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1 January 2012

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Abstract

Adaptation to climate change has become an important policy question in recent years. Agriculture is the economic activity most sensitive to climate change. We evaluate the dynamic effects of productivity change and individual efforts to adapt to climate change. Adaptation actions in agriculture are evaluated to determine how the climate affects production efficiency. In this paper, we use the bi-directional distance function method to measure Japanese rice production loss due to climate. We find that 1) accumulated precipitation has the greatest effect on rice production efficiency and 2) the climate effect on rice production efficiency decreases over time. Our results empirically support the benefit of an adaptation approach.

1. Introduction

Adaptation to climate change has become an important policy question in recent years, especially in the United Nations Framework Convention on Climate Change (UNFCCC). In thirteenth meeting of the Conference of the Parties (COP13), participating nations adopted the Bali action plan, which proposed the implementation of adaptation actions. The UNFCCC funds adaptation and has implemented a project to mitigate climate effects in developing countries. Clearly, the reduction of greenhouse gas emissions is an important part of long-term efforts. Stern (2006) estimated that the impact of climate change on economic activity will reach 5% of the global GDP if action is not taken. Stern warns that if we do not prepare adaptations for climate change, enormous global economic damage will occur (see Tol and Yohe, 2009 for a review of climate modeling). Agriculture is the economic activity most sensitive to climate change, and many studies have estimated the effect of climate change on agriculture (Rosenzweig and Parry, 1994; Reilly et al., 2003; Mendelsohn and Dinar, 2009).

Most of these studies have calculated the potential effect of climate change on the quantity of agriculture production (Chang, 2002; Peng et al., 2004; Falco and Chavas, 2008) and have analyzed the effects of temperature, rainfall, and sunshine as climate variables. Another group of studies has calculated the potential effect of climate change on agricultural economic damage. For example, Mendelsohn et al. (1994) used a Ricardian analysis to estimate the effect of global warming on US agriculture. Schlenker et al. (2005) used a hedonic approach to analyze the impact of irrigation on adaptation. Deschênes and Greenstone (2007) estimated the impact of climate change on the US agricultural sector and used agricultural yields per hectare as the dependent variable to identify variation in yields with respect to weather. Like Deschênes and Greenstone (2007), we analyze the variation in yields by adding land used as an independent variable.

However, these studies do not sufficiently evaluate the dynamic effects of productivity change and individual effort on adaptation to climate change. Few studies have focused on the climate effect on agricultural production efficiency. Thus, it is crucial to evaluate the effect of adaptation on agriculture to determine how the climate affects production efficiency. As described below, not all decision-making units can maximize yields based on particular conditions. In other words, the potential exists for production inefficiency.

We apply directional distance functions (DDF) as a production efficiency technique to measure Japanese rice production loss due to climate change. The DDF method is a nonparametric approach to measure the efficiency of production that takes into account production inefficiency. This method is used to measure production efficiency in many fields (e.g., Kumar and Managi, 2010). Some studies have analyzed agricultural productivity using this method (e.g., Coelli and Prasada Rao, 2003).

In this study, we apply the model of Picazo-Tadeo et al. (2005) to measure the effect of climate change. Picazo-Tadeo et al. (2005) calculated efficiency under strong and weak disposability to measure the opportunity cost of environmental regulation (see Appendix A). In reality, the joint production of several input and output production factors causes difficulties in the measurement of the overall performance of decision making units (DMUs). This is because any DMU may synchronously decrease both desirable and undesirable outputs without changing inputs. Therefore, many previous studies have calculated efficiency under strong disposability to capture the abatement effort of undesirable outputs (e.g., Färe et al., 2007).

However, several inputs have characteristics that decrease the desirable outputs in the agricultural production process, including the climate conditions needed for agriculture. Temperature, rainfall. and sunshine are important factors for agriculture production. However, extremely high temperatures will decrease the quantity of agricultural production, making input factors undesirable for production. Therefore, we expand the Picazo-Tadeo model to consider undesirable (negative) input factors for rice production.

Normally, adaptation for climate change is a more significant problem in developing countries. However, our analysis of Japan has two advantages. First, Japan has several regional climate characteristics despite the country's small size. Thus, we can easily compare how climate factors affect production efficiency in each region. Second, Japan has advanced irrigation equipment and agricultural technology. The results of our analysis can identify the costs of avoiding climate effects with these technologies and investments.

This paper is organized as follows. Section 2 provides a literature review. In section 3, we explain our empirical model and data. Section 4 presents our specification results. In section 5, we compare our index to other indexes, particularly the crop situation index used by the Japanese government and other factors that potentially mediate the climate effect. The final section summarizes our results.

2. Literature Review

Productivity growth in agriculture has been one of the most important research topics in agricultural policy over the last five decades. Economists have examined the sources of productivity growth and productivity differences among regions. A number of analyses of cross-country differences in agricultural productivity were conducted in the 1970s and 1980s, including studies by Kawagoe et al. (1985), Capalabo and Antle (1988), and Lau and Yotopoulos (1989).

There are several efficiency measurement approaches in agriculture. A Stochastic Frontier Analysis (SFA) might be appropriate to focus on the fact that agricultural processes are stochastic. However, the problem with SFA is that it assumes a parametric specification for production technology, which can confound the efficiency results (Reihard et al., 1999). In addition, curvature conditions (i.e., concavity in inputs) are not globally satisfied when using the popular translog specification. Furthermore, SFA makes an explicit assumption about the distribution of the inefficiency term. Data Envelopment Analysis (DEA) has more flexibility so that a parametric specification of technology and assumptions about the distribution of efficiency can be avoided while allowing the curvature conditions to be imposed easily.

