attempts to increase the employability of the youth.

This rather prevalent mindset approach towards youth employment has two drawbacks which can sometimes render the intervention efforts futile altogether. First, the approach ignores one of the large factors of vulnerable employment and youth unemployment, which is the career aspiration gap. Key compendium on youth employment interventions have revealed that due to increased connectivity vis-à-vis globalization, young people in the least developed economies have high aspirations towards their jobs to provide decent earnings, reasonable hours, and good working conditions (Fox and Kaul, 2018; OECD, 2018). Secondly, recent review of youth employment programmes in low-income countries show that unless youth unemployment is properly understood in the broader context of oversupply of labour in the given economy, the impact of interventions may be short-lived (Fox and Kaul, 2018). That is, the overall demand in labour must increase in order for demand for labour supplied by youth to be sustained. In the previous section, we have seen that there is a questionable prospect on the increased demand for labour in agricultural sectors. Therefore, unless rural youth-specific skills development and decent employment opportunities are provided, the under-skilled rural youth will be disproportionately impacted by the technological advancements, as they currently already lack access to both the skills development and decent work opportunities. Moreover, the high prevalence of underqualification (80%) among rural youth in low-income countries (OECD 2018) show that they do not have the right sets of skills to grab the opportunities of high-skill work brought in by the new technology, due to their underqualification. This is not a new tragedy, as this underqualification is a consequence of the chronic lack of infrastructure and opportunities for skills development in rural areas.

**In the Context of New and Old Challenges in Rural Development**

The sparsely-populated, lowly-invested rural areas and its inhabitants have benefitted less from the policy priority and resource allocation that their urban – densely-populated, highly-invested in terms of infrastructure, finance, education, and consumption activities – counterparts have. For this, the implementation of labour rights, social protection, and social welfare mechanisms in rural areas face

[17] Granted, showcasing success stories to promote a certain practice, or to convince potential donors the efficacy of an intervention is not limited to the case of young farmers. See Sumberg *et al.*, 2012.
[18] As an anecdotal example, the title of a side event held during the 45th Committee on World Food Security (CFS) in October 2018 hosted by FAO illustrates this point: "Agriculture is not cool?! Think Again: Closing the generation gap". Also, from repeated observations made during the author's participation in various policy and project intervention activities, changing the mindset of the youth so that they will become part of the labour force in agricultural sectors was a recurring priority for many of the government officials in member states.

more challenges than in urban settings. The relatively low priority of rural areas and agricultural sectors in policy resource allocations is one of the causes of the persisting and widening inequalities in rural areas, and between the rural and urban.

Therefore, the above implications to agricultural labour market and rural youth employment are further contextualized in the existing and newly emerging challenges in rural development, which sets the scene to providing concrete suggestions for policy intervention in the next section. This is so that the underlying assumptions, possible tradeoffs, and long-term effects may be brought to fore in advance, for more transparent and effective interventions.

*Persistence of entrepreneurialism in lieu of wage employment despite the rural market failures*

According to the recent IFAD report which provides an overview of the approaches on agricultural development, one of the saliently observed policy trends is the persistence of entrepreneurialism promotion, and the hesitance of governments' interventions despite the apparent rural market failures (Wiggins, 2016). This tendency towards 'liberalization' of agricultural markets have been noted in many previous streams of research, but it yields two insights particularly useful for contextualizing the policy interventions.

First, the entrepreneurialism-bias provides a glimpse into why states exhibit rather incongruent (or ambivalent) approaches to agricultural development. Whereas on one hand, small-scale production is hailed as the sustainable way, on the other, increasing productivity through industrializing agriculture is pursued at the same time. The mixture of the two systems may be unavoidable due to the presence of already-globally connected agricultural value chains, and of the small, localized markets which support the developmental transition from subsistence farming to commercial farming (Kim, 1984). However, the state's non-intervention in form of this preference over entrepreneurialism has led to further integrating smallholder 'family' farmers to the globalized market system, through various measures including removal of state subsidies, proactive recommendations for cultivating high-value, lucrative cash crops, etc. (Bernstein, 2010).

