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Technological spillover in Japanese rice productivity under long-term climate change: evidence from the spatial econometric model

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Abstract Rice productivity will be affected by climate conditions not only in own region but also in neighboring regions through technological spillover. Measuring such direct and indirect influence of future climate change is important for policy making. This study analyzes socio-economic and climate factors in rice total factor productivity (TFP) and evaluates technological spillover effects by using the spatial econometric model. To consider geographical situation, we use hydrological model in addition to crop-yield and crop-quality models. Results show that spatial autoregressive tendencies were observed in rice TFP, even though the influences of climate factors were removed. Such spatial dependence brings about synergistic effects among neighboring prefectures in northern Japan and depression effects, like a spatial trap, from neighbors in southern Japan. Substantial impacts of climate change were as high as socio-economic factors but different in degrees by regions. Also, future climate change estimated by the global climate model enlarged fluctuation degree in rice TFP because accumulative or cancel out effects of temperature and precipitation occurred year by year. Therefore, technological development in rice production and
provision of precise climate prediction to farmers are important in order to ease and mitigate these influences.

Introduction

Long-term climate change will influence regional rice production in various ways (Watanabe and Kume 2009). According to the fourth report of the Intergovernmental Panel on Climate Change, the average temperature in Japan will increase by 4–6 degrees Celsius (°C) by the year 2100. Occurrence of gigantic typhoons will also become more frequent with climate change. Rice productivity will be affected by climate conditions not only in own region but also in neighboring regions through technological spillover. Measuring such direct and indirect influence of future climate change is important for policy making.

Needless to say, Japanese rice production accounts for only 1 % of gross domestic product, and rice consumption is consecutively decreasing after the 1960's. The peak per capita consumption was more than 110 kg per person in the 1960's, but is now less than 60 kg per person. Although the government has tried to adjust production of rice by increasing the area of set-aside-program, the price of rice continues to descend under the excess supply tendency. Due to a rapid decrease in rice consumption and rice price, many paddy fields are abandoned without usage, and hence, total areas of paddy fields are now 2/3 of the 1960's. However, the range of paddy fields in habitable land areas

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is still dominant, accounting for 20 %. If global warming changes rice production amount and decreases rice price, there is a great possibility of increasing abandoned paddy field areas which used to be the base of hydrosphere ecosystem. In this sense, influences of climate change on rice productivity are not ignorable in view of future land use and sustainability of ecosystems for both producers and consumers.

Kunimitsu et al. (2014) measured the influences of climate and socio-economic factors on rice total factor productivity (TFP) in nine regions of Japan. Their analysis showed that the potential impacts of the yield index were as high as socio-economic factors such as economies of scale and research and development activities. However, there were two issues remaining in this analysis. First, spatial interactions in the objective regions were not considered. Generally, rice production in one region has similarities with conjunctive regions. Climate factors can partly explain such spatial correlations, but there may be other latent factors, such as technological spillover into neighboring prefectures. Polsky (2004) showed that agricultural profitability, measured by farmland price, in US counties had significant spatial autocorrelations, and these spatial effects were rarely removed from the data even with the introduction of climate factors. Their study indicates high needs for consideration of spatial dependence and climate factors to measure regional impacts on rice production. Second, influences of flood, as one causative factor in TFP, were considered by maximum precipitation during the harvest season, but geographical conditions were not taken into account in the previous study. Flood flow and drainage conditions are different from region to region due to the steepness of mountains, width of river catchment areas, and different land uses. A hydrological model is one way to introduce geographical information into the analysis (Park et al. 2009).

The present study analyzes the causative factors and technological spillover shown as spatial dependence in rice TFP with panel data consisting of 38 prefectures and 31 years. Future TFP levels are predicted by estimations of the model and climate projections of the high-resolution version of the "model for interdisciplinary research on climate (MIROC)," a global climate model, for policy implications. Features of this study are that (i) the spatial autoregressive model with panel data is used to measure technological spillover shown by the spatial direct and indirect impacts of socio-economic and climate factors, (ii) estimations use the climate indexes measured from only climate and geographical conditions with a hydrological model in addition to the crop-growth and crop-quality models to avoid endogenous problems in the estimations, and (iii) rice TFP is measured by the Malmquist index which considers regional disparities in production skills

among regions and quantifies relative TFP of each region against other regions.

The structure of this paper is as follows. The second section introduces previous studies and raises scientific questions. The third section explains the working hypothesis and empirical models. The fourth section shows how to quantify dependent and explanatory variables. The fifth section is an explanation about the data sources. The sixth section shows the estimations and discusses future levels of regional rice TFP under climate change projected by MIROC. Based on these findings, the final section provides policy implications as a conclusion.

Literature review and scientific questions

TFP shows the profit level represented by comprehensive productivity that is calculated by the ratio of the total output against the total costs consisting of all input factors. Previous studies measured agricultural TFP and empirically analyzed several causative factors including economies of scale (Thirtle et al. 2008), research and development (R&D) activities (Alene 2010), human capital (Astorga et al. 2011), soil quality (Jayasuriya 2003), and public facilities such as roads, and irrigation and drainage facilities (Suphannachart and Warr 2010; Chen, et al. 2008).

In order to introduce the flexible proportion of inputs under variable return to production scale, recent studies increasingly use the Malmquist index. This index is calculated by non-parametric procedures such as data envelopment analysis (DEA), so no assumptions on statistical distributions are needed (Fare et al. 1994). Also, this index is consistent with real situation where many producers or regions use relatively outdated technology in spite of an existence of high skilled producers or regions, and it shows relative level of comprehensive productivity compared to other regions. In addition, this index can treat multiple outputs with multiple inputs. However, DEA used for this index is weak for the statistical errors existing in the actual data, and the original TFP level cannot be calculated reversely from this index.

Pratt and Yu (2010) estimated agricultural TFP of 63 developing countries based on the Malmquist index, and found that agricultural TFP was growing steadily during the past 20 years, especially in Sub-Saharan countries. Yamamoto et al. (2007) quantified rice TFP by the Malmquist index, and showed that regional gaps in TFP existed and tended to converge over time in Japan until 1995. Umetsu et al. (2003) measured chronological changes in rice TFP of the Philippines by the Malmquist index and showed that rice TFP was improved by the green revolution and this change was different by region.

In terms of climate effects on agriculture, Salim and Islam (2010) showed a negative influence on TFP in

Australian agriculture because of serious drought under long-term climate change, and the degree of this influence was as high as that of R&D expenditures. Their analysis assumed log-linear influences of climate factors at the production level, but influences of climate factors change signs from positive to negative depending on the threshold temperature (Yokozawa et al. 2009). As such, an introduction of non-linear effects of climate factors is an important subject for investigation.

