Aging Labor Force, Climate Change and the Path to Green Total Factor Productivity in Chinese Agriculture

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Abstract

In the context of global climate change and demographic transitions, understanding the determinants of agricultural productivity is essential for ensuring food security and promoting sustainable development. This study examines the impacts of climatic factors and population aging on agricultural green Total Factor Productivity in China from 2005 to 2020. Utilizing comprehensive data from the China Statistical Yearbook and the China Meteorological Data Service Center, we employ a fixed-effects regression model to analyze the influence of growing degree days, harmful degree days, cumulative precipitation, and population aging on green TFP. Our findings indicate that favorable temperature conditions significantly enhance green TFP, whereas extreme heat adversely affects it. Additionally, provinces with a higher level of aging exhibit increased green TFP, potentially due to their experience and ability to engage in labor-intensive green practices. However, the interaction between aging and harmful degree days suggests that extreme heat exacerbates the challenges faced by an aging workforce. This study emphasizes the importance of integrating climatic and demographic factors into policies aimed at improving agricultural productivity and sustainability, highlighting the need for tailored strategies to address the unique challenges posed by climate change and an aging population not only in China but also in other developing countries facing similar challenges.

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1 Introduction

Agriculture remains a cornerstone of global food security and economic stability. Particularly in developing regions like China, the agricultural sector is undergoing significant transitions driven by environmental and demographic shifts. These regions face confront significant challenges in advancing green agriculture, made tougher by limited and unsustainable food production resources, as well as the increasing threats of climate change and natural disasters (Fan & Zhang, 2023). The imperative lies in fostering a robust, environmental-friendly, and inclusive food system, aligning with the global drive for sustainable agricultural practices (Gaupp et al., 2021).

Current literature primarily focuses on how agricultural production structure (D. Liu, Zhu, & Wang, 2021), environmental regulations, such as energy conservation and emission reduction (ECER) (Huang et al., 2022) and carbon trading pilot policy (Yu et al., 2022), green subsidies (Ke & Huang, 2024), green trade barriers (Z. Liu et al., 2023), and factor misallocation (Lei et al., 2023) impact green TFP in agriculture. However, there is a significant lack of detailed and comprehensive understanding of how an aging workforce influences the shift toward green agriculture. The demographic shift towards an aging population poses substantial challenges to food security and agricultural sustainability in China (Ren et al., 2023), posing a call for thorough investigation. Studies have indicated that aging workforce leads to declined business dynamism, decreased labor fluidity and slower economic growth, both in general (Engbom et al., 2019) and specifically in agriculture (Zou, Mishra, & Luo, 2018). The effect of an aging population on green TFP is predominantly negative (Jiang et al., 2023), manifesting through a depressive effect on human capital (Mason, Lee, & Jiang,

2016) including a gradual decline in cognitive ability, physical strength (J. Liu, Dong, Liu, Rahman, & Sriboonchitta, 2020), and overall productive capacity, consequently dampening economic growth and productivity (Choi & Shin, 2015). Conversely, some studies present a more positive perspective on the impact of aging labor force on green TFP, suggesting that an aging labor force poses potential challenges by potentially slowing down the rate of technological adoption and innovation in agriculture, thereby moderating the efficiency gains from renewable energy consumption and technological progress in the long term (Li et al., 2022).

Furthermore, the critical review by Zhang et al. (2021) elaborates on the complexity of factors influencing green TFP, identifying three main streams—technical, economic, and governmental—that interlink and collectively impact the sustainable development of agricultural systems (Zhang et al., 2021). This underscores the need for a multifaceted approach in analyzing the factors that drive the greening of the agricultural sector. Despite these insights, the influence of the aging population on agricultural green TFP remains underexplored, indicating a critical area for future research.

Acknowledging the profound impact of climate change on green TFP is essential. As a multifaceted environmental challenge, climate change directly influences the efficiency and sustainability of agricultural systems by altering growing conditions and resource availability. For instance, climate variables like temperature, precipitation, and humidity significantly impact GTFP, particularly through changes in agricultural output, input usage, and the structural dynamics of farming practices (Song et al., 2022). Additionally, the role of specific climate factors such as rainfall in affecting agricultural inputs is crucial. For example, it adversely impacts machinery power, labor, and fertilizer inputs, highlighting its negative influence on operational efficiency in agricultural systems (Chen et al., 2021). However, findings from D. Liu et al. (2021) indicate that natural conditions have no significant effect on agricultural green TFP. This discrepancy highlights two crucial reasons for incorporating climate change into our analysis: firstly, the impact of climate change on green TFP is subject to conflicting results, necessitating a nuanced understanding. Secondly, a thorough and scientific investigation is needed to clarify the effects of climate change on green TFP within the context of China's unique climatic and agricultural landscape.