Second, such tendency also reflects the lacking capacity (or willingness) of enterprises and public sector entities in low-income countries to create wage employment. However, there are evidences that public-led creation of employment (*i.e.*, Public employment programmes [PEPs]) have directly led to visible increases in rural household incomes (Long, 1977; Wiggins, 2016; Tanzarn and Gutierrez, 2015). PEPs have shown to be effective particularly in contexts where markets have failed to create employment, where it aims to provide the entire source of income, not just as an added income (Lieuw-Kie-Song, Puerto, and Tsukamoto, 2016).

*Exogenous technological interventions exacerbating the existing inequality*

The 'improvement approach' which many international development organizations have utilized since the early period of rural intervention aims to increase smallholder production in rural areas by providing improved technology. Empirical evidences show that such exogenous introduction of productivity-enhancing technology have resulted in reinforces existing inequalities. This is because the technology provided the impetus to increase the disparity between those who possess sizeable proportions of fixed capital (such as land) of production, and those without, as the former group have incentive and immediate returns to adapting the new technology introduced (Long, 1977: 148-157).

Even though the implications of the trends we have observed so far may seem particular to the newly rising automation and AI technologies utilized in agricultural sectors, it is not difficult to place this discussion in the time-long, recurring challenges of rural development shown above. Many of the state and public interventions in rural youth capacity development have clear priority on promoting entrepreneurship; and in order to make this happen, skills development opportunities are provided in the same improvement approach whereby youth participants from rural areas – most of whom have the social and human capital to participate in the first place – are selected based on their 'willingness' and 'availability' which at surface seem to be untethered to their socioeconomic backgrounds.
Recent recommendations from ILO, the World Bank, and other international organizations emphasize the importance of providing adequate skills development opportunities to current and prospective workers for a smooth transition to the future of work. To translate these recommendations into efforts, what has hindered the implementation of the recommendations need to be identified and addressed according to the site-specific context analysis. That is, the preparing the work force towards a smooth transition to the future of work is not merely about aiming to provide skills development and technology to the rural populace; it is rather about understanding what has persisted the disadvantages and underdevelopment in the target areas first. Coupled with the historical evidence of exogenously introduced technology providing impetus to growing disparity in disadvantaged communities (such as rural areas), it is evident that the challenge is now doubled as the agricultural sector faces the urgent need to address both the decent work agenda, and the human-centred agenda.
These old challenges also need to be seen in the light of new challenges facing rural development, as they may act as impact multipliers. Firstly, there are increasing concentration of the tenure of the means of agricultural production in contemporary rural economies. Most notably and notoriously, land, water, and other natural resource appropriation (also known as 'grabbing'. See Sassen 2016; Cotula *et al.,* 2009). Secondly, the increased productivity from advancements in agtech may not necessarily be distributed as increased state revenue in form of corporate taxes. This is in line with the recent concerns raised in the organization of firms that utilize innovative technology (World Bank, 2018). As revisited, most of the policy recommendations suggested in the Future of Work discussions (for example, see Ernst, Merola, and Samaan, 2018) for reducing inequality further exacerbated by technology – namely, strengthening social protection of the vulnerable population, skills development, and increasing portability of the skills – require a lot more policy resource allocation and political commitment in order to materialize to concrete action plans in agricultural sectors and rural economies. The following section attempts to set on this daunting task, by provide the broad strokes of policy considerations for effective intervention.

## Suggestions for Policy Intervention

### Enabling the human-centred agenda in agricultural sectors

*Addressing the employment data gap by mapping the agricultural labour market structure*

Highlighting the attractiveness of the agtech in its contribution to increased productivity, or its potential role in making agriculture enticing for youth is based on the assumption that technology will bring about increased production and employment. This assumption was rebutted by reviewing the job forecasts in agriculture, and revisiting the causes of growing disparity within rural economies. Therefore, understanding the landscape of the agricultural labour market and skills gaps should be a high priority, as its lack thereof can lead to the perpetuation of the existing inequality to access desirable resources.

