Comment

Supplementary information to:

Change mindsets to stop millions of food-production jobs from disappearing

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This Supplementary information comprises:

1. Methodology for the data analysis in the graphic 'The decline of food-production jobs'.
2. Figure S1: a more detailed version of the graphic 'The decline of food-production jobs'.
3. Figure S2: summary of approaches and actions to revert job losses in food production.
4. Acknowledgements

SUPPLEMENTARY INFORMATION

Change mindsets to stop millions of food-production jobs from disappearing

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Materials and methods

Using UN, ILO, Worldbank, and FAOSTATS data from 2019[1], we assembled country-level data, including working age population (population age 15 and older), population forecast, share of employment in agriculture, country's classification based on the UN development categories (Least developed, Developing, Developed),. The population in working age is based on the medium variant of the United Nations World Population Prospects 2019 and was calculated as the sum of the population aged 15 years and older[2]. The population entering working age by 2030 was defined as the population aged 5 to 14 in 2020. Agricultural employment categories include as defined by the UN-ILO: production of annual and perennial crops, fisheries and aquaculture, husbandry, wild-species harvesting, forestry, and pre- and postharvest services[3]. The employment in agriculture indicator is the share of people employed in agriculture among the total employed population and corresponds to the agriculture category of the indicator called 'Employment distribution by economic activity (by sex)' in the ILOSTAT. We use the indicator as a proxy to understand the relative importance of agriculture with regard to employment. Employment comprises all persons of working age who during a specified brief period, such as one week or one day, were in the following categories: a) paid employment (whether at work or with a job but not at work); or b) self-employment (whether at work or with an enterprise but not at work).

We first describe the observed trends in employment in agriculture by country development category for the years 1991 – 2019 (N=180). We use this time period because most country-level data is available after 1990. Next, we used a group-based trajectory analysis to separate the data on the proportion employed in agriculture into groups of countries with different patterns, regardless of development category. The minimum threshold for group size was 5% of the sample, resulting in five groups. We then plotted the countries' group/cluster membership that was identified with the trajectory analysis with the countries' development categories (Figure 1 (main article) and Figure SI-1 showing trends in employment from 1990 to 2019 with Figure SI-1 displaying the five trajectory grounds derived from this analysis. The groups/clusters are based on both the share of total employment in food production since 1991 and projected trends from 2020 to 2030 and show five sets of trends and their distribution within and across UN economic development categories. See Figure SI-1 below.

We then used linear regression to estimate two different models to extrapolate trends and absolute numbers of employment in agriculture for the period 2020 – 2030. Since the extrapolations were based on data up to 2019, they do not consider changes to national employment levels caused by the COVID-19 pandemic. We also tested quadratic and cubic polynomials for these predicted trends but these were less parsimonious and did not fit most countries' data well. For the regressions, we first transformed the data using the arcsine transformation to avoid predicted employment values of less than 0, fit straight lines to the data, and then used the regression coefficients to predict the share of employment in agriculture to 2030. We then back-transformed the predicted values to the original scale. Because we had data about the population of working age for each country, we did not need to weight the employment in agriculture data. The two prediction models represent a range of possible values for the number of people employed in agriculture to 2030, with the main difference being that Model 2 uses the UN's population forecast data while

[1] UN-WB data table (API_SL.AGR.EMPL.ZS_DS2_en_csv_v2_3931931.csv) and FAOSTAT data table (FAOSTAT_data_4-11-2022 (1).csv).

[2] United Nations, Department of Economic and Social Affairs, Population Division (2019). World Population Prospects 2019, Online Edition. Rev. 1. https://population.un.org/wpp/

[3] ILO 2022. International Standard Industrial Classification of All Economic Activities (ISIC) https://ilostat.ilo.org/resources/concepts-and-definitions/classification-economic-activities/

Model 1 does not. In the text and in the figure, we report numbers based on Model 2. The following describes the two models and the variables involved:

NEA = Number of Employed in Agriculture
NET = Number Employed Total
NPWA = Number Population in Working Age

PEA = NEA/NET = Proportion Employed in Agriculture
PET = NET/NPWA = Proportion Employed Total

Where
NEA = PEA x PET x NPWA

Model 1 calculates NEA = PEA x PET x NPWA in past years and runs forecasts of NEA in future years.
Model 2 first runs forecasts of PEA and PET into the future, and then calculates NEA = PEA x PET x NPWA for future years.