Previous studies have also attempted to measure agricultural productivity and production efficiency with a nonparametric frontier analysis of DEA. However, few studies have measured the climate impact on agricultural production efficiency. For example, Mao and Koo (1999) used a nonparametric frontier analysis to measure the Malmquist productivity for Chinese agriculture. However, the study focused on the measurement of productivity itself; the climate effect on agricultural production has yet to be analyzed.

Normally, the crop situation index is used as a benchmark of the climate effect on agriculture production. When the Japanese government evaluates the effect of climate change on crop production, the crop situation index is the common key indicator. The Minister of Agriculture, Forestry and Fisheries of Japan uses this index for policy making in Japan. In Japan, the crop situation index of rice measures the gap between rice quantities at baseline per ton, per acreage, and the actual amount of rice production. The baseline amount of rice production is estimated using a panel model that can control for climate effects. When negative or positive climate effects do not occur, this index is 100%. Values more than 100% mean that climate effects help to increase rice production quantities.

The crop situation index does not consider efforts to avoid climate effects and changes in production inputs. We are aware of only one study that has analyzed climate effects on production efficiency. You et al. (2009) used the Cob-Douglas production function to estimate the climate effect on wheat productivity in China. However, the climate effect cannot be captured by using a linear relationship with output (see Schlenker and Roberts, 2006). Thus, we measure the effect of climate on rice production efficiency by DEA, which is suitable for measuring the nonlinear effects of climate.

3. Methodology

This study measures the association between climate effects and efficiency loss on rice production in Japan. First, we apply simple fixed and random effects specifications to classify whether climate conditions affect rice production positively or negatively. Second, we measure the climate effects on production efficiency using the signs obtained in the panel estimations.

We regress a production function in the first step. We estimate the effects of each output variable on the production function to classify which variables increase or decrease the output amount. These positive/negative signs are used for the choice of DDF. When we measure the production efficiency using DDF methods, we divide positive input (input factors that increase output) and negative input

(input factors that decrease output) before measuring the production efficiency. We consider the effect of climate impacts on Japanese rice production. However, we cannot understand apparent relationships between Japanese rice production quantities and climate impacts. Thus, we first estimate the relationship between climate variables and rice production quantities using a regression model. With these results, we measure the climate impact on Japanese rice production efficiency using a DDF method.

3.1 Fixed and random model: Base specification

This section presents the model of fixed and random specifications. Following previous studies, we use rice production quantity (ton) as an output variable. We estimate the following equation using fixed and random effects specifications:

$$\ln rice_{it} = \alpha + \beta_1 \ln Labor_{it} + \beta_2 \ln Capital_{it} + \beta_3 \ln Land_{it} + \beta_4 \ln Operate_{it} + \beta_5 \ln Rain_{it} \\ + \beta_6 \ln Temp_{it} + \beta_7 \ln Temp_{it}^2 + \beta_8 \ln Sun_{it} + \mu_i + v_{it}, \quad (1)$$

where $Labor_{it}$ refers to hours worked for year t and prefecture i, $Capital_{it}$ denotes the production capital (including cost, using Japanese Yen, of animal power, equipment, and rent)[1], and $Land_{it}$ is acreage under rice cultivation (unit of $100m^2$). $Operate_{it}$ is other operating costs (cost of seeding, manure, agricultural chemical and other material, also using Japanese Yen). To obtain the output and input data in real value terms, it is necessary to convert the nominal value data into real value data

[1] In this study, capital data are flow data in each year.

using deflators (1995 = 100). Input price indices for production capital and current goods use the Törnqvist method, employing their corresponding price indices from the Statistics of Prices and Wages in Rural Areas (SPWRA), which is issued annually by the Ministry of Agriculture, Forestry and Fisheries of Japan. We expect commonly used production factors (*Labor*, *Capital*, *Land*, *Operate*) to have a positive association with rice production.

$Rain_{it}$, $Temp_{it}$, and Sun_{it} represent the climate environment with accumulated precipitation (millimeter), effective accumulated temperature (degree-days), and accumulated sunshine duration during rice growing seasons, respectively. Each climate datum is calculated with a quantity survey. In our model, we add a quadratic term of average temperature to consider high temperature injuries, as explained in section 4.2.[2] With regard to precipitation, we consider the linear effect only because adding the quadratic variable can cause correlations, and the results are not statistically significant. This might be partially because Japan does not experience the harmful situation of too little average precipitation. Note that μ_i is the fixed effect that describes the inherent effect of prefectures on fixed effects specifications. In random specifications, μ_i represents a stochastic variable.

Many studies show that climate change causes land use changes. We would need to take land use changes into account if they occurred during our study period. However, at least for rice in Japan, land use changes did not occur during our study period.

[2] We do not report the quadratic results of accumulated precipitation and accumulated sunshine duration because they are not statistically significant.

First, the correlation in our data between acreage (*Land*) and the climate variable is small (*temp*: -0.087, *Sun*: 0.206, *Rain*: -0.087). The correlation between *Land* and *Sun* is positive and higher than the other climate variables. This correlation shows farmers' preferences for choosing suitable places for farming. However, there is no clear correlation between *Land* and the other climate variables. Note that several studies have pointed out that climate change does not always cause land use change. For example, Taylor et al. (2002) analyzed the influence of land use in the Sahel. They found that recent historical land use changes were not large enough to have been the principal cause of the Sahel drought.

Second, climate change did not clearly occur in our study period. When temperatures increase, farmers might consider changing their cultivated agricultural crops or giving up on agricultural cultivation. However, large temperature changes did not occur in our analysis period. Our regression results show the positive coefficient between temperature and output.

