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Ageing threatens sustainability of smallholder farming in China

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Rapid demographic ageing substantially affects socioeconomic development[1–4] and presents considerable challenges for food security and agricultural sustainability[5–8], which have so far not been well understood. Here, by using data from more than 15,000 rural households with crops but no livestock across China, we show that rural population ageing reduced farm size by 4% through transferring cropland ownership and land abandonment (approximately 4 million hectares) in 2019, taking the population age structure in 1990 as a benchmark. These changes led to a reduction of agricultural inputs, including chemical fertilizers, manure and machinery, which decreased agricultural output and labour productivity by 5% and 4%, respectively, further lowering farmers' income by 15%. Meanwhile, fertilizer loss increased by 3%, resulting in higher pollutant emissions to the environment. In new farming models, such as cooperative farming, farms tend to be larger and operated by younger farmers, who have a higher average education level, hence improving agricultural management. By encouraging the transition to new farming models, the negative consequences of ageing can be reversed. Agricultural input, farm size and farmer's income would grow by approximately 14%, 20% and 26%, respectively, and fertilizer loss would reduce by 4% in 2100 compared with that in 2020. This suggests that management of rural ageing will contribute to a comprehensive transformation of smallholder farming to sustainable agriculture in China.

As life expectancy increases and population fertility rates decline, populations are ageing at an accelerating rate globally[9]. Population ageing introduces additional challenges to achieving several global Sustainable Development Goals (SDGs), mainly in relation to SDG1 'no poverty', SDG2 'zero hunger', SDG4 'quality education', SDG5 'gender equality', SDG8 'decent work and economic growth' and SDG12 'responsible consumption and production'[1–4,10,11]. Labour shortages and innovation constraints may become more pronounced in a society with an ageing population, especially in labour-intensive economic sectors[3]. Policy interventions to increase birth rates seem to be largely ineffective in many countries where ageing issues have been identified[12,13]. Alternative strategies urgently need to be developed to achieve and maintain sustainable development paths for human society. Agriculture as a typical labour-intensive industry could be one of the sectors substantially affected by population ageing, especially in countries where smallholder farming remains the prevalent organization form[8,14]. However, how ageing affects agriculture and rural livelihoods has not been thoroughly studied or well understood so far. This sector is facing substantial challenges in squaring the circle between maintaining food security and improving environmental protection at many levels. Therefore, it is indispensable to identify integrated, comprehensive measures to ensure global food security, while protecting the environment and achieving agricultural sustainability.

Farmers in older age groups typically have relatively lower education levels compared with younger age groups, and are less likely to keep their agricultural skills up to date or to embrace cutting-edge methods[14–16]. Owing to a widespread labour supply shortage in rural communities, they can only operate small-scale farms, which leads to an increase in cropland abandonment as rural populations age[17,18]. Meanwhile, the typical agricultural input mix and crop types (labour-intensive crops or not) are likely to shift with rural ageing, reducing agricultural productivity and efficiency[5–7,19]. These effects are usually worse in smallholder-farming-dominated countries such as China[8]. In rural China, the percentage of people over 65 years of age has tripled between 1990 and 2020, reaching about 18% in 2020 (Fig. 1a; see Supplementary Text for details). In the coming decades, China's population ageing rate is predicted to accelerate[20,21]. Thus, it is urgent and timely to address the threats of ageing to agriculture in China, and other countries and regions globally that are facing similar issues.

Here we explore the relationship between rural population ageing (the proportion of individuals over 65 years old at the household level) and agricultural sustainability based on a multiple regression model (MRM), using survey data from more than 15,000 rural households who cultivated crops but no livestock in China from 2015, 2017 and 2019. Total agricultural input, output, labour productivity, fertilizer input, manure, fertilizer loss, farmer's income, farm size and machine input

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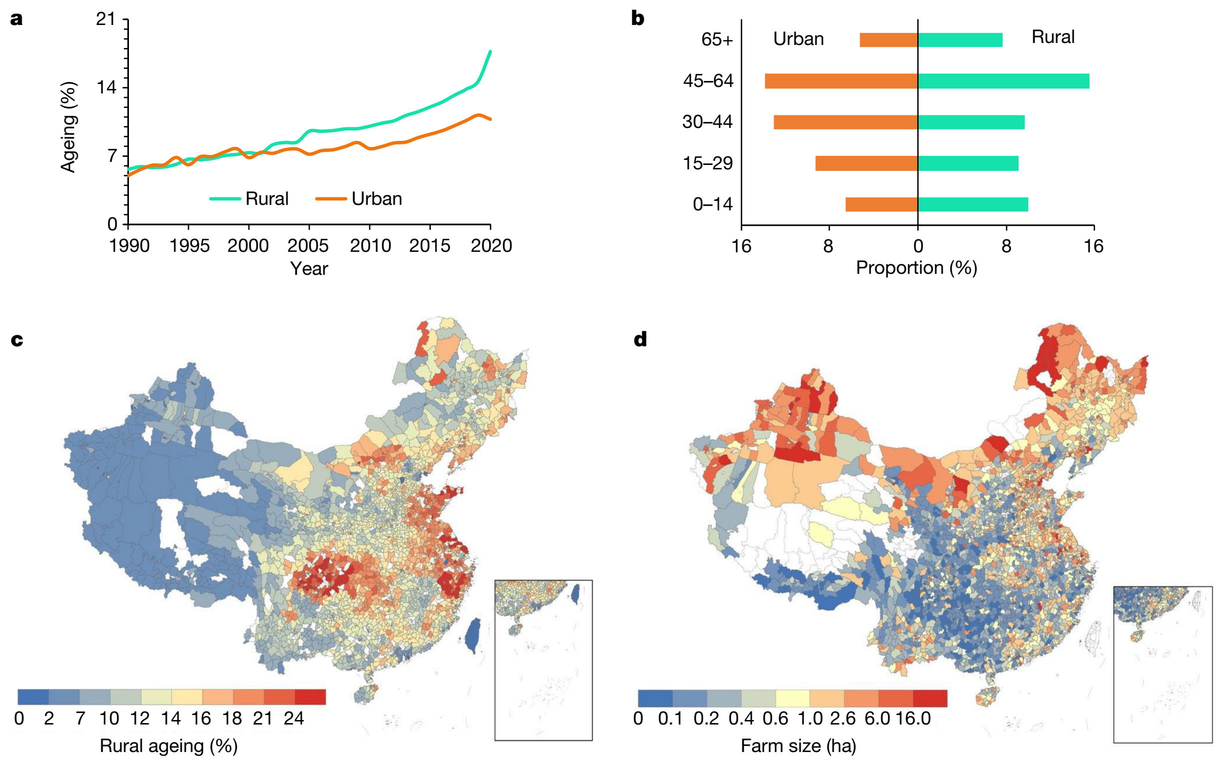

Fig. 1 | Population ageing and farm size in China. a, Ageing trend in rural and urban China from 1990 to 2020. Rural and urban ageing refers to the proportion of people over 65 years of age in rural and urban populations, respectively. **b**, Share of different age groups in the total population in rural and urban China in 2020. Ageing depicts the share of different age groups in the total population. **c**, County-level ageing in 2020. Ageing depicts the ratio of the number of people over 65 years of age relative to the total population at the county level. **d**, Farm size in 2017. The insets in **c** and **d** show the national boundary line of the South China Sea. The base map used in **c** and **d** was applied without endorsement using data from the Database of Global Administrative Areas (https://gadm.org/).

were selected as indicators of agricultural sustainability in terms of economic, social and environmental dimensions. To understand the full range of effects of ageing on agriculture, other variables such as transferred and abandoned cropland, and technology adoption were also incorporated into the analysis. In addition, the analysis quantified the potential of new farming models, such as industrial, family and cooperative farming for contributing to addressing the threats posed by ageing to a predominantly traditional smallholder farming sector. Finally, Shared Socioeconomic Pathway (SSP) scenarios of future development were used to explore options for achieving sustainable agriculture under conditions of ageing rural populations.

How ageing threatens agriculture

Using an MRM based on survey data of rural households with crops but no livestock from 2015, 2017 and 2019, we found that the rural ageing ratio is negatively correlated with the education levels of farmers (Table 1). In China, the lower education across ageing households is mainly due to the younger generations obtaining substantially higher education levels under rapid socioeconomic development. There is a significant positive relationship between education and technology adoption (Supplementary Table 1). This means that ageing farmers with lower education levels are unlikely to manage their cropland efficiently based on scientific, state-of-the-art methods. Meanwhile, we observe a 0.29% decrease in farm size for each percentage point increase in the ageing ratio ceteris paribus, demonstrating that ageing farmers tend to operate small-scale farms, and that croplands are more likely to be abandoned or transferred to others. Smallholder farming is currently most prevalent in regions of Central and South China, where rural ageing is seen to be substantial (Fig. 1c,d).

Ageing is correlated with a decrease in agricultural inputs, with a 0.3% reduction in total inputs for each percentage point increase in the ageing ratio ceteris paribus, mainly concerning chemical fertilizers and manure, and machinery and technology adoption (Table 1 and Supplementary Table 1). Consequently, a 0.33% and 0.14% decline in agricultural output and yield per area, respectively, was related to each percentage point increase in the ageing ratio ceteris paribus, leading to the decline of labour productivity.

To understand how ageing affects agriculture, a structural equation model (SEM) is introduced to show both the direct and the indirect influencing pathways (Fig. 2). A considerable portion of effects are factored in indirectly through farm size and education. For example, the direct effect of ageing on labour productivity has a standardized path coefficient of −0.04, but the indirect effect through farm size and education is −0.07 and −0.02, respectively (Extended Data Table 1). This results in a net effect of −0.13 of ageing on labour productivity, of which the direct effect accounts for one-third, and the indirect effect through farm size and education accounts for two-thirds. Similarly, 37%, 23%, 36% and 37% of the net effect of fertilizer, total inputs, yield and output stem from indirect effects, respectively. This implies that multiple initiatives are needed to mitigate the consequences of rural ageing, such as attracting young people to consider work in the agriculture sector, better education and training, and increasing the average farm size given that the average farm size per rural household is less than 0.6 hectare (ha) currently[22,23].