In spite of the chronic lack of quality data on agricultural labour, policy stakeholders can still attempt to make evidence-based, result-oriented impact by opting to gather data that are relatively more easily accessible, and less costly if comprehensive data gathering is not feasible. The two types of 3-axes graph of labour distribution in agricultural sectors shown in this paper is an example of how rich data (*e.g.*, employment share per jobs in agricultural sectors in the United States) shows clear resolution of entry points for intervention. To produce this graph, the exact percentage share of employment per jobs; the necessary skill level; along with the level of capital investment in the enterprise that creates those jobs, would be needed.

*Ensuring public, and open access to agricultural big data (ag big data) and other means of production*

By reviewing over a thousand peer-reviewed journal articles, reports, and online postings on agricultural big data (ag big data), Wolfert *et al.,* 2017 point out that ag big data not only influence the production phases but throughout the entire agricultural value chain. Given its magnitude, they suggest two diverging scenarios: the first, ag big data become highly privatized and becomes a small part of a vertically integrated agricultural value chain monopolized by the few who have access to and the technology to produce and analyze these data; the second, public governance of ag big data allows its free and open access which empowers the participants of the agricultural value chains (including smallholder farmers), not relegating to mere collectors and users of ag big data.

This public governance of ag big data is especially critical in the wake of the booming investment we have witnessed in the data-enabled agriculture. Currently, there are still technical limitations (such as incoherent data parameters, compatibility across different sources, etc). which stalls the worrisome rise of a data monopoly. This provides the opportune timing for the public sector to proactively develop roadmaps for fair, transparent, and open management of ag big data.

Similarly, the conventional means of production in agriculture – such as land, natural resources, seeds, inputs, etc. – need to remain accessible. That is, the state should actively intervene to prevent the competition-stifling monopolization of these means, which has thus far resulted in high concentration of power and political clout in the hands of a few major corporations. The dialogue among the public, private, and the civil sector should continue to explore a sustainably symbiotic relationship between the local, smallholder, family farmers, and the globalized, vertically integrated agricultural giant players. In the meanwhile, the policy stakeholders should ensure that fair competition is still possible in agriculture and food systems.

*Linking skills development with decent (green) jobs opportunities for the rural youth*

Skills development and education is a prerequisite for promoting both youth employment and entrepreneurship. We have seen that due to low investment from both the public and private sectors to the human capital in the rural economies, providing access to skills development and education has remained a challenge. Moreover, skill-biased technological progress may not be as relevant when utilizing rural labour force (Weiss, 2008), especially the under-educated and low-skill youth, which decreases long-term investment despite the public consent that rural youth skills development is important.

Nevertheless, with proper vocational training, even youth in low skill employment can improve agricultural practices and contribute to the implementation of “resilient” practices (climate smart practice, more environmentally sustainable, more protective of human health). These job opportunities should consist of a sustainable mix of both self-employment and wage employment. Public employment programmes that create green jobs (for example, see UNDP, 2009) may provide effective entry points for low-skill youth who may enhance their skills whom otherwise may not have such opportunity. As a primary sector, agricultural sector will continue to absorb the labour market entrants, and for the time being, the sector will continue to have high demands for low-skill, manual labour. Unfortunately, for the sake of bringing down the production costs, agricultural workers rights (and even human rights) continue to be exploited and sacrificed. To prevent this from further exacerbating, private sector and policy stakeholders can consider providing support to young entrepreneurs with funding for low-risk start-ups, or public employment in the agricultural sectors and in rural areas. This will not only contribute to alleviating the worsening working conditions but also provide entry-level work opportunities to young people, and contribute to ensuring food security and rural development.

