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Fluctuations in Rice Productivity Caused by Long and Heavy Rain Under Climate Change in Japan: Evidence from Panel Data Regression Analysis

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Abstract

The incidence of extreme rain is expected to increase with climate change and affect rice productivity in Japan. This study aims to evaluate the impacts of long and heavy rain on Japanese rice total-factor productivity (TFP) by estimating causality functions. We measured rice TFP by using the Törnqvist-Theil and Malmquist indexes for dependent variables and predicted, the influences of future temperature and rain on rice TFP by the causality function associated with crop models and a hydrological model based on climate projections from the global-climate model (GCM). The results initially showed no significant differences between Törnqvist-Theil and Malmquist indices in the effects of climate factors, although some differences emerged in the causality of socioeconomic factors. Second, the effects of rain were always negative, and absolute TFP elasticity against rain was lower than temperature via yield and quality, but poorly drained surface water as well as flooding reduced rice TFP by 2.5 to 4.5%. Third, changes in predicted rainfall under future climate change caused annual rice TFP to fluctuate, and an impact of rain on TFP fluctuations exceeded that of temperature via yield and quality. This is due to significant variations in annual rainfall, even though the measured elasticity against rain was low. Based on these findings, the implications for research and policy-making are discussed.

Discipline: Agricultural economics
Additional key words: global climate model, hydrological model, Malmquist index, total factor productivity, Tönqvist-Theil index

Introduction

Rice production depends on climate conditions such as temperature, rainfall, solar radiation and atmospheric carbon dioxide concentrations. Amid global warming, heavy rain is becoming increasingly frequent and serious in Japan (Nakakita *et al.* 2011). The rainfall pattern is also supposed to change by future climate change, whereupon Japanese rice productivity will be affected by severe floods caused by heavy rain and poorly drained surface water from long rain. To sustain Japanese rice production under long term climate change and to consider countermeasures, an economic evaluation of the influences of rain on rice productivity is essential.

Long and heavy rain affects rice productivity in mainly two ways. First, flood disasters reduce production, particularly during ripening and harvest seasons. Second, production costs increase due to the poorly drained surface water in paddy fields, slowing down the reaping of the harvest machinery, while increasing farmers' overtime work and rise in the break-down rate of agricultural machinery. Moreover, farmers need to spend more on repairing fields and pumping drainage water. These costs are difficult to estimate by bottom-up methods calculating production and costs item by item. Accordingly, to evaluate the influences of heavy rain, we focused on rice total factor productivity (TFP), which represents both production and cost changes.

Kunimitsu *et al.* (2014) evaluated the influences of climate and socioeconomic factors on Japanese rice TFP. This analysis showed that the influence of climate conditions on TFP via the yield index was equivalent to that of socioeconomic factors such as economies of scale. However, there was insufficient consideration of paddy drainage in this

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analysis, even though maximum rainfall during August to September was introduced as one of the causative factors. Since drainage conditions for floods are regulated by not only rainfall but also geographical situations and drainage systems, a hydrological model is needed to precisely quantify the influences of floods on paddy fields.

The purpose of the present study is to evaluate the impacts of long and heavy rain in addition to a rise in temperature on Japanese rice TFP by estimating the causality function of rice TFP. Rice TFP is measured by the Törnqvist-Theil index (T-index) and Malmquist index (M-index) to determine general effects. Using these indices, we estimate the regression function of rice TFP and causative climate factors associated with crop-yield, crop-quality and hydrological models by applying panel data analysis. Future TFP levels are subsequently predicted by this model according to climate projections of the global-climate model (GCM), Model for Interdisciplinary Research On Climate (MIROC high-resolution version 3), for policy implications.

The structure of this paper is as follows. The second section introduces previous studies and indicates scientific questions. The third section explains methods and the fourth section shows data composition and sources. The fifth section presents estimations and discusses future levels of rice TFP under climate change projected by MIROC. Based on these findings, the final section concludes with research and policy implications.

Literature review and scientific questions

TFP shows technological change and is calculated by the ratio of total output to total costs, as measured by the sum of each input factor weighted with the share rate of factor income. Compared to the production function approach, the TFP index allows many causative factors for TFP changes to be taken into consideration and increases the flexibility of the functional form.

Using the TFP index, Denison (1979) analyzed causalities in US industries and determined economies of scale as the most significant factors in TFP growth. After his work, many studies analyzed agricultural TFP and defined several causative factors including economies of scale (Thirtle *et al.* 2008), research and development (R&D) activities (Alene 2010, Pratt *et al*. 2009), human capital (Astorga *et al*. 2011), soil quality (Jayasuriya 2003), and public facilities such as roads or irrigation and drainage facilities (Suphannachart & Warr 2010, Chen *et al*. 2008).

Salim and Islam (2010) considered climate change as a factor that affected TFP measured by the T-index and showed that the influence of long-term climate change on TFP in Australian agriculture was equivalent to that of R&D expenditures. Nin-Pratt and Yu (2010) estimated the agricultural TFP of 63 developing countries based on the M-index, and found that agricultural TFP had been growing steadily over the past 20 years, particularly in Sub-Saharan African countries, However, they did not consider countries like China, Brazil and India. Yamamoto *et al*. (2007) quantified rice TFP by the M-index, and showed that regional gaps in TFP existed and did not converge over time in Japan. Umetsu *et al*. (2003) measured chronological changes in Philippine rice productivity by the M-index and showed that rice productivity had improved following the green revolution and that such changes were different by region. As such, numerous previous studies have been carried out in this field, but few studies have evaluated differences between T-index and M-index with causative factors. Also, previous studies evaluating climate conditions as a causative factor in Japanese rice TFP are few, so it is important to determine how climate conditions, particularly long and heavy rain, may affect Japanese rice productivity.

Methodology

1. Measurement of TFP

The T-index and M-index are major indices used to quantify TFP and show the technological progress of industries. The T-index is a discrete approximation of the Devisia index and the most harmonized index with a trans-log type production function that is flexible for biased technological progress (Diewart 1976). Analysts assume optimal behavior of producers in the objective industry, when they apply this index to real data. The annual TFP growth rate can be defined by the T-index as follows:

$$\ln(TFP_{r,t}/TFP_{r,t-1}) = \ln(y_{r,t}/y_{r,t-1}) - \sum_i [0.5(\alpha_{i,r,t} + \alpha_{i,r,t-1})\ln(x_{i,r,t}/x_{i,r,t-1})] \quad (1)$$

Here, the suffixes *r*, *t*, and *i* respectively show the region, year and input factors. *y* is the total rice production, *x* is each input factor of production, i.e. farmland area, labor, capital stocks and intermediate inputs. α is the annual production elasticity of each input factor against production. This share rate corresponds to the cost-share rate, when the production function is homogeneous and farmers optimize their production. To compare regional TFP levels, the initial value of TFP_{r,t_0} (t_0=1979) is calibrated in each region by removing *t*-1 terms in Eq. (1) as:

$$\ln(TFP_{r,t_0}) = \ln(y_{r,t_0}) - \sum_i \alpha_{i,r,t_0} \ln(x_{i,r,t_0}) \quad (2),$$

where, t_0 means the initial year of analysis. y_{r,t_0} and x_{r,t_0} are both measured by the monetary unit to obtain a TFP value without dimension. The chronological levels in regional TFP are then calculated by multiplying the growth rate of TFP calculated in Eq. (1) to the initial TFP of 1979 in Eq. (2).