Impacts on agricultural sustainability in 2019

To assess the impacts of ageing on agricultural sustainability, we considered three dimensions: economic, social and environmental, with

Table 1 | MRMs determining the effect of ageing on agricultural indicators

		Farm size and education				Inputs				Outputs		
		ln[Farm size (ha)]	Education (yr)	Transferred-out	Abandoned (ha)	ln[Input (US$ ha^{-1})]	ln[Fertilizer (US$ ha^{-1})]	Manure (US$ ha^{-1})	Machine (US$ ha^{-1})	ln[Output (US$ ha^{-1})]	ln[LP (US$ per person)]	ln[Yield (kg ha^{-1})]
Ageing	Coefficient	−0.293***	−1.509***	0.766***	0.188**	−0.300***	−0.232***	−95.13***	−108.3***	−0.333***	−0.394***	−0.139***
	s.e.	(0.051)	(0.158)	(0.207)	(0.081)	(0.041)	(0.045)	(24.99)	(21.17)	(0.038)	(0.064)	(0.044)
	P values	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
ln[Farm size (ha)]	Coefficient					−0.190***	−0.268***	19.73***	−19.80***	−0.101***	0.613***	−0.083***
	s.e.					(0.014)	(0.016)	(4.981)	(5.602)	(0.012)	(0.017)	(0.013)
	P values					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education (yr)	Coefficient	0.008**		0.034**	−0.006	0.011***	−0.004	10.31***	12.75***	0.034***	0.034***	0.013***
	s.e.	(0.003)		(0.013)	(0.004)	(0.002)	(0.003)	(1.915)	(1.469)	(0.003)	(0.004)	(0.003)
	P values	(0.013)		(0.011)	(0.154)	(0.000)	(0.181)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County		Yes	Yes			Yes	Yes			Yes	Yes	Yes
City				Yes	Yes			Yes	Yes			
N		169,53	169,53	16,311	12,443	15,765	15,600	12,401	16,725	15,460	16,260	11,015
Adjusted R^2		0.51	0.29			0.20	0.21			0.28	0.40	0.23
Model		MRM	MRM	Tobit	Tobit	MRM	MRM	Tobit	Tobit	MRM	MRM	MRM

Each column represents a separate regression model. The asterisks indicate the statistical significance level based on *P* values: *P<0.1, **P<0.05, ***P<0.01. Standard errors (s.e.) are clustered at the county level. Farm size is the total cultivated area covering all crops. Education refers to average years of education of family members aged 15 and over. Transferred-out is the ratio of transferred-out cropland area to other farmers to the current total cropland area. Abandoned indicates the area of abandoned cropland by farmers. Labour productivity (LP) is the agricultural output per labour input, including family labour and hired labour. County and city mean county-level or city-level regional effect is controlled, respectively. Income ratio from non-agricultural sectors, crop type, plot number and year effects have been controlled in all regression equations. In the equations whose explained variable is log-transformed output and yield, fertilizer input was further controlled.

various sub-indicators in each dimension[24]. Total agricultural input, output, labour productivity, fertilizer input, manure, fertilizer loss, farmer's income, farm size and machine input were selected to measure the three dimensions of agricultural sustainability in this paper, mainly referring to the indicators used by ref. [24] (see Supplementary Methods for details)[24]. Only 5.6% of the population was aged 65 or older in 1990, far below the 7% mark that is typically seen as the beginning of an ageing society[21]. We therefore consider the population age structure in 1990 as a reasonable baseline to represent the state before accelerated ageing of the society began for counterfactual analysis.

The results show that ageing populations are associated with an average farm size reduction by 4% (2–7% across different provinces) in 2019 (Fig. 3 and Extended Data Fig. 1). This means that the average farm size could have increased by 4% nationally by 2019 if the ageing ratio had remained constant at 1990 levels. Approximately 4 million ha of cropland area was abandoned associated with ageing ratio changes

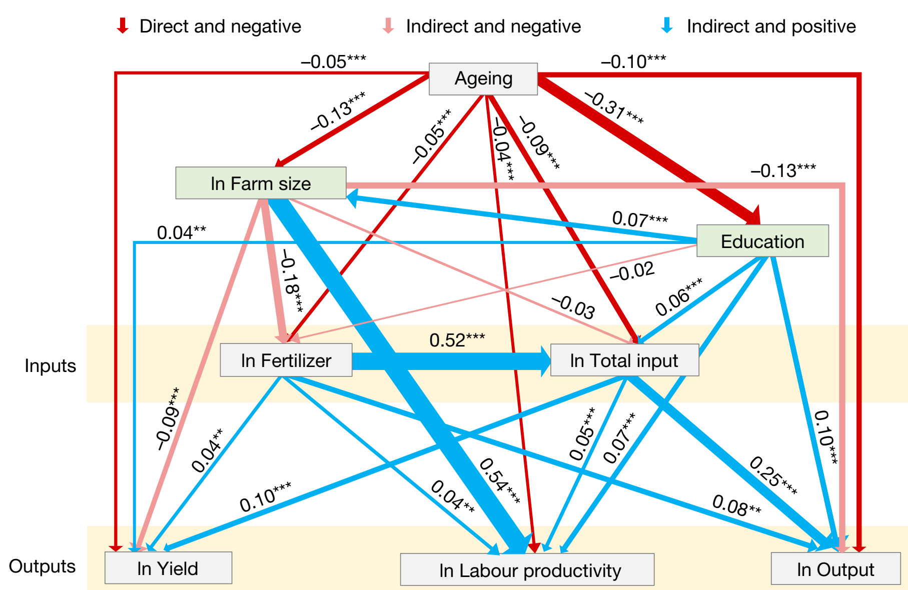

Fig. 2 | SEM of ageing impacts on agriculture. The asterisks indicate the statistical significance level based on *P* values: *P < 0.1, **P < 0.05, ***P < 0.01. The numbers adjacent to the lines are the standardized path coefficients, indicating the degree of standard deviation changes in dependent variables if each of the independent variables change by one standard deviation. The blue and red lines represent positive and negative effects, respectively. The dark red and light red lines indicate the direct and indirect negative effects of ageing on agriculture, respectively. The line width is proportional to the strength of the standardized path coefficient. Exact *P* values are listed in Supplementary Table 7.

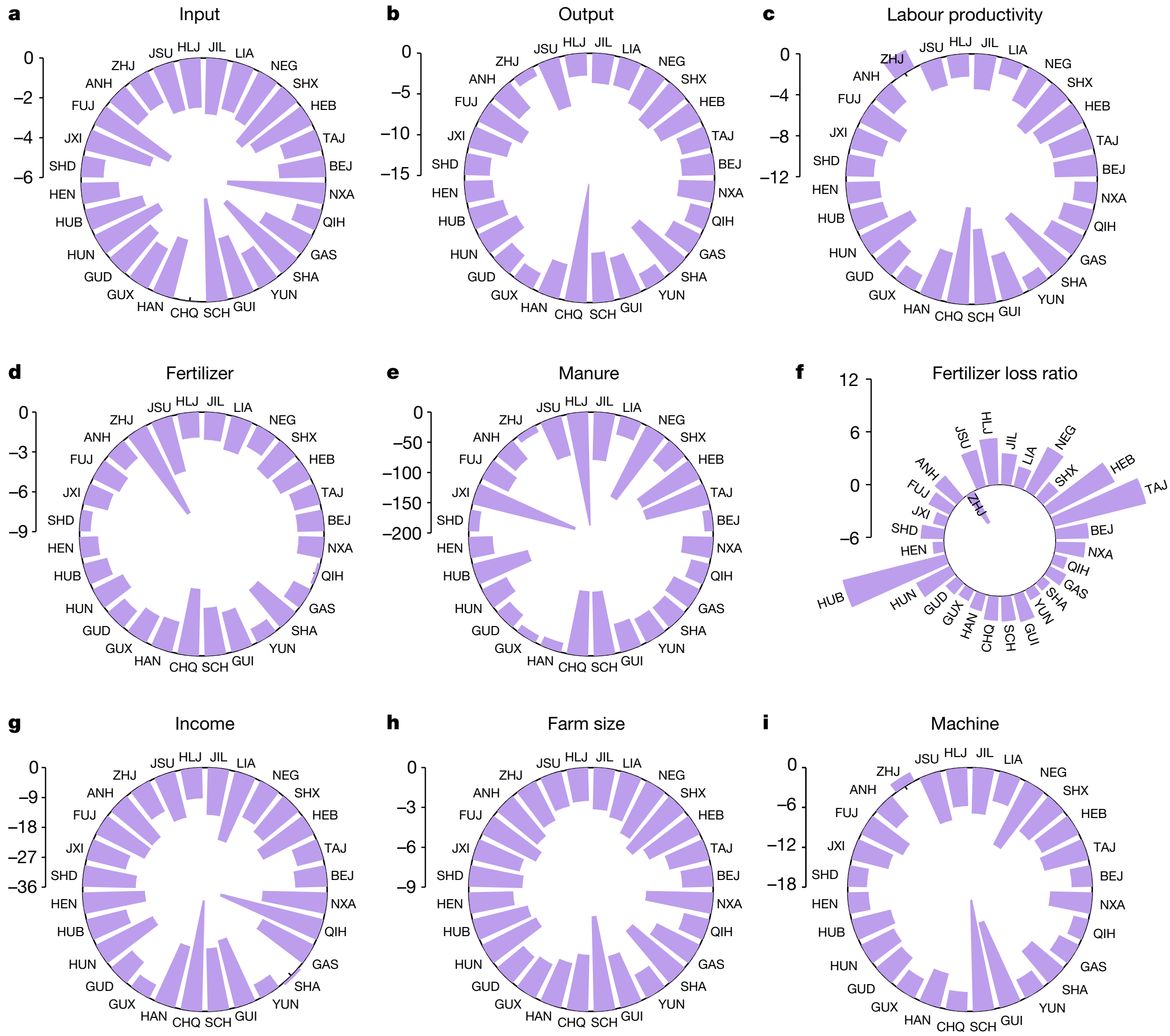

Fig. 3 | Impact of ageing on agricultural sustainability across China's provinces in 2019. a, Total agricultural input. **b**, Agricultural output. **c**, Labour productivity. **d**, Fertilizer use. **e**, Manure use. **f**, Fertilizer loss ratio. **g**, Per capita disposable income from agricultural sector. **h**, Farm size. **i**, Machine input. Panels **a**–**c**, **d** and **e**, and **g**–**i** show the economic, environmental, and social impacts of agricultural sustainability, respectively. The impact is calculated by determining the difference between the counterfactual values with ageing ratio equivalent to 1990 and the observed values in 2019 divided by the observed values in 2019 at the province level, in percentage terms. The population age structure in 1990 is taken as a counterfactual benchmark to reflect ageing changes. The acronyms for 31 provinces, autonomous regions and municipalities directly under the Central Government are listed in Supplementary Table 4. Shanghai, Tibet and Xinjiang are not depicted owing to data limitation.

(Supplementary Table 2). The abandonment ratio was higher in hilly areas and comparatively lower in plain areas[18]; for example, a 16% abandoned ratio was estimated in Guizhou where 93% of its land area is mountainous and hilly. This poses a severe threat to the preservation of croplands as a key contributor to safeguarding food security.

The decline in farm size further leads to a reduction in the use of agricultural fixed inputs such as machinery[25]. We found that machinery inputs decreased by about 6% on average with ageing changes, and the largest decrease was estimated at 17% for hilly Chongqing (Fig. 3). In addition, chemical fertilizers and manure increased by an average of 2% and 64%, respectively. Total agricultural inputs decreased by about 3%. The decrease in agricultural inputs further reduced the agricultural output per area and labour productivity by 5% and 4%, respectively. However, the reduction in fertilizer use did not contribute to a reduction in fertilizer losses, which is expressed as a ratio of the difference between the nitrogen (N) applied during crop planting and the N detected in the harvested yields to the total N applied, with ageing related to an increase of 3% in fertilizer-related losses to the environment. Finally, farmers' disposable income from the agricultural sector was reduced by 15%, ranging from an increase of 0.8% to a decrease of 33% across different provinces.