Furthermore, integrating climate change into our analytical framework is crucial, as omitting this factor could lead to significant gaps in understanding its dual impact on both green TFP and human capital. Climate change is a pervasive force that not only threatens the immediate productivity of agricultural systems through extreme weather events but also affects the health, labor capacity, and productivity of the agricultural workforce. It is widely recognized that climate change has considerably influenced agricultural productivity, often nullifying years of advancements in farming practices. While some regions may experience temporary boosts in agricultural yields due to extended growing seasons, overall, the effects tend to be negative, especially in warmer regions where productivity is already compromised (Tao et al., 2014; Schlenker & Roberts, 2009; Ortiz-Bobea et al., 2021). Moreover, the influence of climate change extends beyond direct impacts on agricultural output. Recent research has highlighted its significant effects on cognitive functions, particularly among the elderly, further contributing to the depreciation of human capital. Studies such as those by Wanka et al. (2014) explore how climate change compromises cognitive functioning and social participation, emphasizing its implications for successful aging. Similarly, the potential connections between weather patterns and cognitive decline in older adults, indicating that variability in climatic factors like precipitation could have profound cognitive effects (Finlay et al., 2020). Zuelsdorff and Limaye (2024) provide a framework to assess the heightened risk and burden of dementia linked to climate change, highlighting the growing threat to cognitive health among aging populations exposed to environmental stressors. Additionally, Guo et al. (2022) analyze how perceptions of climate change and cognitive evaluations influence the sustainable livelihood capacities of farmers, thereby connecting the broader socioeconomic impacts of climate-related cognitive decline to agricultural productivity. Collectively, these studies underscores the necessity of addressing both the direct impacts of climate change on agricultural productivity and its indirect effects on human capital through cognitive decline.

In light of the literature reviewed, it is clear that evaluating the effect of aging on agricultural green TFP in China necessitates considering climate change within the analytical framework. Ignoring the impact of climate change could skew the insights into how environmental factors interact with demographic trends such as an aging labor force. Therefore, to ensure a comprehensive evaluation of the factors influencing green TFP, it is essential to consider how climate change directly and indirectly shapes agricultural productivity and labor dynamics. This integrated approach will mitigating endogeneity issues associated with omitted variables in the empirical model and enable a more accurate assessment of the resilience and sustainability of agricultural practices in the face of evolving environmental and demographic challenges.

Despite the well-documented individual impacts of climate change and demographic shifts on agriculture, there remains a significant research gap in studies that integrate these factors with green TFP outcomes. This study aims to address this gap by examining the dual impact of climate change and an aging labor force on agricultural green productivity, a critical aspect of sustainable agricultural practices. By incorporating these elements into the analysis, this research seeks to mitigate the biases associated with omitted variables, thus enabling a more comprehensive exploration of the causal relationships between the aging labor force and green TFP in agriculture. This approach not only enhances the robustness of the model but also ensures that policy recommendations are grounded in a holistic understanding of the factors driving agricultural productivity under the pressures of population aging and climatic changes.

2 Empirical Analysis

We analyze the relationship between the annual green TFP, measured for each province in China as a function of variability and cumulative exposure to beneficial/harmful temperature and rainfall during the crop growing season and the aging level of agricultural labor force using a fixed-effect regression model that accounts for time-invariant differences across counties in unobservable determinants of the agricultural green TFP.

2.1 Data and Variable Construction

There are two major distinct data sources for this study: the China Meteorological Data Service Center (CMDC) and the China Statistical Yearbook. Additionally, the study utilizes the China Population Statistical Yearbook and the China Rural Statistical Yearbook to supplement certain variables. All the datasets are publicly available.

China Statistical Yearbook

The China Statistical Yearbook is an annual publication by the National Bureau of Statistics of China, providing comprehensive data on China's economic, social, and developmental activities at both national and provincial levels. This yearbook is essential for analyzing trends and assessing policy impacts across various sectors. The China Population Statistical Yearbook delivers detailed demographic data, including population size, structure, and changes, along with rates of birth, death, and migration. It's vital for demographic research and social planning. The China Rural Statistical Yearbook focuses on rural development, documenting agricultural production, economic conditions, land use, and living standards in rural areas, supporting evaluations of rural policies and development programs.

These statistics collectively facilitate the construction of variables for this study, which utilizes the data to calculate Green Total Factor Productivity (TFP) in agriculture at the province-year level and to assess the aging level of the agricultural labor force. Specifically, the aging level for each province is defined by the ratio of the population aged 65 and older to the total population within that province for a given year, as a proxy for aging of agricultural labor force, due to data limitation.

Green TFP at the provincial level in agriculture is calculated through a refined methodology that accounts for both desired and undesired outputs, utilizing the Slacks-Based Measure (SBM) index to effectively integrate these outputs into a comprehensive framework. The calculation begins by gathering essential inputs such as the agricultural labor force, total area of cultivated land including crops and aquaculture, the application of chemical fertilizers quantified in pure weight, the total power of agricultural machinery, diesel fuel consumption, usage of agricultural plastic film, pesticide application, and the volume of water used for effective irrigation. The outputs are classified into two categories: desired outputs, which include the total economic value generated from agriculture, and undesired outputs, notably the carbon emissions and non-point source pollution produced by agricultural activities. The SBM model, which underlies the efficiency calculations, incorporates non-zero slack variables to allow for potential reductions in inputs and minimization of undesired outputs. This model is mathematically represented to maximize efficiency by finely adjusting the relationship between inputs and outputs, thus providing a nuanced measure of green productivity across various provinces.

Unlike radial efficiency models which only allow proportional changes in inputs and outputs, the SBM model incorporates slack variables that account for non-proportional inefficiencies in both inputs and outputs, offering a more accurate assessment of operational efficiency. Tone (2001) introduced the standard SBM model to address the shortcomings of radial models, specifically their tendency to overestimate efficiency when non-zero slacks are present. However, this model could not compare multiple efficient Decision-Making Units (DMUs) within the same period. To solve this, the super-efficiency SBM model was developed, merging the SBM approach with super-efficiency analysis to allow comparisons among efficient DMUs.