**Macroeconomic considerations**

Policy stakeholders should consider the macroeconomic context in which their agricultural sectors are placed. That is, the significance of the agricultural sectors against the backdrop of their mid- to long-term national development priorities. For example, some of the questions that policy stakeholders could pose to draft the framework would include: is the main function of the agricultural sectors in the country to provide an entry point for low-skilled workers?; Does it mostly aim to productively utilize the ageing rural population?; Is the goal of increasing agricultural productivity in the end to supply surplus labour to secondary and tertiary sectors?; Is their agricultural sector export-oriented?; If so, is the aim to target premium priced market by focusing key trade partners, or to maintain competitveness in multilateral free trade settings? Depending on the current role and strategic future role of agriculture within their economies, how and the degree to which the government would want to intervene in the subject matter of agtech adoption would differ vastly. These factors should be discussed *prior to* devising concrete, agricultural-sector specific, action plans.

In this vein, efforts to increase productivity in agriculture should be further specified down to the desired outputs, and its expected impact not only to the production in agriculture, but also to its labour market. Increasing productivity in agriculture has earned an almost unchallenged global policy priority, especially in the light of the expected increase in population and the exacerbating environmental degradation, including climate change. Whether indeed increased production is the key solution, or there are other more efficient pathways to this issue – such as rethinking the (global) distribution of food production and consumption, and promoting less resource-taxing diet – are important considerations to make at both individual country and global level, as it will allow a sovereignty to assess its potential role and strategic position in the global agrifood sector. On a wider level, global dialogue on how food is produced, distributed, and consumed is a key to ensuring its sustainability.

Granted, it is difficult to assume that national strategies have long-term plans that outlives the political expiration date of elected officials in many of the modern organization of governments. Hence, the frequent appearance of the term “Agrarian populism” in the rural development literature. Despite this, however, policy stakeholders should note that setting the key directions for their agricultural sectors will have prolonged impact not only on food and nutrition, but also rural development and natural resource management. Some examples of the axes of contention include the cheap food policy versus establishing resilient food systems; priority over export-oriented cash crop cultivation versus food self-sufficiency; and the immediate and long-term losses and gains over adapting sustainable practices in agriculture (green agriculture).

In the traditionally marginalized and low-policy priority areas such as the rural areas and agricultural sectors, the deliberative scepticisms around the expanded social welfare and protection attest to the fact that the ongoing debate is an issue of organization of work, and governance. Therefore, this paper concludes by reiterating the critical importance of timely intervention by policy stakeholders to address these challenges, and to harness the developmental potential in the agricultural technological development, and to minimize its negative impact on the agricultural labour market.

## Abbreviations

| | |
|---|---|
| FAO | Food and Agriculture Organization of the United Nations |
| IFAD | International Fund for Agricultural Development |
| ILO | International Labour Organization |
| OECD | Organisation for Economic Co-operation and Development |
| UNDP | United Nations Development Programme |
| UNEP | United Nations Environment Programme (UN Environment) |

## References

AgFunder, 2015. *Agtech Investing Report 2014*, https://agfunder.com/research/agtech-investing-report-2014.

AgFunder, 2016. *Agtech Investing Report 2015*, https://agfunder.com/research/agtech-investing-report-2015.

AgFunder, 2017. *Agtech Investing Report 2016*, https://agfunder.com/research/agtech-investing-report-2016.

AgFunder, 2018. *Agrifood Tech Investing Report 2017,* https://agfunder.com/research/agrifood-tech-investing-report-2017.

AgFunder, 2019. *Agrifood Tech Investing Report 2018*, https://agfunder.com/research/agrifood-tech-investing-report-2018.

Autor D., Salomons A. 2018. *Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*, w24871, Cambridge, MA, National Bureau of Economic Research, https://doi.org/10.3386/w24871.

Bernstein H., 2010. *Class Dynamics of Agrarian Change*, Agrarian Change & Peasant Studies, Fernwood Publishing.

Cotula L., Vermeulen S., Leonard R., Keeley J., 2009. *Land Grab or Development Opportunity? Agricultural Investment and Land Deals in Africa*, IEED, FAO, IFAD.

Daron A., Autor D., 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings, *Handbook of Labor Economics* 4, 1043-1171, https://doi.org/10.1016/S0169-7218(11)02410-5.