In contrast, the climate environment has a more complex relationship with output. The relationship between rainfall and rice production is not clear. In Japan, farmers have better irrigation and drainage technology than in other areas (Seino, 1995). Thus, accumulated precipitation might not affect rice production. However, if rainfall increases from typhoons (which are accompanied by strong winds of up to around 200 km/h, known as hurricanes in the Atlantic Ocean), β_5 is expected to have a negative sign in our regression. A minimum average temperature is required for efficient rice production. Therefore, β_6 is expected to have a positive sign in our regression. Note that excessively high or low temperatures cause high and low temperature injuries. We expect a negative relationship between average temperature-squared and rice production. Accumulated sunshine duration is expected to have a positive sign in our specification.

We estimate another model to examine the productivity change in Japanese rice production. In this model, we add the time trend (*time*) and its squared term ($time^2$) as proxy variables for productivity change.

3.2 Directional distance function

This study applies DDF methodology by modifying Picazo-Tadeo et al. (2005).[3] Picazo-Tadeo et al. (2005) analyzed a DDF model to measure desirable output loss considering decreasing undesirable output. The climate change effect cannot be considered an output because climate plays a key role in agriculture products. Thus, in our model, we consider climate factors as inputs.

Consider a production process that uses a vector of inputs, $x \in \Re_+^L$, to obtain a set of desirable outputs denoted by the vector $y \in \Re_+^M$, a vector of climate factors that cause efficiency loss (negative climate factors), $b \in \Re_+^R$, and a vector of climate factors that increase output (positive climate factors), $c \in \Re_+^s$. Next, define the production possibilities set by

$$P \equiv \{(x, y, b, c) : (x, b, c)\, can\ produce\ y\}.$$

[3] For a graphical representation of the DDF method, see Appendix B.

In particular, we assume a weak disposability of desirable outputs and climate factors to explicitly consider that climate factors may affect rice production quantities, as is commonly assumed in traditional production theory. When a farmer faces climate change, some climate factors cause efficiency loss. The axiom of weak disposability of inputs constitutes an appropriate assumption of the technology. In other words, climate that otherwise could have a productive use (i.e., production of desirable outputs) has to be diverted to reduce the negative influence of climate change. The directional technology distance function can generalize both the input and output of Shephard's distance functions, which provides a complete representation of the production technology. We formally define the presence of climate factors as

$$\vec{D}(x, y, b, c; g_x, g_y) = \sup\left\{\beta : \left(y + \beta g_y\right) \in P\left(x - \beta g_x, b, c\right)\right\}. \tag{2}$$

Under weak disposability, this directional technology distance function, $\vec{D}^W$, can be computed for prefecture k, which solves the following programming problem:

$$\vec{D}^W(x, y, b, c; g_x, g_y) = Maximize \quad \beta^k$$

$$
\begin{aligned}
s.t. \quad & \sum_{i=1}^{N} \lambda_i^k x_{li} \le x_{lk} - \beta^k gx_l && (l = 1, 2, \cdots, L) \\
& \sum_{i=1}^{N} \lambda_i^k y_{mi} \ge y_{mk} + \beta^k gy_m && (m = 1, 2, \cdots, M) \\
& \sum_{i=1}^{N} \lambda_i^k b_{ri} = b_{rk} && (r = 1, 2, \cdots, R) \\
& \sum_{i=1}^{N} \lambda_i^k c_{si} \le c_{sk} && (r = 1, 2, \cdots, S) \\
& \lambda_i^k \ge 0 && (i = 1, 2, \cdots, N),
\end{aligned}
\qquad (3)
$$

where x_{li} is the l th input factor for prefecture i in an $L \times N$ input factor matrix X, y_{mi} is the m th output in a $M \times N$ output factor matrix Y, b_{ri} is the r th negative climate factor in a $R \times N$ matrix B, and c_{ri} is the s th negative climate factor in a $S \times N$ matrix C. In addition, gx_l is the directional input vector of the l th input factor, gy_m is the m th directional output vector of desirable output factors, β^k is the inefficiency score of the kth prefecture, and λ_i^k is the variable weight for the i th prefecture. To estimate the inefficiency score of all areas, the model needs to be independently applied N times for each area.

Alternatively, we consider the case that prefectures do not face a negative climate effect. Strong disposability of negative climate factors constitutes a convenient characterization of the technology because it allows for the possibility that farmers do not face a negative climate effect. That is, in the absence of climate constraints, farmers can produce rice at the most efficient production level. In this scenario, the distance function $\overrightarrow{D}^S$ for prefecture k arises as the solution to the following programming problem:

$$\overrightarrow{D}^S(x,y,b,c;g_x,g_y)=Maximize \quad \beta^k$$

$$\begin{aligned}
s.t. \quad & \sum_{i=1}^{N}\lambda_i^k x_{li} \le x_{lk}-\beta^k gx_l && (l=1,2,\cdots,L) \\
& \sum_{i=1}^{N}\lambda_i^k y_{mi} \ge y_{mk}+\beta^k gy_m && (m=1,2,\cdots,M) \\
& \sum_{i=1}^{N}\lambda_i^k b_{ri} \le b_{rk} && (r=1,2,\cdots,R) \\
& \sum_{i=1}^{N}\lambda_i^k c_{si} \le c_{sk} && (r=1,2,\cdots,S) \\
& \lambda_i^k \ge 0 && (i=1,2,\cdots,N).
\end{aligned} \tag{4}$$

