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A Ricardian analysis of climate change impacts on Japan's agriculture: Accounting for solar radiation

This study evaluated the effects of climate change on the net revenue of farmers in Japan. We adopted the Ricardian model, which implicitly accounts for farmers' full adaptation. The main findings of this study are as follows. First, the Ricardian regression shows that changes in temperature significantly impact farmers' net revenue. In contrast, changes in precipitation have limited effects on farmers' net revenue. The results of future predictions showed that the effects of climate change are positive across the country, with varying degrees between north and south. These results are more optimistic than those in the existing literature, which frequently reveal negative climate change impacts in southern Japan. However, it should be noted that this model assumes full adaptation and does not consider the transition costs of farmers, and understanding the actual adaptive measures is an important remaining issue.

keywords: climate change; Ricardian analysis; solar radiation; adaptation measures

1. Introduction

IPCC (2021) states that global warming will continue in the 21st century unless greenhouse gas emissions are drastically reduced. Agriculture is one of the economic activities most vulnerable to climate change, and understanding the impact of climate change on agriculture and adopting effective adaptation measures is critical for establishing a sustainable food supply chain.

A large body of scientific literature in Japan has assessed the effects of climate change on agriculture (Ministry of Environment, 2020). Because rice is the most widely produced and consumed crop in Japan, many studies have been conducted to evaluate the impact of climate change on rice production (e.g., Okada et al., 2011). These studies indicate that rice yields are most likely to increase within the 21st century, except in climate scenarios with extremely large temperature increases. Studies have also shown that extremely high temperatures during the ripening period degrade the rice quality (Wakamatsu et al., 2007; Kunimitsu et al., 2014). According to an econometric study conducted by Kawasaki and Uchida (2016), the net effect of climate change on farmers' revenue is negative if no adaptation measures are implemented.

Perennial crops have narrower climate adaptability than annual crops. Agronomic studies have indicated that climate change can degrade the fruit quality. For example, agronomic evidence has shown that high air temperatures lead to poor grape coloration by interfering with anthocyanin biosynthesis in the skin (Sugiura, 2018). Poor fruit coloration has also been reported in other fruits such as apples, persimmons, and satsuma mandarins (Sugiura 2012). Although climate change affects all agricultural products in Japan, perennial crops and rice are more likely to be affected by global warming than other crops (Ministry of Environment, 2020).

With climate change, farmers will implement adaptation strategies, such as planting temperature-tolerant crops or shifting cropping seasons. Adaptation lessens the impact of climate change, resulting in higher yields and higher net revenue or less severe yield and farm income losses. Hence, it is important to consider the positive effects of farmers' adaptation measures when evaluating the effects of climate change on agriculture.

This study aims to shed empirical light on the effects of climate change on Japan's agricultural sector, while accounting for farmers' adaptive behavior. We conducted a Ricardian analysis in which the cross-sectional net revenue was regressed against climate, soil characteristics, and other control variables (De Salvo et al., 2014). The Ricardian model, as opposed to the production function approach, implicitly accounts for farmers' adaptive behavior. Approaches that do not account for adaptation tend to overestimate the agricultural sector's economic damage caused by climate change because they do not consider the positive effects of farmers' adaptation measures.

Ricardian analyses have been conducted in in many regions, such as the United States (Mendelsohn et al., 1994; Schlenker et al., 2006), Europe (De Salvo et al., 2013; Van Passel et al., 2017; Moretti et al., 2021), and other continents (Liu, 2004; DePaula, 2020); however, there have been no studies which focuses on Japan. As previously stated, the degradation of rice quality caused by high temperatures could become a major issue in the near future. Therefore, understanding the effects of climate change on Japan's agricultural sector is critical. Although many econometric studies have estimated the effects of climate change on Japan's agriculture (e.g., Kawasaki and Uchida, 2016), adaptive measures are rarely considered. A few studies that account for adaptation have considered only limited adaptive measures, such as shifting the crop season (Kawasaki and Uchida, 2016; Matsumoto and Takagi, 2017) or double cropping (Kawasaki, 2019). However, anecdotal studies show that Japanese farmers adopt various adaptive measures (Morita, 2011), and taking them into account is important when assessing the impacts of climate change on agriculture. Thus, this study developed the first Ricardian model that implicitly considers full adaptation to estimate the economic impact of climate change on agriculture in Japan[1].

This study adds to the existing literature by including solar radiation as a climatic variable in the Ricardian model. The Ricardian model was first estimated using quadratic seasonal temperature and precipitation (Mendelsohn et al., 1994). Researchers have attempted to use various functional forms to estimate the effects of temperature and precipitation on farmers' land value and net revenue. These forms include degree days (Fisher et al., 2012), four-season average temperature and precipitation, two growing seasons (Vaitkeviciute et al., 2019), and temperature bins (Massetti and Mendelsohn, 2020). However, in Ricardian analysis, discussions related to additional climate variables, such as sunshine duration or solar radiation, are relatively scarce (Zhang et al. 2017). This study includes solar radiation, which has been shown in agronomic literature to have a positive relationship with rice yield (e. g. Okada et al., 2011), as one of the climate variables in the Ricardian model. Including more climate variables is expected to reduce the omitted variable bias, which is a known weakness of Ricardian cross-sectional models.

The remainder of this paper is organized as follows. Section 2 presents the data used in the study. Section 3 provides an overview of the methodology and the model specifications. Section 4 presents empirical findings, including the marginal effects and future predictions of farmers' net revenue. Finally, Section 5 summarizes the main findings and offers conclusions.

[1] Furthermore, Japan has a large latitudinal extent and diverse climatic conditions. It is preferable to conduct a Ricardian analysis across large geographical areas (Mendelsohn and Massetti, 2017)

2. Methodology

2.1. Ricardian analysis

With the aid of extensive observational data, economists have developed various approaches to understand the effects of climate change on agriculture. The cross-sectional Ricardian approach developed by Mendelsohn et al. (1994) differs significantly from the production function approach, which was widely used until the mid-1990s. Using this method, we can investigate the effect of long-term climate (average weather over 30 years) on farmers' net revenue or land value (Mendelsohn and Massetti, 2017).