The super-efficiency SBM model is expressed mathematically as:

$$\theta^* = \min_{\lambda, s^-, s^+} \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}^t}}{1 - \frac{(\sum_{r=1}^{q} s_r^+ + \sum_{k=1}^{h} s_k^-)}{q+h}}$$

subject to:

$$\begin{aligned}
x_{i0}^t &\geq \sum_{t=1}^{T} \sum_{j=1, j\neq 0}^{N} \lambda_{jt}^t x_{ij}^t - s_i^-, \quad i = 1, 2, \ldots, m \\
y_{r0}^t &\leq \sum_{t=1}^{T} \sum_{j=1, j\neq 0}^{N} \lambda_{jt}^t y_{rj}^t + s_r^+, \quad r = 1, 2, \ldots, q \\
b_{k0}^t &\geq \sum_{t=1}^{T} \sum_{j=1, j\neq 0}^{N} \lambda_{jt}^t b_{kj}^t - s_k^-, \quad k = 1, 2, \ldots, h \\
\lambda_j^t &\geq 0 \quad (\forall j), \quad s_i^- \geq 0 \quad (\forall i), \quad s_r^+ \geq 0 \quad (\forall r), \quad s_k^- \geq 0 \quad (\forall k)
\end{aligned} \tag{1}$$

In this model, x represents the input variables; y represents the desired outputs; b represents the undesired outputs; i represents the number of input variables. Among these, s_j^- represents the slack variable for input excess, which is the excessive amount of input i compared to the benchmark x_{i0}; s_k^- represents the slack variable for reducing the undesired output k for the zeroth DMU; b^t_{k0} represents the k-th undesired output of the zeroth DMU at time t.

Weather Data

For daily temperature data, we use the raw daily temperature data from the China Meteorological Data Service Center (CMDC) affiliated with the National Meteorological Information Center of China.[1] The CMDC records weather information for 820 weather stations in China on a daily basis, including the minimum, maximum, and average temperatures, precipitation, relative humidity, wind speed, as well as sunshine duration. This article matches the weather data for those 30 provinces included in our agricultural dataset using the inverse-distance weighting (IDW) method, which is widely used in existing studies to impute either weather or pollution data (Currie & Neidell, 2005; Deschênes & Greenstone, 2007; Schlenker & Walker, 2016). For each of the 2495 counties, this method calculates the weighted average of all weather stations within a certain radius of the centroid of that county, where inverse distance square is the weight. This article chooses 100 km (km) as the threshold radius and the results are robust to different radius.

We transform daily temperature data into annual metrics utilizing the agronomic concept of degree days while preserving the intra-annual variability in daily weather patterns. The growing degree day represents a specific instance of time-separable growth, generally calculated as the sum of truncated degrees between two thresholds. As proposed by Ritchie and Nesmith (1991), these thresholds are 8°C and 32°C for beneficial heat. For instance, a day with a temperature of 9°C contributes one degree day, while a day of 10°C contributes

[1] The daily weather dataset is available at `http://data.cma.cn/`.

two degree days, up to a temperature of 32°C, which contributes 24 degree days. Any temperature above 32°C also contribute 24 degree days.

Denoting the bound as b, we follow Schlenker's sine interpolation of daily temperatures for reference to compute degree days (DD) bounded by temperature b as follow:

$$DD_b(t_{min}, t_{max}) = \begin{cases} 0 & \text{if } t_{max} \leq b \\ t_{avg} - b & \text{if } b \leq t_{min} \\ \frac{\left((t_{avg}-b)\times\tau+\frac{1}{2}(t_{max}-t_{min})\times\sin\tau\right)}{\pi} & \text{if } t_{min} < b < t_{max} \end{cases} \tag{2}$$

where t_{min} and t_{max} are the daily minimum and maximum temperature values. t_{avg} is defined by the average value of the daily maximum and minimum temperature. In the third case, $\tau = \arccos\frac{2b-t_{max}-tmin}{t_{max}-tmin}$. Thus, the daily degree days is calculated as follows: $DD(\boldsymbol{t}_d) = DD_{b,d}$, denoting $\boldsymbol{t}_d$ as the daily temperature information, i.e., $t_{min,d}$ and $t_{max,d}$ in day d.

There has been ongoing debate regarding the precise point at which temperatures become harmful, particularly in scenarios where crops receive ample water. Researchers have applied various thresholds for the upper bound of beneficial temperature ranges. For instance, Schlenker and Roberts (2009) find that yields increase with temperature up to 29°C for corn, 30°C for soybeans, and 32°C for cotton but that temperatures above these thresholds are sinificantly harmful. Roberts and Schlenker (2011) have implemented degree days between 10°C to 29°C as the beneficial range, and degree days above 29°C as the harmful range. Lobell et al. (2017) define extreme degree days as the cumulative degree days above 30°C. Schlenker, Hanemann, and Fisher (2006) use bounds of 8°C and 32°C for growing degree days, and above 34°C for harmful degree days.