Next, we compare the additive efficiency measures obtained from the DDFs under the weak and strong disposability to compute an index of the impact on prefectures' performance, considering climate constraints that prevent the efficient production of rice (see Hernández-Sancho et al., 2000; Picazo-Tadeo et al., 2005; Piot-Lepetit et al., 2007). In our technology constraints, we assume that negative climate factors force desirable output to shrink (which is also shown in the results of Equation (1)) so that the impacts of negative climate factors can be measured in terms of desirable output losses. The efficient production (EP) of desirable output *m* relative to the unconstraint frontier of region *k* is

$$EP^S(y_m^k)=\left\{y_m^k+\overrightarrow{D}^S\left(x_k,y_k,b_k,c_k;gx,gy\right)\times y_m^k\right\}, \tag{5}$$

while the projection on the boundary of the constrained output set is

$$EP^W(y_m^k)=\left\{y_m^k+\overrightarrow{D}^W\left(x_k,y_k,b_k,c_k;gx,gy\right)\times y_m^k\right\}. \tag{6}$$

The climate impact index (CI) for region *k* and good *m* is then computed as the difference between efficiency projections of desirable *m* on both regulated and unregulated frontiers. That is,

$$\begin{aligned} CI^{k}(y_m) &= EP^{S}(y_m^k) - EP^{W}(y_m^k) \\ &= \left\{ \overrightarrow{D}^{S}\left(x_k, y_k, b_k, c_k; gx, gy\right) - \overrightarrow{D}^{W}\left(x_k, y_k, b_k, c_k; gx, gy\right) \right\} \times y_m^k. \end{aligned} \tag{7}$$

This CI always takes values equal to or greater than zero. A value of zero implies that climate changes are not economically binding, and consequently, the constraint does not hinder the strong disposability of negative climate factors. Conversely, a positive index indicates that climate constraints hinder efficient rice production.

4. Applications

4.1 Data

In the first step, fixed and random specifications use panel data from 1961 to 1995. In this study, we apply data from 1961-1995 because of unavailable climate data before 1960 and changes in the definition of price indices after 1996. This analysis covers all of the key agricultural prefectures in Japan (39 prefectures out of 47). The Appendix lists 39 prefectures and area classifications. We exclude the prefectures of Chiba, Kanagawa, Tokyo, Okinawa, Osaka, Saitama, Shiga, and Yamaguchi due to limitations of the data. The data on *Rice* (quantity of rice production), *Labor, Capital*, *Land,* and *Operate* are obtained from the Ministry of Agriculture, Forestry and Fisheries in Japan. Climate data (such as *Rain*, *Temp*, and *Sun*) are obtained from the Japan Meteorological Business Support Center (2006). Annual climate data are compiled from daily data in each prefectural capital during rice-growing seasons from the heading to harvesting period. The effective accumulated temperature is calculated based on a daily mean temperature: below 10 $^{\circ}C$ contributes 0 degree days, between 10 and 30 $^{\circ}C$ contributes the difference between a daily mean temperature and 10 $^{\circ}C$, and above 30 $^{\circ}C$ contributes 20 degree days (Ebata, 1990a,b). Accumulated precipitation and sunshine duration are calculated by summing the daily data.

The efficiency loss analysis in the second step is conducted using the same data on fixed and random specifications. Inputs are *Labor, Capital*, *Land,* and *Operate*, and input climate factors are *Rain*, *Temp*, and *Sun*. In the first step, we classify climate factors into negative climate factors and positive climate factors. From the result, we can decide which climate factors should be used as negative or positive factors in our DDF model to measure efficiency loss.

4.2 Result of fixed and random specifications

Table 1 shows the result of fixed and random specifications to understand the sign of climate factors to production quantities. In this table, we also add the ordinary least square (OLS) result to check the robustness of our estimations. The fixed effect result shows that all production factors (*Labor, Capital, Land*, and *Operate*) are positive and significantly associated with production quantities.

The *Land* coefficient shows the largest effect on production quantities. Some previous studies found similar results. This demonstrates the Japanese policy effect on agricultural land use. Since the

1970s, the Japanese government has implemented a rice acreage reduction policy to adjust production quantities of rice because farmers had difficulty expanding the cultivated area. Therefore, the scale of the cultivated area is the most important factor for rice production. Previous studies have shown the coefficient between rice production quantities and the scale of the cultivated area. For example, Kondo and Hiromasa (1986) estimated the elasticity of cultivation for rice production quantities to be 0.6-0.7 in the Tohoku and Hokuriku districts in Japan. However, each climate factor has a different association with output.

Temp and *Sun* have a positive relationship with output, but *Rain* and $Temp^2$ have a negative relationship with output. Excessively high temperatures and rainfall, however, decrease rice production quantities. The negative sign of $Temp^2$ and the positive sign of *Temp* imply that temperature leads to the maximum output. However, we note that the current maximum temperature is below the peak associated with the maximum output. Therefore, we add *Temp* as a good climate factor. In addition, differences between the aforementioned result and another specification with the time trend are provided. We find that time trends are not significant.

High temperatures have the potential to decrease future production quantities. In addition, considering future negative effects and the negative synergetic effect of rain, we add temperature to bad climate factors in a separate model as follows, and we consider *Rain* a bad climate factor in the DDF analysis.

4.3 Measurement of efficiency loss

Based on the above results, we classify each climate factor as negative or positive to measure the production efficiency. Because we consider average temperature a positive and negative factor for rice production, we develop two models. Table 2 presents the combination of variables for each model.