The Ricardian model assumes that farmers maximize their net revenue by selecting the optimal quantity of endogenous inputs, given exogenous conditions (Mendelson et al., 1994; Vanschoenwinkel et al., 2019). This approach has the advantage of implicitly considering the long-term adaptation measures of farmers. Because of this advantage, the Ricardian approach has been broadly applied to various geographical contexts and scales, despite receiving criticism (De Salvo et al., 2014).

One criticism is that cross-sectional regression analysis suffers from omitted variable bias (Carter et al., 2018). A panel regression approach is proposed to deal with the omitted variable problems (Deschênes and Greenstone, 2007; Blanc and Schlenker, 2017). This method controls for time-invariant unobservable factors and provides a more precise causal inference between climatic conditions and farmers' productivity. Meanwhile, panel estimation cannot account for the long-term adaptation of farmers; consequently, it can overestimate the impacts of climate change on agriculture (Mendelsohn and Massetti, 2017). The primary objective of this study was to evaluate the impact of climate change on farms considering long-term adaptation. Therefore, we use the cross-sectional Ricardian method and introduce exogenous variables to reduce omitted variable bias as much as possible.

Another criticism of the Ricardian model is related to adjustment costs, as pointed out by Kelly et al. (2005). Ricardian analysis assumes full adaptation, which includes both crop and input changes and other cropping practices that often incur significant costs. Hence, the results of the Ricardian model should be interpreted as a rather optimistic case.

2.2. Model specification

2.2.1. Basic Ricardian model

In Ricardian analysis, farmland value or farmland rent values are frequently used as a proxy for agricultural productivity. However, these values are strictly regulated in Japan (Shigeto et al., 2008). In other words, the variation in farmland rent values is primarily explained by institutional factors rather than climatic or geographical factors. As a result, we consider farmland values or farmland rent values inappropriate for expressing farmers' productivity in Japan's case and instead use net revenue per hectare.

We referred to the existing Ricardian and Japanese crop science literature to develop the estimation equation. The crop science literature indicates that temperature and precipitation during the growing season have nonlinear effects on rice yield and quality. Hence, we assume a quadratic relationship between climate and farm productivity. Four-season climatic data are often used as climatic variables (Moretti et al., 2021; Vanschoenwinkel et al. 2020). However, the correlation across the seasons was very high (0.955–0.991), when we calculated the correlation coefficient between the four seasonal temperatures using the datasets described in Section 3. Therefore, we included the annual average temperature and seasonal precipitation in the regression model[2].

We added exogenous variables in addition to climatic conditions to reduce the omitted variable bias. The control variables included geographical, soil, market variables, and farmer characteristics. Variables like labor, capital, and crop choice are excluded from the Ricardian regression in Equation (2) because they are endogenous and presumed to be optimized (Vanschoenwinkel et al., 2020)

2.2.2. Solar Radiation

Solar radiation is one of the most critical climatic conditions that affect rice yield and quality. According to agronomic literature, poor ripening is caused by low solar radiation and high temperatures (e.g., Murata, 1964). Therefore, statistical models for evaluating rice and other crops assume a positive linear relationship between solar radiation, temperature, and crop yield or quality (Okada et al., 2011; Kamada et al., 2021).

[2] Previous study shows that including climatic conditions outside of the cropping season is important (Vaitkeviciute et al., 2019). We did not use limited seasons of temperature because this study focuses on a wide variety of farmers that includes farmers who grow crops during seasons other than summer.

The solar radiation variable used in this study included both direct (global) and indirect solar radiation, as observed by stations of the Japan Meteorological Agency. Direct solar radiation originates from sunlight, which directly reaches the Earth's surface. Indirect solar radiation includes reflected sunlight on the ground surface and scattered sunlight from the atmosphere, including clouds, aerosols, and water vapor (Japan Meteorological Agency, 2022). The measured solar radiation data were then processed to one-kilometer level mesh data by Japan's National Agriculture and Food Research Organization (NARO).

We checked the variation in solar radiation between regions in Japan and found that the cross-sectional variation in solar radiation is different from that in temperature or precipitation. This implies that the intensity of solar radiation does not necessarily correlate with temperature. In fact, the absolute values of the correlation coefficient between seasonal solar radiation and other climatic conditions were between 0.014 and 0.513[3]. This suggests that solar radiation and other climatic conditions were not highly correlated.

Based on the discussion above, we constructed estimation Equation (1). It includes a quadratic form of yearly temperature and seasonal precipitation, linear form of seasonal solar radiation, and set of exogenous variables. The estimation equation is as follows:

$$y = \alpha + T\beta_{T1} + T^2\beta_{T2} + \sum_{i=1}^{4} P_i\beta_{P1,i} + \sum_{i=1}^{4} P_i^2\beta_{P2,i} + \sum_{i=1}^{4} S_i\beta_{S,i} + E\mu + \varepsilon \quad (1)$$

where y is the yearly net revenue per hectare; T and P reflect the annual temperature and seasonal precipitation, respectively; E is a collection of exogenous control variables; ε is a random error term; and i represents seasons[4]. To account for the non-constant variation in error terms between cities, we estimate Equation (1) and calculate the city-level cluster-robust standard errors.

2.2.3. Spatial autocorrelation

It is well known that without considering spatial autocorrelation, OLS estimates are often biased and inconsistent and/or inefficient (Anselin, 1988). To consider spatial autocorrelation more directly, we used a spatial econometric tool based on a weight matrix

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[3] Values are calculated from the dataset described in section 3.

