JARQ 56 (4), 375-388 (2022) https://www.jircas.go.jp

Reproducibility of Forecasting Agricultural Price Fluctuations Several Months Ahead of the Harvest Time

Yoji KUNIMITSU[1]* and Toshichika IIZUMI[2]

[1] Institute for Rural Engineering, National Agriculture and Food Research Organization, Tsukuba, Japan

[2] Institute for Agro-Environmental Sciences, National Agriculture and Food Research Organization, Tsukuba, Japan

Abstract

To minimize climate risks of agricultural price hikes during meteorological disasters, this study aims to demonstrate the feasibility of forecasting agricultural prices several months ahead and evaluates the reproducibility of annual price fluctuations. We use the crop yields forecasted by the crop model and apply the quasi-dynamic large-scale global computable general equilibrium (CGE) model with 88 countries/regions to evaluate as many countries as possible worldwide. From the simulation results, the model's accuracy to trace actual crop price fluctuations, which was measured by the regional average correlation coefficient data during 1995-2015, ranged from 0.13 to 0.26 per crop, and almost 30% of targeted countries marked statistically significant traceability. Such accuracy was higher in the developed liberal countries. Regarding forecasting 3-6 months ahead of the harvest, in approximately 20% of the targeted countries, the CGE model can reproduce actual price fluctuations, and a 3-month extension of the forecast period reduces the reproducibility by 16.7% for the correlation coefficient on average of four crops. Thus, the reproducibility of the model was not high, but in countries with statistically significant reproducibility, forecasting price fluctuations several months ahead can be used to prepare for meteorological disasters.

Discipline: Social Science

Additional key words: crop model, global climate model, quasi-dynamic large-scale global computable general equilibrium model, seasonal climate forecast

Introduction

In the future global warming scenario, the possibility of agricultural damage due to meteorological disasters, such as droughts, heat waves, and floods would increase (Tigchelaar et al. 2018, Intergovernmental Panel on Climate Change 2019, Gaupp et al. 2020). These meteorological disasters would affect the supply and demand balance in the agricultural market and increase the risk of food price hikes that promote global political and economic turmoil (Wright 2011). In fact, the global food price index in 2021 skyrocketed by 1.3 times compared to last year due to the meteorological disasters and pest damage, in addition to COVID-19 (Food and Agriculture Organization, FAO, 2021). If agricultural price hikes could be predicted based on climate forecasts several months before the harvest, most farmers would be able to change their cropping plan, thereby reducing the risk of meteorological disasters. Furthermore, a reliable agricultural price forecast can reduce the speculation that occurs during crop failures and suppress unnecessary soaring of agricultural prices. Therefore, forecasting agricultural prices several months ahead can be one of the most effective adaptation measures against climate change, contributing to food security and social stability.

Wang et al. (2020) reviewed previous studies and showed that forecasting of agricultural prices has mainly relied on time series analysis, such as the autoregressive integrated moving average (ARIMA) model (Li et al. 2017) and vector autoregressive (VAR) model (Kalliovirta et al. 2019), artificial intelligence (AI) forecasting techniques (Jha & Sinha 2014), and hybrid forecasting methods, which combine time series analysis and the AI technique (Wang et al. 2018). These methods predict the future data series based on the assumption that the relation between a present point in the data series

*Corresponding author: ykuni@affrc.go.jp

Received 12 November 2021; accepted 9 February 2022.

and a past point in time will be preserved. Therefore, to the best of our knowledge, these methods are unsuitable for predicting situations that have never occurred, such as simultaneous global crop failures due to climate change, and considering trade changes between multiple countries is difficult in these methods.