Conversely, the M-index is the geometric mean of output-based technological gaps in two periods. Technological gaps are measured by the distance from production of individual decision-making units (or a specific region) to the production frontier, as observed by non-parametric procedures such as the data envelopment analysis (DEA) (Fare *et al*. 1994). This allows decision-making units to produce with relatively outdated technology. In addition, the M-index can treat multiple outputs with multiple inputs. However, measurement error tends to cause significant problems in the DEA used for this index as compared to other indices, and the original TFP level cannot be calculated reversely from this index.

Chronological changes in TFP by the M-index are defined as:

$$TFP_{r,t+1} / TFP_{r,t} = \left[\frac{d_{r,t}(\mathbf{x}_{t+1}, \mathbf{y}_{t+1})}{d_{r,t}(\mathbf{x}_t, \mathbf{y}_t)} \times \frac{d_{r,t+1}(\mathbf{x}_{t+1}, \mathbf{y}_{t+1})}{d_{r,t+1}(\mathbf{x}_t, \mathbf{y}_t)} \right]^{½} \quad (3),$$

where $d(\cdot)$ is the function used to measure the distance between the production frontier and production point, as represented by the output vector **y** and input matrix **x**. Hereafter, gothic characters show vectors or matrices. A greater value than one in Eq. (3) indicates positive TFP growth from periods t to t+1 in region r. The concrete values for $d(\cdot)$ in this equation are calculated by a linear-programming method in DEA that constructs a piece-wise surface over data (Coelli 2008). The initial value of TFP_{r,t_0} for the M-index is also calculated by the DEA method with cross-sectional data in the first year of the data period. To compare the M-index and T-index, initial values of the T-index of Hokkaido, where the cross-sectional M-index becomes the highest value of 1, is multiplied by the initial value of the M-index calculated as above in all regions. The estimation coefficients of causative factors in the latter regression analysis are the same as the case of the raw initial M-index, because the same value is multiplied by the M-index in all regions and regression functions for TFP causality are of the log-linear type.

2. Model for causalities in rice TFP

Based on previous studies (Kuroda 1989, 1995), we assume economies of scale and R&D investments to be the best candidates for causative factors to increase rice productivity. In addition to these socioeconomic factors, rice TFP is also influenced by climate factors due to changes in harvest quantity, quality and drainage situations (Kunimitsu *et al*. 2014). The regression model assumed here is:

$$\begin{aligned} \ln(TFP_{r,t}) = {} & \beta_0 + \beta_1 \ln(MA_{r,t}) + \beta_2 \ln(KKn_t + KKp_{r,t}) + \\ & \beta_3 POP_{r,t} + \beta_4 \ln(CHI_{r,t}) + \beta_5 \ln(CQI_{r,t}) + \\ & \beta_6 \ln(CRI_{r,t}) + \beta_7 \ln(CFI_{r,t}) + \varepsilon_{r,t} \end{aligned} \quad (4)$$

where, MA, KKn, KKp and POP are socioeconomic causative factors and CHI, CQI, CRI and CFI are climate causative factors. β*'s* are the parameters to be estimated, and ε is the error term.

MA is economies of scale represented by the average farm management area per management organization; KKn represents nationwide R&D capital stocks of the central government, universities and private companies, while KKp represents R&D capital stocks of the prefectural government. KKn is assumed to be pure public goods and uniformly improve rice TFP in all regions, so the same KKn is used for all regions without any r suffix, whereas KKp is assumed to represent local knowledge and influence only prefectural TFP. POP is the population density within the area of inhabitable land, representing the influence of urbanization. Labor costs and agricultural service prices would be higher in urban than rural areas due to competition for input factors both among industries and farmers producing different agricultural crops. When such competition intensifies, β_3 becomes significant and negative.

CHI is the rice-yield index; CQI is the rice-quality index; CRI is the long-rain index representing poorly drained surface water in the crop fields; and CFI is the flood index caused by heavy rain. CHI, CQI and CFI are estimated by only climate conditions such as temperature, solar radiation and rainfall with crop-yield, crop-quality and hydrological models, respectively. CRI is measured by total rainfall during August and September of rice maturing and harvest seasons. By such treatments, no endogenous problems occur in the reverse interrelation between dependent and independent variables, because climate conditions (such as temperature and rainfall) are the basis for estimated climate factors and cannot be affected by TFP.

3. Socioeconomic factors

Socioeconomic factors, i.e. average farm management area per management organization, MA, and population density, POP, are directly obtained from the statistics, but KKn and KKp need to be estimated from annual R&D expenditures. We employed the perpetual-inventory (PI) method to quantify R&D capital stocks, based on a report by the Cabinet Office of Japan (2010). This method fits circumstances where technology diffuses to producers with time lags (Lag) and is used and then abandoned after several years (N). Such relationships are expressed by:

$$KKn_t = In_{t-Lag} + In_{t-Lag-1} + \cdots + In_{t-Lag-N} \quad (5),$$

$$KKp_t = Ip_{t-Lag} + Ip_{t-Lag-1} + \cdots + Ip_{t-Lag-N} \quad (6).$$

Here, In and Ip are R&D expenditures by sector.

The Cabinet Office of Japan (2010) showed that the time lag was approximately three years and durable years were about 10 years. These years were measured by questionnaires distributed to the managers of private companies. Based on the survey results, Lag=3 and N=10 are set in Eqs. (5) and (6).

4. Climate factors

The crop-yield model to estimate CHI is based on Kawazu *et al*. (2007) and newly estimated by the latest data (Table A1 in Appendix). The model used here is:

$$CHI_{r,t}/(SR7_{r,t}+SR8_{r,t}+SR9_{r,t})=a_0+a_1\cdot TM7_{r,t}+a_2\cdot TM7^2_{r,t}+a_3\cdot TM8_{r,t}+a_4\cdot TM8^2_{r,t}+a_5\cdot TM9_{r,t}+a_6\cdot TM9^2_{r,t}+\varepsilon_{r,t} \quad (7),$$

where, $SR7$, $SR8$, $SR9$ represent the average daily solar radiation in July, August and September; $TM7$, $TM8$, $TM9$ are the average daily temperature in July, August and September; a's are the coefficients to be estimated and ε is the error term.

In the estimation results of Eq. (7), a_2, a_4 and a_6 became negative and showed non-linear relationships between yield and temperature. Temperature increased rice yield until a threshold temperature of approximately 20.0°C in July and August, but after this level, higher temperatures decreased rice yield. For temperatures in September, the estimated threshold value was too high to restrict rice yield, simply showing increases with diminishing marginal effects under actual circumstances.