Figure 1 presents the average efficiency loss of rice production in each year as a percentage of efficiency loss (EP^{s} - EP^{w}) using DDF. In almost all of our study periods, efficiency loss tended to decline on average. In the 1970s, however, efficiency loss fluctuated widely. The efficiency loss clearly decreased after the 1970s, but our results show that negative climate factors affect the fluctuation of efficiency loss. Figure 2 shows the total rice production quantity loss each year. These trends are similar to those in Figure 1.

Between 1961 and 1970, efficiency loss from negative climate effects showed a sharp decline in each prefecture. These results are expected due to improvements of cultivar and irrigation equipment. In these periods, cultivar improvements focus on low temperature injuries. The Japanese government is committed to maintaining irrigation equipment; improving irrigation equipment protects the rice plant from the negative effects of low temperatures. In reality, the gap between model 1 and model 2 was largest in the 1960s (with an average inefficiency of 0.75%). This gap suggests the inefficiency of rice production that is due to the temperature. In the 1970s and later, improvements in cultivar and irrigation led to decreases in inefficiency due to negative temperature effects. These effects increase adaptation ability to decrease the CI.

During the 1970s, efficiency loss fluctuated widely. Efficiency loss was particularly high in 1976, when Japan experienced several typhoons. For example, the typhoon “Fran” caused record rainfall in many prefectures and destroyed 80,304 ha of cultivated area (National Astronomical Observatory of Japan, 1997). Thus, efficiency loss increased in this year.

Table 3 shows the average percentage of efficiency loss and a summary of CI in key areas and regions where the prefectures were aggregated into three districts (detailed area classification is given in Appendix C). We take simple average values in the tables. The Tohoku region is the most important rice production area. The Hokkaido region became one of the major rice production areas in these years, and the Kyushu region is a major production area but has high temperature injuries caused by climate change. Thus, we focus on efficiency loss in these regions.

Table 3 shows that the Tohoku region has a lower percentage of efficiency loss than the other prefectures. Negative climate factors do not affect efficiency in the Hokkaido region. We expect the characteristics of each of the region prefectures to affect efficiency loss. For example, the CI of West Japan (including the Kyushu area) is larger than other regions. The Kyushu region has more precipitation during the rice-growing seasons than other districts in Japan because of heavy rainfall in the early summer rainy season, called “Baiu.” This region also has storm and flood damage from many typhoons each year. In North Japan (including Tohoku and Hokkaido), however, the typhoons do not have a large impact.

We also investigate the correlation coefficient of these models (see Table 4). Our calculations reveal a high correlation between the two models. The correlation coefficient between model 1 and 2 is 0.813. This result implies two possibilities. First, trends in efficiency loss are similar in the models. Second, the climate effect of production inefficiency is mainly caused by accumulated precipitation.

5 Discussion

In summary, our study reveals two important results. First, accumulated precipitation is the most effective factor in rice production efficiency. Second, the climate effect on rice production efficiency decreases over time. We provide two discussions based on these results. First, we investigate the other factors that influence climate effects on rice production. In particular, heavy rainfall causes floods, and the associated policy response is of interest. Thus, we analyze the relationship between CI and investment for river improvement.

Second, we compare our results (CI) with the crop situation index. As mentioned above, the crop situation index does not clarify efforts to avoid climate effects and change production inputs. Thus, we compare CI and the crop situation index. If these two correlations are high, our proposed index is not needed because of its complexity.

5.1 Relationship between public investment and other effective factors

Investment in avoiding floods and other weather crises has the potential to affect rice production efficiency loss. Therefore, we investigate the relationship between constraints that impact rice production and public investment for river improvements at the prefecture level. Figure 2 presents the scatter plots and shows a negative correlation between the amount of public investment (one million Japanese Yen) and CI in each year. The data on public investment are obtained from the Cabinet Office, Government of Japan (2007).

Figure 3 shows the possibility that public investment for river improvements may decrease the efficiency loss of the climate effect. We apply public investment as a flow variable. Ideally, accumulated stock has an impact on production loss, but a stock variable was not available in this study. Therefore, we use the flow amount of public investment as a proxy. The reduced loss effect of public investment is most likely small because investment in climate change adaptation has a low priority for public investment decision making. Therefore, the indirect effects of public investment might prevent harm to human life and other economic activities. If policy makers increase the priority of investment for adaptation, this effect may increase.

Other important factors also decrease the impact of climate on rice varieties. Improvements in rice varieties were begun in Japan in the early nineteenth century. Almost all of these improvements focused on reducing cold summer damage in the northern areas of Japan. Our data show that the average temperature during our analysis periods was sometimes low. Thus, improvements in rice varieties that reduce cold summer damage play a significant role in decreasing the negative climate impact. In addition, some farmers cultivate several types of rice at the same time to reduce the risk of climate effects. Such efforts might reduce the climate impact on rice production in Japan.

5.2 Comparison with crop situation index

The crop situation index does not control for adaptation efforts and productivity changes to mitigate the climate effects. The fluctuation of the crop situation index is larger than our measurement (see Figure 4). In addition, the correlation between our measurement and the crop situation index is weak (see Table 4). Therefore, the crop situation index does not capture the climate effect on production efficiency. Policy makers must evaluate not only the crop situation index but also the production efficiency when planning for adaptation to climate change.

6. Conclusion

In this paper, we measured the climate effect on rice production efficiency in Japan using a directional distance function method. Our results contribute to the understanding of crop production management. Until the 1980s, low temperature injuries were one of the most significant problems for rice production in Japan. However, in the near future, climate changes will increase average temperatures.