Considering spatial dependence caused by technological spillover in production studies is another important issue. Esposti (2010) estimated the spatial autoregressive (SAR) model (spatial lag model) to show the causative factors on divergence in agricultural TFP for 20 Italian regions during 1951–2002. They concluded that (i) technological spillovers were the key convergence force and (ii) public agricultural R&D mostly behaved as a divergence force because it prevalently affected productivity through its region-specific part. Unfortunately, they did not consider climate factors. Polsky (2004) used the SAR model to explore relationships between humans and the environment associated with climate sensitivities, and showed influences varied over space and time in US agriculture. They showed that agricultural productivity measured by land value was influenced by neighboring counties, net effects of the specified climate, and other socio-economic factors. In their estimations, the spatial lag coefficients relating to the technological spillover took significant values in all periods studied. DiGiacinto and Nuzzo (2006) also used spatial econometric methods to analyze TFP gaps in manufacturing sector in the Italian regions and showed that TFP gaps changed due to five factors, i.e., the degree of agglomeration economies, efficacy of political and social institutions, transportation infrastructures, development of financial markets, and R&D expenditures. Although spatial influences were significant in their spatial error model (SEM), a slight difference was found in estimated coefficients of explanatory variables with and without spatial specifications. Actually, results from most studies favor the SEM that considers only spatial autocorrelations in the error term rather than SAR model that takes direct affects of neighboring regions into consideration (Fingleton and Lppez-Bazo 2006). Unfortunately, there were few empirical studies that applied the spatial econometric method to rice production, so it is important to see how spatial interactions affect regional rice productivity in Japan.

Empirical model

Based on previous studies (Kuroda 1989, 1995), economies of scale and R&D investments are strong candidates for causative factors that increase rice productivity. Also,

urbanization is another candidate for a causative factor, if we consider the Von-Thunen's model that explains location of agricultural production areas with different yields. As explained by this model, urbanized areas tend to have high costs due to strong competition for input resources with other industries. Hence, rice TFP in urbanized areas is probably low under evenly allocated set-aside areas in Japan. In addition to these socio-economic factors, rice TFP is influenced by climate factors through changes in harvest quantity, quality, and production cost affected by heat stress and floods. Considering these factors, we assume the following relationships.

$$\ln(TFP_{r,t}) = \beta_0 + \beta_1 \ln(MA_{r,t}) + \beta_2 \ln(KKn_t + KKp_{r,t})$$
$$+ \beta_3 \ln(POP_{r,t}) + \beta_4 \ln(CHI_{r,t})$$
$$+ \beta_5 \ln(CQI_{r,t}) + \beta_6 \ln(CFI_{r,t}) \quad (1)$$

where suffix r indicates region, t indicates year, and β's are coefficients to be estimated. MA represents economies of scale measured by the average farm management area per management organization. KKn is the nationwide R&D capital stocks of the central government, universities, and private companies. KKp is R&D capital stocks of the prefectural government and becomes the source of technological spillover among regions. Nationwide R&D capital stocks are assumed to be pure public goods and uniformly improve rice TFP in all regions, so the same KKn is used for all regions and has no r suffix. POP is the population density within the inhabitable land area, representing the influence of urbanization. CHI is the rice yield index, CQI is the rice quality index, and CFI is the flood index. CHI, CQI, and CFI are estimated from only climate and geographical conditions with the crop-growth model, crop-quality model, and hydrological model, respectively. Using these models, we can avoid endogenous problems that occur in the reverse interrelationship between the dependent variable, TFP, and the independent variables, such as climate indexes. Namely, these indexes, which are estimated only by climatic and geographical conditions, have 'one-way effect' on the dependent variable, and the indexes calculated are not influenced by TFP.

Equation 1 can be exhibited as following ordinary least square estimation (OLS).

$$\mathbf{TFP} = \mathbf{Z\beta} + \boldsymbol{\varepsilon}, \quad (2)$$

where $\mathbf{TFP}$ is the vector of $\ln(TFP_{r,t})$, $\mathbf{Z}$ is the matrix for causative factors, $\boldsymbol{\beta}$ is the vector of estimation coefficients, and $\boldsymbol{\varepsilon}$ is the error terms. Hereafter, gothic characters show vector or matrix. To consider time lag effects, the following dynamic autoregressive (DAR) model is used. Also, SAR model, i.e., spatial lag model, is assumed as follows to introduce spatial dependence between neighboring prefectures (Anselin et al. 2004).

(Dynamic autoregressive model; DAR)

$$\mathbf{TFP}_t = \mathbf{Z\beta} + \lambda \cdot \mathbf{TFP}_{t-1} + \mathbf{\varepsilon}_t, \qquad (3)$$

and

(Spatial autoregressive model; SAR)

$$\mathbf{TFP}_r = \mathbf{Z\beta} + \rho\mathbf{W} \cdot \mathbf{TFP}_r + \mathbf{\varepsilon}_r, \qquad (4)$$

where μ and ρ are, respectively, the dynamic autoregressive coefficient and the spatial autoregressive coefficient. $\mathbf{W}$ is the spatial weight matrix to show the conjunctive structure of each prefecture to neighboring prefectures.

If λ and ρ are statistically insignificant, Eqs. (3) and (4) result into the OLS model in Eq. (2). If λ becomes statistically significant, it means that present technology depends on past technological level, showing dynamic technological transmission effect. If ρ becomes significant, it can be interpreted as existence of the technological spillover effects among neighboring regions (LeSage and Pace 2009). In this case, TFP at the r-th region is influenced by TFP at other regions defined by W with non-zero element. TFPs at regions with zero element in W including own region have no influence to TFP concerned as dependent region. Since climate factors are included in explanatory variables, Z, ρ shows effects of spatial dependence other than climate factors.

Coefficients, $\mathbf{\beta}$, in Eq. (3) show temporal effects, so ultimate effects at the steady-state situation are calculated as $(1-\lambda)^{-1}\mathbf{Z\beta}$. In terms of Eq. (4), estimated coefficients, $\mathbf{\beta}$, show direct effect of explanatory variable. Other than such direct effect, indirect effects via neighboring regions exist. Total effects are calculated as $(\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{Z\beta}$.

Quantification of independent and explanatory variables

Objective region

The data are composed as panel data with 38 prefectures and 31 years (1979–1992, 1994–2010). Using the panel data instead of single regional data allows us to (i) find regional differences in rice TFP, (ii) increase the degrees of freedom for estimations, and (iii) remove effects of common latent factors that equally change TFP in all regions. However, spatial dependence cannot be removed by simple panel data analysis, because this effect partially influences the data of the certain region group. Hence, spatial econometric models are needed to treat such heterogeneity.

Figure 1 shows the location of each prefecture of the objective region. These exclude nine prefectures, i.e., Tokyo, Kanagawa, Yamanashi, Osaka, Nara, Wakayama, Saga, Nagasaki, and Okinawa, where rice production is relatively low and cost data are not published as official statistics. Providing that spatial dependence occurs through rice production, technological spillover effects for the above excluded prefectures are small, and spatial relationships between rice producing prefectures and low rice producing prefecture are negligible. Data period is 31 years from 1979 to 2010 except for 1993. In 1993, serious damage occurred due to cold weather, and cost data were not observed in the major rice production prefectures.