The crop-quality model used to estimate CQI is also based on Kawazu *et al*. (2007). This model assumes that extremely high temperatures and insufficient solar radiation cause rice quality to decline by causing a chalky color and cracked rice. The equation is as follows and is newly estimated in Table A2 of the Appendix:

$$CQI_{r,t}=b_0+b_1\cdot SR7_{r,t}+b_2\cdot SR8_{r,t}+b_3\cdot ABS(TL78_{r,t}-\overline{TL})+\varepsilon_{r,t} \quad (8).$$

Here, b*'s* are parameters and ε is the error term. $SR7$ and $SR8$ are the average solar radiation in July and August, the critical months for maturing after heading time. $TL78$ is the average minimum daily temperature during July and August. $\overline{TL}$ is the threshold temperature, and is set at the best-fit estimation with respect to log likelihood values, as estimated by changing the threshold temperature by 0.01 from 18 to 25°C. At a temperature of 19.34°C (Table A2), estimations showed the highest log likelihood value. This temperature exceeds the average minimum temperature in northern Japan, including Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima and Nagano prefectures, but is lower than in other prefectures. Accordingly, positive influences dominate in these prefectures, but negative influences are frequent in other prefectures under present circumstances.

The long-rain index, CRI, is measured by the sum of rainfall during August and September. To quantify CFI that

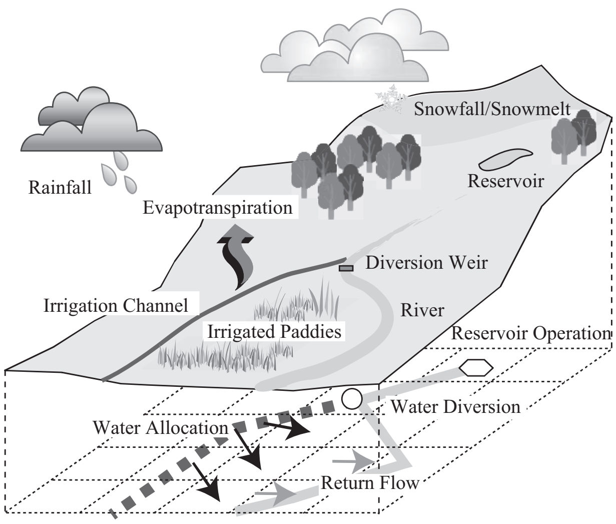

Fig. 1. Conceptual diagram of the hydrological (distributed water circulation) model Source: Yoshida *et al*. (2012)

indicates floods during the maturity and harvest stages of rice in August and September, a hydrological model (distributed water circulation model) was used (Fig. 1). The model used is based on Masumoto *et al*. (2009) and Yoshida *et al*. (2012). CFI is measured as the total unit outflow per terrain mesh area during the typhoon season in August and September as follows:

$$Q_{out\,j}=f(Ea_j, RAIN_j, Q_{in}, \mathbf{GEO}_j) \quad (9),$$

$$CFI_{r,t}=\max_t\left(\sum_{j\in r} Q_{out\,j,day,t}\right)/AREA_r \quad (10),$$

where, $f(\cdot)$ shows the function that calculates outflow, Q_{out}, from j-th terrain mesh. Ea is the evapotranspiration, $RAIN$ is the daily rainfall, and Q_{in} is the inflow to the terrain mesh. **GEO** represents geographic structures, such as land use, land slope, the conditions of rivers and geology of each terrain mesh, and is quantified by a geographical information system. The $\max_t(\cdot)$ function selects the maximum value of daily outflow to show the most severe floods in year t, and assumes that more outflow causes flood disasters to worsen. After calculating outflow for each mesh, only paddy meshes with paddy fields inside are selected and aggregated as the total outflow. Subsequently, the maximum total outflow among total outflows in paddy meshes is selected and divided by the total area of the paddy meshes, $AREA$, in each prefecture to eliminate the regional scale effects.

The parameters of the hydrological model are the same as Kudo *et al*. (2013). Typical outflow and rainfall relationships are shown in Fig. 2. These variables correlate, but some years show extreme values in either variable, because the steepness and use of land determine the rate of unit outflow against rainfall, which differs by region. In general,

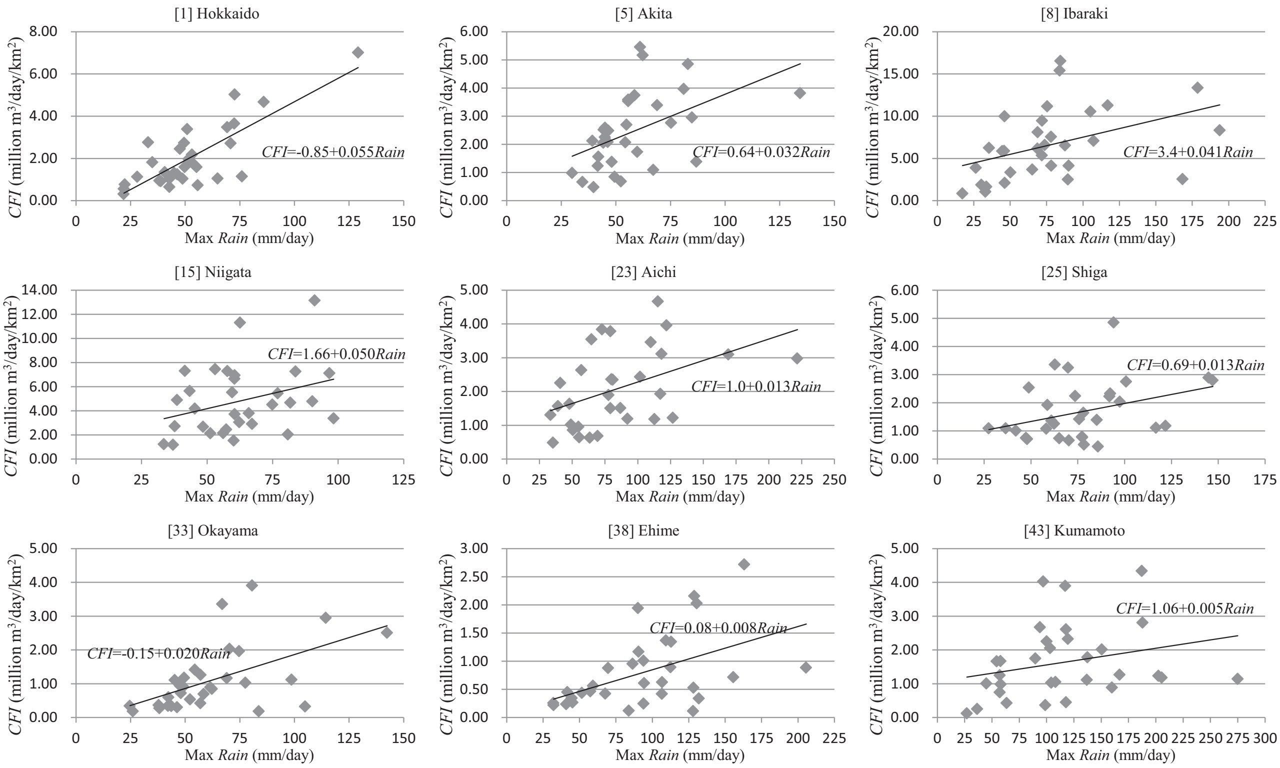

Fig. 2. Relationships between outputs of the hydrological model and rainfall

Note: The vertical axis is the maximum unit outflow estimated by the hydrological model and the horizontal axis shows the actual maximum rainfall during August and September for each year. The tangent of the approximate curve shows the geographical characteristics of the catchment area. Numbers in square brackets are prefectural codes designated by the Ministry of Internal Affairs and Communications.

the slope of unit outflow against rainfall is steep in regions with a large catchment area.