As it is assumed that socioeconomic factors other than demographics remain constant at 2019 levels, the impact of ageing could be underestimated to some extent. For instance, ageing would affect technological innovation that has impacts on agricultural sustainability, which is not quantified in this study. Therefore, managing ageing in the real world may have a larger contribution to agricultural sustainability than what we have estimated in this study. Moreover, our results suggest that rural ageing has a considerable detrimental effect on all three dimensions of agricultural sustainability in China. In other words, agriculture may achieve much improvement in all three dimensions of sustainability if the rural population ageing could be addressed in most provinces in China (Fig. 3). However, in some hilly areas such as Zhejiang province, the impacts of ageing are diverse, which requires extra attention to manage ageing for synergies among the three dimensions of sustainability.

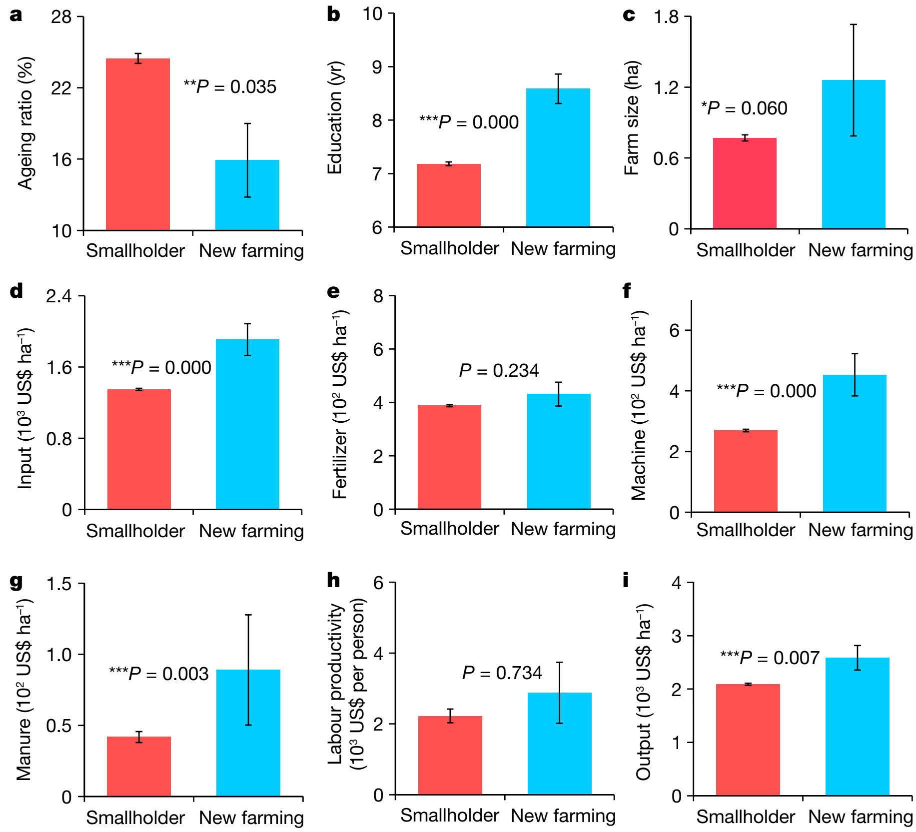

Fig. 4 | Comparison of smallholder and new farming models on agricultural indicators in 2019. a, Ageing ratio of the investigated household. **b**, Average years of education of family members aged 15 and over. **c**, Farm size. **d**, Total agricultural input. **e**, Fertilizer use. **f**, Machine input. **g**, Manure input. **h**, Labour productivity. **i**, Agricultural output. $^{*}P < 0.1$, $^{**}P < 0.05$, $^{***}P < 0.01$, which indicates the significance level of the difference between smallholder and new farming in the averages of agricultural indicators. On the basis of more than 6,000 samples in 2019 from the CRHPS database, a two-sample *t*-test was used to determine whether the averages of agricultural indicators across two groups (smallholder and new farming models) are equal or not (see Methods for details). Error bars are standard errors.

New farming models matter

Chinese agriculture is currently dominated by smallholder farms, normally operated by rural households, with a high degree of cropland fragmentation[23,26]. New agricultural farming models have been encouraged by the Chinese government and increasingly emerging since the 2010s, mainly including family, cooperative and industrial farming, to transform the smallholder-dominated status quo and improve overall agricultural performance[27,28]. Family farming is still managed by rural households, but with larger farm size, compared with traditional smallholders' farming. Cooperative farming is characterized by shared agricultural equipment, such as machinery, across several families with much larger farm size. Industrial farms are large-scale agricultural enterprises targeting marketing and sales with large scales and professional production to maximize profits. Also, young farmers with higher education levels are drawn to industrial farms. Here we consider these three models together as new farming models.

New farming models were observed to have overall better performance than traditional smallholder farming across several indicators in 2019 based on the results of two-sample *t*-tests (Fig. 4). Compared with traditional farming, the ageing ratio in new farming models was significantly reduced by 35% on average, while showing a 20% higher average education level. In addition, the average farm size is significantly larger (by 64%) in new farming models compared with traditional farming. New farming models tend to attract younger farmers to take up agriculture, who have a higher education level and capability to operate large-scale farming to save labour. Total input, manure and machinery input in new farming models were 41%, 113% and 68% higher than for traditional farming methods, respectively, improving farm management and practices. Consequently, output per area increased by 24% and labour productivity was improved by 29% in new farming models. In addition, there is no statistically significant difference in fertilizer input compared with the traditional smallholder farming, potentially reducing agricultural pollution.

The younger farmers have opportunities to realize higher incomes by working in non-agricultural sectors in cities, which means they face substantial opportunity costs if they decide to engage in farming. For example, per capita disposable income in urban China was approximately US$6,000 in 2017, compared with US$2,300 in rural China[29]. This indicates a 2.6-times-higher opportunity cost for young labourers choosing to return to farm work in rural areas, not even accounting for the additional social benefits of urban life, such as better access to health care and education systems, and larger pensions. To offset the large opportunity cost, the younger farmers have to increase their income by increasing farm size and improving farm management. By contrast, elder farmers in traditional farming do not have such opportunities to work in cities and are thus not likely to respond to incentives. Thus, we can see a shift in agricultural input mix as well as an increase in output and labour productivity under new farming models. Furthermore, the younger and well educated farmers are more likely to have scientific knowledge and embrace new technologies[15], resulting in increased mechanization and reduced fertilizer loss, contributing to agricultural modernization and long-term sustainability.

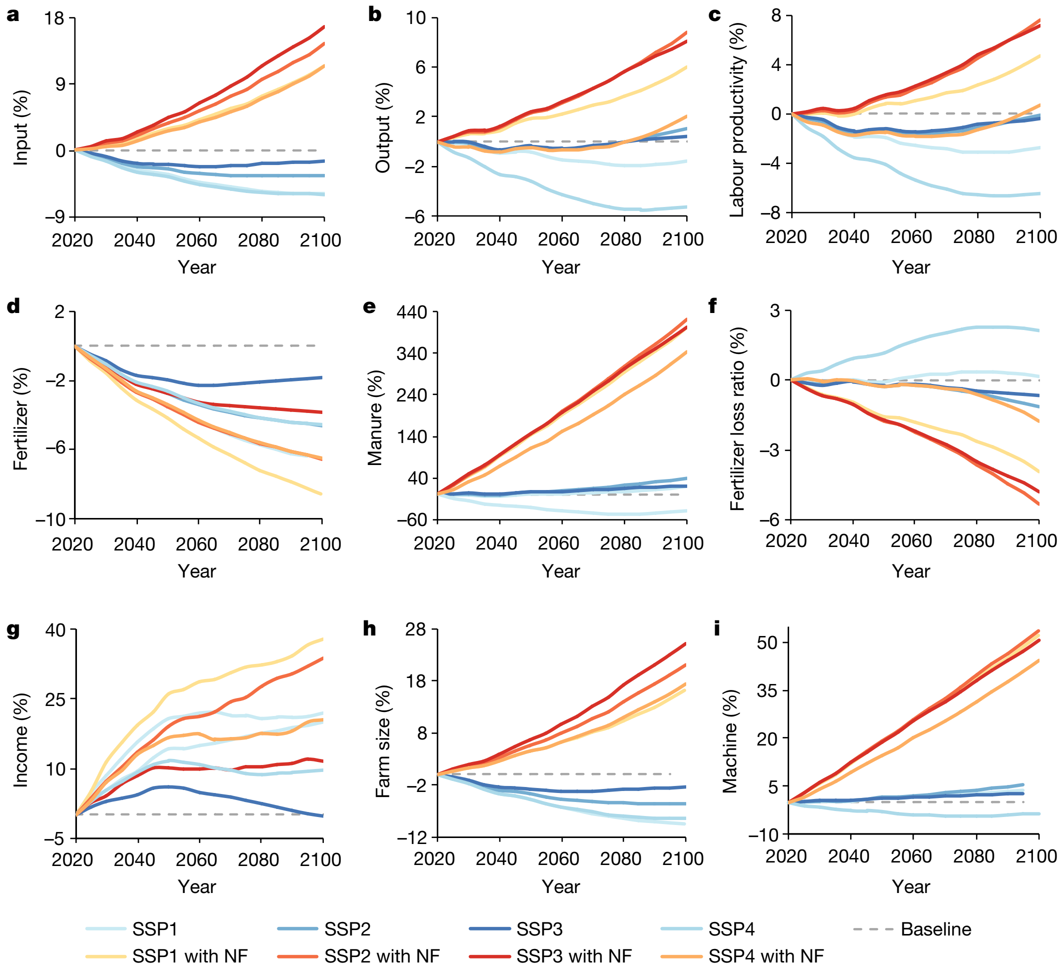

Fig. 5 | Relative changes of agricultural sustainability owing to ageing under SSP scenarios by 2100. a, Total agricultural input. **b**, Agricultural output. **c**, Labour productivity. **d**, Fertilizer use. **e**, Manure use. **f**, Fertilizer loss ratio. **g**, Per capita disposable income from agricultural sector. **h**, Farm size. **i**, Machine input. Panels **a**–**c**, **d** and **e**, and **g**–**i** show the economic, environmental, and social changes of agricultural sustainability, respectively. The baseline assumes no changes in the future. Relative change means value changes compared with 2020, in percentage terms. NF, new farming.

Mitigation pathways towards 2100

To quantitatively assess future trends of ageing and its impacts, we accounted for demographic and education change in SSP scenarios[30]. SSP1 (taking the green road), SSP2 (middle of road), SSP3 (a rocky road) and SSP4 (a road divided) are included in this analysis[31]. SSP5 (taking the highway) is excluded owing to it having a similar population structure to SSP1. SSP1, which has the highest education level and the lowest overall population by 2100 in China, has more than 60% of its population over the age of 65 (Extended Data Fig. 2). Even with a high education level, urbanization rates and economic growth, high levels of ageing would exert substantial negative impacts on socioeconomic development and agricultural production. SSP3 comprises the smallest rate of ageing, with only 25% over the age of 65 in 2100. However, in this scenario, China's population will still be substantial—about 1 billion people—by 2100, with a low level of education, a rate of urbanization of just 62% and a marked slowing in economic growth.