In terms of neighboring structure, the row-wise values for spatial weight, $\mathbf{W}$, are firstly assigned one in the column of prefectures conjunct to the objective prefecture, and 0 otherwise. For example, row values for Hokkaido are 1 at only Aomori, and 0 otherwise, whereas row values of Aomori are 1 at Hokkaido, Iwate, and Akita, and 0 otherwise. Then, these values are standardized row-wise as commonly done in spatial econometric estimations.

TFP by the Malmquist index

The Malmquist index is the geometric mean of output-based technological gaps in two periods and can be calculated by the panel data. Technological gaps are measured by the distance from production of individual decision-making units (or certain region) to the production frontier observed by the DEA. Chronological changes in TFP by the Malmquist index are defined as

$$TFP_{r,t+1}/TFP_{r,t} = \left[\frac{d_{r,t}(\mathbf{x}_{t+1}, \mathbf{y}_{t+1})}{d_{r,t}(\mathbf{x}_t, \mathbf{y}_t)} \times \frac{d_{r,t+1}(\mathbf{x}_{t+1}, \mathbf{y}_{t+1})}{d_{r,t+1}(\mathbf{x}_t, \mathbf{y}_t)} \right]^{1/2} \qquad (5)$$

where $d(\cdot)$ is the function to measure the distance between the production frontier and production point represented by output vector $\mathbf{y}$ and input vector $\mathbf{x}$. A greater value than one in Eq. (5) indicates positive TFP growth from period t to period $t + 1$ in region r. The concrete values of $d(\cdot)$ are calculated by the linear programming method in DEA that constructs a piece-wise surface over data as production frontier (Coelli 2008). The initial value of TFP_{r,t_0} in Eq. (5) is also calculated by the DEA method with cross-sectional data in the first year of the data period.

Socio-economic factors

The average farm management area per management organization, MA, and population density, POP, are directly obtained from the statistics. KKn and KKp are quantified by the perpetual inventory method as follows (Cabinet Office of Japan 2010).

$$KKn_t = In_{t-Lag} + In_{t-Lag-1} + \cdots + In_{t-Lag-N} \qquad (6)$$

and

$$KKp_t = Ip_{t-Lag} + Ip_{t-Lag-1} + \cdots + Ip_{t-Lag-N} \qquad (7)$$

Here, In and Ip are R&D expenditures by sectors. Lag is time lag of which new technology prepares to diffuse, and N is durable year of each technology invested. The Cabinet Office of Japan (2010) showed that the time lag was approximately 3 years and the 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. (6) and (7).

Climate indexes

Three climate indexes, CHI, CQI and CFI, are preliminarily estimated by the crop-growth model, crop-quality model, and hydrological model, respectively. Using

crop-yield and crop-quality models is the same as Kunimitsu et al. (2014). In addition to these models, this study uses the flood index, CFI, calculated by the unit out-flow within the paddy mesh area. This index indicates degree of flood during the mature and harvest stages of rice in August and September as follows.

$$CFI_{r,t} = \max_t \left(\sum_{s \in r} Q_{out_{s,day}} \right) / AREA_r \qquad (8)$$

where Q_{out} is the out-flow from s-th terrain mesh during the typhoon season, August and September, and is estimated by the hydrological model. Function $\max_t (\cdot)$ selects the maximum value of the daily out-flow during the typhoon season to show the most severe flood in year t. After calculating out-flow in each mesh, only paddy meshes, that have paddy fields inside, are selected and aggregated as the total amount of out-flow. Then, the maximum total out-flow among total out-

Fig. 1 Location of prefectures in nine regions studied. Tohoku includes six prefectures, such as [2] Aomori, [3] Iwate, [4] Miyagi, [5] Akita, [6] Yamagata, and [7] Fukushima. Kanto includes six prefectures, such as [8] Ibaraki, [9] Tochigi, [10] Gunma, [11] Saitama, [12] Chiba, and [20] Nagano. Hokuriku includes four prefectures, such as [15] Niigata, [16] Toyama, [17] Ishikawa, and [18] Fukui. Tokai includes four prefectures, such as [21] Gifu, [22] Shizuoka, [23] Aichi, and [24] Mie. Kinki includes three prefectures, such as [25] Shiga, [26] Kyoto, and [28] Hyogo. Chugoku includes five prefectures, such as [31] Tottori, [32] Shimane, [33] Okayama, [34] Hiroshima, and [35] Yamaguchi. Shikoku includes four prefectures, such as [36] Tokushima, [37] Kagawa, [38] Ehime, and [39] Kochi. Kyushu includes five prefectures, such as [40] Fukuoka, [43] Kumamoto, [44] Oita, [45] Miyazaki, and [46] Kagoshima. Other nine prefectures, where polygons are white and numbers luck, are excluded, because the data of rice production cannot be obtained in statistics
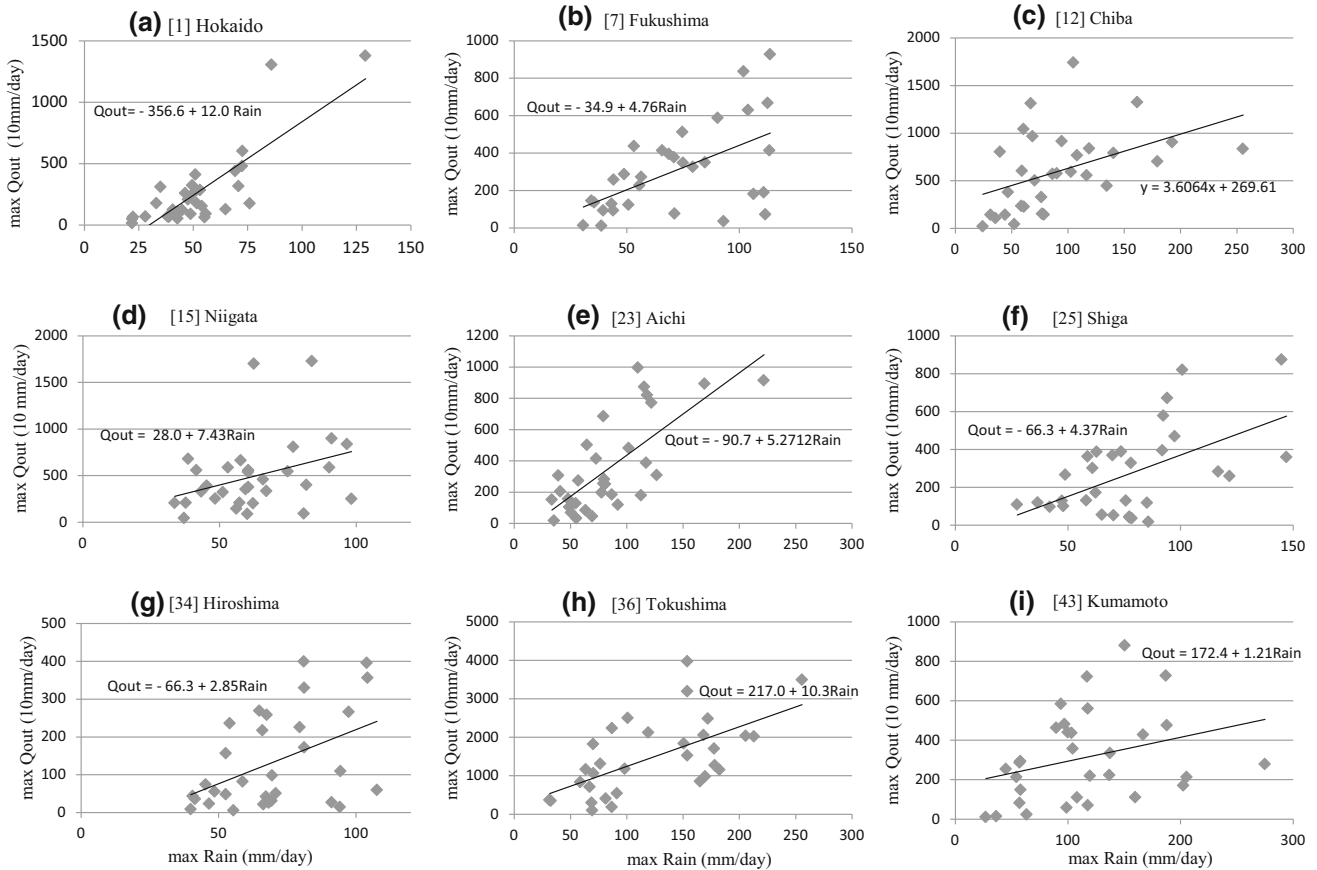
Fig. 2 Relation between hydrological model and precipitation. The vertical axis is maximum unit out-flow estimated by the hydrological model, and the horizontal axis shows actual maximum precipitation during August and September. Other prefectures are not shown because of the space limitation