Our results reveal that the temperature effect on rice production is weak in Japan because Japanese agriculture has advanced cultivar and irrigation technologies to improve rice varieties. In addition, climate change increases not only average temperature but also the scale of storm and flood damage from typhoons (IPCC, 2007). Our results show that significant public investments have the potential to decrease the climate effect on rice production. Of course, other adaptation factors (the development of rice varieties to prevent low temperature injury, the cultivation of rice varieties that reduce the risk of climate effects on rice production) are important as well. Adaptation to climate change has become important for rice production in Japan.

High temperature injuries in rice production occur in tropical regions, including many developing countries. Many previous studies have noted the importance of adaptation in developing countries (Parry et al, 2004; Stern, 2006). Although the Japanese case may not directly apply to developing countries, our results suggest the importance of several adaptation methods, such as public investment, developing new agricultural varieties, and efforts to reduce the risk of climate effects.

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Table 1. Estimation of Production Function (amount of rice production base)

	OLS	Random Effect	Fixed Effect	(add time trend)
Labor	0.058***	0.080***	0.076***	0.094***
	(3.98)	(5.36)	(4.92)	(3.10)
Capital	0.047***	0.075***	0.070***	0.075***
	(2.97)	(4.51)	(3.98)	(3.98)
Land	0.818***	0.805***	0.782***	0.809***
	(37.71)	(32.21)	(27.43)	(25.31)
Operate	0.163***	0.113***	0.106***	0.067**
	(7.52)	(4.84)	(4.43)	(2.50)
Temp	10.670***	9.337***	9.265***	8.798***
	(7.13)	(7.32)	(7.28)	(7.00)
$Temp^2$	-0.816***	-0.704***	-0.698***	-0.656***
	(-6.96)	(-7.04)	(-7.00)	(-6.66)
Sun	0.111***	0.087***	0.084***	0.076***
	(6.40)	(5.20)	(4.99)	(4.40)
Rain	-0.044***	-0.015***	-0.014***	-0.027***
	(-8.44)	(-6.02)	(-5.70)	(-5.86)
Time				-0.012
				(-0.84)
$Time^2$				0.003
				(0.53)
Constant	-33.475***	-29.39***	-28.934***	-27.358***
	(-6.99)	(-7.22)	(-7.13)	(-6.82)
R^2	0.931	0.930	0.930	0.932
Hausman test	-	44.57***		

Note: *Significant at 10% level, **Significant at 5 %, ***Significant at 1% level. Values in parentheses are t-values.

Table 2 Combination of variables in each model of DEA

		model 1	model 2
Good input	*Sun*	✔	✔
	Temperature		✔
Bad input	*Rain*	✔	✔
	Temperature	✔	
Output	*Production quantity*	✔	✔

Table 3 Average of efficiency loss and *CI* in each region

	EP^s - EP^w		Climate impact(*CI*)	
	model1	model2	model1	model2
Tohoku region	0.0064	0.0044	17311.900	11360.043
Hokkaido region	0	0	0	0
Kyushu region	0.0147	0.0119	17864.010	14079.567
Other region	0.0177	0.0094	83576.279	42555.821
North Japan	0.0055	0.0037	17311.900	11360.043
East Japan	0.0128	0.0070	43045.355	21753.076
West Japan	0.0199	0.0120	58394.934	34882.311

Note: The results of model 1 and model 2 are based on quantity of rice production (t).

Table 4 Correlation between each model results

	model 1	model 2
model 1	-	0.813
Crop situation index	-0.177	-0.222

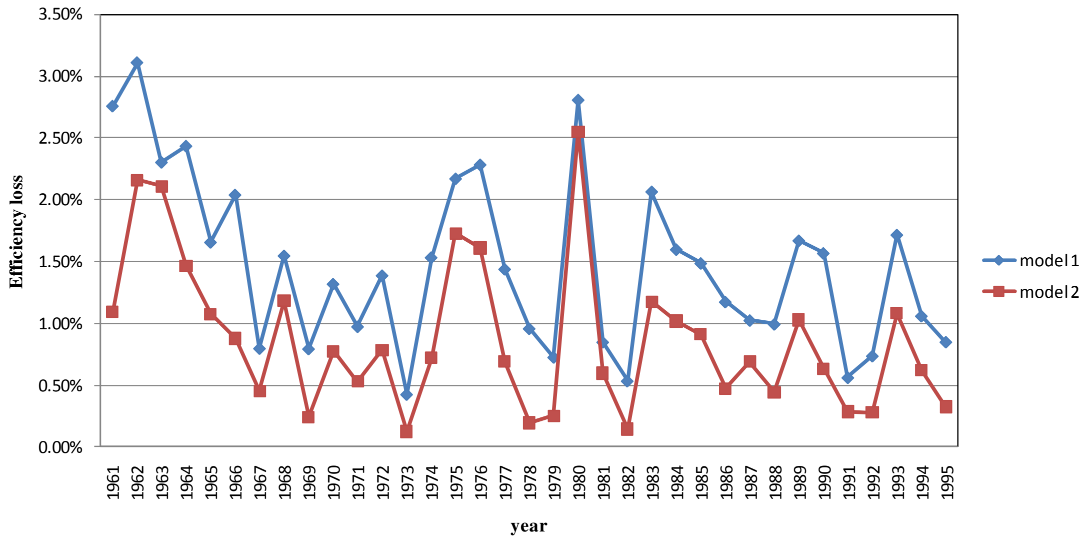

Figure 1 Percentage of Efficiency loss (average of all result)