To avoid such controversy, some researchers exclude the concept of harmful degree days in their analysis (Schlenker, Hanemann, & Fisher, 2007), or use a single bound to model the cumulative heat during the growing season, which reflects both the beneficial and harmful part of heat. In this study, we also test robustness of our results using alternative thresholds, including ranges of 8°C and 30°C, 8°C and 32°C, 10°C and 30°C, and 10°C and 32°C for growing degree days and above 30°C and 32°C for harmful degree days.

The daily degree days are then summed over the entire growing season, which is usually defined based on the crop-growing months, such as during March to August (Schlenker & Roberts, 2009) or from April to September (Schlenker et al., 2007). In this study, the growing season is defined as from March through September. $\sum_{d=1}^{D} DD(\boldsymbol{t}_d)$ denotes the cumulative growing degree day from day one to day D, where $d = 1$ stands for March 1st. $d = D$ represents September 31st, the last day in the growing season in a year. Subsequently, the cumulative daily degree days during the growing season are aggregated to the province-year level. Similarly, the precipitation levels are initially available for each day during the growing season (March to September). Then, they are aggregated for the whole growing season from the first day of March through the last day of September. These data are then aggregated at the province level.

The weather variables in this study, province-year level cumulative degree days at various bounds and precipitation, are joined with the variable of interest, green TFP in agriculture, at province-year level, to form panel data. The integration of the two datasets and construction of the key variables enable us to identify the relationship between green TFP in agriculture and weather conditions, as well as the aging agricultural workforce for each province during 2005 to 2020.

2.2 Descriptive Analysis

2.2.1 Summary Statistics of Key Variables

Table 1 provides summary statistics for the key variables of interest in the regression analysis. Agricultural green TFP of in a province in a year vary between 0.765 and 2.362 in the data. A green TFP value greater than 1 indicates that the province is efficiently converting inputs into outputs while also incorporating environmentally sustainable practices. This means that the province is achieving more output per unit of input in an environmentally friendly manner compared to the benchmark or base year. Conversely, a green TFP value less than 1 suggests that the province is less efficient in its production processes, possibly due to higher resource consumption, waste, or environmental degradation. In this scenario, the province is producing less output per unit of input relative to the benchmark.

Average agricultural green TFP is 1.056, suggesting that, on average, provinces are slightly above the benchmark in terms of green productivity, indicating a general trend towards improved environmental efficiency in agricultural production.

2.2.2 Green TFP in Agriculture

Figure 1 shows the histogram and box plot of green TFP across provinces in China, which reveals a right-skewed distribution, signifying a concentration of provinces with relatively lower productivity levels, while a smaller number exhibit significantly higher green TFP values. The modal peak of the distribution is positioned near the lower end of the

Table 1: Summary statistics of key variables

Variable	Mean	Std. dev.	Min	Max
Green TFP	1.056	0.093	0.765	2.362
Technical efficiency of green TFP	1.009	0.119	0.549	2.607
Technical change of green TFP	1.056	0.121	0.535	2.362
Growing degree days 8°C to 30°C (GDD_{8-30})	3113.241	1173.972	631.029	6616.701
Growing degree days 8°C to 32°C (GDD_{8-32})	3074.664	1142.319	631.029	6363.474
Growing degree days 10°C to 30°C (GDD_{10-30})	2619.862	1069.520	343.679	5954.701
Growing degree days 10°C to 32°C (GDD_{10-32})	2570.402	1028.006	343.679	5633.474
Degree days above 30°C (HDD_{30})	5.345	10.903	0.000	97.813
Degree days above 32°C (HDD_{32})	0.389	1.984	0.000	28.903
Precipitation (in mm)	966.786	458.008	190.954	2238.741
Aging	0.112	0.036	0.050	0.261
Provincial agricultural expenditure (in ten thousand yuan)	3934098	2977106	118418	13400000
Primary industry added value (in hundred million yuan)	1671.704	1276.207	65.340	5556.580
Number of observations: 480				

scale, suggesting that a majority of provinces operate at or below a GTFP score of 1.0. Conversely, the tail extending towards higher values up to 2.5 indicates the presence of outlier provinces achieving substantially higher productivity, possibly due to advanced green agricultural practices or more effective environmental policy implementations.