flows in paddy meshes is selected and divided by the total area of the paddy meshes, *AREA*, in each prefecture to remove scale effects of regional areas. When heavy rain or typhoons increase, *CFI* increases, and consequently rice productivity is degraded not only by a decrease in rice harvest but also by an increase in costs required to pump excess water and to repair damaged field facilities.

The hydrological model (distributed water circulation model) is based on Masumoto et al. (2009) and Yoshida et al. (2012) and calculates water flow of each meshed area from climate conditions. In the model, data from a geographical information system are used to consider topographical conditions of each terrain mesh. Parameters of the hydrological model are the same as Kudo et al. (2013). Typical relationships between *CFI* and maximum precipitation are shown in Fig. 2. These variables correlate, but some years show extreme values in either variables. This is because out-flow is influenced by precipitation on and before the day concerned. Furthermore, the slopes of two variables, which correspond to the marginal unit out-flow and reflect geographical situations, are different by region, causing different unit out-flows from precipitation.

In general, the slope of out-flow against precipitation tends to be steep in regions where the catchment area is large.

CHI is estimated by the crop-growth model based on Iizumi et al. (2009) and Yokozawa et al. (2009). Growth and flowering of rice are formulated by the non-linear functions in the model. Roughly speaking, the marginal effects of temperature, *Temp*, change according to the threshold temperature, $\tilde{T}$:

$$\begin{cases} \partial \text{CHI}/\partial Temp > 0 & for\ Temp \le \tilde{T} \\ \partial \text{CHI}/\partial Temp < 0 & for\ Temp > \tilde{T}. \end{cases} \quad (9)$$

These tendencies show rice yield can increase until a threshold temperature, but decreases afterward.

An extremely high temperature and insufficient solar radiation degrade the quality of rice by causing chalky color and cracked rice. To measure such influences, the crop-quality model is used for estimation of *CQI* based on Kawazu et al. (2007). We added non-linear tendency of temperature. The equation of this model is as follows and is newly estimated in the Appendix.

$$CQI_{r,t} = f(SR7_{r,t}, SR8_{r,t}, Tmin78_{r,t}, Tmax8_{r,t}) + \varepsilon_{r,t}, \quad (10)$$

where *SR7* and *SR8* are, respectively, the average solar radiation in July and August, which are the critical months for maturation after heading time. *Tmin78* is the average minimum daily temperature during July and August, and *Tmax8* is the average maximum daily temperature in August. ε is the error term. Estimation results (Appendix) showed that *SR7* and *SR8* had positive coefficients (i.e., rice quality increases with solar radiation), whereas *Tmin78* was positive or negative against TFP in the total (i.e., rice quality increases with a rise in temperature until a threshold value but decreases over the threshold). According to the estimations of the quadratic function and absolute value function, the threshold temperature was 19.5 °C. This threshold value is higher than average minimum temperature in northern Japan, such as Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, and Nagano, but lower than that in other prefectures. Comparing Akaike's information criterion, AIC, and adjusted R-square among the functional types, the absolute value function (non-linear function 3) is used for prediction.

Data sources

Table 1 shows the descriptive statistics of variables used for estimation of causative factors in rice TFP. The data for **y** and **x** to calculate the Malmquist index (Eq. (5)) are obtained from *Cost Research for Rice Production* (Ministry of Agriculture, Forestry and Fishery (MAFF)). All nominal values are deflated by the price indexes published in the *Economic Accounts for Agriculture and Food Related Industries* (MAFF). The farm management area per farm organization, *MA*, is also from *Cost Research for Rice Production* (MAFF). R&D expenditures, *In* and *Ip*, in Eqs. (6) and (7) are collected from the statistics of *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 *CQI* are based on "*The Percentage of Premium Grade Rice*" (Official Document of MAFF based on the Agricultural Products Inspection Act, http://www.maff.go.jp/j/study/suito_sakugara/05/). Climate conditions for calculation of climate indexes, i.e., *CHI*, *CQI*, and *CFI*, are taken from the data of the Automated Meteorological Data Acquisition System (AMeDAS) from 1979 to 2010. For predictions, future climate conditions, such as temperature, solar radiation, and atmospheric CO_2 concentrations, are drawn from the down-scaled outputs of 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 is A1B, which shows balanced growth with rapid economic growth, low population growth, and rapid introduction of more efficient technology in the Special Report on Emission Scenario (Nakicenovic and Swart 2000).