Despite the different assumptions for future development paths, the ageing trend continues to increase in all scenarios (Extended Data Fig. 2). We projected future changes in agricultural sustainability towards 2100 using the ageing and education changes under SSP scenarios based on the coefficients of the MRMs in Table 1. We found that for China, the abandonment ratio of croplands is projected to increase from 5% in 2020 to 6–15% (average 11%) across different SSP scenarios by 2100 nationally with ageing changes, whereas the average farm size would decrease by 2–9% (average 7%; Fig. 5 and Extended Data Figs. 3 and 4). Meanwhile, fertilizer inputs would decrease by 2–7% and manure and machinery inputs would slightly increase by 2100. In addition, the overall input per area would decrease by 1–6%, leading to a decrease in output of 1% on average. Labour productivity is projected to decrease by about 0–6% (average 2%). In addition, the fertilizer loss ratio would increase under the SSP1 and SSP4 scenarios by about 1%. Without interventions, food security challenges and environmental degradation will pose substantial threats to ecosystem and human health and well-being, damaging agricultural sustainability.

The decline in agricultural performance related to ageing can be reversed by promoting an increasing uptake of new farming models. Although the Chinese government started to support new farming models in the first decades of the twenty-first century[32], adoption has so far been slow, at about 2% in 2019 according to the China Rural Household Panel Survey (CRHPS) database. The Ministry of Agriculture and Rural Affairs of China has declared that it will continue to encourage new farming models in the future[32]. On the basis of the relative 2% share of new farming models in 2019, we hypothesize an annual increase of about 1.2%, which would reach approximately 100% by 2100.

With new farming models, the average farm size would increase by 16–25% (average at 20%) across different SSP scenarios from 2020 to 2100, with the abandonment ratio being eased to 3–10% (Fig. 5 and

Extended Data Fig. 3). Projections for 2100 show a 14% increase in total inputs, a 50% increase in mechanization and a 6% decrease in fertilizer use on average. Owing to the low input value of manure (US$24 ha^{-1}) into cropland compared with chemical fertilizers (US$310 ha^{-1}) in 2019, future manure input is projected to increase by 3–4 times its current level under new farming models. Only about 40% of manure's nutrients was recycled in 2017 (ref. [33]). This means a substantial loss of nutrients to the environment in forms of ammonia, nitrous oxide and methane, which poses a serious threat to climate change, and human and ecosystem health[34]. Recycling manure to cropland is an efficient and feasible method to decrease environmental pollution, improve resource-use efficiency and boost crop yields, although there is a considerable transportation cost[35–37]. China's livestock production would produce more manure in the future if current trends continued[33,35]. Fortunately, manure recycling to cropland is one of the best ways for sustainable agriculture[35].

Output and labour productivity would increase by about 6% and 5% in 2100 compared with that in 2020, respectively. Without taking inflation on account, farmers' disposable income would increase by 12–39% (average 26%) under the different SSP scenarios, from US$167 per capita currently to US$186–230 in 2100. The fertilizer loss ratio would be reduced by 4%. Although trade-offs exist among the different dimensions of agricultural sustainability, especially between food and nutrition security and the socioeconomic and environmental dimensions under smallholder farming[38], there is a synergistic trend with new farming models.

Policy changes and feasibility

Promoting new farming models is an integrated, comprehensive strategy for ensuring food security while also protecting the environment and revitalizing rural areas (see Supplementary Text for more details). There is a package of policy interventions mainly including providing direct subsidies, tax breaks, credit incentives and investments in agricultural infrastructure for farmers who are engaged in new farming models (Supplementary Text). The ongoing policy changes related to rural-to-urban migration and land tenure systems would promote the implementation of new farming models. It has been reported that the Jiangsu governments have compensated farmers who give up their small piece of cropland and migrate to cities with a cash transfer equal to five times their annual income as social security[27]. This effectively encourages rural-to-urban migration, especially for rural ageing people. The croplands of these migrating farmers can be integrated for large-scale farming and their homesteads can also be reclaimed for farming[39]. Over 40,000 ha of homesteads have been reclaimed during past decade in China[40]. The average farm size can increase from less than 0.6 ha to over 16 ha through land consolidation in some regions[41], providing great support for the implementation of new farming models in China.

Future policies should consider the trade-off between the social, economic and environmental dimensions of sustainability when promoting new farming models. For instance, the European Common Agricultural Policy is a long-term strategy that favours large industrial farming while not sufficiently supporting small-scale family farms[42]. An overly monoculture, industrialized production process under large-scale industrial farming may threaten the ecological functions of a local agricultural system and the preservation of rural landscapes with biodiversity loss, soil erosion and nutrient loss[43,44]. By contrast, over-protection of small-scale farming, although potentially beneficial in terms of food security and socioeconomics, may undermine environmental benefits[38]. This suggests that a single agricultural policy may be not enough for agricultural sustainability. Even though our findings highlight that new farming models is an important pathway to a sustainable agriculture, multiple matched policies should be designed to promote its feasibility and reduce the potential trade-offs.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-023-05738-w.

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Methods

Data sources

We used data from the CRHPS database, which includes the Chinese Family Database of Zhejiang University, and data of the China Household Finance Survey conducted by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics, China. From this database, rural household-level data concerning age, education, income, farm size and agricultural inputs and outputs in 2015, 2017 and 2019 were obtained for statistical analysis, resulting in about 15,000 observations after being screened. This database is openly available at http://ssec.zju.edu.cn/dataset/CRHPS/. Details about how the survey was conducted and its representativeness is in Supplementary Information.

The province- and country-level population ageing and rural ageing data were derived from the China Population and Employment Statistics Yearbook (available at https://data.cnki.net/yearBook/single?id=N2022040097), which is also the data source for Fig. 1a,b. County-level population ageing data in 2020 shown in Fig. 1c are taken from the Sixth National Census in 2010 (available at http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch.htm) and weighted by province-level ageing data for 2020 from the Seventh National Census (available at http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/qgrkpcgb/). County-level farm size data in Fig. 1d are from the statistics of the Second National Pollution Census (non-public database) in 2017, which is averaged by investigated household farm size.

We obtained future population and education data across all age groups towards 2100 based on the SSP database generated by the IIASA Energy Program (https://tntcat.iiasa.ac.at/SspDb). Population projections in this database go beyond the consideration of population size alone, further considering the interactions of age, sex, level of education and socioeconomic development, and their evolution across generations. By using the methods of multidimensional mathematical demography, national populations, fertility, mortality, migration and educational transitions that correspond to the five SSP storylines are projected[45]. In this paper, scenario SSP5 was not considered as its population change is the same as that of scenario SSP1.

Statistical analysis

CRHPS data allowed estimation of the relationships between population ageing and agricultural performance. We mainly used rural household samples that cultivated grain and cash crops, and excluded samples with livestock. This prevents statistical inaccuracies as cropland and livestock farming are two separate systems with distinct input types, output units and size definitions. In addition, samples with implausible extremes are excluded, such as those with no agricultural inputs but declaring agricultural outputs. Ageing ratio, the proportion of people 65 years and older in rural households, was adopted as an indicator to demonstrate population ageing at the household level. Adult farmers ratio, defined as the proportion of people over 15 but less than 64 years old in rural households, was also considered to demonstrate age groups. Agricultural sustainability indicators, such as farm size, agricultural inputs and outputs, are considered as dependent variables. Meanwhile, other indicators that are indirectly related to agricultural sustainable indicators, such as transferred-out cropland and abandoned cropland, have been incorporated into analysis. The detailed indicators and their regression results are listed in Table 1 and Supplementary Table 1, with their interpretations documented in Supplementary Methods.

To explore the relationships between population ageing and agricultural indicators, we first used an MRM to conduct the longitudinal analysis, while controlling for confounding factors such as crop type, plot number, county and year effect. We estimated the following equation using data on households from 2015, 2017 and 2019:

$$\begin{aligned}\text{Agriculture}_{it} &= \alpha + \beta \times \text{Ageing}_{it} + \gamma \\ &\times \text{Education}_{it} + \delta \times \text{Farm size}_{it} + \theta_1 \times \text{Adult}_{it} \\ &+ \theta_2 \times \text{Income ratio}_{it} + \theta_3 \times \text{Crop type}_{it} + \theta_4 \\ &\times \text{Plot number}_{it} + \sigma_k + \varepsilon_t + \mu_{it}\end{aligned} \tag{1}$$

where subscript i, k and t denote household, county and time, respectively. Agriculture$_{it}$ refers to the agricultural indicators on household level, including fertilizer inputs and total inputs, agricultural outputs, farmer's income and labour productivity. Ageing refers to the proportion of people ≥65 years old in rural households. Education refers to average years of education of family members aged 15 and over. Farm size is the logarithm of total cultivated area covering all crops. Adult$_{it}$, Income ratio$_{it}$, Crop type$_{it}$ and Plot number$_{it}$ refer to the adult farmers ratio, income ratio from non-agricultural sectors, crop type and plot number, respectively. α is a constant, σ_k, ε_t and μ_{it} are error items. β, γ, δ and θ are coefficients that need to be estimated. In addition, we also considered education as a dependent variable to explore their relationship with ageing based on the MRM. The detailed results are listed in Table 1 and Supplementary Table 1.

The county-level intercept σ_k is incorporated to account for time-invariant factors within counties that may skew the estimation, such as topography and soil conditions. Meanwhile, a year-level intercept ε_t is also included to control for time trends across the whole country such as political revolution. We set other controlling variables including adult farmers ratio, income ratio from non-agricultural sectors, crop type and plot number that may affect dependent variables. Both the ageing ratio and the adult farmers ratio are used to depict the demographic character of rural households. Income ratio from non-agricultural sectors reveals rural households' part-time employment, which determines how much time farmers will commit to farming. Crop type is a category variable that identifies the primary crop that a farmer grows. Plot number is a typical indicator of land fragmentation, which is a crucial factor determining the mix of agricultural inputs and outputs[46,47]. We use these control variables to investigate the net relationship between independent and dependent variables under the same conditions, providing insights into the respective independent variables' effects ceteris paribus.

The model incorporates county time-invariant controls and year time effects. To separate the impact of exogenous changes in ageing and farm size on agricultural performance, these controls are necessary. However, one drawback is that they might absorb ageing and farm-size changes. Supplementary Table 6 shows the R^2 and standard deviation of residual of ageing and farm-size variance that is not absorbed by year and county effects. For instance, merely having year effect preserves a large amount of farm-size variance, but including county effects significantly reduces the remaining variation, implying that geographical differences account for a significant part of farm-size variation. Accordingly, cluster-robust standard errors on the county-level are used when doing regression analysis. The related results are also listed in Table 1 and Supplementary Table 1.