Data

The data comprised panel data to estimate regression models. Using panel data instead of individual regional data allows us to: (i) determine regional differences in rice TFP, (ii) increase the degrees of freedom for estimations and (iii) eliminate the effects of latent factors that equally change TFP for all regions (Kitamura 2005). Data covered around 38 prefectures and 31 years from 1979 to 2010, except 1993 when serious damage from cold weather occurred and cost data were not observed in the statistics for the major rice-producing prefectures. The objective 38 prefectures are shown in Fig. 3. Tokyo, Kanagawa, Yamanashi, Osaka, Nara, Wakayama, Saga, Nagasaki and Okinawa were excluded because rice production was relatively small and cost data in these prefectures were not published as official statistics.

Data to calculate the T-index and M-index were obtained from *Cost Research for Rice Production* (Ministry of Agriculture, Forestry and Fishery; MAFF). All nominal values were deflated by the price index published in *Economic Accounts for Agriculture and Food Related Industries* (MAFF). The farm management area per farm organization, *MA*, also came from *Cost Research for Rice Production* (MAFF). R&D expenditures, *In* and *Ip*, were collected from the statistics of the *Investigation Report on R&D Expenditures for Scientific Technology* (Statistics Bureau of Ministry of Public Management, Home Affairs, Posts and Telecommunications, every year). The data for climate conditions used in *CHI*, *CQI*, *CRI* and *CFI* were taken from the data of the Automated Meteorological Data Acquisition System (AMeDAS) from 1979 to 2010 (except for 1993 as with the other variables) (Okada *et al*. 2009). Table 1 shows the descriptive statistics of the variables.

For predictions, future climate conditions, including temperature, solar radiation and rainfall, were drawn from the downscaled outputs of the global-climate model, the high-resolution version of MIROC (K-1 Model Developers 2004, Okada *et al*. 2009). The greenhouse gas emission scenario used here was A1B, which represented balanced growth alongside rapid economic growth, low population growth and the rapid introduction of more efficient technology in the Special Report on Emission Scenario (SRES) (Nakicenovic & Swart 2000). In terms of socioeconomic factors, trends of R&D expenditures from 1966 to 2010

Fig. 3. Location of prefectures in the 9 regions studied

Note: Tohoku includes 6 prefectures: [2] Aomori, [3] Iwate, [4] Miyagi, [5] Akita, [6] Yamagata and [7] Fukushima. Kanto includes 6 prefectures: [8] Ibaraki, [9] Tochigi, [10] Gunma, [11] Saitama, [12] Chiba and [20] Nagano. Hokuriku includes 4 prefectures: [15] Niigata, [16] Toyama, [17] Ishikawa and [18] Fukui. Tokai includes 4 prefectures: [21] Gifu, [22] Shizuoka, [23] Aichi and [24] Mie. Kinki includes 3 prefectures: [25] Shiga, [26] Kyoto and [28] Hyogo. Chugoku includes 5 prefectures: [31] Tottori, [32] Shimane, [33] Okayama, [34] Hiroshima and [35] Yamaguchi. Shikoku includes 4 prefectures: [36] Tokushima, [37] Kagawa, [38] Ehime and [39] Kochi. Kyushu includes 5 prefectures: [40] Fukuoka, [43] Kumamoto, [44] Oita, [45] Miyazaki and [46] Kagoshima. The remaining 9 prefectures, where polygons are white and numbers missing, are excluded because data for rice production cannot be obtained from statistical databases.

were assumed to continue until 2100. The future values of *MA* were set until 2100, based on past *MA* trends in each region.

Empirical findings and discussion

1. Chronological change in TFP by regions

Figure 4 shows the chronological changes in actual rice TFP for each region, as calculated by the T-index and M-index. Nine of a total 38 prefectures were selected to represent different locations in Japan[1]. Northern regions, including Hokkaido, Akita and Niigata, marked higher productivity than southern regions, because of differences in socioeconomic factors as well as climate conditions.

Chronologically, rice TFPs of most regions increased from 1979 to 2010, showing improvements in rice productivity. The correlation coefficients of both indices exceeded 0.7 for 27 prefectures, but 11 prefectures, i.e. Ibaraki,

[1] Nine prefectures, i.e. Hokkaido, Akita, Ibaraki, Niigata, Aichi, Shiga, Okayama, Ehime and Kumamoto, were selected from 9 representative regions classified by the "Agricultural Census" (Ministry of Agriculture, Forestry and Fishery). The rice-production areas in these prefectures except for Shiga are the largest within each region. Shiga, which is the second largest rice-production prefecture in the Kinki area, was selected rather than Hyogo, because Hyogo is next to Okayama that was selected for the Chugoku region.

Table 1. Descriptive statistics of variables used to estimate TFP and CQI functions

Variables	Contents	Unit	Average	Std. Dev.
TFP_T	Rice TFP (T-index)	-	1.81	0.39
TFP_M	Rice TFP (M-index)	-	2.01	0.39
MA	Mangement area per farm household	ha/farmer	0.98	0.79
KKn	Knowledge capital (nation wide)	100 billion yen	18.74	3.94
KKp	Knowledge capital (Prefecture)	100 billion yen	0.43	0.24
CHI	Rice yield per area (actual)	ton/ha	4.93	0.52
*CHI**	*CHI* estimated by the crop growth model (Appendix)	-	4.95	0.53
CQI	Percentage of the 1st grade rice (actual)	%	67.64	20.06
*CQI**	*CQI* estimated by the crop quality model (Appendix)	-	67.64	9.07
CRI	Long rain index representing illdrained surface water on the crop fields	100 mm/two months	5.80	2.36
CFI	Flood index estimated by the hydrological model	10 million m^3 /day /km^2	2.44	2.53
SR7	Solar radiation in July	MJ/m^2	16.85	2.31
SR8	Solar radiation in August	MJ/m^2	17.33	2.20
SR9	Solar radiation in September	MJ/m^2	13.45	1.45
TM7	Maximum daily temperature in July	Deg.C	23.71	2.00
TM8	Maximum daily temperature in August	Deg.C	24.87	1.71
TM9	Maximum daily temperature in September	Deg.C	21.12	2.03
TL78	Average minimum daily temperature during July and August	Deg.C	20.82	1.73
POP	Population density (pop. per inhabitable area)	1000 people /km^2	0.94	0.56

Note: *CHI* and *CQI* are the actual values used to estimate crop-growth and crop-quality models, and *CHI** and *CQI** are the fitted values of the estimations. To estimate *CHI** and *CQI**, the fixed-effect models shown in Table A1 and A2 were used with actual climate conditions, but the fixed-effect coefficients were not used to eliminate latent effects in the estimations.