Empirical findings and discussion

Chronological change in TFP by prefectures

Figure 3 shows the annual levels of rice TFP in representative prefectures calculated by the Malmquist index. Because of space limitations, nine prefectures, where rice production was relatively large, were selected as representation for nine broader areas (Fig. 1) designated in *Agricultural Census* (MAFF), and results of other prefectures were not shown. Rice TFP levels in the northern regions, i.e., Hokkaido, Fukushima and Niigata, were higher than other prefectures located in the southern part of Japan. Chronologically, rice TFPs of most prefectures increased from 1979 to 2010. Growth rate in Northern regions was also higher than southern regions. Due to these different growth rates, the coefficient of variation (CV) of TFP chronologically increased to 0.212 for the 1980's, 0.261 for the 1990's, and 0.308 for the 2000's, revealing an increase

Table 1 Descriptive statistics of variables used for estimation of TFP

Variables	Contents	Unit	Average	SD
TFP	Rice TFP measured by Malmquist index (Eq. 5)	–	0.99	0.19
MA	Management area per farm household	ha/farmer	0.98	0.79
KKn	Knowledge capital (nation wide) (Eq. 6)	100 billion yen	18.74	3.94
KKp	Knowledge capital (prefecture) (Eq. 7)	100 billion yen	0.43	0.24
POP	Population density (population per inhabitable area)	1000 people/km^2	0.95	0.62
CFI	Flood index estimated by the hydrological model (Eq. 8)	10 mm/day	40.00	47.27
CHI	Crop-yield index estimated by the crop-yield model (Eq. 9)	ton/ha	4.86	0.60
CQI	Crop-quality index estimated by the crop-quality model (Eq. 10, Appendix)	%	67.64	8.90

(a) North-eastern prefectures

Hokkaido
Fukushima
Chiba
Niigata
Aichi

(b) South western prefectures

Shiga
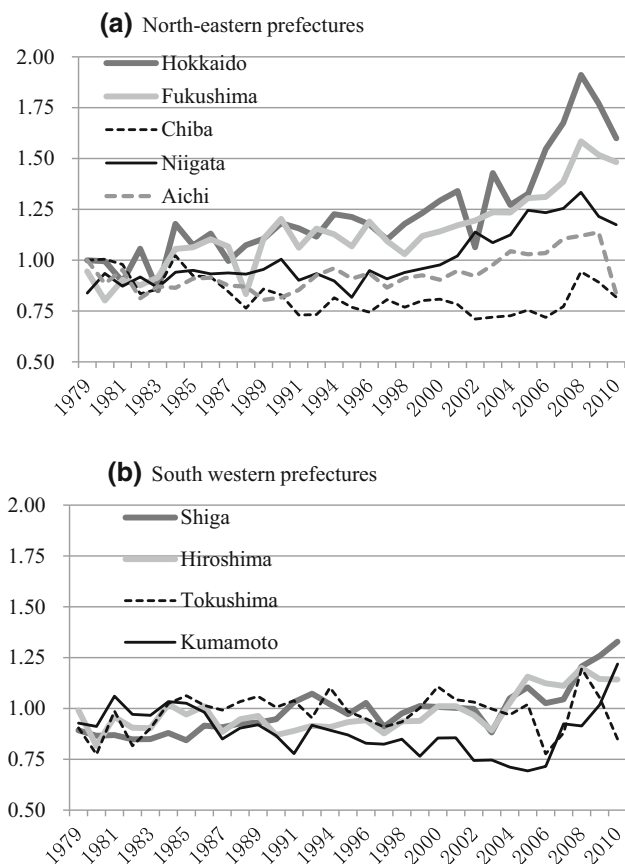Hiroshima
Tokushima
Kumamoto

Fig. 3 Rice TFPs by prefectures. Other prefectures are not shown because of the space limitation

in regional gaps. This tendency indicates a regional non-convergence in the rice productivity of Japan and is different from Yamamoto et al. (2007) which showed regional convergence in rice TFP until 1995.

Spatial dependence in TFP

Table 2 shows the estimation results of TFP function in Eqs. (2), (3), and (4) by the panel data analysis. We used the spatial economic packages "plm" (Croissant and Millo 2008), "spdep" (Bivand 2013), and "splm" (Millo and Piras 2012) with the statistical software, R (version 3.2). In this table, there are 3 models, i.e., OLS model shown by Eq. (2), the DAR model with time-lagged dependent variable shown by Eq. (3), and the SAR model considering spatial lag shown by Eq. (4). Both the fixed effect estimation and random effect estimation were conducted for OLS and SAR. The fixed effect models were chosen based on the Hausman statistics and are shown in this table.

Comparing AICs and adjusted R-squared values among models, SAR was superior to OLS and DAR. After estimating SAR, the parameter μ of serial correlation in residuals, i.e., $\hat{\varepsilon}_{r,t} = \mu_r \hat{\varepsilon}_{r,t-1} + v_{r,t}$ where $\hat{\varepsilon}$ is residuals and v is assumed to be independently identically distributed errors, was estimated. Estimated coefficients μ were significant in 31 out of 38 prefectures about estimations of OLS, but μ were significant only in 6 prefectures about SAR. Therefore, there are few affects of serial correlation in SAR estimations.

Table 2 Estimation results of causative factors for TFP change

Items	OLS (basic model) Coeff. (t-stat.)	DAR (time lag) Coeff. (t-stat.)	SAR (spatial lag) Coeff. (t-stat.)
Constant	−1.3617 (−4.08***)	−1.1596 (−3.01***)	−1.0281 (−8.56***)
ln(MA)	0.3260 (6.32***)	0.1466 (2.84***)	0.2501 (8.71***)
ln(KKn + KKp)	0.1773 (4.07***)	0.1305 (2.35**)	0.1168 (5.78***)
POP	−0.7917 (−6.52***)	−0.3902 (−3.42***)	−0.6315 (−7.44***)
ln(CHI)	0.1893 (1.86*)	0.1944 (1.70*)	0.1494 (5.09***)
ln(CQI)	0.1065 (3.54***)	0.1033 (3.60***)	0.0871 (4.54**)
ln(CFI)	−0.0136 (−2.63***)	−0.0100 (−1.80*)	−0.0088 (−2.99***)
ln(TFP_{t-1}) [λ]	–	0.4931 (12.77***)	–
ln(W·TFP)[ρ]	–	–	0.3070 (10.77***)
Adjusted R^2	0.678	0.767	0.769
Log Likelihood	1011	1148	1431
AIC	−1.641	−1.935	−2.353
Hausman Test (χ^2)	24.631 ($p = 0.000$***)	–	50.221 ($p = 0.000$***)

Total panel observations are 1178 (38 × 30: 1979−1992, 1994−2010). All estimation models are the fixed effect model according to Hausman Test statistics. OLS estimation is estimated by the Ordinary Least Square method. DAR with time lag of dependent variable and SAR with spatial lag of dependent variable are estimated by the maximum likelihood estimation method. AIC is the Akaike's information criterion. The signs "***", "**", and "*", respectively, show significant level at 1, 5, and 10 %

To check random effects, the serial correlation, and spatial dependence in the residuals of OLS, we conducted Lagrange Multiplier diagnostics by the BSK test (Baltagi et al. 2003) and the BSJK test (Baltagi et al. 2007).[1] These test statistics suggest existence of serial correlations, random effects, or spatial dependence in the error terms of OLS, so OLS estimations without the autoregressive term have a high possibility of bias. Since the possibilities of the random effect and serial correlation were low about residuals of SAR, the above statistical tests consequently suggest spatial dependence in the TFP data. From these statistical observations, it can be said that an introduction of spatial lag term in SAR can remove most effects from serial correlation. Therefore, SAR is suitable to explain regional rice TFP.