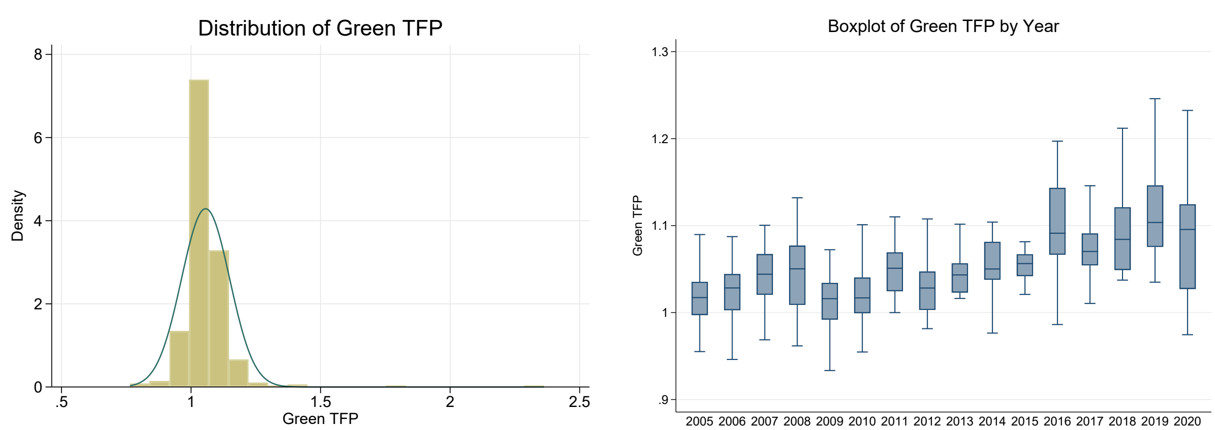

Figure 1: Histogram and box plot of green TFP

This right skewness in the distribution highlights a disparity in green productivity across the provinces, with a substantial number of regions lagging behind a few high performers. Such a pattern suggests the potential for considerable improvement in green TFP, especially in the lower-performing provinces. The broad spread of the distribution further underscores the heterogeneity in agricultural efficiency, influenced by factors such as local policy environments, technological adoption, and resource management practices.

Given the variability observed in the histogram, it is clear that policy interventions and resource allocations to enhance green TFP should be customized to provincial specifics. Tailored approaches are essential to elevate the productivity of lower-performing provinces and to harness the potential of higher-performing ones, thereby reducing regional disparities in green agricultural productivity.

The box plot of green TFP in Chinese provinces from 2005 to 2020 shows a slight upward trend in the median green TFP over the years, with some yearly variations. The distance between the lower and upper quartiles becomes smaller over time, indicating that the differences in green TFP across provinces are decreasing. This suggests that provinces are becoming more consistent in their green agricultural practices and efficiencies.

The median green TFP particularly increases after 2011, which may reflect improvements in sustainable agricultural technologies or the impact of new policies. There are also outliers in several years, showing that some provinces have unusually high or low green TFP compared to the rest, pointing to uneven adoption or success of green practices.

The time series plots for green TFP across various Chinese provinces from 2005 to 2020, presented in figure 2, reveal a generally upward trajectory in green productivity in agriculture. Each line represents a province's green TFP over time, illustrating diverse growth patterns, some showing steady increases while others exhibit more volatile trends.

This indicates that while overall progress is being made, the pace and consistency of growth in green agricultural productivity vary widely among the provinces.

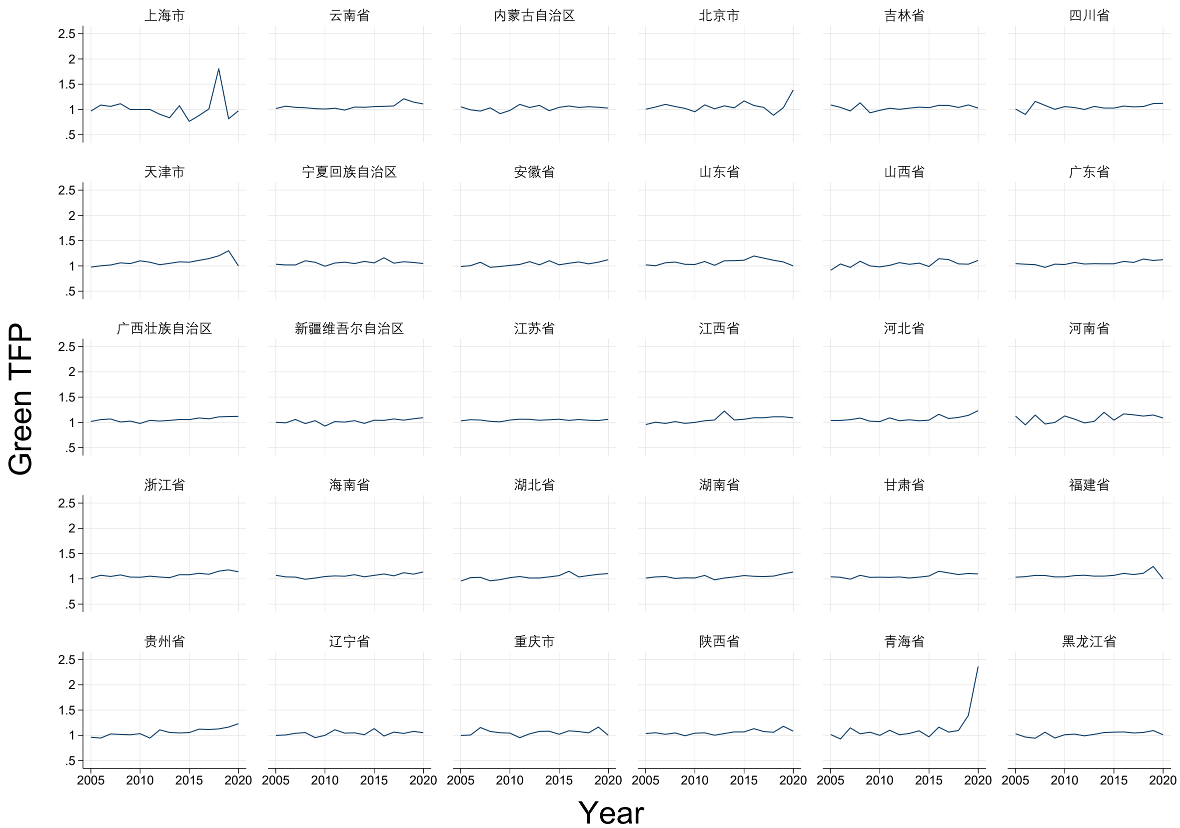

Figure 2: Trend of green TFP in Agriculture by Province

Several provinces, particularly those with initially lower green TFP values, demonstrate significant growth, potentially indicating successful implementation of green agricultural practices and supportive policies over the period. In contrast, provinces that started with higher green TFP values show varying degrees of growth, with some plateauing or experiencing minimal increases. This suggests that these provinces may be approaching the efficiency frontier of current green agricultural technologies and practices, where gains become harder to achieve due to existing high levels of efficiency.