[4] Log-linear functional forms are adopted in case the dependent variable is strictly positive (e.g. Schlenker et al. (2006)). However, in our case, some observations (590) have negative net revenues and we regard it inappropriate to adopt log-linear functional form.

using the distance between observations. Spatial econometric analyses are often used in the Ricardian framework by incorporating the spatial lags of either the dependent or explanatory variables (e.g., Nicita et al., 2020) or the spatial lag of the error term (e.g., Schlenker et al., 2006). In this study, we used a spatial econometrics tool to deal with the spatial autocorrelation between the error terms and not to estimate the spillover effects of the dependent variable. Therefore, we estimated a spatial error model (SEM) in addition to the OLS model. The formulation of the SEM in this analysis is:

$$\boldsymbol{y} = \boldsymbol{\alpha I}_n + \boldsymbol{X\beta} + \boldsymbol{E\mu} + \boldsymbol{u}, \quad \boldsymbol{u} = \rho \boldsymbol{W u} + \boldsymbol{\varepsilon} \tag{2}$$

where $\boldsymbol{y}_{n\times1}$ is a vector of explanatory variables; $\boldsymbol{X}_{n\times k_1}$ and $\boldsymbol{E}_{n\times k_2}$ are matrices of climatic and exogenous variables, respectively; $\boldsymbol{W}_{n\times n}$ is an inverse-distance spatial weighting matrix; $\boldsymbol{\varepsilon}_{n\times1}$ is a vector of error terms; $\boldsymbol{I}_n$ is a unit matrix; ρ is a parameter of spatial correlation; and n, k_1, and k_2 are the sample size, number of climatic variables, and number of exogenous control variables, respectively.

The maximum distance between the two observations was set to 50 km, and the weights of observations more than 50 km apart were set to zero. The spatial weight matrix is symmetric, its diagonal elements are zero, and it is normalized such that its largest eigenvalue is one (Kelejian and Prucha, 2010). We adopt the maximum likelihood method to estimate Equation (2).

3. Data

Table 1 provides an overview and descriptive statistics for the variables. To determine farmers' net revenue, we used farm-level data from the statistical survey on farm management (SSFM) collected by the Ministry of Agriculture, Forestry, and Fisheries in 2012, 2013, and 2014. SSFM is uniformly and regularly collected throughout Japan and covers a variety of farms, including those that grow rice, vegetables, fruits, and livestock. When calculating the variables, we used three-year averages for each year. Because SSFM is unbalanced panel data, the sample size decreased from 2,747 to 2,468 after we calculate the three-year average of variables.

Table 1 Overview and descriptive statistics of the explained and explaining variables

Variable name	Description	Mean	S. D.	Min	Max	Source
Farm-specific socioeconomic variables						
Gross revenue	The sum of total agricultural revenue per utilized land, including self-consumption, and uses as a gift (100,000yen/ha, average from 2012 to 2014)	21.89384	17.1512	1.959603	147.5504	SSFM
Costs	The sum of total agricultural costs per utilized land, such as seeds, fertilizer, utility power, machinery, equipment, buildings, and hired labor costs (100,000yen/ha, average from 2012 to 2014)	15.37775	10.91585	2.21024	109.5603	SSFM
Net revenue	Gross revenue minus costs (100,000yen/ha, average from 2012 to 2014)	6.532779	9.127399	-13.3273	49.92805	SSFM
Farm size	Total agricultural land (10ha, average from 2012 to 2014)	0.844161	1.237095	0.0206	10.7298	SSFM
City-level socioeconomic variable						
Population density	Population density in 2015 (1000 people/km^2)	0.43326	0.76653	0.003839	10.07274	Census of Japan
Rural community level geographical variables						
Elevation	Mean elevation calculated from 250m square mesh (km)	0.134769	0.172706	-0.004	1.6789	Geographical Survey Institute
Slope	Minimum slope angle calculated from 250m square mesh (°)	1.121803	1.799025	0	19.7	Geographical Survey Institute
Paddy field ratio	The ratio of paddy fields to total arable land in the rural community	0.570897	0.374514	0	1	Census of Agriculture and Forestry
Field ratio	The ratio of the fields (for growing wheat, soybeans, vegetables, etc) to total arable land in the rural community	0.287791	0.334582	0	1	Census of Agriculture and Forestry
Soil type: andosol	The ratio of andosol area to total arable land in the rural community	0.013883	0.102733	0	1	Soil inventory, NARO
Soil type: LS	The ratio of lowland soil area to total arable land in the rural community	0.515002	0.41364	0	1	Soil inventory, NARO
Soil type: BFS	The ratio of brown forest soil area to total arable land in the rural community	0.079715	0.218983	0	1	Soil inventory, NARO
Rural community level climatic variables						
Prec. Winter (Dec.-Feb.)	Average precipitation 1990-2020 during winter (mm/day)	2.969764	1.991782	0.769637	12.87392	GSD, NARO
Prec. Spring (Mar.-May.)	Average precipitation 1990-2020 during spring (mm/day)	3.865489	1.459902	1.15287	10.05582	GSD, NARO
Prec. Summer (Jun.-Aug.)	Average precipitation 1990-2020 during summer (mm/day)	6.228826	2.597442	2.570011	17.99538	GSD, NARO
Prec. Autumn (Sep.- Nov.)	Average precipitation 1990-2020 during autumn (mm/day)	4.983194	1.325331	2.372659	11.07694	GSD, NARO
Temp. all season	Yearly average air temperature 1990-2020 (°C)	13.12682	3.536352	4.14692	24.17442	GSD, NARO
SR winter (Dec.-Feb.)	Average solar radiation 1990-2020 during winter (MJ/m^2/day)	7.818102	2.002927	0.709183	11.78585	GSD, NARO
SR spring (Mar.-May.)	Average solar radiation 1990-2020 during spring (MJ/m^2/day)	15.24829	2.509686	1.08761	18.69108	GSD, NARO
SR summer (Jun.-Aug.)	Average solar radiation 1990-2020 during summer (MJ/m^2/day)	15.70891	2.556067	1.391199	19.52244	GSD, NARO
SR autumn (Sep.- Nov.)	Average solar radiation 1990-2020 during autumn (MJ/m^2/day)	10.39114	1.937856	1.11532	13.57197	GSD, NARO
Sample size	2,468					

The dataset provides extensive information about farm structure and assets, production costs, revenues, and farming activities (e.g., conservation of resources and environment and business related to agricultural products) that can be input directly into the estimation model. Net revenue per hectare was calculated by subtracting costs from gross revenue. Gross revenue is the sum of all revenues from agricultural products. We included farmers' self-consumption and use as a gift in gross revenue because the Ricardian model assumes farmers' profit-maximizing behavior.