Influences of climate and socio-economic factors

The estimated coefficients, β, correspond to the elasticity of TFP with respect to explanatory variables. The signs and values of estimated coefficients were almost the same as the results of Kunimitsu et al. (2014).[2] The elasticity value with respect to economies of scale, MA, was 0.15–0.33, and the influence of MA was high among the causative factors considered here. The impact of R&D capital on rice TFP was 0.12–0.18. However, nationwide R&D capital stocks increase TFPs in all regions at the same time (as assumed in the model), so the total impacts of R&D throughout the country are much higher than the elasticity value we measured.

As shown by the estimations of SAR, the elasticity values with respect to the yield index, CHI, and quality index, CQI, were almost the same as R&D capital, KK. The impacts of the yield index and quality index were potentially large,[3] but the influences of these indexes were non-linear. Fig. 4 shows the elasticity of TFP with respect to temperature through CHI and CQI and with respect to precipitation through CFI. The effects of temperature via CHI and CQI changed the sign according to the threshold value. Until the 2020's, the effect of temperature via CHI remained positive, but after the 2020's, the effect became negative in most regions. Only Hokkaido increased rice TFP even under global warming until 2100. Impacts of

CQI were positive in Hokkaido and Fukushima until 2010, but became negative afterward. Other prefectures suffered from negative impacts of temperature via CQI for most periods. As such, negative influences of temperature by both indexes are multiplied when the temperature is over the threshold level.

The elasticity value with respect to CFI was −0.01, showing a negative effect of flood caused by heavy precipitation. As compared to other climate indexes, the potential impact of the flood index was small. This is because only limited areas of paddy fields are damaged by flood, depending on the course of the typhoon and locations of partial heavy rain. However, effects of flood were constantly negative, so extreme precipitation under future climate change certainly damages rice productivity.

Prediction of future rice TFP

Comparing absolute values of the estimated coefficient, DAR and SAR show relatively lower estimation coefficients than OLS. Theoretically, the estimated coefficients in DAR and SAR models show the direct effects of the explanatory variables on rice TFP. In addition to direct effects, these models consider indirect effects via other regions that change rice TFP. The total effects can be calculated by multiplying $(1 - \mu)^{-1}$ or $(\mathbf{I} - \rho\mathbf{W})^{-1}$ to the direct effects.

Figure 5 shows the prediction results of rice TFP by DAR and SAR with consideration of direct and indirect effects. For these predictions, climate conditions were set as forecast results of MIROC, and socio-economic factors were set along with the past trends of MA, KKn, and KKp. The chronological path of rice TFP fluctuated over time because of changes in climate factors. The path of total effects by SAR almost corresponds to the path of DAR, but some prefectures, such as Hokkaido and Fukushima, show some differences in these paths. These prefectures marked high growth rate of TFP, so there might be upward bias of dynamic autoregressive coefficient. The ratios of direct effects versus total effects show degree of spatial dependence caused by technological spillover. These rations were higher in the northern prefectures than southern prefectures. Northern prefectures indicated relatively high TFP levels, so there is a positive synergistic effect via technological spillover. However, TFP levels of southern prefectures were low, so there is a depression effect in these prefectures, becoming a spatial trap.

The fluctuation range in Fig. 5 became wider as time passed. This change was only due to climate change. Fig. 6 shows the average level and CV in TFP's for 2011–2030, 2041–2060, and 2081–2100. The CV's were almost stable in the northern prefectures, whereas CV's in most of the southern prefectures increased. In the northern prefectures,

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[1] The BSK one-sided joint test statistic (LM-H) was 3309.7 ($p = 0.00$), and conditional Lagrange multiplier statistics LM* was 27.7 ($p = 0.00$). The BSJK joint test statistic was $LM\text{-}j = 3108.6$ ($p = 0.00$)

[2] These values of MA are bit lower and those of R&D capital are bit larger than previous study ($\beta_{MA} = 0.32$ and $\beta_{KK} = 0.08$ in Kunimitsu et al. 2014).

[3] Theoretically, the elasticity of yield index, CHI, is one, if only yield changes but production costs remain constant. However, in reality, when yield is changed under climate change, production costs and prices also change by adaptation behavior of farmers as well as the market, so elasticity of CHI should be lower than one.
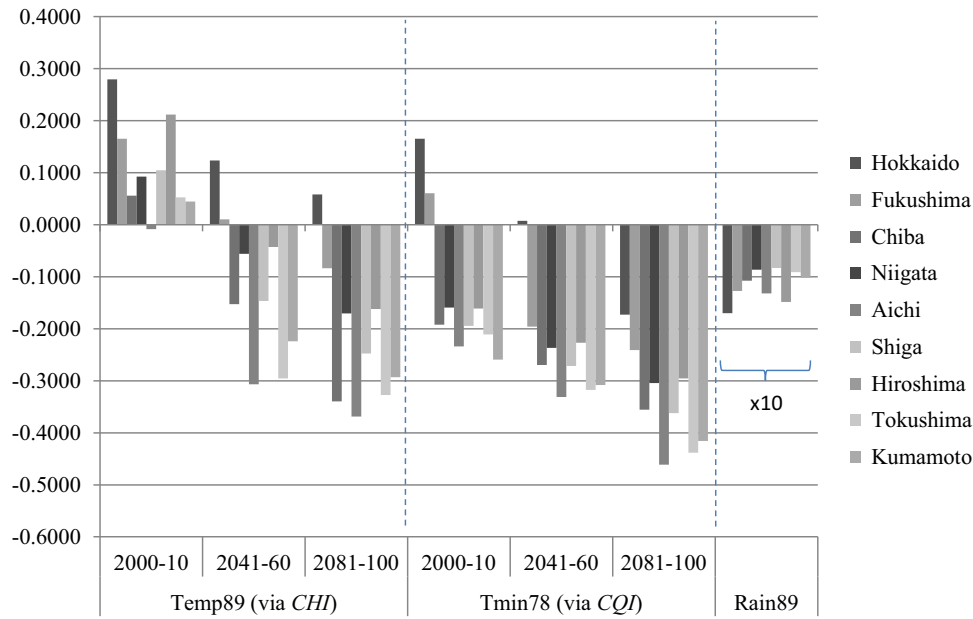
Fig. 4 Elasticity of rice TFP with respect to temperature. 2000–10 is from year 2000 to 2010, 2041–60 is from year 2041 to 2060, and 2081–100 is from year 2081 to 2100. The elasticity values at "Temp89 (via *CHI*)" columns show the effect of daily average temperature through crop-yield index (*CHI*) during August and September, and the values at "Tmin78 (via *CQI*)" columns show the effect of daily minimum temperature through crop-quality index (*CQI*) during July and August. Elasticity value of TFP with respect to temperature via *CHI* and *CQI* and with respect to precipitation via *CFI* can be calculated as follows by using marginal effect of temperature (*Temp*) or precipitation (*Rain*), where variable with upper bar shows average value:

$$\eta_{CHI\_temp} = \frac{\partial TFP}{TFP} \frac{\overline{Temp}}{\partial Temp} = \frac{\partial TFP}{TFP} \frac{\overline{CHI}}{\partial CHI} \frac{\overline{Temp}}{\overline{CHI}} \frac{\partial CHI}{\partial Temp} = \beta_4 \frac{\partial CHI}{\overline{CHI}} / \frac{\partial Temp}{\overline{Temp}},$$

$$\eta_{CQI\_temp} = \beta_5 \frac{\partial CQI}{\overline{CQI}} / \frac{\partial Temp}{\overline{Temp}}, \text{ and } \eta_{CFI\_Rain} = \beta_6 \frac{\partial CQI}{\overline{CFI}} / \frac{\partial Rain}{\overline{Rain}}$$
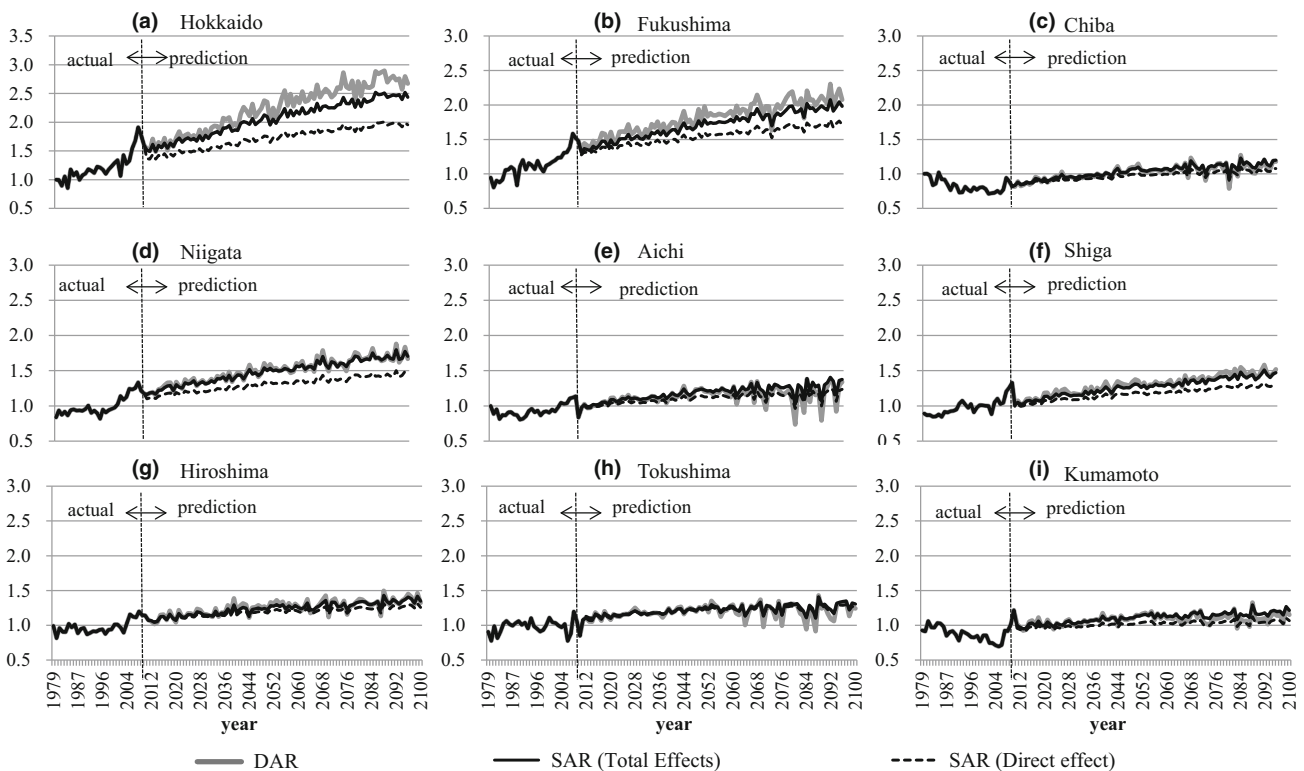

Fig. 5 Prediction of TFP under long-term climate change. Prediction values were calculated by the DAR fixed effect model, the SAR fixed effect model for total effect, and the SAR fixed effect model for only direct effect. Future values of explanatory variables were assumed to grow along to the chronological trend (socio-economic variables) and climate prediction of MIROC

Fig. 6 Changes in average TFP and its coefficient of variation (CV) under climate change within 20 years
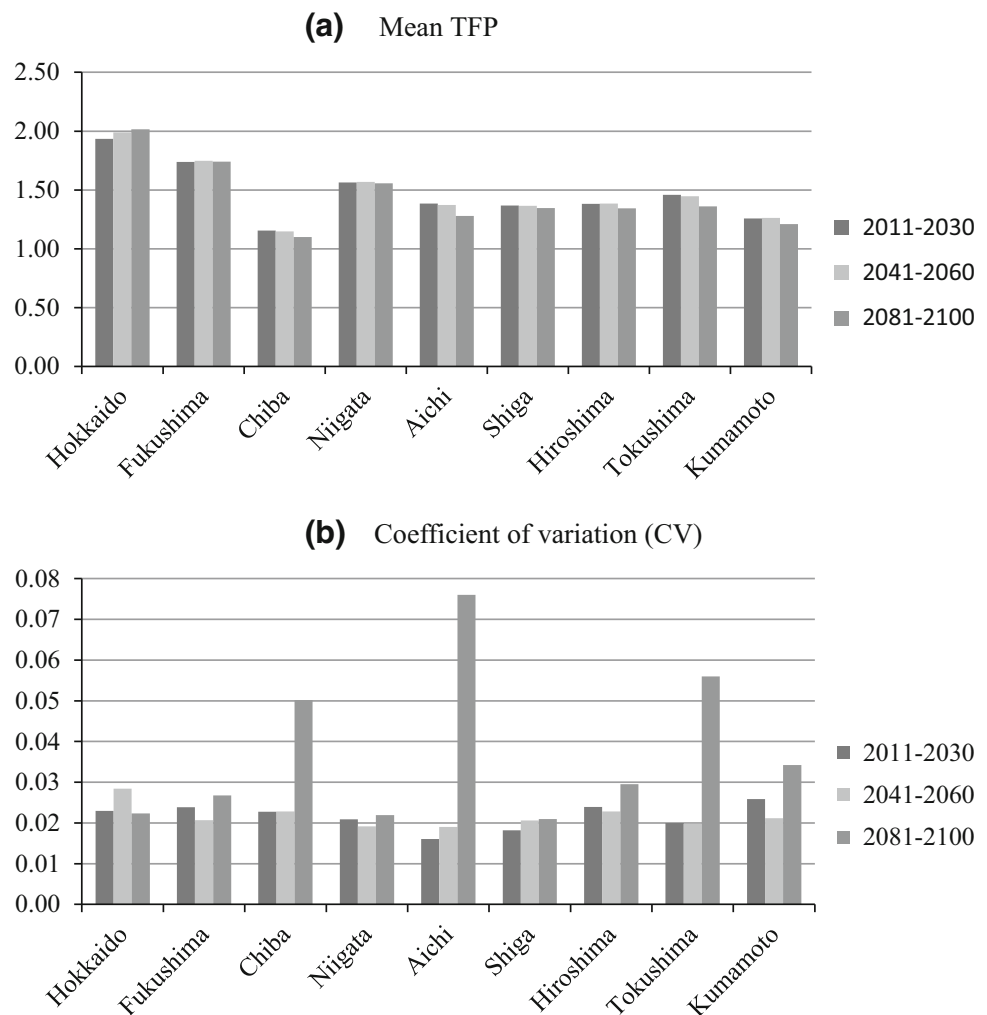
future temperature was still lower than the threshold value for many years, so positive impacts of *CHI* and negative impacts of *CQI* canceled each other. However, in the southern prefectures, future temperatures were beyond the threshold value for many years, so negative impacts of both *CHI* and *CQI* accumulated and increased variations in annual TFPs. Negative effects by precipitation added to these accumulated effects. From these tendencies, it can be said that global warming is favorable in the northern prefectures, but unfavorable in the southern prefectures.