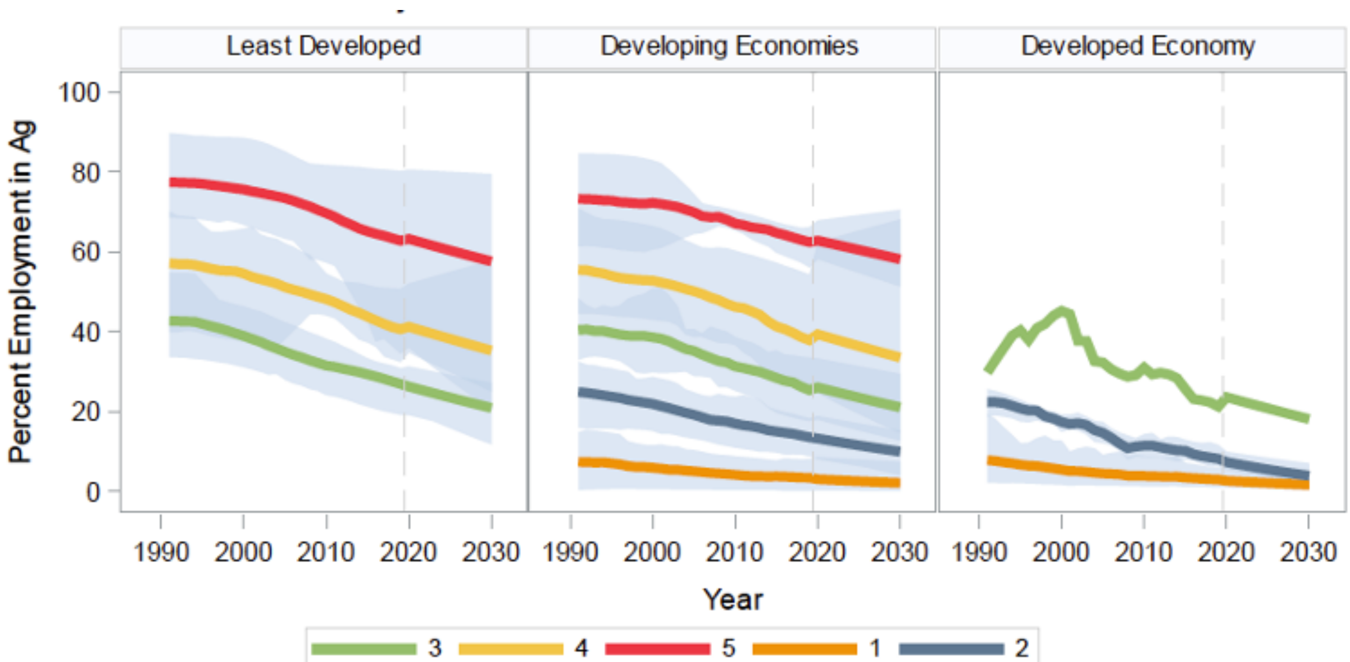

Figure S1: Average observed (1991-2019) and projected (2020 to 2030) job losses in food production across 'trajectory groups' (1-5) of countries within each economic development category according to the UN Country Classification System as of 2021 and based on employment categories according to classification of the UN-ILO. This figure offers a more detailed version of Figure 1 (main text), which is intended to show the mean observed and projected trends in employment in agriculture and variation among the 180 countries analyzed. The 'trajectory groups' were derived using group-based trajectory analysis on the proportion employed in agriculture as described in this Supplementary Information. Shaded area represents the 5th and 95th percentile range within a 'trajectory group'. Number employed in agriculture is calculated as the product of the proportion employed in agriculture, the proportion employed total, and the number population in working age. Projected values are based on linear time trend for each of the 180 countries.