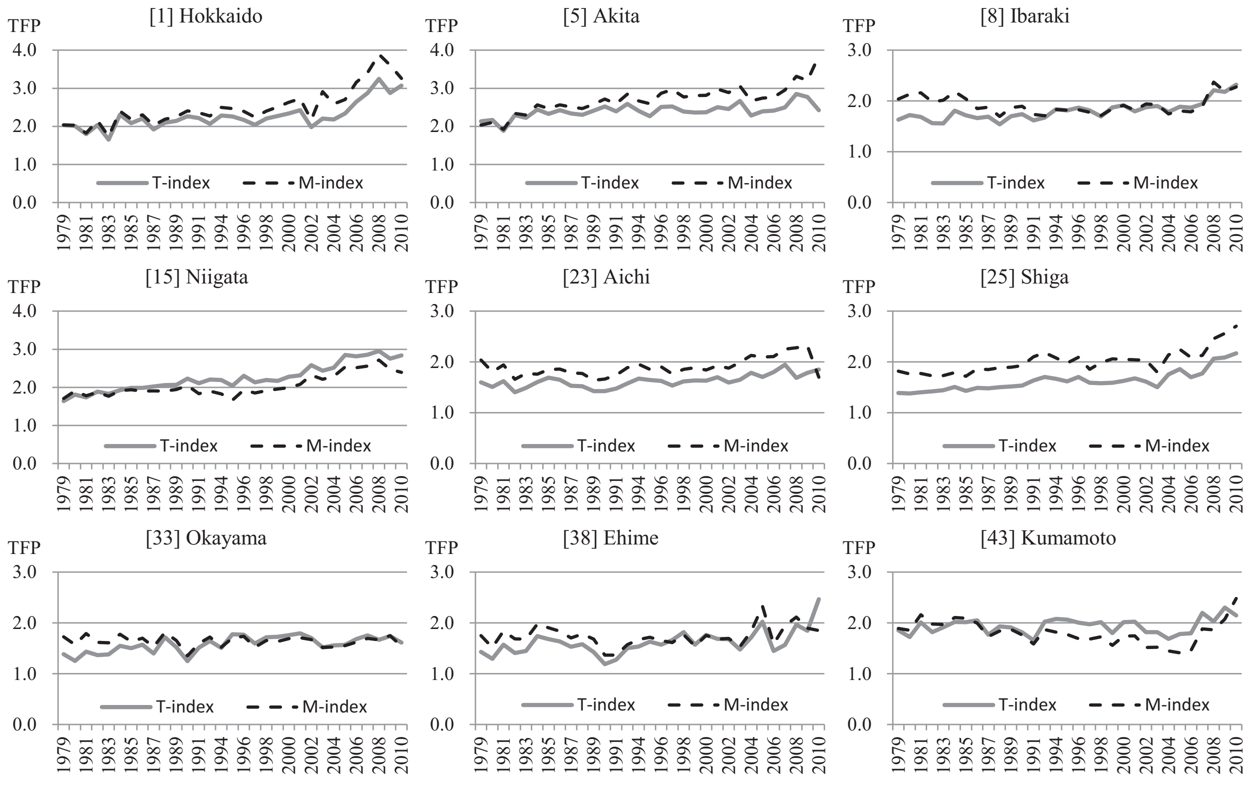

Fig. 4. Rice TFPs by regions

Note: Prefectures selected from 38 regions to represent different locations.

Table 2. Estimations of causative factors for TFP changes

Items	T-index (Törunqvist-Theil index)				M-index (Malmqist index)			
	Fixed Eeffect (Model 1)		Random Eeffect (Model 2)		Fixed Eeffect (Model 3)		Random Eeffect (Model 4)	
	Coeff.	t-statistics	Coeff.	t-statistics	Coeff.	t-statistics	Coeff.	t-statistics
Variables								
Constant	-0.814	-7.10 ***	-0.783	-7.20 ***	-0.025	-0.19	-0.361	-2.92 ***
ln(*MA*)	0.291	10.92 ***	0.282	12.00 ***	0.357	11.40 ***	0.271	10.78 ***
ln(*KKn*+*KKp*)	0.267	13.74 ***	0.281	15.45 ***	0.134	5.88 ***	0.150	7.28 ***
POP	0.035	0.65	-0.060	-2.01 **	-0.327	-5.23 ***	-0.081	-3.00 ***
ln*(CHI)*	0.225	5.60 ***	0.227	5.72 ***	0.204	4.30 ***	0.219	4.75 ***
ln*(CQI)*	0.080	4.44 ***	0.083	4.61 ***	0.104	4.90 ***	0.107	5.07 ***
ln*(CRI)*	-0.044	-3.61 ***	-0.044	-3.66 ***	-0.046	-3.26 ***	-0.040	-2.89 ***
ln*(CFI)*	-0.007	-1.96 *	-0.007	-1.88 *	-0.004	-0.93	-0.006	-1.36
Adjusted R^2		0.83		0.57		0.67		0.35
Log likelihood		1182		1160		991		948
AIC		-1.93		-1.89		-1.61		-1.60
Redundant Fixed Effects Test (F)		49.08 (p=0.00)				33.45 (p=0.00)		
Hausman Test (χ^2)		11.80 (p=0.10)				37.73 (p=0.00)		

Note: Total panel observations were 1178 (38 prefectures × 31 years: 1979-92; 1994-2010). Variables are explained in Table 1. "***," "**" and "*" respectively show that the estimation coefficients are significant compared to the t-statistic at 1, 5 and 10% levels.

Tochigi, Chiba, Nagano, Gifu, Kyoto, Okayama, Yamaguchi, Kagawa, Ehime and Kumamoto, showed low correlations. Differences between these indices are attributable to measurement methods and background assumptions. Generally, the M-index ranks regions low in TFP, when such regions use extremely large amounts of a single input, and this index changes TFP of all regions even if only one region changes inputs. Contrarily, the T-index tends to measure the average level of all inputs, and an influence of one regional change in inputs remains within own region. These features mean TFP in 11 prefectures showed different chronological paths for both indices.

2. Causality of rice TFP growth

Table 2 shows the estimation results of the TFP causality function (Eq. (4)). In this table, there are four estimations for each TFP index, i.e. the fixed-effect model with T-index (Model 1), the random-effect model with T-index (Model 2), the fixed-effect model with M-index (Model 3) and the random-effect model with M-index (Model 4).

Hausman-test statistics (χ^2 value) suggested the fixed-effect models (Models 1 and 3) were suitable. Kunimitsu *et al*. (2014) showed similar estimation results for causality functions, and also selected the fixed-effect model. In that estimation however, only nine regions were used, whereas here we used 38 regions. Moreover, the crop-yield and crop-quality models used here were different from those used in Kunimitsu *et al*. (2014) and we also introduced population density as an explanatory variable in the model. Despite these differences, both results preferred the fixed-effect models, showing the existence of latent factors other than climate and socioeconomic elements.