Variables of transferred-out and -in cropland, abandoned cropland, machine and manure input contain a fraction of the variables with values of 0, but are continuously distributed at positive values. These variables can be expressed in the following form:

$$\begin{cases} y_{it} = y_{it}^* & \text{if } y_{it}^* > 0 \\ y_{it} = 0 & \text{if } y_{it}^* \leq 0 \end{cases} \tag{2}$$

The tobit regression model is adopted to validate the relationship between these variables and ageing, based on the following equation using data on households in 2015, 2017 and 2019:

$$\begin{aligned} y_{it}^* &= \alpha + \beta \times \text{Ageing}_{it} + \gamma \times \text{Education}_{it} + \delta \times \text{Farm size}_{it} \\ &+ \theta_1 \times \text{Adult}_{it} + \theta_2 \times \text{Income ratio}_{it} + \theta_3 \times \text{Crop type}_{it} \\ &+ \theta_4 \times \text{Plot number}_{it} + \sigma_j + \varepsilon_t + \mu_{it}\end{aligned} \tag{3}$$

where subscript i, j and t denote household, city and time, respectively. y^*_{it} refers to the variables including transferred-out and -in cropland, abandoned cropland, machine and manure input in each household. Ageing refers to the proportion of people over 65 years old in rural households. Education refers to average years of education of family members aged 15 and over. Farm size is the logarithm of total cultivated area covering all crops. Adult_{it}, Income ratio_{it}, Crop type_{it} and Plot number_{it} refer to adult farmers ratio, income ratio from non-agricultural sectors, crop type and plot number, respectively. α is a constant and μ_{it} is the error item. σ_j and ε_t are city-level and year intercept, respectively. β, γ, δ and θ are coefficients that need to be estimated. The regional effect can only be controlled on the city level owing to data limitations. Farm size was removed in explaining variables in the equation with explained variable of transferred-out and -in and abandoned cropland considering multicollinearity. The results are listed in Table 1 and Supplementary Table 1.

Furthermore, a logit regression model was adopted as technology adoption (Tech), which is a binary variable. This model is formulated as follow based on household-level data from 2015, 2017 and 2019:

$$\begin{aligned}&\text{logit}\{P_{it}(\text{Tech}_{it}=1)\}=\alpha+\beta_1\times\text{Age}_{it}+\beta_2\times\text{Age}^2_{it}+\gamma\\&\times\text{Education}_{it}+\delta\times\text{Farm size}_{it}+\theta_1\times\text{Adult}_{it}\\&+\theta_2\times\text{Income ratio}_{it}+\theta_3\times\text{Crop type}_{it}+\theta_4\\&\times\text{Plot number}_{it}+\sigma_j+\varepsilon_t+\mu_{it}\end{aligned}\tag{4}$$

where subscript i, j and t denote household, city and time, respectively. P_{it} is the probability of the occurrence of Tech ($\text{Tech}_{it}=1$, event occurs; $\text{Tech}_{it}=0$, event does not occur). Age refers to the log-transformed age of the head of the investigated household. Education refers to education years of the head of the investigated household. Farm size is the logarithm of total cultivated area covering all crops. Adult_{it}, Income ratio_{it}, Crop type_{it} and Plot number_{it} refer to adult farmers ratio, income ratio from non-agricultural sectors, crop type and plot number, respectively. α is a constant and μ_{it} is the error item. σ_j and ε_t are city-level and year intercept, respectively. β, γ, δ and θ are coefficients that need to be estimated. The results are listed in Supplementary Table 1.

A two-sample t-test was used to compare the overall agricultural performance of traditional and new farming models. The two-sample t-test hypothesis is that the averages of agricultural indicators across two groups (smallholder and new farming models) are equal. P values are the statistics to prove or disprove this hypothesis. If the P value is less than 0.1, the hypothesis is disproved, indicating that there is a significant difference between the mean values of the two groups. The significance level of difference in averages are also determined by the P values. The two-sample t-test is based on more than 6,000 samples in 2019 from the CRHPS database. The results are shown in Fig. 4. To comprehensively investigate why new farming outperforms traditional farming, a binary variable indicating the occurrence of new farming (NF_{it}) ($\text{NF}_{it}=1$, event occurs; NF = 0, event does not occur) was introduced based on equations (1) and (3). The equations are expressed in the following forms:

$$\begin{aligned}&\text{Agriculture}_{it}=\alpha+\omega\times\text{NF}_{it}+\beta\times\text{Ageing}_{it}+\gamma\\&\times\text{Education}_{it}+\delta\times\text{Farm size}_{it}+\theta_1\times\text{Adult}_{it}\\&+\theta_2\times\text{Income ratio}_{it}+\theta_3\times\text{Crop type}_{it}+\theta_4\\&\times\text{Plot number}_{it}+\sigma_k+\varepsilon_t+\mu_{it}\end{aligned}\tag{5}$$

$$\begin{aligned}&y^*_{it}=\alpha+\omega\times\text{NF}_{it}+\beta\times\text{Ageing}_{it}+\gamma\times\text{Education}_{it}\\&+\delta\times\text{Farm size}_{it}+\theta_1\times\text{Adult}_{it}+\theta_2\times\text{Income ratio}_{it}\\&+\theta_3\times\text{Crop type}_{it}+\theta_4\times\text{Plot number}_{it}+\sigma_j+\varepsilon_t+\mu_{it}\end{aligned}\tag{6}$$

ω, β, γ, δ and θ are coefficients that need to be estimated. Related results are listed in Extended Data Table 2. ω represents the difference in new farming compared with traditional farming responding to the dependent variables. For example, if the dependent variable is agricultural output, it can be interpreted as an increase in new farming over traditional agriculture by ω. It is noted that as new farming models are not yet widely established in China, data on new farming are so far limited; for example, in 2017, no new farming data were provided in the CRHPS database. In addition, the definition of new farming models diverges between 2015 and 2019 to some extent, making it impossible to directly compare new farming data for the period from 2015 to 2019. To reduce statistical errors, data on new farming models in 2015 were removed. Thus, new farming models were investigated using a separate model based on cross-sectional data from 2019 instead of adding this variable to equations (1) and (3), which would affect the amount of data available for statistical analysis of other variables.

For a robust check, we replaced the ageing ratio with the age of the investigated household's head, and replaced the average education years with the head's education. Supplementary Tables 1 and 3 show the detailed results of this check. When we apply alternative models to assess, the primary findings of our study remain, suggesting the robustness of our findings.

We then used an SEM to understand the direct and indirect effects of population ageing on agriculture[48]. One MRM can only correlate to one dependent variable, offering ceteris paribus direct effects by handling numerous independent variables. However, one of the shortcomings is that it is impossible to compare the results of different MRMs to derive indirect effects. For instance, a 1% increase in ageing results in, ceteris paribus, a 1.5-yr reduction in the average number of schooling years of rural households, according to the −1.5 coefficient of ageing on education in Table 1. Similarly, a 1% increase in ageing is correlated with a 0.29% decrease in farm size. However, this does not mean that ageing has a larger effect on education. The units and magnitude of the explained variables, such as education and farm size, vary in the different MRMs, which substantially influence the size of the coefficient of ageing. Even if we transform all coefficients in MRMs into standardized ones based on sensitivity analysis, calculating the direct and indirect effects of ageing through MRMs is complicated and unwise owing to the multiple control variables and regional effects we set in the models. By contrast, an SEM could support the derivation of comparable effects by incorporating the multiple relationships between variables using standard deviation coefficients. The direct and indirect impacts of ageing on each agricultural indicator can be immediately shown using an SEM. Meanwhile, the SEM addressed the issue that some indicators, such as agricultural total inputs and fertilizer, are partly correlated with each other. We accordingly used the SEM and the MRM at the same time in this study.

It is challenging to directly compare the results of the MRM and SEM analyses as the coefficients of various MRMs are not directly comparable. However, in both models, the influence of each independent variable on the dependent variable is consistently assessed. This suggests that all the correlations between ageing and agricultural variables found can be considered robust. It should be noted that in the SEM, latent variables are not specified; rather, standardized path coefficients are obtained based on the path analysis. We also excluded variables with nonlinear relationships with ageing (for example, machine and manure input) to deduce comparable standardized path coefficients. The income ratio from non-agricultural sectors was controlled when doing SEM analysis. Finally, the direct and indirect relationships between ageing and each agricultural indicator were determined.

In this model, the goodness-of-fit statistics are within expected ranges based on CRHPS data in 2019: non-normed fit index (NNFI) > 0.90, comparative fit index (CFI) > 0.90, root mean square error (RMSE) < 0.05 and standardized root mean square residual (SRMR) < 0.05. Using the results from the SEM, the direct and indirect effects of ageing with standardized path coefficients are shown in Fig. 2 and Extended Data Table 1.

Summary statistics for main variables used in statistical regression analysis are listed in Supplementary Table 5. We did all statistical analysis using Stata12.0 software.

Impact of ageing on agricultural sustainability

We consider the population age structure in 1990 as a benchmark for counterfactual analysis. In 1990, the percentage of people aged 65 and over was only 5.6%, considerably below the 7% threshold of the starting point an ageing society[21]. Meanwhile, the female fertility rate fell to the replacement level of 1.5 births per woman from the 1990s onwards, which is the starting point for an accelerated population ageing process[21]. We decided to take the age structure in 1990 as a benchmark considering both ageing and fertility rate. Province-level rural population data for 1990 from the China Population and Employment Statistics Yearbook were introduced after weighting by the difference between this data and the CRHPS data to reduce the error caused by variations in data stemming from different databases. Then province-level rural population data were downscaled to household level proportionally. Finally, ageing and adult farmers ratio in 1990 and their disparities compared with 2019 were deduced. We assume that other variables such as education and socioeconomic level remained at the 2019 level and calculated the counterfactual value of agriculture with ageing ratio equivalent to 1990 on each household based on coefficients estimated in equation (1). This means that the impact of ageing in 2019 we estimated is from only demographic changes. For household *i*, we first calculated the differences of explained variables of agricultural sustainability due to ageing changes (AG) between 2019 and 1990 as follows:

$$\Delta \ln Y_{ij}^{\mathrm{AG}} = \beta_j \times \Delta \mathrm{Ageing}_{ij} + \theta_{1j} \times \Delta \mathrm{Adult}_{ij} \tag{7}$$

where the subscript *i* and *j* denote household and explained variable, respectively. $\Delta\mathrm{Ageing}_{ij}$ and $\Delta\mathrm{Adult}_{ij}$ refer to the differences of ageing and adult farmers ratio between 2019 and 1990, respectively. $\Delta \ln Y_{ij}^{\mathrm{AG}}$ includes farm size, output, input, labour productivity and fertilizer.