Daron A., Restrepo P., 2018a. Low-Skill and High-Skill Automation, *Journal of Human Capital* 29.

Daron A., Restrepo P., 2018b. *Modeling Automation,* Working Paper 24321, National Bureau of Economic Research, https://doi.org/10.3386/w24321.

Daron A., Restrepo P., 2018c. The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment, *American Economic Review* 108 (6), 1488-1542, https://doi.org/10.1257/aer.20160696.

Ekkehard E., Merola R., Samaan D., 2018. The Economics of Artificial Intelligence: Implications for the Future of Work, *ILO Future of Work Research Paper Series* 5, 41.

FAO, 2012. Green Jobs for a Revitalized Food and Agriculture Sector, http://www.fao.org/fileadmin/user_upload/suistainability/pdf/FAO_green_jobs_paper_March_31.pdf.

FAO (ed.), 2017. *The Future of Food and Agriculture: Trends and Challenges*, Rome, Food and Agriculture Organization of the United Nations.

FAO and African Union Commission, 2018. *Sustainable Agricultural Mechanization: A Framework for Africa*, Adidis Ababa, http://www.fao.org/3/CA1136EN/ca1136en.pdf.

Fox L., Kaul U,. 2018. *The Evidence Is In: How Should Youth Employment Programs In Low-Income Countries Be Designed?,* Policy Research Working Papers, The World Bank, https://doi.org/10.1596/1813-9450-8500.

Global Commission on the Economy and Climate, 2018. Unlocking the Inclusive Growth Story of the 21st Century: Accelerating Climate Action in Urgent Times, https://newclimateeconomy.report/2018/.

Goldin C., Katz L.F., 2007. The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005, Working Paper 12984, National Bureau of Economic Research, https://doi.org/10.3386/w12984.

Hajra R., Ghosh T., 2018. Agricultural Productivity, Household Poverty and Migration in the Indian Sundarban Delta, *Elementa: Science of the Anthropocene* 6 (1), 3. https://doi.org/10.1525/elementa.196.

ILO, 2015. *Toward Solutions for Youth Employment,* A 2015 Baseline Report, https://www.ilo.org/employment/areas/youth-employment/WCMS_413826/lang--en/index.htm.

ILO, 2018. *World Employment and Social Outlook*, Trends 2018, Report. http://www.ilo.org/global/research/global-reports/weso/2018/WCMS_615594/lang--en/index.htm.

ILO, 2019. *Work for a Brighter Future – Global Commission on the Future of Work*, https://www.ilo.org/global/topics/future-of-work/publications/WCMS_662410/lang--en/index.htm.

ILO, UNEP, 2012. *Working towards Sustainable Development: Opportunities for Decent Work and Social Inclusion in a Green Economy: [A Report by the Green Jobs Initiative]*,Edited by Peter Poschen, Ana Lucía Iturriza, Xinxing Li, Steven Tobin, and Elodie Dessors, Geneva, International Labour Organisation.

Hye-Soon K., 1984. *The Periodic Market in Contemporary Korea: Its Continuing Role in Rural Development*, University of Hawaii, https://scholarspace.manoa.hawaii.edu/bitstream/10125/10282/uhm_phd_8508788_r.pdf.

KPMG, 2016. *Venture Pulse Q4 2015*, https://assets.kpmg/content/dam/kpmg/pdf/2016/01/venture-pulse-q4-report.pdf.

KPMG, 2017. *Venture Pulse Q4 2016*, https://assets.kpmg/content/dam/kpmg/xx/pdf/2017/01/venture-pulse-q4-2016-report.pdf.

KPMG, 2018a. *KPMG Venture Pulse: Global Analysis of Venture Funding (Q2 2018)*, https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2018/07/kpmg-venture-pulse-q2-2018.pdf.

KPMG, 2018b. *Venture Pulse Q4 2017*, https://home.kpmg/content/dam/kpmg/us/pdf/2018/01/venture-pulse-4q17-report.pdf.