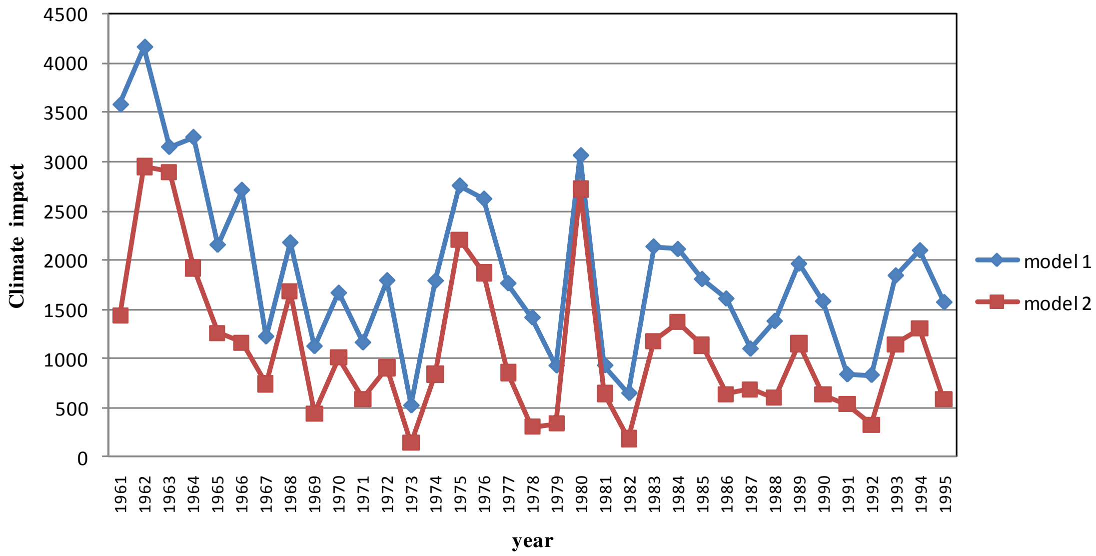

Figure 2 Summations of climate impact (amount of rice production)

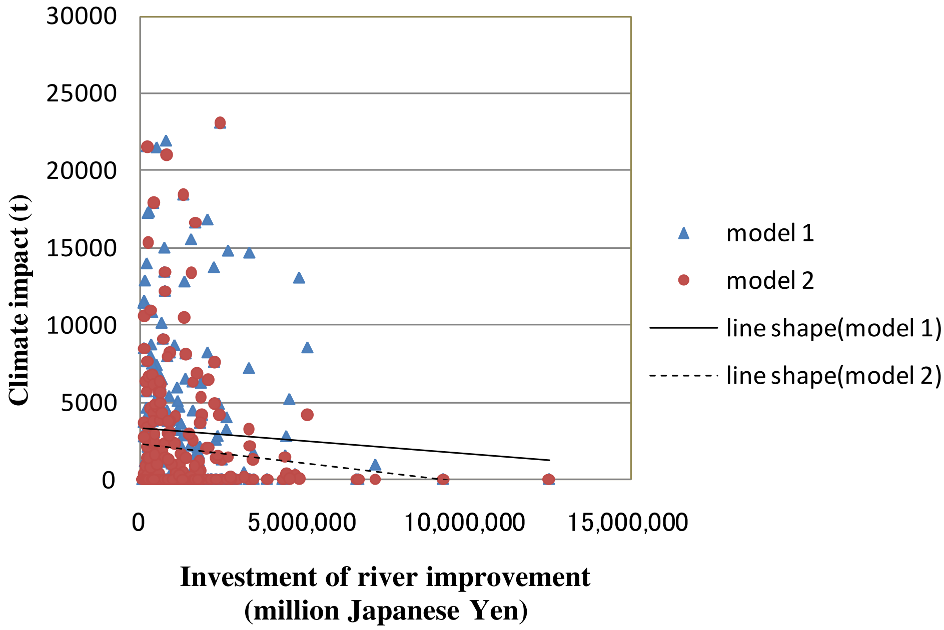

Figure 3 Relationship between investments for river improvement and climate Impact (amount of rice production)

Note: Figure 3 shows plots every five years because census data are available every five years.