Then the counterfactual value with ageing ratio equivalent to 1990 is calculated as follows:

$$Y_{ij}^{\mathrm{AG\ in\ 1990}} = \exp(\ln Y_{ij}^{\mathrm{Observed}} - \Delta \ln Y_{ij}^{\mathrm{AG}}) \tag{8}$$

$Y_{ij}^{\mathrm{Observed}}$ refers to the observed value of agricultural indicators of each household in 2019. $Y_{ij}^{\mathrm{AG\ in\ 1990}}$ is the deduced counterfactual value with ageing ratio equivalent to 1990. Finally, the impact of ageing is the difference between the actual observed value and the counterfactual value:

$$\mathrm{Impact}_{ij}^{\mathrm{AG}} = Y_{ij}^{\mathrm{Observed}} - Y_{ij}^{\mathrm{AG\ in\ 1990}} \tag{9}$$

For explained variables of agricultural sustainability without log-transformation, such as machine, manure and abandoned cropland, their differences owing to ageing changes are based on coefficients estimated in equation (3). The calculation is derived as follows:

$$Y_{ij}^{\mathrm{AG}} = \beta_j \times \Delta \mathrm{Ageing}_{ij} + \theta_{1j} \times \Delta \mathrm{Adult}_{ij} \tag{10}$$

where the subscript *i* and *j* denote household and explained variable, respectively. $\Delta Y_{ij}^{\mathrm{AG}}$ includes machine, manure and abandoned cropland. Then the counterfactual value with ageing ratio equivalent to 1990 is calculated as follows:

$$Y_{ij}^{\mathrm{AG\ in\ 1990}} = Y_{ij}^{\mathrm{Observed}} - \Delta Y_{ij}^{\mathrm{AG}} \tag{11}$$

Finally, the impact of ageing is the difference between the actual observed value and the counterfactual value:

$$\mathrm{Impact}_{ij}^{\mathrm{AG}} = Y_{ij}^{\mathrm{Observed}} - Y_{ij}^{\mathrm{AG\ in\ 1990}} \tag{12}$$

It is noted that we first derived the counterfactual value of farm size with ageing ratio equivalent to 1990. The remaining variables were finally calculated based on the counterfactual value of farm size as it is one of explained variables. In addition, the counterfactual value of input, output and family size—which is computed by dividing the difference between agricultural output and input by the size of the family—was used to calculate farmers' disposable income.

According to the household-level observed and counterfactual values, the provincial averages of different indicators of agricultural sustainability can be estimated. The provincial means of these indicators are averaged after weighting by the total cultivated area on the province level with exceptions of labour productivity, farm size and income. Labour productivity is weighted with the total labour input on the province level. Farm size and income are arithmetic averages. Then, fertilizer loss ratio can be calculated using provincial fertilizer and crop output data. Owing to data limitations, the fertilizer loss ratio is evaluated using N surplus as a measure of environmental pollution, with just three grain crops (wheat, rice and maize) being included, calculated as the difference between the N input and the N in the harvested crops. Grain crop application rates were estimated by assuming that the sample's average N application rate was equal to that in ref. [49]. By comparing the province average expenditure of fertilizer to the overall average, application rates (N_{app}) in each province were calculated. Using crop yield data from the CRHPS and the absorption rate from the literature, the levels of N contained in harvested crops (N_{har}) were estimated[7,50,51]. After that, the fertilizer loss ratio was estimated as follows:

$$\text{Fertilizer loss ratio}_j = \frac{\sum_m (\mathrm{N}_{\mathrm{app},j}^m - \mathrm{N}_{\mathrm{har},j}^m) \times 100\%}{\mathrm{N}_{\mathrm{app},j}^m} \tag{13}$$

where the subscript *j* and *m* stand for province and crop, respectively. Provincial crop yield and fertilizer data are available through CRHPS averaged household data for the estimation of fertilizer loss ratio. The counterfactual value of fertilizer and agricultural output has been derived in equation (8). The counterfactual value of each crop yield is calculated by multiplying the counterfactual output by the observed crop yield to total output ratio.

Scenario analysis

We based our analysis of future socioeconomic development on the SSP scenarios to determine the impact of population ageing on agricultural sustainability. We obtained the country-level population age and education data (2020–2100) from the SSP database and derived ageing, adult farmers ratio and education years data on the country level. Then the country-level data were downscaled to the provincial level based on the country-to-province population ratio in 2019. We undertook a comparison between the population age and education data for 2019 and 2020 in the CRHPS and SSP databases, respectively, and weighted data on the province level by their difference to reduce the error. We then derived household-level ageing and adult farmers ratio and education data (2020–2100) based on provincial averages and household data distribution patterns within provinces in 2019, as well as the constraint that the ageing and adult farmers ratio does not exceed 1. In this process, country-level data were downscaled to the household level. Finally, the predicted values (Y_{ijt}^{SSP}) of agricultural sustainability indicators under future ageing and education were calculated referring to the forms of equations (7)–(12) under the hypothesis that other variables remained stable at the 2019 levels. The equations are expressed in the following forms:

$$\Delta \ln Y_{ijt}^{\mathrm{SSP}} = \beta_j \times \Delta \mathrm{Ageing}_{ijt} + \theta_{1j} \times \Delta \mathrm{Adult}_{ijt} + \gamma_j \times \Delta \mathrm{Education}_{ijt} \tag{14}$$

$$Y_{ijt}^{\mathrm{SSP}} = \exp(\ln Y_{ij,2019}^{\mathrm{Observed}} - \Delta \ln Y_{ijt}^{\mathrm{SSP}}) \quad (15)$$

$$\Delta Y_{ijt}^{\mathrm{SSP}} = \beta_j \times \Delta \mathrm{Ageing}_{ijt} + \theta_{1j} \times \Delta \mathrm{Adult}_{ijt} + \gamma_j \times \Delta \mathrm{Education}_{ijt} \quad (16)$$

$$Y_{ijt}^{\mathrm{SSP}} = Y_{ij,2019}^{\mathrm{Observed}} - \Delta Y_{ijt}^{\mathrm{SSP}} \quad (17)$$

Δ refers to the value difference between year 2019 and year t. Equations (14) and (15) are used to project farm size, output, input, labour productivity and fertilizer. Equations (16) and (17) are used to project manure and machine input. Finally, the fertilizer loss ratio and farmers' income were estimated according to projected input, output and fertilizer.

China's land is state-owned and cannot be traded on the market. As a result, China's average farm size has hardly increased in recent years, with smallholders continuing to dominate. The government aims to improve agricultural performance and moderately increase farm size by promoting new farming models, thus primarily driving the process through government interventions. To improve agricultural performance and estimate the effectiveness of mitigating negative impacts of future population ageing, we assume that new farming models will be promoted gradually as a key element of future agricultural sector development. On the basis of the 2% share of the new farming models in 2019, we hypothesize that its coverage will increase by about 1.2% annually, reaching approximate 100% by 2100. For household i, the predicted value of agricultural sustainability indicators under new farming is calculated according to the estimated coefficients of equations (5) and (6) as follows:

$$Y_{ijt}^{\mathrm{NF}} = \exp(\ln Y_{ij,2019}^{\mathrm{Observed}} - \Delta \ln Y_{ijt}^{\mathrm{SSP}} + \omega_j \times \mathrm{Coverage}_t) \quad (18)$$

where the subscript i, j and t denote household, explained variable and year, respectively. Y_j includes farm size, output, input, labour productivity and fertilizer. Y_{ijt}^{NF} is the predicted value under new farming (NF) models. ω_j refers to estimated coefficients of new farming responding to explained variable j. The results of these estimated coefficients are detailed in Extended Data Table 2, which rigorously investigate how new farming models respond to agricultural indicators while considering ageing ratio, education and other confounding factors. Coverage$_t$ means the assuming coverage of new farming in year t.

For explained variables without log-transformation, the prediction is calculated as follows:

$$Y_{ijt}^{\mathrm{NF}} = Y_{ij,2019}^{\mathrm{Observed}} - \Delta Y_{ijt}^{\mathrm{SSP}} + \omega_j \times \mathrm{Coverage}_t \quad (19)$$

Y_j includes ageing, education, manure and machine input. Finally, the fertilizer loss ratio and farmers' income were estimated according to projected input, output and fertilizer.

It is noted that the gradual introduction of new farming models towards 2100 would further change rural ageing and education under the SSP scenarios by attracting young farmers with high levels of education. Accordingly, we first adjusted rural ageing and education in the SSP scenarios according to the response of new farming to ageing and education based on MRMs in Extended Data Table 2. Then the predicted farm size was calculated using adjusted ageing and education. The remaining variables were calculated based on adjusted rural ageing and education and predicted farm size. Finally, farmers' income and the fertilizer loss ratio were calculated. This also explains why we used both a two-sample t-test and an MRM to explore the effects of new farming on agriculture. The results of the MRM give the response of new farming to agriculture under conditions of ageing and education, allowing for the correction of bias caused on by their correlations.

Limitations

Our study has some limitations that potentially affect the robustness of our findings. The main objective of this study was to assess the impact of ageing on agricultural sustainability. The time period for this study covers only three years (2015, 2017 and 2019); however, it comprised a substantial sample of over 15,000 surveyed rural households with grain and cash crops but without livestock. Furthermore, although the research uses cluster-robust standard errors on the county level, heterogeneity that is invariant across time is not captured, especially for individual and family characteristics at the rural household level. Despite the data limitations, the findings of relationships between ageing and agricultural input indicators are consistent with previous research. For example, ageing decreases agricultural inputs, including fertilizer inputs[52]; ageing increases cropland abandonment and hinders agricultural mechanization and technology adoption[16,18]. This indicates that the study's main findings are robust and valid, despite the fact that conducting the research on such limited data may introduce bias. Furthermore, it is beyond the scope of this study to cover all agricultural sustainability indicators in detail, concerning economic, environmental and social dimensions. For example, we did not address the economic aspects of government financial support and credit information, the environmental aspects of biodiversity, the social aspects of farmers' rights and equality, and so on. Evaluating all indicators of the three dimensions of agricultural sustainability at the same time is inherently difficult owing to data limitations.

In addition, we quantified the impact of ageing on agricultural sustainability in 2019 by assuming that socioeconomic conditions other than demographics remain at 2019 levels. This would actually underestimate the impact of ageing to some extent, mainly due to the high-speed social progress in China in recent years, with economic levels, policy completeness and infrastructure in 2019 far exceeding those in 1990. However, it is challenging to get around this limitation. In response to demographic changes, several socioeconomic factors change, such as tax regulations, per capita wages and agricultural investment. It would require substantial additional analyses and data, which are beyond the scope of this article, to comprehensively understand how these changes relate to demography and how they further affect agriculture. We are aware of this limitation and identify key research to improve it in the future.

Our scenario results are affected by the type of future scenario we employed and the analysis model design. We cannot account for abrupt changes in some future variables, such as significant national agricultural restructuring, although we incorporate year and county effects in our regression models to anticipate changes in agricultural indicators towards 2100. Furthermore, as we have only limited access to new farming data, developing future predictions with such limited data may be biased to some extent. Instead of constructing a robust and valid regression model based on new farming data to anticipate how agriculture will change if new farming is introduced, this study can only use the relative performance differences between new farming and traditional agriculture with some inaccuracies. Finally, there are some uncertainties associated with assuming that the future implementation rate of new farming models can reach 100% in 2100, as a 100% implementation rate of new farming models might involve trade-offs instead of synergies of sustainability in terms of its economic, social and environmental dimensions.