Costs include variable costs such as costs for seeds, fertilizer, energy, and depreciation and usage fees for machinery, equipment, and buildings. In addition, hired labor costs were included. However, household labor costs are not included because they can be measured in terms of hours but are difficult to value (Mendelsohn and Dinar, 2009: p.100).

This study focuses on farmers who mainly cultivate rice, vegetables, and fruits, and omits farms that mainly grow in greenhouses because climate affects them less. We also omit farmers who mainly engage in livestock farming because converting land from crop farming to livestock production, and vice versa, is expected to be very costly[5]. Some observations have extremely high or low net revenue. Therefore, we excluded observations with net revenues in the top and bottom 1 percentile. In addition, we dropped observations for which complete information on costs and revenues is not available. Consequently, 2,468 observations were extracted.

Control variables were selected based on previous Ricardian literature (Mendelsohn et al., 1994; Schlenker et al., 2006; Vanschoenwinkel et al., 2020). The variables included geographical (e.g., elevation, slope, paddy field ratio, field ratio, and soil type), socioeconomic (e.g., population density), and farmers' characteristics (e.g., farm size), which were also combined with the SSFM. The descriptions and sources of each variable are presented in **Table 1**. Except for farm size, all control variables used in the Ricardian analysis are at the village or rural community level and are presumed to be exogenous. Hence, this study does not violate the exogeneity assumption for the explanatory variables.

To create climate variables, we used the Agro-Meteorological Grid Square Data (GSD) created by the method of Ohno et al. (2016) and provided by NARO. Then, we combine

[5] Farmers who are engaged in livestock production and institutional vegetable production on the side are included in this analysis.

GSD with the SSFM. In contrast to the observed climatic data from meteorological observatories, the benefit of GSD is that it can available 1km mesh data and it enables to capture of the variation of climatic conditions more seamlessly. Daily average temperature, average precipitation, solar radiation, and other climatic conditions were available in one-kilometer grid square climatic datasets. In this study, we used the 30-year average from 1990 to 2020. We combined the climate data with the SSFM based on the rural communities in which farms are located[6].

As shown in **Table 1**, gross revenue, costs and net revenue vary across farmers. To see these differences across locations, we show the variation in gross revenue, cost, and net revenue between cities in **Fig. 1**. According to **Fig. 1**, the northern part of Japan (Hokkaido, Tohoku, and Hokuriku areas) shows lower gross revenues and costs per hectare. As for net revenue, these areas show fewer areas with larger net revenues than the southern regions. These areas are the main producers of rice and wheat in Japan, and farmers in these areas have larger agricultural areas. Therefore, the difference in net revenue can be partly attributed to the regional agricultural structure.

In the following section, we explore how the differences in net revenue are explained by a set of exogenous variables and estimate the future climatic effects on farmers' net revenue under the assumptions of the Ricardian analysis.

[6] Exact farmers' location information is unavailable due to privacy reasons.

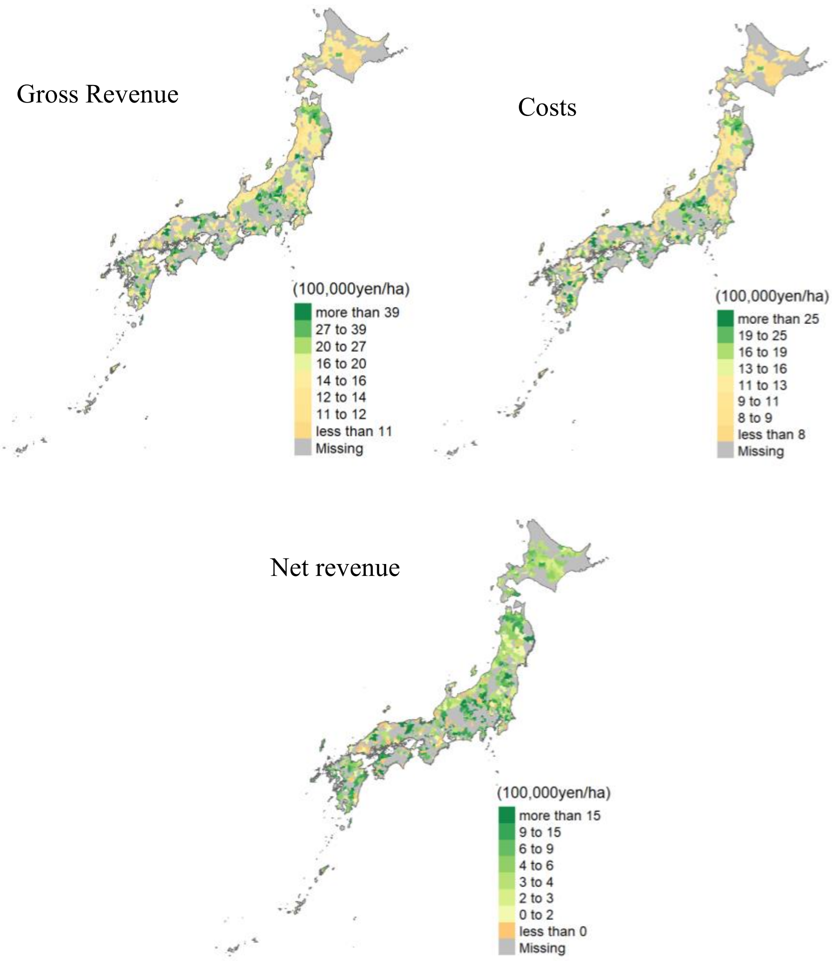

Fig. 1 Variation of gross revenue, costs, and net revenue across cities

Note: Gray areas indicate that we have no observations. The scale in the legend was set to the integer closest to the octile.