The signs of estimated coefficients were the same in both Models 1 and 3, with a little difference in the coefficient values of economies of scale (*MA*). Climate factors took almost the same values as the estimated coefficients. However, R&D capital stocks and population density showed different degrees in terms of the estimated coefficients between both indices. The estimated coefficient of R&D capital stocks with the M-index (Model 3) was approximately half of the T-index (Model 1). The estimated coefficient of population density was insignificant in the T-index, but significant in the M-index. As explained earlier, the M-index is measured by comparing other regions whereas the T-index only refers to the previous year productivity. Moreover, the growth rates of the M-index in 11 prefectures, where correlation coefficients between both indices were low, were lower than that of the T-index. These 11 prefectures are famous for horticulture and fruit production. As explained in Kunimitsu (2013), differences between both indices in rice TFP were mainly attributable to variation in intermediate inputs including agricultural services. In addition, the M-index tended to evaluate cross-sectional differences for each input factor. In this sense, the M-index in this case probably considers the cross-sectional differences in intermediate inputs showing stronger diversity in agricultural products of each prefecture. In terms of climate factors, no significant differences in causality emerged, despite differences in socioeconomic factors. Accordingly, prediction of TFP by future socioeconomic factors depends on the indices measured, but prediction of TFP by future climate change shows similar results with either index.

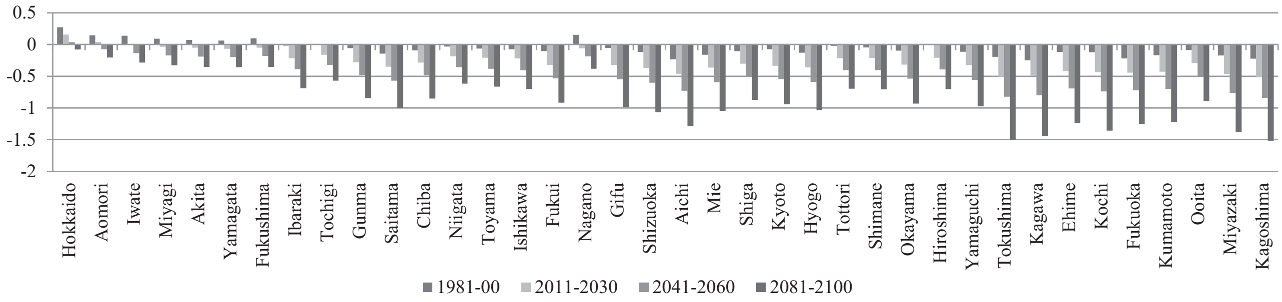

Fig. 5. Elasticity values for TFP (T-index) with respect to temperature via the crop-yield index (*CHI*)

Fig. 6. Elasticity values of TFP (T-index) with respect to temperature via the crop-quality index (*CQI*)

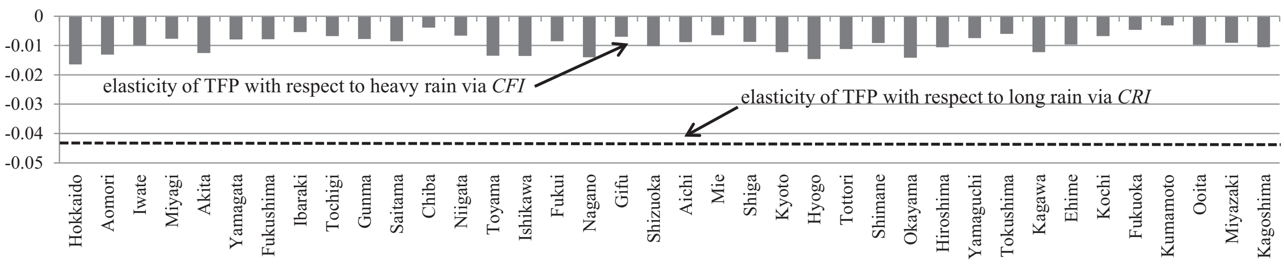

Fig. 7. Elasticity values of TFP (T-index) with respect to rainfall via long rain index (*CRI*) and flood index (*CFI*)

The estimated coefficient, $\boldsymbol{\beta}$, corresponds to TFP elasticity with respect to explanatory variables. Most estimated signs were the same as Kunimitsu *et al*. (2014), but the estimation values differed slightly due to differences in regional classifications and the variables used. As shown by the estimations of Models 1 and 3, the elasticity values with respect to economies of scale, *MA*, were 0.29-0.36, while the elasticities of the yield index, *CHI*, were almost the same as *MA*. The impacts of *CHI* were substantially large[2], but those of other climate factors were relatively small.

To see the impacts of temperature and rain on rice TFP via the above climate indices, we calculated TFP elasticities with respect to temperature via yield (*CHI*) and quality (*CQI*), and calculated TFP elasticities with respect to rain via poorly drained surface water (*CRI*) and flooding (*CFI*) (Figs. 5 to 7). Only the results of the T-index are shown due to limited space but the M-index marked similar values because the estimated coefficients of climate factors were similar between both indices (Table 2). Elasticity of TFP with respect to temperature via yield differed depending on the prefecture and year. In general, prefectures in northern Japan such as Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima and Nagano achieved positive effects of temperature via *CHI* until the early periods and subsequently showed negative effects with small values. However, all southern prefectures showed negative effects of temperature via *CHI*. A similar tendency emerged in terms of the effects of temperature via quality. The negative effects of temperature shown by these two indices are multiplicative where temperature exceeds the threshold value in both indices.

The TFP elasticity against long rain via poorly drained

[2] Theoretically, the elasticity of yield index, *CHI*, is one where only yield changes but production costs remain constant. However, in reality, when yield changes under climate change, production costs and prices also change with the adaptive behavior of farmers as well as the market, so the elasticity of *CHI* should be less than one.