Furthermore, to enhance the reproducibility of agricultural price fluctuations, AI techniques and regression models must consider socioeconomic factors other than supply and demand, such as oil prices, exchange rates, speculative money, and regional conflicts (Headey & Fan 2008, Wright 2011). At the forecasting stage, these exogenous variables become a problem because predicting them several months ahead is almost impossible. Hence, there is room for using the partial equilibrium econometric model (Furuya et al., 2015) and the computable general equilibrium (CGE) model (Kunimitsu et al. 2020, Wang et al. 2021). These models clearly define the influence path of supply and demand changes and consider the commodity trade among countries. However, many researchers are concerned about the accuracy of price forecasts predicted by these economic models. Valenzuela et al. (2007) verified the reproducibility of the Global Trade Analysis Project (GTAP) CGE model in wheat price fluctuations. They used the parameters presented by the GTAP8 database and found the cross-sectional correlation coefficient between estimated and actual fluctuations, measured by standard deviation of wheat prices to be 0.28 among the 13 regions studied. Such reproducibility is thought to be practical; however, their analysis was limited to wheat prices, and the reproducibility of agricultural prices estimated from seasonal climate forecasts several months ahead was not analyzed and remains unknown.[1]

On the other hand, the global climate model (GCM) with a fine calculation grid size has been improved to forecast extreme climate conditions several months ahead. Generally, the GCMs used in long-term predictions are not good at forecasting the timing of changes in climatic conditions because of the butterfly effects. Nevertheless, the GCM for seasonal forecasts was modified to predict climatic conditions months ahead by introducing the characteristics of ordinal daily weather forecast models in the long-term model. Generally, crop forecasting does not require timepoint forecasting as much as daily weather forecasting (Watson et al. 2015). Considering such situations, Iizumi et al. (2018) analyzed the prediction accuracy of the crop model in global crop yields estimated from the GCM's climate forecasts 3 and 6 months ahead. Their results demonstrated that the yields of major crops, estimated from past seasonal climate forecasts of the GCMs, were consistently reproduced in the actual yields in more than 23% of the world's areas, although no analyses of economic influences were included.

This study aims to show the feasibility of forecasting agricultural prices and to evaluate the reproducibility of annual agricultural price fluctuations worldwide. To forecast agricultural prices, we use crop yields forecasted by the crop model based on outputs of GCMs and apply the quasi-dynamic large-scale global CGE model. The features of this study are threefold. First, we apply the large-scale global CGE model to verify the reproducibility of the CGE model on four major crops—rice, wheat, maize, and soybean—and in as many countries as possible worldwide. Second, we introduce the quasi-dynamic structure in the global CGE model to retroactively estimate the past level of price from the recent base year. Third, we use the directional symmetry index, such as the quadratic weighted kappa score (QW-κ), in addition to error-based metrics, such as correlation coefficients (R), to evaluate the reproducibility of price fluctuations during extreme weather. Based on the analysis, we discuss policy implications for the construction of a sustainable food system and propose issues for future analysis. Note that the forecast of agricultural prices targeted in this paper is not the price level itself, but the fluctuation in the target price.

The remainder of this paper is organized as follows. In Section 2, the method used, including the crop and CGE models, is explained. Section 3 shows evaluation on the accuracy of the estimated theoretical price and reproducibility of price forecasts 3 and 6 months ahead, estimated by the global CGE model with crop model and GCMs. Section 4 proposes policy implications of the results, and Section 5 summarizes the analytical results and presents the conclusions.

Methodology

1. Analytical scheme

The analysis estimates the price of four major crops—rice, wheat, maize, and soybean—by putting the seasonal forecasts of crop yields into the CGE model. Virtually forecasted crop prices are estimated at each timepoint 3 and 6 months ahead of the actual harvest time in the past (1993-2015). The crop yields' seasonal forecasts are

[1] In the field of meteorology, a climate forecast several months ahead is called a "seasonal forecast." In economics, this term is confused with other meanings, such as seasonal index. In the latter part of this study, the term "seasonal forecast" is used for climate forecast by the global climate model (GCM) and the crop yield forecast by the crop model; for price forecast, the term "forecast" is used with the phrase "several months ahead."

estimated by the crop model based on GCMs' seasonal climate forecasts at each timepoint in the past. Hereinafter, such forecasts several months ahead of the harvest in the past timepoints are referred to as a "reproduced forecast value," and "_ *y3*" (or "_ *y6*") is attached to the variable name if the forecast is 3 months (or 6 months) ahead.