KPMG, 2019. *Venture Pulse Q4 2018*, https://assets.kpmg/content/dam/kpmg/xx/pdf/2019/01/kpmg-venture-pulse-q4-2018.pdf.

Lieuw-Kie-Song M., Puerto S., Tsukamoto M., 2016. Employment Policy Department EMPLOYMENT Working Paper No. 203, *Working Paper* No. 203, ILO.

Long N., 1977. *Introduction to the Sociology of Rural Development*. Law Book Co of Australasia.

Manyika J., Chui M., Miremadi M., Bughin J., George K., Willmott P., Dewhurst M., 2017. *Harnessing Automation for a Future That Works*, McKinsey Global Institute, https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works.

Manyika J., Lund S., Chui M., Bughin J., Woetzel J., Batra P., Ko R., Sanghvi S., 2017. *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*, McKinsey Global Institute. https://www.mckinsey.com/~/media/mckinsey/featured%20insights/future%20of%20organizations/what%20the%20future%20of%20work%20will%20mean%20for%20jobs%20skills%20and%20wages/mgi-jobs-lost-jobs-gained-report-december-6-2017.ashx.

McKinsey Global Institute. 2017. “Technology, Jobs, and the Future of Work.” https://www.mckinsey.com/featured-insights/employment-and-growth/technology-jobs-and-the-future-of-work.

OECD, 2018. *The Future of Rural Youth in Developing Countries: Tapping the Potential of Local Value Chains,* Development Centre Studies, OECD Publishing, https://read.oecd-ilibrary.org/development/the-future-of-rural-youth-in-developing-countries_9789264298521-en.

Restuccia D., Tao Yang D., Zhu X., 2008. Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis, *Journal of Monetary Economics* 55 (2), 234-50, https://doi.org/10.1016/j.jmoneco.2007.11.006.

Sassen S., 2016. A Massive Loss of Habitat: New Drivers for Migration, *Sociology of Development* 2 (2), 204-33. https://doi.org/10.1525/sod.2016.2.2.204.

Shoham Y., Perrault R., Brynjolfsson E., Clark J., Manyika J., Niebles J.C., Lyons T., Etchemendy J., Grosz B., Bauer Z., 2018. *The AI Index 2018 Annual Report*, Human-Centered AI Initiative, Stanford University, Stanford, CA, AI Index Steering Committee,http://cdn.aiindex.org/2018/AI%20Index%202018%20Annual%20Report.pdf.

Sumberg J., Irving R., Adams E., Thompson J., 2012. Success-Making and Success Stories: Agronomic Research in the Spotlight, *Contested Agronomy: Agricultural Research in a Changing World*, edited by James Sumberg and John Thompson, Pathways to Sustainability.

Tanzarn N., Gutierrez M.T., 2015. Public Works Programmes: A Strategy for Poverty Alleviation, *ILO Employment Working Paper* 194, 90.

Tasso A., Restuccia D., 2018. *Geography and Agricultural Productivity: Cross-Country Evidence from Micro Plot-Level Data*, w24532, Cambridge, MA, National Bureau of Economic Research, https://doi.org/10.3386/w24532.

UNDP, 2009. *Green Jobs for the Poor: A Public Employment Approach*, http://www.undp.org/content/undp/en /home/librarypage/poverty-reduction/green-jobs-for-the-poor-a-public-employment-approach.html.

Walker D., Kurth T.,Van Wyck J., Tilney M., 2016. *Lessons from the Front Lines of the Agtech Revolution*, Boston Consulting Group, AgFunder.

Weiss M., 2008. Skill-Biased Technological Change: Is There Hope for the Unskilled?, *Economics Letters* 100 (3), 439-41, https://doi.org/10.1016/j.econlet.2008.03.022.

Wiggins S., 2016. *Agricultural and Rural Development Reconsidered: A Guide to Issues and Debates*, 01, IFAD Research Series. IFAD.