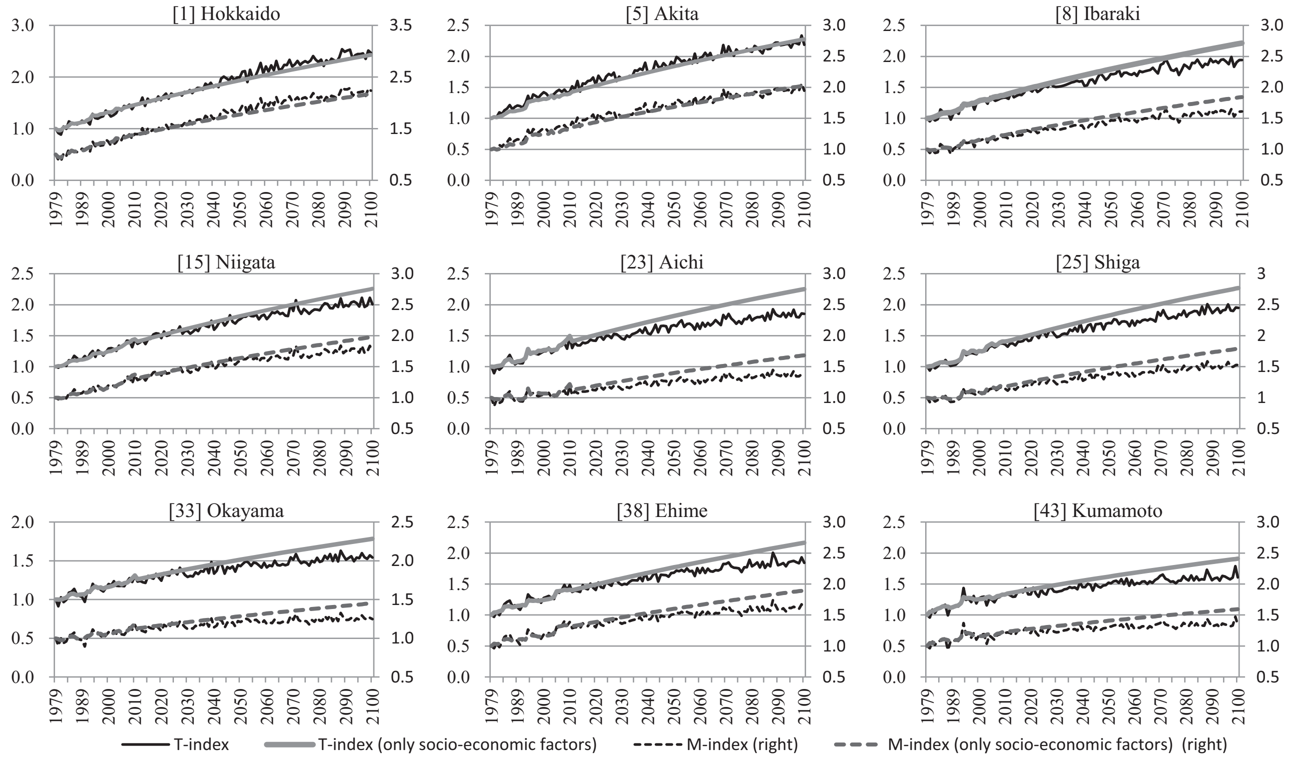

Fig. 8. Projection of TFP level (1979=1.0)

Note: To compare the two indexes in a single figure, the right-side vertical axis for the M-index was set 0.5 points higher than the left-side axis for the T-index.

surface water, *CRI*, was -0.044 and always negative, while TFP elasticity against heavy rain via flooding, *CFI*, was less than -0.02. The low estimated coefficients meant TFP elasticities against rainfall via *CRI* and *CFI* were lower than against temperature via *CHI* and *CQI*. In particular, TFP elasticity against heavy rain via flooding was the lowest in absolute value terms. This is because only limited areas of paddy fields are damaged by floods depending on the course of the typhoon. Anyway, it is reasonable to accept a working hypothesis in which poorly drained surface water caused by a long rain mainly increased production costs. The effects of floods from heavy rain are relatively minor and mainly result in a small decline in production with the small increase in costs due to pumping drainage water and repairing fields. In this sense, long term climate change affects rice TFP, not only by reducing the production amount via *CHI*, *CQI* and *CFI*, but also by increasing the costs via *CRI*.

3. Prediction of future rice TFP

Figure 8 shows chronological changes in future rice TFP, using Model 1 (T-index) and Model 3 (M-index) alongside the MIROC forecast results. As shown by the increase in TFP level by the bold line, socioeconomic factors mainly explained the average chronological trends of TFP, whereas climate factors added a variation to those tendencies and caused annual TFP level to fluctuate. Prediction lines of both models were similar, but the growth rate of Model 3 was slightly smaller than Model 1, because the estimated coefficient of R&D capital stocks was low in Model 3.

In prefectures of northern Japan, such as Hokkaido and Akita, the line for all factors was higher than that without considering climate factors, because temperatures in these regions remained under the threshold value. The TFP from climate factors in other prefectures increased until the 2020s, but the line was subsequently located below that for only socioeconomic factors. This is because temperatures in these regions were beyond the threshold value for most years. Conversely, the influences of rain via *CRI* and *CFI* were always negative and the contribution of rain to all causative factors, including socioeconomic factors, was -2.5 to -4.5%.

Figures 9 and 10 show the standard deviations, as calculated from the TFP levels with consideration of only climate factors to show the fluctuations in TFP. Although TFP elasticity against temperature via yield and quality far exceeded that against rain, annual fluctuations in rain and floods also far exceeded that of temperature, as shown by these figures. This occurred due to high variations in *CRI* and *CFI* as shown by the high standard deviation of these

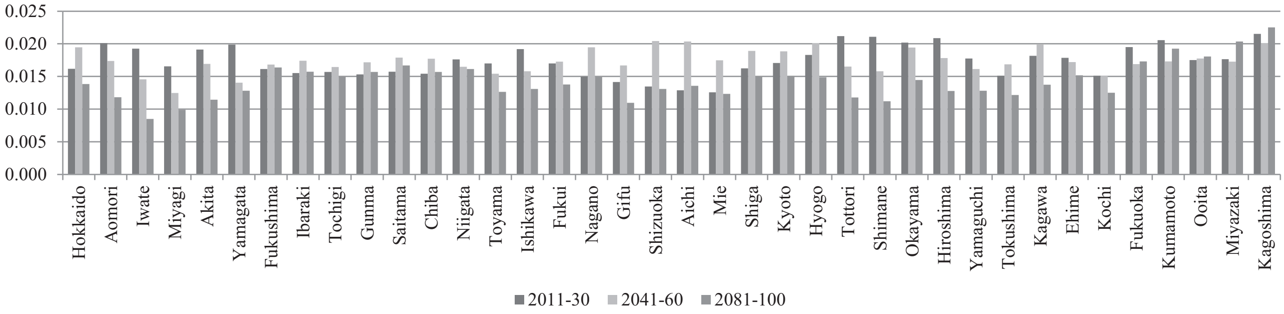

Fig. 9. Standard deviations for TFP (T-index) caused by temperature change via the yield and quality indices (*CHI* and *CQI*)
Note: TFP values were calculated by using the estimated coefficients of *CHI* and *CQI* in Model 1 of Table 2.

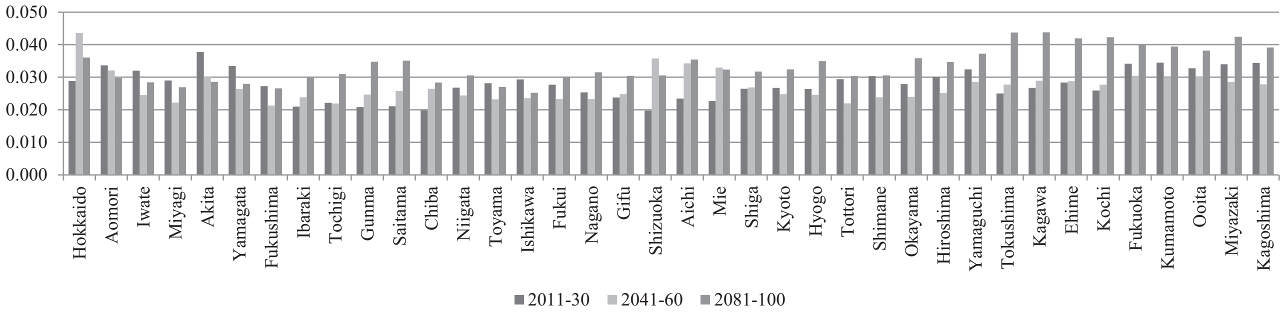

Fig. 10. Standard deviations for TFP (T-index) caused by rainfall change via long rain and flood indices (*CRI* and *CFI*)
Note: TFP values were calculated by using the estimated coefficients of *CRI* and *CFI* in Model 1 of Table 2.

indices in Table 1. Consequently, it is highly possible that annual fluctuations in rain may result in unstable rice TFP.