Despite these limitations, this research contributes to advancing the scientific understanding of how rural demographic changes and agricultural sustainability are connected. We highlighted that new farming models could offer efficient and cost-effective pathways to mitigate the impact of rural ageing and contribute to agricultural sustainability and rural revitalization. Our findings not only shed light on the impact of ageing on agricultural sustainability but also contribute essential evidence to potential barriers to the attainment of the SDGs focusing on 'no poverty' and 'zero hunger', especially for China and other countries and regions globally that are facing similar issues.

Data availability

Rural household survey data supporting this study are openly available at http://ssec.zju.edu.cn/dataset/CRHPS/. Source data are provided with this paper.

Code availability

All analyses were performed using Stata version 12.0. The codes are available in Supplementary Information, which allows the estimates to be reproduced.

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Author contributions B.G. designed the study. C.R. conducted the research. B.G. and C.R. wrote the first draft of the paper. S.R. revised the paper. C.W., Y.G., Y.D., S.S. and W.L. processed the raw data. X.Z. and J.X. contributed to the discussion of the paper.

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Additional information
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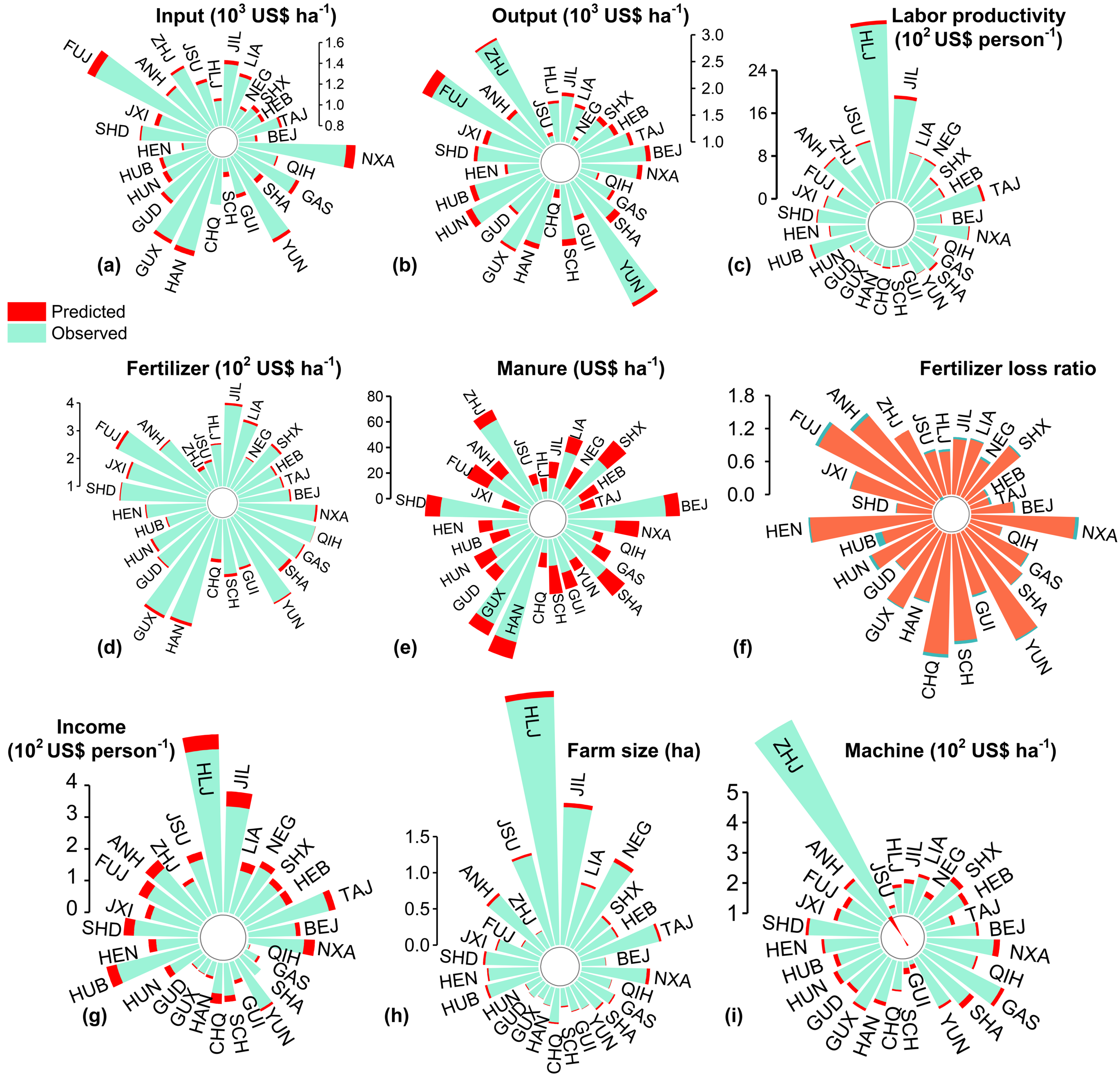
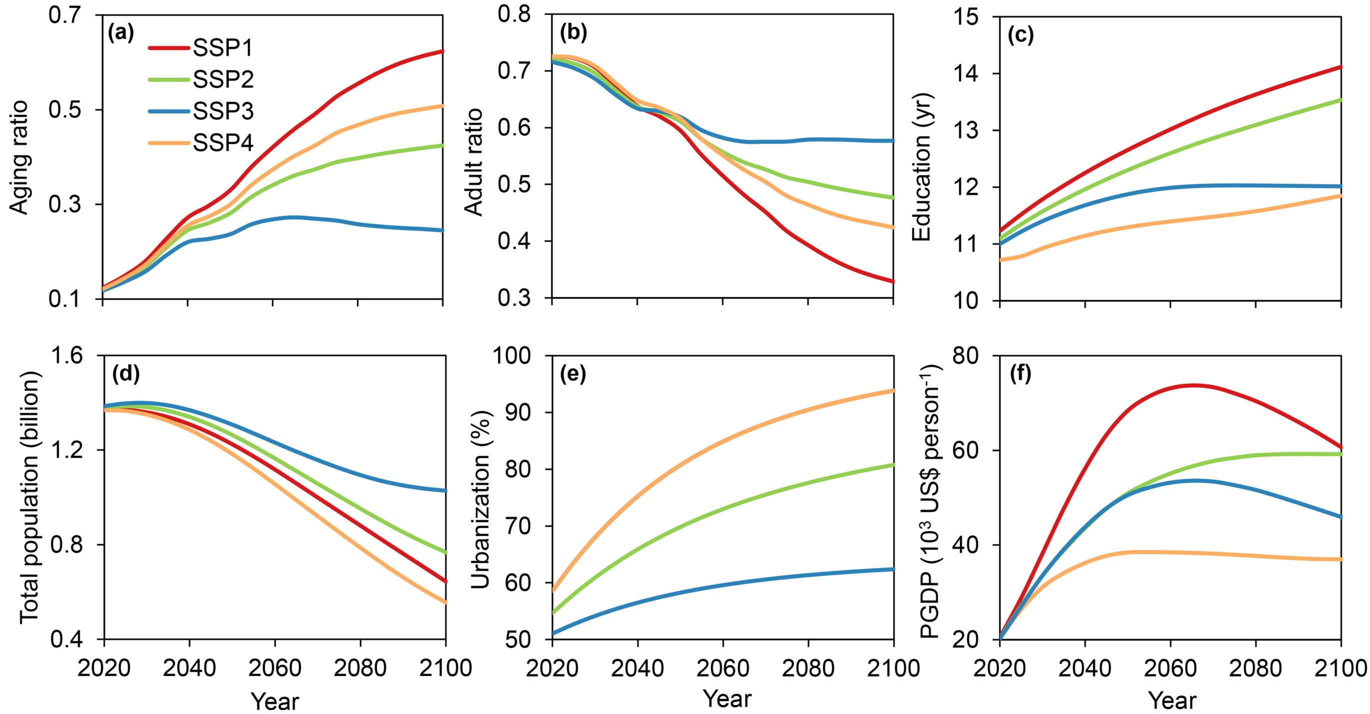
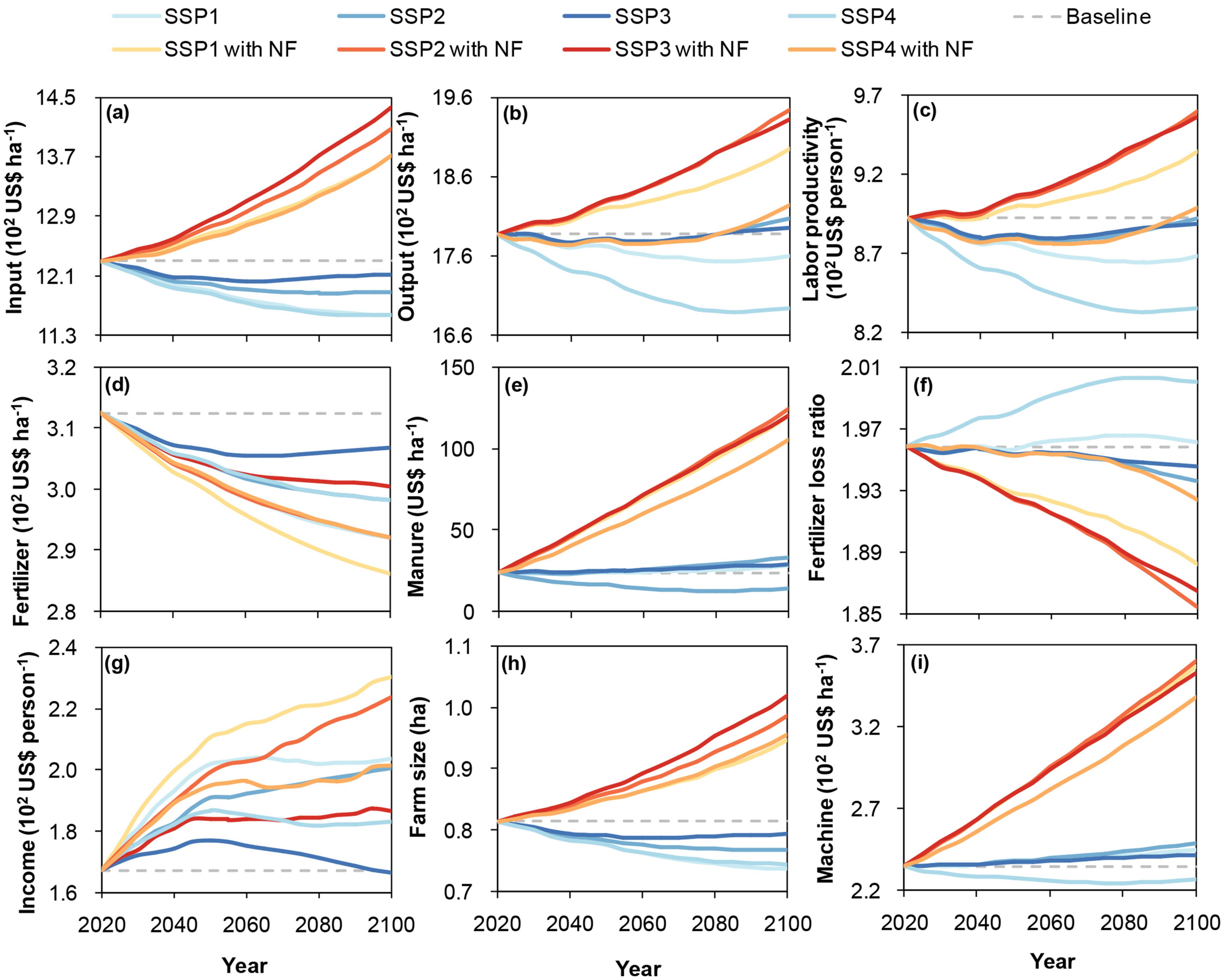