4. Results

4.1. Marginal effects

The first column of **Table 2** shows the results of the full model (Equation (1)) estimated by ordinary least squares (OLS) with cluster-robust standard errors. To check for spatial autocorrelation in OLS, we conducted the Moran test. We reject the null hypothesis that the error terms of OLS are independent and identically distributed ($\chi_1^2 = 96.60$), indicating that error terms of OLS are spatially correlated. As mentioned previously, the results of Moran test show that without considering spatial correlation, the estimated coefficients can be biased. Moreover, the value of the Akaike Information Criteria (AIC) is lower for the SEM than for OLS, indicating that the SEM is a more appropriate model in terms of information criteria. Hence, we focus on the SEM results in the interpretation of the results discussed below.

In the middle column of **Table 2**, we show the results of the full model estimated by SEM (Equation (2)). The coefficient of spatial correlation is positive and significant, indicating that the term $\rho \boldsymbol{W} \boldsymbol{u}$ in Equation (2) controls for positive spatial correlation between the error terms.

Most coefficients of the control variables exhibit the expected signs. Population density was positive and statistically significant. This is presumably because densely populated areas have high demand for food, higher farmers' net revenue. The slope coefficient was negative, which is consistent with the results of previous studies. Contrary to existing Ricardian studies, elevation is significantly positive. In regions with high altitudes, crops that cannot be produced in lower regions are grown. This may increase the value of those agricultural products. The coefficients for paddy field ratio and field ratio are negative, meaning that net revenues per hectare for rice and field crop production are lower than for the reference category, orchards. In terms of the soil type, only the Andosol coefficient was significant. Andosol is a soil that has exceptional water retention and nutrient capacity, and is suitable for vegetable cultivation. These characteristics may result in higher net revenue in andosol areas.

The coefficients of climate variables were the key parameters of interest in this study. According to the existing literature, precipitation variables significantly affect farmers' productivity (e.g., Van Passel et al., 2017; Zhang et al., 2017; Moretti et al., 2021). In this study, only spring precipitation had a significant effect on farmers' net revenue. Most farmers in Japan have access to irrigation and drainage systems, and only a few rely on rain-fed agriculture. This could partly explain why the precipitation coefficient is statistically insignificant during all seasons, except spring, when farmers require a large amount of water.

Table 2 Estimation results of the Ricardian model

	Full model						Without SR		
	OLS			SEM			SEM		
Farm size	-0.258	(0.109)	**	-0.138	(0.169)	***	-0.094	(0.168)	
Population density	0.798	(0.383)	**	0.807	(0.286)	***	0.930	(0.283)	***
Elevation	8.502	(1.693)	***	8.821	(1.659)	***	8.039	(1.585)	***
Slope	-0.332	(0.132)	**	-0.354	(0.122)	***	-0.373	(0.121)	***
Paddy field ratio	-11.747	(1.212)	***	-11.184	(0.920)	***	-11.465	(0.921)	***
Field ratio	-4.331	(1.392)	***	-3.481	(1.022)	***	-3.641	(1.030)	***
Soil type: andosol	0.097	(1.422)		-0.311	(2.342)		-2.228	(2.290)	
Soil type: LS	0.510	(0.508)		0.500	(0.529)		0.640	(0.530)	
Soil type: BFS	-0.532	(1.187)		-0.347	(0.928)		-0.100	(0.927)	
Prec. winter	0.365	(0.618)		0.615	(0.648)		0.435	(0.428)	
Prec. winter sq	-0.025	(0.045)		-0.039	(0.046)		-0.032	(0.037)	
Prec. spring	-3.197	(1.352)	**	-3.875	(1.435)	***	-3.820	(1.338)	***
Prec. spring sq	0.189	(0.120)		0.275	(0.134)	**	0.285	(0.130)	**
Prec. summer	-0.059	(0.578)		-0.052	(0.658)		-0.332	(0.619)	
Prec. summer sq	0.002	(0.029)		-0.005	(0.033)		0.009	(0.032)	
Prec. autumn	1.105	(1.268)		0.887	(1.251)		0.835	(1.181)	
Prec. autumn sq	-0.078	(0.105)		-0.054	(0.101)		-0.046	(0.100)	
Temperature	1.572	(0.467)	***	1.632	(0.575)	***	2.778	(0.454)	***
Temperature sq	-0.034	(0.019)	*	-0.033	(0.024)		-0.085	(0.016)	***
SR winter	0.062	(0.500)		0.117	(0.565)		-0.490	(3.798)	
SR spring	0.156	(0.767)		0.154	(0.853)				
SR summer	0.489	(0.389)		0.502	(0.499)				
SR autumn	-0.209	(0.854)		-0.185	(0.886)				
ρ				0.766	(0.078)	***	0.747	(0.079)	***
Adj-R^2	0.194								
Pseudo- R^2				0.191			0.185		
Log-likelihood	-8675.7			-8641.149			-8648.302		
AIC	17399.4			17334.3			17340.6		
Sample size				2,463					

Note: LS = Lowland soil; BFS = Brown forest soil; SR = Solar radiation. ***P<0.01, **P<0.05, *P<0. The figures in parentheses are standard errors. ρ is a parameter of the spatial correlation.

On the other hand, the coefficient of the linear temperature variable is positive and statistically significant, indicating that temperature has a positive effect on farmers' net revenue. The squared term for temperature was negative but not statistically significant. These results do not statistically support the hypothesis that temperature changes have a nonlinear effect on farmers' net revenue. However, when simulating future climate change effects, we used insignificant coefficients following previous research.

We calculated the marginal effect of temperature using Equation (3), the derivative of Equation (1):

$$ME = \frac{\partial y}{\partial T} = \beta_{T1} + 2\beta_{T2}T \quad (3)$$

where ME is the marginal effect of annual temperature. In **Fig. 2**, we show the regional differences in the marginal effect of temperature, that is, the change in net revenue per hectare caused by a 1°C increase in annual temperature. This shows that rising temperatures have a positive marginal impact in most parts of Japan. As mentioned previously, the Ricardian approach assumes farmers' full adaptation. This result shows that if all farmers in Japan fully adapt, the marginal effect of temperature may be positive in most of the country. Looking at **Fig. 2**, the positive impact of climate change is more noticeable in the north than in the south.