Summarizing approaches and solutions to revert loses and enhance job opportunities across the food system

In preparing the article, we carried out an extensive review of approaches and solutions to advance environmentally sustainable and socially inclusive food production systems. Figure SI-2 summarizes approaches used around the world to advance the three areas of action discussed in the paper: 1- Recognizing & reframing the social-cultural values of employment in diverse food systems; 2-Orienting incentives to transitions to resilient, regenerative, and inclusive food production; and 3- Localizing value-aggregation closer to production areas from rural to urban. This is not intended to be an exhaustive list of approaches and solutions.

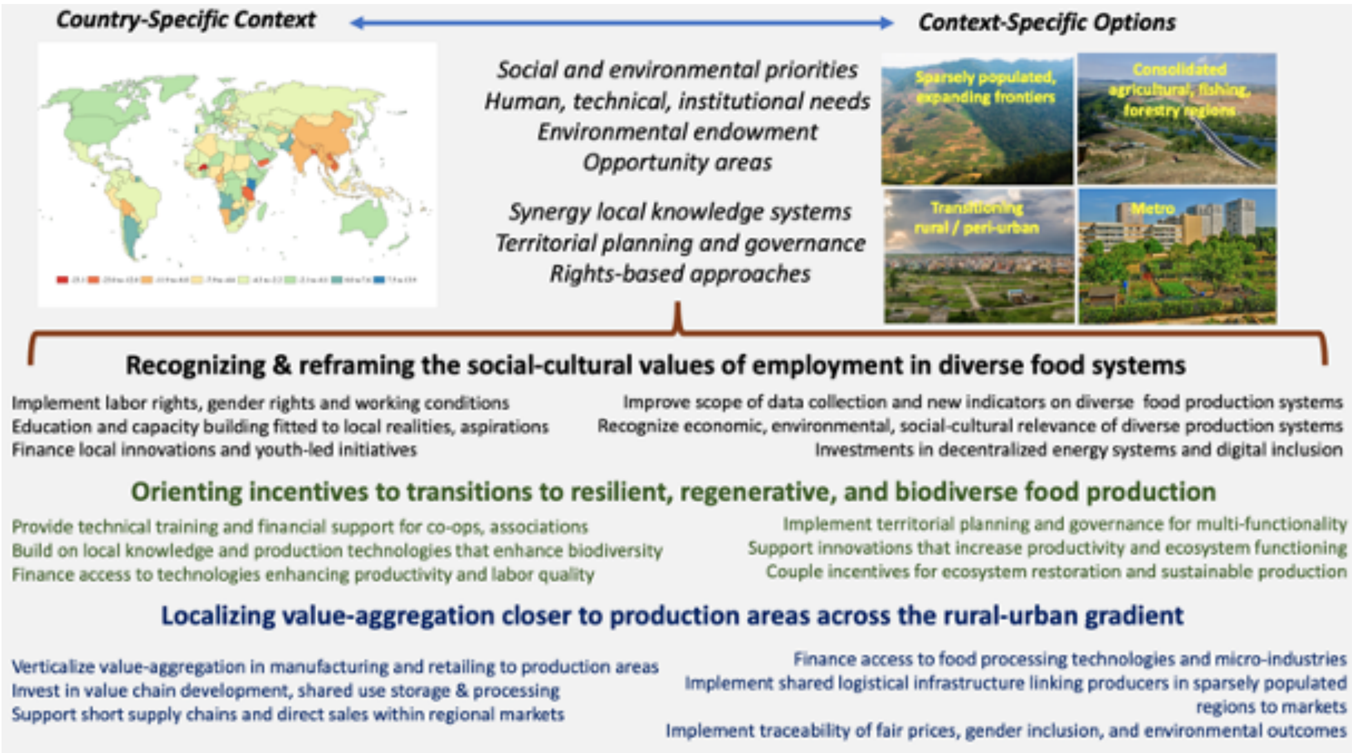

Figure SI-2 presents an non-exhausted summary from reviewed sources of approaches and actions to revert job losses in food production in line with environmental sustainability and economic development goals. The figure calls attention to the importance of recognizing food production systems along the rural-urban gradient, highlighting that these approaches and actions are both country and context specific. Map values represent the change in proportion employed in agriculture per country between 2019 (observed) to 2030 (estimated). Countries blue are expected to gain agricultural jobs while greenish to red will lose proportionally the most.

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