Focusing on the top five agricultural provinces by expenses in 2020 — Sichuan, Henan, Xinjiang, Guangdong, and Yunnan — we observe specific trends that reflect regional strategies and investments in green agriculture. Sichuan and Henan, for example, show steady and significant increases in green TFP, suggesting effective leveraging of green technologies and policies. Xinjiang's green TFP displays gradual growth with some fluctuations, likely reflecting the challenges posed by its unique geography and climate. Guangdong's trend is relatively stable with a modest upward trajectory, indicating a mature agricultural sector where green practices are incrementally enhancing productivity. Yunnan exhibits a notable upward trend, possibly due to its focus on sustainable and organic farming practices.

These detailed observations highlight a broad improvement in agricultural sustainability across China, although the rate of progress and the level of green TFP vary considerably by province. The variability in growth rates highlights the differential regional impacts of agricultural policies and the adoption rates of sustainable practices. This suggests that targeted regional strategies might be necessary to further enhance green productivity uniformly across the country. Implementing tailored approaches that consider the unique economic, climatic, and geographical characteristics of each province could optimize the outcomes of China's green agricultural initiatives, ensuring that all regions can effectively contribute to and benefit from the country's sustainability goals.

2.3 Regression Methods

Given that the outcome of interest, agricultural green TFP, exhibits right-skewness, indicating a few provinces with exceptionally high green productivity values, we apply a natural logarithm transformation to address this skewness and improve the statistical properties of our regression model. Log-transforming green TFP (log(GreenTFP)) also linearizes the multiplicative relationships between green TFP and the explanatory variables, facilitating a more accurate representation of these relationships in the regression model. This transformation stabilizes the variance of residuals, thereby enhancing the reliability of coefficient estimates and their standard errors. Furthermore, the coefficients in the log-transformed model can be interpreted as semi-elasticities, providing insights into the percentage changes in green TFP in response to unit changes in the explanatory variables.

We estimate a fixed effect linear panel regression as a starting point to identify the impact of temperature and precipitation on annual agricultural green TFP, treating within-state variation in degree days, cumulative precipitation, and aging as exogenous, controlling for potential confunders such as provincial agricultural expenditure and primary industry added value. To maintain consistency and interoperability, these control variables are also log-transformed.

The regression specification is as follows:

$$\begin{aligned}\log(\mathrm{GreenTFP}_{it}) = \alpha &+ \beta_1 \mathrm{GDD}_{8-30,it} + \beta_2 \mathrm{HDD}_{30,it} + \beta_3 \mathrm{Prec}_{it} \\ &+ \beta_4 \mathrm{Aging}_{it} + \beta_5 (\mathrm{HDD}_{30,it} \times \mathrm{Aging}_{it}) \\ &+ \beta_{\mathbf{6}} \log(\mathrm{AgriExpenditure}_{\mathbf{it}}) + \beta_{\mathbf{7}} \log(\mathrm{PrimaryIndustryValue}_{\mathbf{it}}) \\ &+ \gamma_i + \delta_t + \epsilon_{it} \qquad (3)\end{aligned}$$

In the regression model, $\log(\mathrm{GreenTFP}_{it})$ represents the natural logarithm of the green total factor productivity for province i in year t. The variable $\mathrm{GDD}_{8-30,it}$ indicates the growing degree days between 8°C and 30°C for province i in year t, cumulated over the growing season from March 1st to September 30th. Similarly, $\mathrm{HDD}_{30,it}$ denotes the harmful degree days above 30°C for the same province and period. Prec_{it} refers to the cumulative precipitation in millimeters over the growing season for province i in year t. The term Aging_{it} captures the proportion of the elderly population (aged 65 and above) in province i in year t. An interaction term between harmful degree days and aging, $(\mathrm{HDD}_{30,it} \times \mathrm{Aging}_{it})$, is included to explore the effect of extreme heat on aging through the adverse impact on cognition on elder people (Yi et al., 2023). The control variables include $\log(\mathrm{AgriExpenditure}_{it})$, which is the natural logarithm of the provincial agricultural expenditure (in ten thousand yuan), and $\log(\mathrm{PrimaryIndustryValue}_{it})$, which is the natural logarithm of the primary industry added value (in hundred million yuan), both for province i in year t. γ_i represents the province fixed effects that account for time-invariant characteristics of each province, while δ_t captures the year fixed effects that control for common time trends across all provinces. Finally, ϵ_{it} is the error term.

3 Results

We start with the fixed effects model including aging and weather variables only, respectively as the baseline regressions to set the stage for the following analysis. For robustness-check purposes, we developed various specifications with linear and quadratic formats of precipitation and growing degree days, respectively, in the preliminary regression analysis. The specification of linear precipitation and growing degree days is presented in the results.