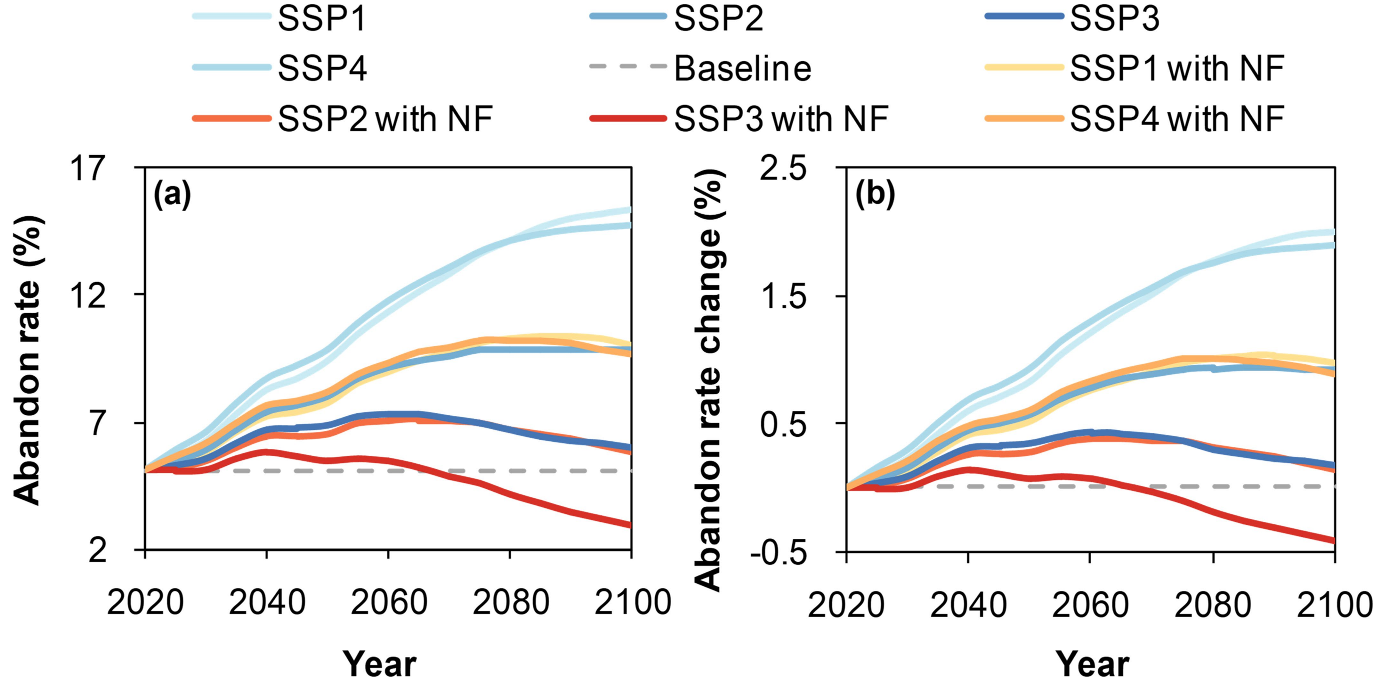
Extended Data Fig. 1 | Changes of agricultural sustainability with ageing in 2019. (a) Total agricultural input; (b) Agricultural output; (c) Labour productivity; (d) Fertilizer use; (e) Manure use; (f) Fertilizer loss ratio; (g) Per capita disposable income from agricultural sector; (h) Farm size; (i) Machine input. (a)-(c), (d)-(e), (g)-(i) show the economic, environmental and social impacts of agricultural sustainability, respectively. The predicted means the counterfactual value with ageing ratio equivalent to 1990. The observed means the observed value in 2019. The input, output, fertilizer, manure and machine are all weighted with the total cultivated area on province-level. Labour productivity is weighted with the total labour input on province-level. Farm size and income are arithmetic averages. Acronyms for 31 provinces, autonomous regions, and municipalities directly under the Central Government are listed in Table S4. Shanghai, Tibet and Xinjiang are not depicted due to data limitation.



Extended Data Fig. 2 | Demographic and socioeconomic changes in China under different scenarios by 2100. (a) Ageing ratio; (b) Adult labour ratio; (c) Average education years; (d) Total population; (e) Urban population ratio; (f) Gross domestic product per capita (PGDP). SSP1–4 refers to Shared Socioeconomic Pathways (SSPs) scenarios. Urbanization in SSP1 is consistent with it in SSP4 in panel (e). Data are from SSP Database.



Extended Data Fig. 3 | Future agricultural sustainability changes due to ageing under SSP scenarios by 2100. (a) Total agricultural input; (b) Agricultural output; (c) Labour productivity; (d) Fertilizer use; (e) Manure use; (f) Fertilizer loss ratio; (g) Per capita disposable income from agricultural sector; (h) Farm size; (i) Machine input. (a)-(c), (d)-(e), (g)-(i) show the economic, environmental and social impacts of agricultural sustainability, respectively. The Baseline assumed no changes in the future. SSP1–4 refers to Shared Socioeconomic Pathways (SSPs) scenarios. NF is the abbreviation of new farming. The input, output, fertilizer, manure and machine are all weighted with the total cultivated area. Labour productivity is weighted with the total labour input. Farm size and income are arithmetic averages.



Extended Data Fig. 4 | Abandoned cropland changes under SSP scenarios by 2100. (a) Abandoned cropland ratio change; (b) Relative change of abandoned cropland ratio compared to 2020. Abandoned cropland ratio is abandoned cropland area to the total cropland area across the whole country. Relative change is carried out in percentage terms. NF, New farming. SSP1–4 refers to Shared Socioeconomic Pathways (SSPs) scenarios. The Baseline assumed no changes in the future.

Extended Data Table 1 | Summary of the structural equation model shown in Fig. 2

	Fertilizer		Input		Labor productivity		Yield		Output	
	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio
Direct effect	-0.05	63%	-0.09	77%	-0.04	31%	-0.05	64%	-0.10	64%
Indirect effect from Farm size	0.023	29%	0.016	14%	-0.068	52%	-0.014	18%	0.023	15%
Indirect effect from Education	0.006	8%	0.010	9%	-0.022	17%	-0.011	18%	-0.034	22%
Net effect	-0.02		-0.08		-0.13		-0.05		-0.11	

Direct effects are derived from the standardized path coefficient from ageing to explained variables based on Fig. 2. Indirect effects were calculated as the product of all effects in a single path. Net effects are the sum of all direct and indirect effects. Ratio is the absolute value of direct or indirect effects divided by the sum of the absolute values of all effects.

Extended Data Table 2 | New farming mitigates ageing and its impacts on agriculture

		Aging, Farm size and Education				Inputs				Outputs		
		Ln Age	Aging	Ln Farm size (ha)	Education (yr)	Ln Input (US$ ha^{-1})	Ln Fertilizer (US$ ha^{-1})	Manure (US$ ha^{-1})	Machine (US$ ha^{-1})	Ln Output (US$ ha^{-1})	Ln LP (US$ person^{-1})	Ln Yield (kg ha^{-1})
New farming	Coefficient	-0.055***	-0.044	0.234	0.840***	0.201*	0.044	77.32	104.5	0.062	0.301	-0.037
	SE	(0.020)	(0.034)	(0.149)	(0.287)	(0.102)	(0.099)	(53.10)	(64.15)	(0.145)	(0.232)	(0.101)
	p-values	(0.005)	(0.198)	(0.116)	(0.004)	(0.050)	(0.656)	(0.145)	(0.103)	(0.670)	(0.196)	(0.717)
Aging	Coefficient			-0.364***	-1.752***	-0.166***	-0.205***	-121.3***	-41.22	-0.259***	-0.385***	-0.110
	SE			(0.079)	(0.233)	(0.060)	(0.074)	(36.47)	(31.88)	(0.062)	(0.114)	(0.067)
	p-values			(0.000)	(0.004)	(0.005)	(0.006)	(0.001)	(0.196)	(0.000)	(0.001)	(0.101)
Ln Farm size (ha)	Coefficient					-0.124***	-0.209***	19.42**	-11.93	-0.116***	0.584***	-0.085***
	SE					(0.017)	(0.021)	(7.575)	(7.906)	(0.018)	(0.027)	(0.017)
	p-values					(0.000)	(0.000)	(0.010)	(0.131)	(0.000)	(0.000)	(0.000)
Education (yr)	Coefficient			0.001		0.009**	-0.011**	9.578***	12.92***	0.034***	0.035***	0.016***
	SE			(0.785)		(0.004)	(0.005)	(2.705)	(2.093)	(0.004)	(0.007)	(0.004)
	p-values					(0.018)	(0.031)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County		Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes	Yes
City								Yes	Yes			
Adult farmer's ratio				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income ratio				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		7,448	7,450	6,007	6,007	5,693	5,554	5,992	5,869	5,488	5,609	5,133
Adjust R^2		0.13	0.06	0.52	0.29	0.18	0.17			0.29	0.38	0.19
Model		MRM	MRM	MRM	MRM	MRM	MRM	Tobit	Tobit	MRM	MRM	MRM

Each column represents a separate regression model. Stars indicate statistical significance level based on p-values: *p <0.1, **p <0.05, ***p <0.01. Standard errors (SE) are clustered at the county-level. LP, Labour Productivity. MRM, Multiple Regression Model. Age refers to the age of the head of the investigated household. Ageing refers to the proportion of people over 65 in rural households. Farm size is the total cultivated area covering all crops. Education refers to average years of education of family members aged 15 and over. Labour productivity (LP) is the agricultural output per labour input, including family and hired labours. New farming is binary variable indicating whether there is a new farming model. County and city mean county-level or city-level regional effect is controlled, respectively. "Yes" in lines of County, City, Adult farmer's ratio and Income ratio indicates their effects have been controlled. Crop type and plot number have been controlled in all regression equations. And in the equations whose explained variable is log-transformed output and yield, fertilizer input was further controlled. For all models in this table, we only use data in 2019 due to data limitation.