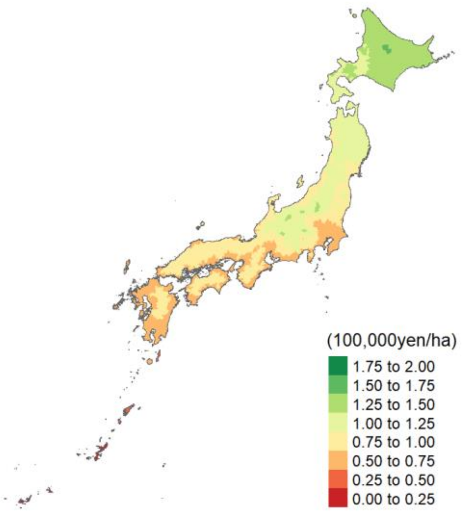

Fig. 2 Regional difference of marginal effects of temperature with 1°C

Previous research shows positive relationships between solar radiation in the cropping season and agricultural products' yield and quality. Although the coefficients of solar radiation in the winter, spring, and summer shows positive value, these results are not statistically significant. Unlike previous studies, this study assumes full adaptation. Therefore, the assumed adaptation measures have reduced the effects of solar radiation which is detected by previous studies on a single crop. As mentioned previously, when simulating future climate change effects, we used all coefficients including insignificant coefficients.

To examine the effects of including solar radiation in the regression analysis, we show the results of SEM without solar radiation in the last column of **Table 2**. We can see that the value of log-likelihood is lower, and AIC is higher in the model without solar radiation, indicating that the full model is more appropriate than the model without solar radiation in terms of log-likelihood and information criteria. No significant differences were observed in the precipitation coefficients. The precipitation coefficients of the full model were within the 95% confidence interval of the precipitation coefficients of the model without solar radiation, indicating that the differences between these coefficients were statistically undetectable. On the other hand, for temperature, the coefficients of the full model fall outside the 95% confidence interval of the coefficients of the model without solar radiation. This result implies that a model without solar radiation can overestimate the effects of temperature on the net revenue of farmers.

In addition to the results in **Table 2**, we performed a robustness check using farmers' rent values on the same explanatory variables as in **Table 2**. The result is that temperature showed significant and hill-shaped effects on farmers' rent values, but the model is not good at explaining the dependent variable (R^2=0.042). This may be partly because rent value is strongly influenced by institutional factors rather than climatic or geographical factors.

4.2. Future prediction

We calculated the non-marginal effects using future climate scenarios to estimate the long-term effects of climate change on agriculture. We use a "Bias-corrected future climate scenario based on CDFDM method using CMIP5" (hereafter BCS) calculated by Ishizaki et al. (2020) to assess changes in climatic conditions by 2100. BCS was calculated based on the GSD data. In BCS data, Representative Concentration Pathways (RCP) 2.6 and RCP8.5 were used as GHG emission scenarios. Four atmosphere-ocean coupled general circulation models (MIROC5, MRI-CGCM3, GFDL-CM3, and HadGEM2-ES)[7] based on

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[7] The source of each scenario is as follows: MIROC5: The University of Tokyo/National Institute for Environmental Studies/Japan Agency for Marine-Earth Science and Technology; MRI-CGCM3: Meteorological Research Institute (Japan); GFDL-CM3: National Oceanic and Atmospheric Administration (United States); HadGEM2-ES: The Met Office Hadley Centre (the UK).

these GHG scenarios were used in BCS. In this study, we used MIROC5 based on RCP8.5, as this scenario is often referenced in climate change impact projections in Japan (e. g. Okada et al., 2011; Kunimitsu et al., 2014) and shows similar current temperature changes to actual changes of temperature. We show how each of the climate variables changes by 2100 per region for MIROC5 based on RCP 8.5, as shown in **Appendix Fig. 1** This shows that the temperature increases are higher in the north than in the south. Solar radiation is expected to increase in the future because the changing climate will result in the decrease of cloud cover in Japan Shiogama et al. (2020).

Fig. 3 presents maps of the predicted changes in net revenue in percentage for the selected climate scenario by 2100[8]. The map on the left-hand side of **Fig. 3** is based on the coefficients of the full model (including solar radiation), whereas that on the right-hand side is based on the model without solar radiation[9].

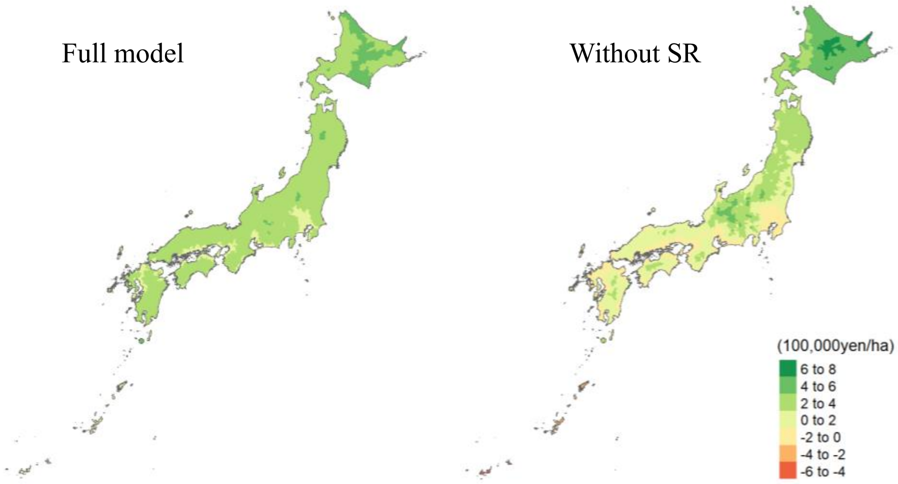

Fig. 3 Estimated change in net revenue per hectare from present to 2100

According to future predictions based on the full model, most of Japan will not experience negative net revenue changes due to climate change. The national average effect on net revenue was 241,800 yen/ha. The estimated increase as a percentage of current net revenue is about 37% (241,800/653,200). In northeast Japan, climate change has a more favorable

[8] When calculating future predictions, we used the difference between the thirty-year average from 1990 to 2020 and the thirty-year average from 2070 to 2100.
[9] Future predictions are made using the SEM regression coefficient.

effect on farmers' net revenue. Meanwhile, the southwest island (Okinawa) has experienced adverse effects from climate change. This value is large and optimistic compared with previous studies. As discussed below, we should be cautious about the assumptions of the Ricardian model when interpreting this value.