3.1 Preliminary results

Table 2 presents the regression results of the baseline model estimating the determinants of the natural logarithm of green TFP. The table encompasses six different specifications to assess the robustness of the results. Regression (1), (2), and (3) use standard errors, whereas models (4), (5), and (6) employ clustered standard errors at the province level to account for within-province correlation. Key variables in these regressions include growing degree days between 8°C to 30°C (GDD_{8-30}), harmful degree days above 30°C (HDD_{30}), precipitation, aging, an interaction term between aging and harmful degree days, log of agricultural expenditure, and log of primary industry added value.

The coefficient for growing degree days (GDD_{8-30}) is consistently positive and statistically significant at the 1% level in models where it is included (regressions 1, 3, 4, and 6). For example, in regression (1), the coefficient is 0.128 ($p < 0.01$), suggesting that an increase in favorable temperature conditions correlates with higher green TFP. A one standard deviation increase in GDD_{8-30} is associated with approximately a 12.31% (0.108×1.140) increase in green TFP, holding all other variables constant. This finding implies that provinces expe-

Table 2: Regression results of the baseline model

	(1)	(2)	(3)	(4)	(5)	(6)
GDD_{8-30}	0.128***		0.108***	0.128**		0.108**
	(3.484e-02)		(3.602e-02)	(5.157e-02)		(4.912e-02)
HDD_{30}	-0.143***		0.084	-0.143**		0.084
	(4.320e-02)		(1.411e-01)	(6.434e-02)		(1.212e-01)
Precipitation	0.001		-0.001	0.001		-0.001
	(2.438e-02)		(2.462e-02)	(1.876e-02)		(2.087e-02)
Aging		0.333**	0.373**		0.333**	0.373*
		(1.644e-01)	(1.847e-01)		(1.573e-01)	(1.960e-01)
Aging × HDD_{30}			-1.401*			-1.401**
			(8.283e-01)			(5.137e-01)
ln(Ag expenditure)	0.001	-0.002	-0.001	0.001	-0.002	-0.001
	(9.886e-03)	(1.007e-02)	(9.924e-03)	(1.098e-02)	(1.166e-02)	(1.101e-02)
ln(Added value)	0.064***	0.057***	0.055**	0.064**	0.057*	0.055*
	(2.107e-02)	(2.171e-02)	(2.141e-02)	(2.824e-02)	(3.125e-02)	(2.979e-02)
Constant	-0.796***	-0.359***	-0.690***	-0.796***	-0.359***	-0.690***
	(1.168e-01)	(6.207e-02)	(1.298e-01)	(1.710e-01)	(7.302e-02)	(1.710e-01)
Observations	480	480	480	480	480	480
AIC	-1263.08	-1250.76	-1264.39	-1265.08	-1252.76	-1266.39
BIC	-1238.03	-1234.06	-1231.00	-1244.21	-1240.24	-1237.17
Cluster s.e.	N	N	N	Y	Y	Y

Standard errors and cluster standard errors at the province level in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

riencing more beneficial heat accumulation tend to exhibit greater agricultural productivity.

In contrast, the coefficient for harmful degree days (HDD_{30}) is negative and significant at the 1% level in regressions (1) and (4) ($\beta_2 = -0.143$, $p < 0.01$), indicating that extreme heat negatively impacts green TFP. However, it is worth noting that when the interaction term between aging and harmful degree days is included in regressions (3) and (6), the direct effect of harmful degree days becomes insignificant. This suggests that the detrimental effect of extreme heat operates through the depreciation of human capital among the aging population, primarily due to the adverse impact of extreme heat on cognitive function.

Aging emerges as a significant factor in regressions (2), (3), (5), and (6), with coefficients ranging from 0.333 to 0.373, significant at the 5% level. A one standard deviation increase in the aging variable (0.0359) is associated with approximately a 1.195% increase in green TFP, holding all other variables constant. This positive relationship suggests that provinces with a higher proportion of elderly population tend to have increased green TFP, potentially due to experienced labor forces or more conservative resource management practices.

The interaction term between aging and harmful degree days is notably negative and marginally significant in regression (3) with $\beta_5 = -1.401$ and $p < 0.1$, and reaches significance at the 5% level in regression (6) ($\beta_5 = -1.401$, $p < 0.05$). Again, this indicates that the detrimental impact of extreme heat on green TFP is more pronounced in provinces with a higher proportion of elderly population. Given that HDD_{30} represents extreme heat, which has a negative impact on the cognition of older people, this interaction term suggests that extreme heat further depreciates the human capital of an aging labor force, compounding the negative effects on productivity.

Interestingly, the log of agricultural expenditure is not statistically significant in any model, suggesting it does not directly affect green TFP. Conversely, the log of primary industry added value consistently shows a positive and significant relationship, indicating that higher economic output in the primary sector is associated with increased green TFP.

In summary, the findings emphasize the significant impact of growing degree days and aging on green TFP, while also revealing complex interactions between aging population and harmful degree days. The use of clustered standard errors in some models enhances the robustness of the results by accounting for within-province correlation. Furthermore, alternative specifications, including quadratic terms for growing degree days and different bounds for degree days (such as between 10°to 32°), confirm the robustness of the findings. In some alternative specifications, the interaction term between growing degree days and aging was also included, but it was consistently insignificant. Therefore, these interaction results are not reported in this paper.