Wilder B., Dilkina B., Tambe M., 2018. Melding the Data-Decisions Pipeline: Decision-Focused Learning for Combinatorial Optimization, *Association for the Advancement of Artificial Intelligence* 8.

Wolfert S., Ge L, Verdouw C., Bogaardt M.J., 2017. Big Data in Smart Farming – A Review, *Agricultural Systems* 153 (May), 69-80, https://doi.org/10.1016/j.agsy.2017.01.023.

World Bank, 2017. Special Section: Skills Development in Sub-Saharan Africa, *Africa's Pulse*, Africa's Pulse, 16 (October), 1-100.

World Bank, 2018. *2019 World Development Report: The Changing Nature of Work*, http://documents. worldbank.org /curated/en/816281518818814423/pdf/2019-WDR-Report.pdf.

## Annex 1. List of forecasted green jobs in agricultural sectors

| Jobs | Required skill level* | Investment | Labour intensity |
|---|---|---|---|
| Jobs from FAO 2012 | | | |
| No-till farmer | 3 | Low | Low |
| Organic farmer | 3-4 | Low | High |
| Push-pull farmer | 4 | Low | High |
| Skilled labour pest system manager | 4 | Low | High |
| Cocoa integrated crop/pest system manager | 4 | Low | High |
| Community biological pest manager | 4 | Low | Mid |
| Afforestation and reforestation workers | 1 | Low | High |
| Urban and peri-urban green space managers | 2? | Low | High |
| Improved watershed managers | 2? | Low | High |
| Forest protection managers | 2? | Low | High |
| Recreation site managers | 2? | Low | High |
| Agroforestry manager | 4 | Mid | Low |
| Agroforestry worker | 3 | Low | High |
| Triple bagging system management | 2 | Low | Low |
| Livestock manure biogas producer | 3 | Mid | Mid |
| Non-CAFO (large-scale confined animal feedlot operations) livestock manager | 3 | Mid | High |
| Draught animal powered mechanization user | 3 | Mid | Low |
| Fish stock assessment, monitoring, control and protection workers | 3 | Mid | Mid |
| Fish researcher | 5 | High | Low |
| Integrated Food Energy Systems (in aquaculture) | 4 | Low | Mid |
| Filter feeders and extractive species growers | 2 | Mid | High |
| Mechanized operation farmer | 3 | Mid | Low |
| Eco-tourism manager | 3 | Mid | Low |
| Jobs from Walker *et al.* (2016) | | | |
| New crops researcher | 5 | High | Low |
| Genetics researcher | 5 | High | Low |
| Seeds researcher | 5 | High | Low |
| Sensor and connectivity developer | 5 | Mid | Low |
| Data storage and aggregation manager | 5 | Mid | Low |
| Optimization hardware developer | 5 | Mid | Low |
| Software platforms | 5 | Mid | Low |
| Big Data analytic | 5 | High | Low |
| Electrification manager | 4 | Mid | Low |
| Autonomous equipment developer | 5 | High | Low |
| Drones developer | 5 | High | Low |
| Robotics developer | 5 | High | Low |
| Food security and traceability developer | 4 | High | Low |
| Asset and fleet optimization developer | 4 | Mid-High | Low |
| Indoor agriculture developer | 4 | Mid | Low |

* Jobs whose required skill levels were not clear from the indicated sources have been marked with a question mark. For these job skills, the estimation is based on the author's assessment.