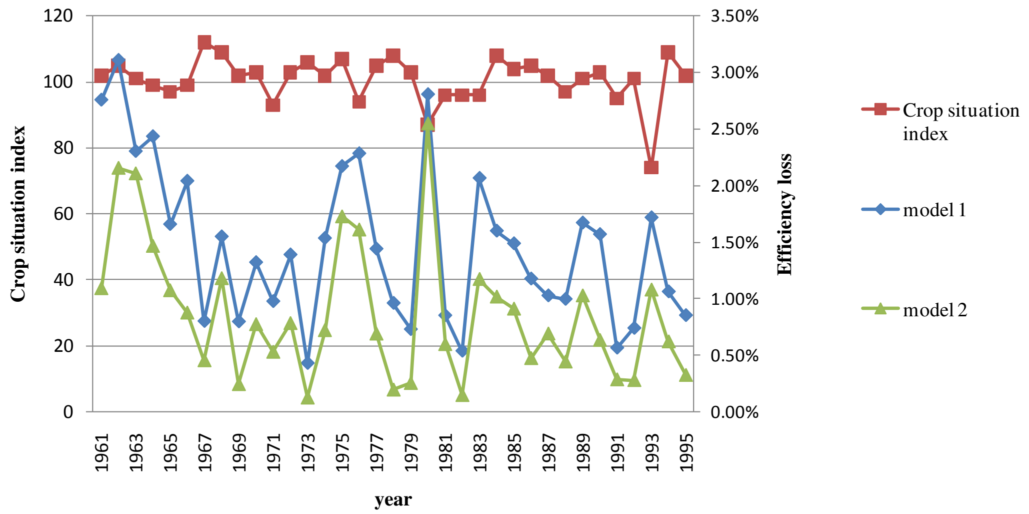

Figure 4 Crop situation index and percentage of efficiency loss

for rice production quantity

Appendix A: Strong disposability and Weak disposability

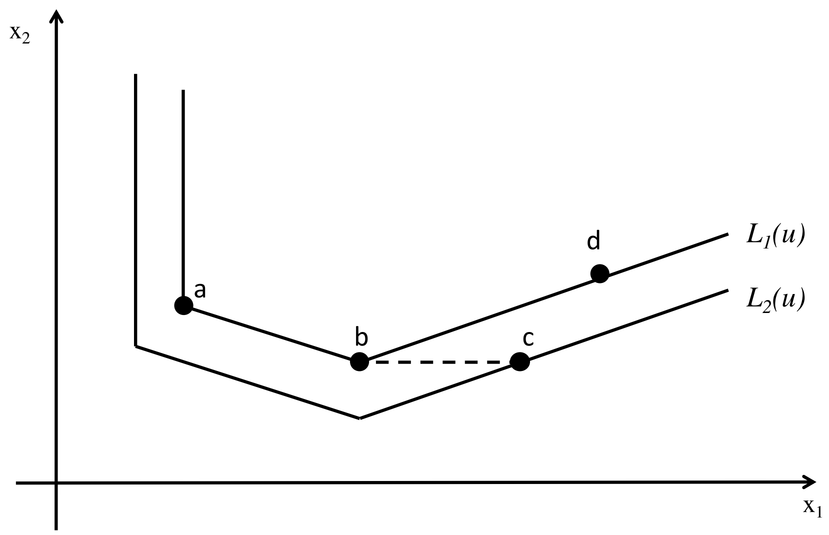

Figure A Strong disposability and Weak disposability of input

Figure A shows the weak and strong disposability of inputs and the indifferent curve based on two inputs (x_1 and x_2) for the production of one output. Starting at point b, an increase in x_1 causes a reduction in output when x_2 is held constant (from b to c) or requires an increase in x_2 to maintain constant output (from b to d), so the input x_1 is weakly disposable. Starting at point a, an increase in x_2 can be disposed of freely without the cost calculated as reduced output or as an increased use of x_1.

Appendix B: Directional Distance function

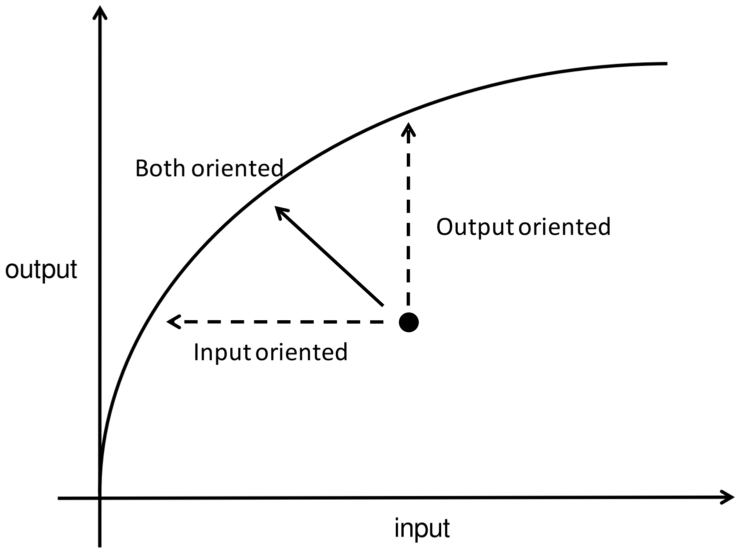

Figure B Measurement method of inefficiency

Figure B illustrates how to measure distance to the frontier. Input- or output-oriented approaches are the primary methods to measure production inefficiency. The input-oriented method has the ability to reduce input to produce the same amount of output as the present situation. Conversely, the output-oriented approach has the ability to increase output using the same amount of input as the present situation. In this study, we use a method that considers both input and output to measure production inefficiency. This approach considers both savings in input and increases in output.

Appendix C

List of prefectures and area classification

No	Prefecture name	Region	Part	No	Prefecture name	Region	Part
1	Hokkaido	-	North	21	Kyoto	Other	West
2	Aomori	Tohoku	North	22	Hyogo	Other	West
3	Iwate	Tohoku	North	23	Nara	Other	West
4	Miyagi	Tohoku	North	24	Wakayama	Other	West
5	Akita	Tohoku	North	25	Tottori	Other	West
6	Yamagata	Tohoku	North	26	Shimane	Other	West
7	Fukushima	Tohoku	North	27	Okayama	Other	West
8	Ibaraki	Other	East	28	Hiroshima	Other	West
9	Tochigi	Other	East	29	Tokushima	Other	West
10	Gunma	Other	East	30	Kagawa	Other	West
11	Niigata	Other	East	31	Ehime	Other	West
12	Toyama	Other	East	32	Kochi	Other	West
13	Ishikawa	Other	East	33	Fukuoka	Kyushu	West
14	Fukui	Other	East	34	Saga	Kyushu	West
15	Yamanashi	Other	East	35	Nagasaki	Kyushu	West
16	Nagano	Other	East	36	Kumamoto	Kyushu	West
17	Gifu	Other	East	37	Oita	Kyushu	West
18	Shizuoka	Other	East	38	Miyazaki	Kyushu	West
19	Aichi	Other	East	39	Kagoshima	Kyushu	West
20	Mie	Other	East				