3.2 Robustness check

Table 3 presents the regression results of the baseline model using an alternative specification for growing degree days, specifically focusing on the range between 10°C to 30°C (GDD_{10-30}). This robustness check aims to verify whether the findings from the baseline model are sensitive to changes in the definition of growing degree days. By adjusting the temperature range for growing degree days, we assess the consistency of the key variable coefficients and their significance levels.

In comparison to Table 2, which uses growing degree days between 8°C to 30°C, the results in Table 3 demonstrate consistency in the key coefficients, confirming the robustness of our findings. The coefficient for GDD_{10-30} remains positive and significant across relevant models, similar to the results for GDD_{8-30}. The coefficient for harmful degree days (HDD_{30}) also remains negative and significant in models (1) and (4), indicating that extreme heat negatively impacts green TFP. The aging variable and its interaction with harmful degree days continue to show significant relationships. Overall, the results in Table 3 support the findings from the baseline model, reinforcing the robustness of the relationships between growing degree days, harmful degree days, aging, and green TFP.

Table 3: Regression results of the baseline model with growing degree days between 10°C to 30°C

	(1)	(2)	(3)	(4)	(5)	(6)
GDD_{10-30}	0.120***		0.097**	0.120**		0.097*
	(3.765e-02)		(3.882e-02)	(5.702e-02)		(5.428e-02)
HDD_{30}	-0.139***		0.093	-0.139**		0.093
	(4.347e-02)		(1.419e-01)	(6.569e-02)		(1.234e-01)
Precipitation	0.001		-0.002	0.001		-0.002
	(2.460e-02)		(2.482e-02)	(1.766e-02)		(1.986e-02)
Aging		0.333**	0.402**		0.333**	0.402*
		(1.644e-01)	(1.848e-01)		(1.573e-01)	(1.966e-01)
Aging × HDD_{30}			-1.429*			-1.429**
			(8.321e-01)			(5.186e-01)
ln(Ag expenditure)	0.001	-0.002	-0.001	0.001	-0.002	-0.001
	(9.921e-03)	(1.007e-02)	(9.954e-03)	(1.107e-02)	(1.166e-02)	(1.112e-02)
ln(Added value)	0.064***	0.057***	0.055**	0.064**	0.057*	0.055*
	(2.114e-02)	(2.171e-02)	(2.148e-02)	(2.847e-02)	(3.125e-02)	(3.005e-02)
Constant	-0.718***	-0.359***	-0.608***	-0.718***	-0.359***	-0.608***
	(1.093e-01)	(6.207e-02)	(1.214e-01)	(1.595e-01)	(7.302e-02)	(1.588e-01)
Observations	480	480	480	480	480	480
AIC	-1259.52	-1250.76	-1261.44	-1261.52	-1252.76	-1263.44
BIC	-1234.48	-1234.06	-1228.05	-1240.65	-1240.24	-1234.22
Cluster s.e.	N	N	N	Y	Y	Y

Standard errors and cluster standard errors at the province level in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

4 Conclusion

This study examines the relationships between climatic factors, population aging, and agricultural green Total Factor Productivity in China from 2005 to 2020. Using comprehensive data from the China Statistical Yearbook and the China Meteorological Data Service Center, we employ a fixed-effects regression model to analyze how growing degree days, harmful degree days, cumulative precipitation, and the aging population impact green TFP.

Our findings highlight the significant influence of climate variables on agricultural productivity. Favorable temperature conditions, measured by growing degree days, positively affect green TFP, indicating that optimal temperature ranges are crucial for enhancing agricultural productivity. Conversely, harmful degree days negatively impact green TFP, showing the adverse effects of extreme heat on agricultural efficiency.

The study also reveals the effects of population aging on green TFP. Provinces with a higher proportion of elderly agricultural workers tend to have increased green TFP, possibly due to the experience and resource management practices of older farmers.

However, the interaction term between aging and harmful degree days indicates that extreme heat exacerbates the challenges faced by an aging workforce, likely due to its adverse impact on cognitive and physical abilities. Additionally, older farmers may have more time to engage in labor-intensive green practices, such as applying smaller amounts of fertilizer more frequently, which is more environmentally sustainable than applying a large amount at once and then pursuing off-farm income opportunities. In contrast, younger farmers, who often have more off-farm income opportunities, might have less time to invest in such labor-intensive green technologies. The propensity of older farmers to remain in the village and devote more time to farming activities enables them to adopt these practices more readily. However, the interaction between aging and harmful degree days indicates that extreme heat exacerbates the challenges faced by an aging workforce, likely due to its adverse impact on cognitive and physical abilities.

To ensure the robustness of our results, we conduct several robustness checks, including using different definitions of growing degree days, such as the range between 10°C to 30°C. The consistency of key coefficients across these specifications confirms the reliability of our findings. The inclusion of a linear time trend further helps control for long-term temporal variations, ensuring that the results are not driven by year-specific shocks or trends.

In conclusion, this study provides valuable insights into the critical interplay between climate conditions, population aging, and agricultural green TFP in China. The findings highlight the importance of considering both environmental and demographic influences in shaping agricultural productivity and sustainability. Policymakers aiming to enhance the sustainability and efficiency of the agricultural sector should adopt a multifaceted approach that integrates climatic and demographic considerations. By addressing the unique challenges posed by climate change and an aging workforce, China can foster a resilient and sustainable agricultural system capable of meeting future food security and environmental goals.

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