**Annex 2. List of jobs categorized under agricultural sectors as according to O*NET database**

| Code | Occupation | Projected Growth (2016-2026) | Projected Job Openings (2016-2026) | Job Group (Skills) | Employs (# of people, as of 2016) | Employment percentage |
|---|---|---|---|---|---|---|
| 13-1074.00 | Farm Labor Contractors | Average | 300 | 2 | 3,000 | 0.131% |
| 45-2021.00 | Animal Breeders | Slower than average | 1400 | 2 | 9,000 | 0.392% |
| 45-2093.00 | Farmworkers, Farm, Ranch, and Aquacultural Animals | Decline | 38600 | 1 | 268,000 | 11.688% |
| 45-2092.00 | Farmworkers and Laborers, Crop, Nursery, and Greenhouse | Little or no change | 76800 | | 504,000 | 21.980% |
| 45-2092.01 | Nursery Workers | | | 2 | | 10.990% |
| 45-2092.02 | Farmworkers and Laborers, Crop | | | 1 | | 10.990% |
| 45-2091.00 | Agricultural Equipment Operators | Average | 10200 | 2 | 64,000 | 2.791% |
| 45-1011.00 | First-Line Supervisors of Farming, Fishing, and Forestry Workers | Slower than average | 6500 | | 49,000 | 2.1369% |
| 45-1011.05 | First-Line Supervisors of Logging Workers | | | 2 | | 0.534% |
| 45-1011.06 | First-Line Supervisors of Aquacultural Workers | | | 4 | | 0.534% |
| 45-1011.07 | First-Line Supervisors of Agricultural Crop and Horticultural Workers | | | 3 | | 0.534% |
| 45-1011.08 | First-Line Supervisors of Animal Husbandry and Animal Care Workers | | | 3 | | 0.534% |
| 45-4029.00 | Logging Workers, All Other | Decline | 500 | 2* | 5,000 | 0.218% |
| 45-4022.00 | Logging Equipment Operators | Decline | 4200 | 1 | 39,000 | 1.7008% |
| 19-1011.00 | Animal Scientists | Average | 700 | 5 | 6,000 | 0.262% |
| 45-2099.00 | Agricultural Workers, All Other | Slower than average | 1800 | 2* | 12,000 | 0.523% |
| 45-4021.00 | Fallers | Decline | 800 | 1 | 8,000 | 0.349% |
| 45-2041.00 | Graders and Sorters, Agricultural Products | Little or no change | 5700 | 1 | 43,000 | 1.875% |
| | Fishing and Hunting Workers | Faster than average | 3100 | | | |
| 45-3011.00 | Fishers and Related Fishing Workers | | | 1 | 27,000 | 1.177% |
| 45-3021.00 | Hunters and Trappers | | | 1 | | |
| 45-4011.00 | Forest and Conservation Workers | Decline | 2100 | 3 | 14,000 | 0.611% |
| 39-2011.00 | Animal Trainers | Faster than average | 7000 | 2 | 55,000 | 2.399% |
| 19-1032.00 | Foresters | Average | 1100 | 4 | 12,000 | 0.523% |
| 11-9013.00 | Farmers, Ranchers, and Other Agricultural Managers | Little or no change | 74300 | | 1,029,000 | 44.876% |
| 11-9013.01 | Nursery and Greenhouse Managers | | | 3 | | 14.950% |

| | | | | | | |
|---|---|---|---|---|---|---|
| 11-9013.02 | Farm and Ranch Managers | | | 4 | | 14.950% |
| 11-9013.03 | Aquacultural Managers | | | 4 | | 14.950% |
| 19-4011.00 | Agricultural and Food Science Technicians | Average | 3000 | 3* | 28,000 | 1.221% |
| 19-4011.01 | Agricultural Technicians | | | 3 | | 0.611% |
| 19-4011.02 | Food Science Technicians | | | 3 | | 0.611% |
| 17-2021.00 | Agricultural Engineers | Average | 200 | 4 | 3,000 | 0.131% |
| 37-3012.00 | Pesticide Handlers, Sprayers, and Applicators, Vegetation | Average | 5000 | 2 | 38,000 | 1.657% |
| 49-3041.00 | Farm Equipment Mechanics and Service Technicians | Average | 4500 | 3 | 43,000 | 1.875% |
| 19-1013.00 | Soil and Plant Scientists | Average | 2200 | 5 | 20,000 | 0.872% |
| 13-1021.00 | Buyers and Purchasing Agents, Farm Products | Decline | 1400 | 4 | 14,000 | 0.611% |

* Jobs whose groups (skills) were not indicated are marked with asterisks. For these job skills, the estimation is based on the author's assessment.