The results from the model without solar radiation on the right-hand side of **Fig. 3** show negative effects in the southern areas (Kyushu and Okinawa). The overall estimated effect was less beneficial than that of the full model, and the national average effect on net revenue was 19,300 yen/ha. The estimated increase, expressed as a proportion of the existing net revenue, is approximately 3% (241,800/653,200). Regional differences—climate change is beneficial in northern areas and harmful in southern areas—are consistent with past literature in Japan (e.g. Kunimitsu et al., 2014; Kawasaki and Uchida, 2016). The difference between the full model and the model without solar radiation can be attributed to the difference in the estimated marginal effects of the temperature, as shown in **Table 2**.

We divided the changes in net revenue of the full model according to climatic conditions, as shown in **Appendix Fig. 2**. When considering only temperature, the estimated change in net revenue is positive in most areas, except for Okinawa. In addition, when considering only solar radiation, the estimated change is also positive across Japan but less than the temperature. In contrast, the estimated change caused by precipitation was negative in most parts of Japan. These results show that the estimated changes in the full model were primarily driven by changes in temperature.

To investigate the mechanisms and validity of future predictions, we compared them with the results of existing studies that did not consider full adaptation. Unlike the results of this study, existing studies show that increasing temperatures result in a reduction of crop yield and degradation of quality, especially in the southern part of Japan (Kunimitsu et al., 2014; Kawasaki and Uchida, 2016). The difference between the results of this study and the existing literature on Japanese agriculture would have resulted from Ricardian analysis's implicit assumption of farmers' adaptation to climate change. As shown in **Fig. 1**, farmers have less net revenue per land in the northern part of Japan (Hokkaido), partly because they produce lower-value agricultural products. The fact that Ricardian analysis implicitly assumes a conversion from low-to high-profit crops may have led to the results of this study. In addition, in the southern region, this study may implicitly assume fundamental changes in cropping methods, including double cropping (Kawasaki, 2019). If we follow the assumptions of the Ricardian analysis, farmers do not have to incur adjustment costs and autonomously invest in infrastructure that is suitable for crops with higher net revenue (Kelly et al., 2005). Therefore, we should be cautious that these estimates can be interpreted as a rather positive scenario of climate change impacts on Japanese agriculture.

5. Summary and Conclusions

This study conducted Ricardian analysis to assess the effects of climate change on Japanese agriculture. To account for the situation in Japan, where rice is the main agricultural product, we incorporated solar radiation when estimating Ricardian regression. The main findings of this study are as follows: First, the coefficients of Ricardian regression show that changes in temperature significantly impact farmers' net revenue, even after accounting for the adaptation measures. In contrast, except for spring, the effect of precipitation change on farmers' net revenue was not statistically significant. Although the inclusion of solar radiation can improve the fitness of the model in terms of information criteria, solar radiation did not show a statistically significant impact on farmers' net revenue. Taking these factors into consideration, the results do not necessarily support the point made by Zhang et al. (2017), which shows that incorporating a climatic condition that is important for crops in the studied region—in this case, rice—is important when modeling a Ricardian regression.

As a result of our future predictions based on Ricardian regression, negative effects of climate change are not observed in most regions in Japan, and northern regions are expected to benefit more than the southern regions. This result indicates that it is possible to increase agricultural productivity and mitigate the negative impacts of climate change if farmers adopt full adaptation strategies. However, as mentioned previously, full adaptation includes adaptation measures with high economic costs, such as the development of agricultural production infrastructure, which are assumed to be implemented voluntarily. Therefore, this result can be interpreted as a more optimistic scenario for climate change impacts on agriculture.

Finally, we briefly discuss this study's limitation and issues to be addressed in the future, The Ricardian assumption is valid only if there is no cost for adaptation measures, such as crop changes or double cropping, but in fact, farmers must bear the costs. To evaluate farmers' adaptation potential, it may be useful to adopt the long-difference model (Burke and Emerick, 2016), which used long panel data to evaluate the adaptation potential of farmers. In addition, assessing the relationship between climate change and farmers' adaptation behavior may provide valuable insights into climate change adaptation policies (Cui, 2020). Hence, in addition to relying on the assumption of implicit adaptation in Ricardian analysis, studies on farmers' explicit adaptation should be addressed in future research.