Implications and conclusions

The present study evaluated the impacts of long and heavy rain under long-term climate change on Japanese rice TFP by applying panel data analysis. Based on the estimated causality function associated with crop-yield, crop-quality and hydrological models, future levels of rice TFP were predicted by using the projection results of MIROC. The estimation results showed the following points:

First, there were no significant differences in the effects of climate factors between T-index and M-index. This indicates that the prediction of rice TFP from future climate change does not differ due to measurement indices and remains fairly stable. Contrarily, the estimated coefficients of R&D capital stocks and population density showed differences between both indices emerging. Since the M-index tends to evaluate cross-sectional differences for each input factor, such differences are probably attributable to cross-sectional differences in intermediate inputs showing the diversity of agricultural products in each prefecture. Agricultural research should consider such differences when either or both indices are used.

Second, TFP elasticity against temperature changed signs from positive to negative according to the region and year. In northern Japan, a rise in temperature under future climate change increased rice TFP via yield and quality. However, a rise in future temperature reduced rice TFP in southern Japan. Therefore, future temperature change is beneficial for rice TFP in northern Japan but harmful in southern Japan. Compared to the effects of temperature, the effects of rain were always negative, and absolute TFP elasticity against rain was lower than that against temperature via yield and quality. Nevertheless, both poorly drained surface water caused by long rain on the fields and floods caused by heavy rain decreased rice TFP by 2.5 to 4.5%.

Third, changes in rainfall under future climate change cause annual rice TFP to fluctuate. The influences of rain on TFP fluctuations exceeded those of temperature via yield and quality, even though the effect of rain measured by elasticity was much lower than temperature. This is due to high variation in annual rainfall compared to temperature. Considering these tendencies, it is important for the Japanese rice sector to mitigate the negative and unstable influences of rain to make its rice production more competitive. However, countering floods and poorly drained surface water on the fields is difficult for farmers and government support is needed. For example, consolidating drainage systems in fields would be helpful.

Limitations of this analysis and the remaining issues are as follows: Analyses of other agricultural products and other countries, evaluation of other causative factors such as human capital and public physical capital, and evaluation of the ripple effects of changes in rice TFP on whole economies are important issues that remain to be clarified in future studies.

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Appendix

Table A1 shows estimations of the crop-yield model using Eq. (7). Panel data with 38 regions and 31 years (1979-1992, 1994-2010) were used for estimations. The fixed-effect model showed statistical superiority over the random-effect estimations, as shown by Hausman statistics, adjusted R^2 and other statistics. The coefficients of temper-

Table A1. Estimations of the crop-growth model (*CHI*) in Eq. (7)

Variable	Fixed Effect model			Random Effect model		
	Coeff.	t-statistic		Coeff.	t-statistic	
Constant	-385.888	-9.50	***	-265.469	-7.00	***
TM7	16.519	7.59	***	14.616	6.79	***
$TM7^2$	-0.356	-7.61	***	-0.327	-7.05	***
TM8	18.223	5.86	***	15.654	5.06	***
$TM8^2$	-0.410	-6.41	***	-0.357	-5.62	***
TM9	7.265	2.84	***	2.386	0.98	
$TM9^2$	-0.116	-1.93	*	-0.022	-0.37	
Adjusted R^2		0.694			0.133	
Log likelihood	4172			4056		
AIC		-7.009			-6.874	
Redundant Fixed Effects Test (F)		39.02	(p=0.00)			
Hausman Test (χ^2)		212.54	(p=0.00)			

Note: Total panel observations were 1178 (38 prefectures × 31 years: 1979-92; 1994-2010). The fixed-effect model was chosen to predict *CHI** based on Hausman test statistics (p=0.00 shows p-value). "***," "**" and "*" respectively show that significant estimation coefficients compared to the t-statistic at 1, 5 and 10% levels.

Table A2. Estimations of the crop-quality model (*CQI*) in Eq. (8)

Variable	Fixed Effect model			Random Effect model		
	Coeff.	t-statistic		Coeff.	t-statistic	
Constant	54.799	12.42	***	56.377	12.39	***
SR7	0.647	2.93	***	0.604	2.75	***
SR8	0.940	3.83	***	0.916	3.77	***
ABS(TL78-19.34)	-6.703	-10.53	***	-6.914	-11.44	***
DYR	-39.063	-13.89	***	-39.460	-14.05	***
Adjusted R^2	0.48			0.22		
Log likelihood	-4794			-4821		
AIC	8.21			8.19		
Redundant Fixed Effects Test (F)		14.29	(p=0.00)			
Hausman Test (χ^2)		16.46	(p=0.00)			

Note: Total panel observations were 1178 (38 prefectures × 31 years: 1979-92; 1994-2010). ABS(•) is the function to calculate the absolute values. *DYR* is the dummy variable that is one of the negative spikes, showing a rapid drop of -20% in a specific year and rapid recovery the following year, and 0 otherwise. The fixed-effect model was chosen to predict *CQI** based on Hausman test statistics (p=0.00 shows p-value). "***," "**" and "*" respectively show that the estimation coefficient is significant compared to the t-statistic at 1, 5 and 10% levels.

ature and quadratic temperature showed that rice yield changes from an increase to a decrease at temperatures around 20.0°C. This tendency resembles the crop models developed by Iizumi *et al*. (2009) and Yokozawa *et al*. (2009) that analyzed more precise growth-processes of rice. Therefore, the model estimated here shows good performance and can be used to estimate the yield index. To estimate *CHI** for Eq. (4), the estimated coefficients of fixed regional constants were not used to show only climate effects and to exclude latent effects on production. For the same reason, the future level of *CHI* is predicted by future climate conditions without using fixed-regional constants.

Table A2 shows the estimations of the crop-quality model in Eq. (8). The fixed-effect model was shown to be statistically superior to the random-effect estimations, based on Hausman statistics, adjusted R^2 and other statistics. Unfortunately, the adjusted R^2 was approximately 0.5, showing limited scope to explain the estimations. The estimated coefficients showed a decline in rice quality due to a higher minimum temperature over the threshold temperature and longer periods of sunshine. These tendencies in the coefficients correspond to the results of Kawazu *et al*. (2007). Using these estimations, *CQI* for the causality function was calculated. In the stage of the *CQI* estimation, only climate conditions were used and the fixed-regional constants were not used for the same reason in *CHI*.

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