Policy implications and conclusions

The present study analyzed socio-economic and climate factors in rice TFP and evaluated technological spillover effects by using the spatial econometric model. In addition to OLS and DAR models, SAR model with the spatial lag term was estimated to show spatial dependence existing in rice TFP. The long-term impacts of climate change were projected by the estimated model associated with the crop-yield, crop-quality,

and hydrological models. The future climate conditions as inputs were calculated by a high-resolution version of MIROC.

The results and policy implications are as follows. First, spatial autoregressive tendency was observed in rice TFP, even though the influences of climate factors that cause regional similarities were removed. In this sense, empirical results of ordinary panel data analysis without consideration of spatial dependence have a high possibility of estimation bias. Such spatial dependence can be interpreted as technological spillover from neighboring prefectures. Technological spillover brings about synergistic effects among neighboring prefectures in northern Japan and depression effects, like a spatial trap, from neighbors in southern Japan.

Second, substantial impacts of climate change were as high as knowledge capital stocks accumulated by R&D activities but different in degrees by regions. However, climate change showed a positive effect on rice TFP in the northern regions of Japan, but rice TFP decreased in the southern regions along with a decrease in rice yield and quality after the 2050's. The influence of precipitation via flood, which occurred mostly in the cost side change, was always

Table 3 Descriptive statistics of variables used for the crop-quality (CQI) model

Variables	Contents	Unit	Average	SD
CQI*	Percentage of the 1st grade rice (actual)	%	67.64	20.06
SR7	Average solar radiation in July	MJ/m^2	17.09	1.94
SR8	Average solar radiation in August	MJ/m^2	17.09	1.94
Tmin78	Average of minimum daily temperature in July and August	°C	20.82	1.73
Tmax8	Average of maximum daily temperature in August	°C	29.29	1.93
DT	Spiked data dummy which takes 1 when yield level was rapidly decreased only one year and recovered in the next year, 0 otherwise	1 or 0	0.02	0.15

Table 4 Estimation results of the crop-quality (CQI) model

Items	Linear function Coeff. (t-stat.)	Non-linear func. 1 Coeff. (t-stat.)	Non-linear func. 2 Coeff. (t-stat.)
Constant	111.698 (8.86***)	−603.282 (−8.54***)	54.944 (12.46***)
SR7	0.290 (1.16)	0.548 (2.28**)	0.633 (2.87**)
SR8	0.966 (3.35***)	1.137 (4.11***)	0.899 (3.67***)
Tmin78	−3.155 (−4.45***)	67.086 (9.76***)	–
Tmin78^2	–	−1.729 (−10.27***)	–
ABS(Tmin78-19.5)	–	–	−6.624 (−10.44***)
DT · Tmax8	–	–	−1.312 (−13.78***)
Adjusted R^2	0.35	0.41	0.48
Log likelihood	−4925	−4873	−4796
AIC	8.43	8.35	8.21
Hausman Test (χ^2)	31.70 ($p = 0.00$***)	24.56 ($p = 0.00$***)	17.56 ($p = 0.00$***)

Total panel observations are 1178 (38 × 30: 1979–1992, 1994–2010). All estimation models are the fixed effect model according to Hausman Test statistics. AIC is Akaike's information criterion. The signs "***", "**", and "*", respectively, show significant level at 1, 5, and 10 %

negative. In total, the northern part of Japan, where temperature stays below the threshold value, can increase rice TFP even under global warming, but southern regions suffer from a decrease in future TFP with accumulative effects of temperature and flood. To decrease such negative impacts of long-term climate change, new technologies need to be developed by R&D activities, such as more heat-tolerant rice species, and new planting techniques to shift rice planting season to cooler period. Furthermore, provision of reliable and accurate climate information to farmers is critical for farmers to adopt new technologies and decrease risk.

Third, an increase in fluctuations of productivity in addition to a decrease in the average productivity creates unstable rice production especially in the southern regions where initial rice TFP is low. Such unstable situations may result in an increase in abandoned paddy fields and change in future land use. Land use change increases occurrence of flood and changes the ecosystem. To avoid such changes, it is important for our society to take appropriate measures, such as mitigation policies for global warming. Against flood problems caused by land use change, maintaining paddy field areas inside the country by increasing rice productivity and management scale of farmers is a critical issue for policy making.

Limitations of this analysis and remaining issues are as follows. This study could not simultaneously treat serial correlations and spatial dependence in the estimations, so a more advanced econometric method such as a dynamic panel analysis is needed. Furthermore, 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.

Appendix

Based on the previous study (Kawazu et al. 2007), we newly estimated the crop-quality model using recent data. Table 3

shows statistics of the variables used for estimation of the *CHI* index. Table 4 shows the estimations of the crop-quality model in Eq. (10). In the case of non-linear function 3 with absolute value of temperature, the best fitted estimation with respect to log likelihood value was picked, which was estimated by changing threshold temperature by 0.5 from 18 to 25 °C. At temperature of 19.5 °C, estimations marked the highest log likelihood value, and showed similar threshold temperature as the quadratic function.

The fixed effect model showed statistical superiority over the random effect estimations, as shown by the Hausman statistics, adjusted R^2, and other statistics. Unfortunately, the adjusted R^2 was approximately 0.5, showing limited explanation power of the estimations. Using these estimations, *CQI* used in Eqs. (1)–(4) was calculated.

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