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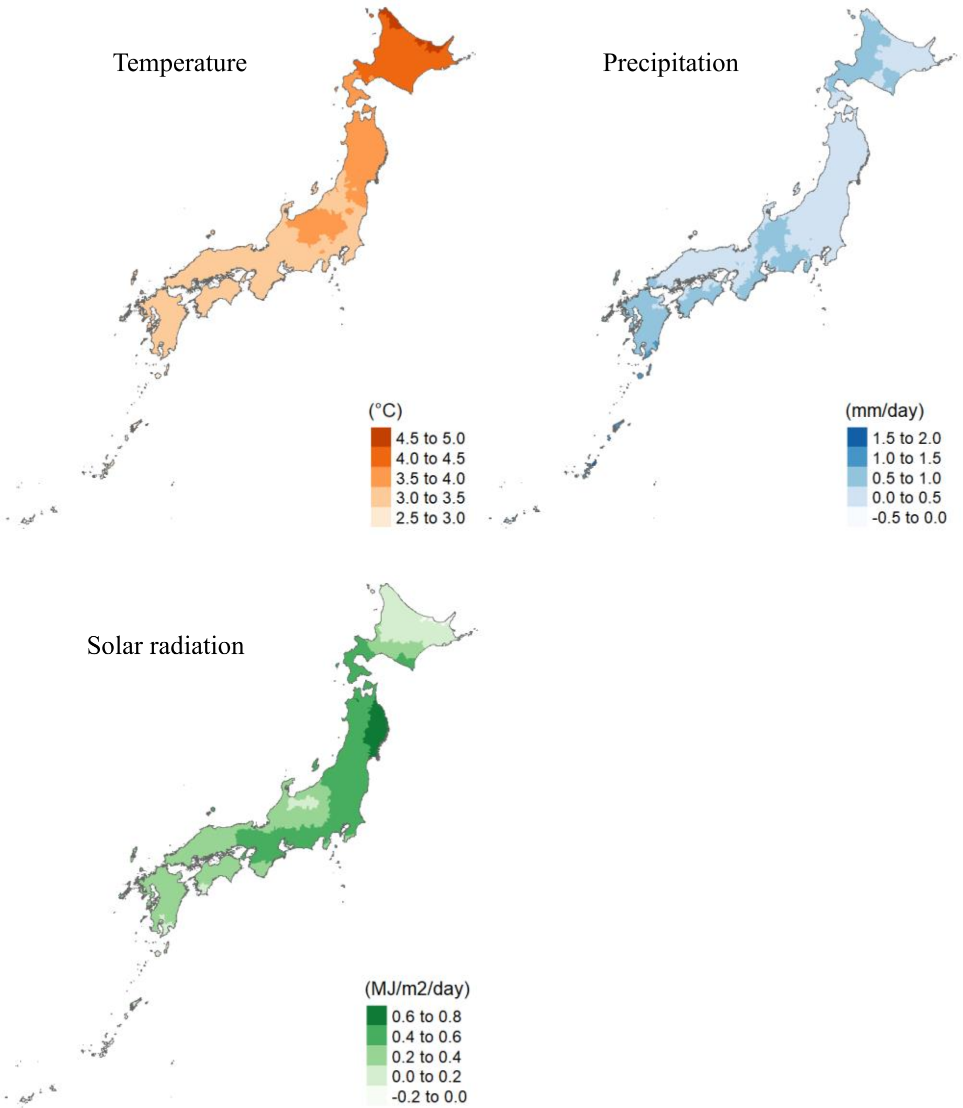
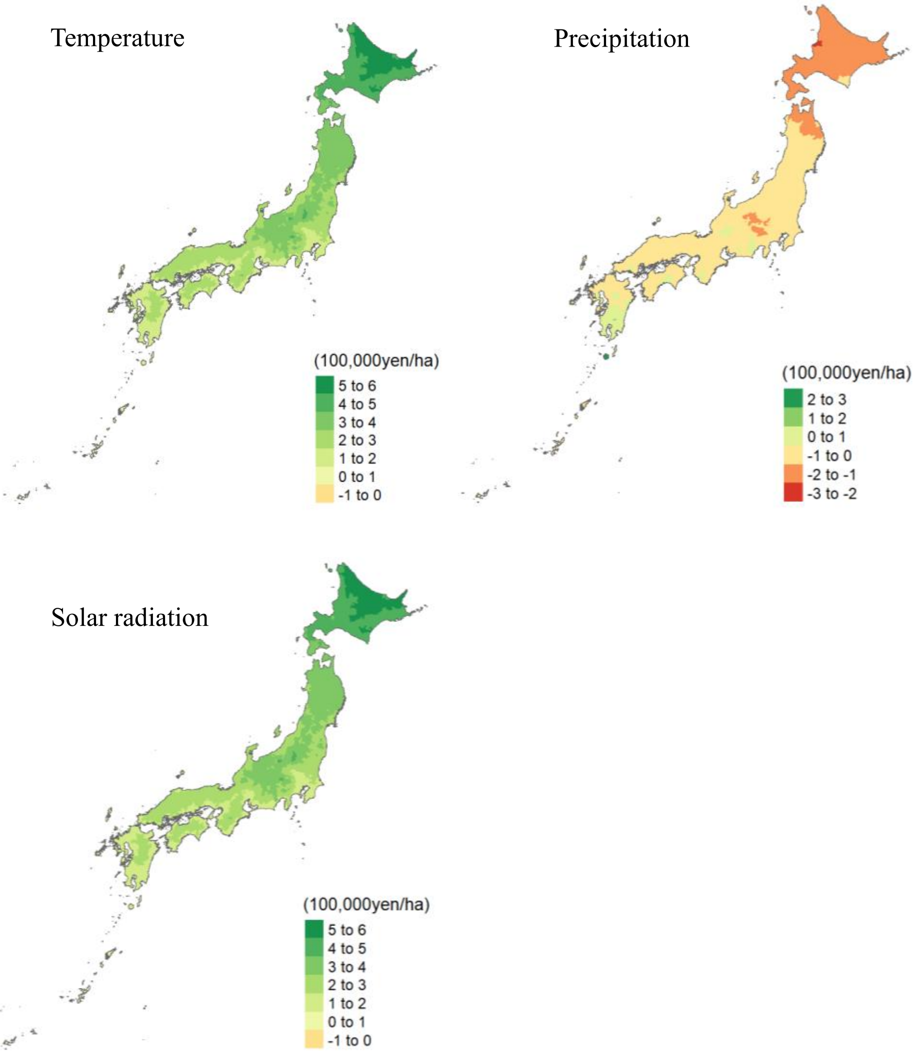


Appendix Fig. 1 Changes in each climatic conditions to 2100 in MIROC5 based on RCP8.5 scenario



Appendix Fig. 2 Estimated changes in net revenue to 2100 by each climatic condition based on the full model estimated by SEM