Next, the accuracy of the forecast prices is evaluated by comparing them with actual price data. Hereinafter, the actual price published in FAO statistics is referred to as the "actual value" and is distinguished by adding "*_FAO*" after the variable name. Before assessing the reproducibility of *P_ y3* and *P_ y6* that include errors in the crop model and the CGE model, traceability of the CGE model is quantified by using the actual yield data published in FAO statistics. Hereinafter, prices estimated by the quasi-dynamic large-scale CGE model with the actual yield data are referred to as the "theoretical estimation value," corresponding to the perfect crop yield forecast, and "*_T*" is added after the variable name to distinguish them. Traceability of the CGE model is assessed by comparing *P_T* with *P_FAO*. Afterward, reproduced forecast prices, *P_ y3* and *P_ y6*, are compared with the actual price, *P_FAO*, to evaluate the accuracy of all models used.

Furthermore, we verify the stability of estimation results against possible changes in economic structure during simulation periods by performing the same simulations with data of two different years from the GTAP database and examining the difference. We also check the robustness of estimation results by changing the simulation period. These results are shown in the Appendix.

2. Evaluation index for short-term forecasts

Generally, time series data on crop yields, price, and production in each country have trend components due to economic growth, population growth, and changes in eating habits in addition to other social factors. As this study focuses on short-term forecasts (i.e., forecasts 3 and 6 months ahead) caused by yield changes, the annual price changes from trends must be measured. Therefore, we use the index of annual change against referenced level (ACR), in which the past trend level is calculated as the reference level by the moving averages of the previous years from $t-1$ to $t-3$. ACR is computed as follows:

$$ACR_t = P_t \Big/ \left(\frac{1}{3} \sum_{tt=t-1}^{t-3} P_{tt} \right), \tag{1}$$

where P_t refers to either the actual value, theoretical value, or reproduced forecast value for the price as of year *t*. In other words, the denominator on the right-hand side of Equation (1) works to remove the trend components from chronological price data.

When the annual price fluctuations of *P_T* and *P_FAO* are compared using the correlation coefficient (R) of ACRs in each country, the reference level [i.e., the denominator of the right-hand side of Equation (1)] of ACRs on *P_T* and *P_FAO* are calculated by own each price in the previous 3 years. Note that, when reproduced forecast prices, *P_ y3* and *P_ y6*, are compared with the actual price, *P_FAO*, the reference level of ACR on *P_ y3* and *P_ y6* is calculated by *P_T* as $\frac{1}{3}\sum_{tt=t-1}^{t-3} P\_T_{tt}$ for both prices, rather than using the previous *P_ y3* or *P_ y6* prices. This is because, at the time of price forecasting, the prices in the previous year are known or can be estimated more reliably using the unit yield at that time than *P_ y3* or *P_ y6*.

In the case of actual price forecasts, it is practical to use the moving average of *P_FAO* over the past 3 years as the reference level for *P_T*, *P_ y3*, and *P_ y6*, which are the prices estimated by the model. This method is acceptable when only predictions are targeted, but it is problematic when the prediction results need to be evaluated. This is because the denominator of ACR for the actual price and that for the predicted price are the same, and then, the correlation between the two would become high. Such a high correlation is fake. Hence, in this study, the denominator of the ACR of the predicted price is set by the value calculated from *P_T*, which is the value estimated by the model.

In addition to error-based metrics, such as R, the concordance rate on the movement direction of the target variable as shown by "rising," "falling," or "the same as status quo" is measured by using the quadratic weighted kappa score (QW-κ) (Kundel & Polansky 2003). When the ACR of the target variable exceeds the level of mean plus standard deviation ($\mu+\sigma$) it is regarded as "rising;" when the ACR is less than the level of $\mu - \sigma$, it is regarded as "falling;" and when the ACR stays within the range of $\mu \pm \sigma$, it is regarded as "the same as the status quo." If the price change follows a normal distribution, 68.27% of the data falls within the range of $\mu \pm \sigma$.

3. Seasonal forecasts of crop yield by the crop model

Iizumi et al. (2018) developed the statistical crop models for the four major crops used in this study to predict annual fluctuations in crop yields in each country:

$$\Delta y_{i,g,s,t} = a0_{i,g,s} + a1_{i,g,s} \cdot \Delta T_{t,g,s} + a2_{i,g,s} \cdot \Delta RN_{t,g,s} + \varepsilon_{i,g,s,t} \tag{2}$$

Here *i*, *g*, *s*, and *t* represent the type of crop, grid division, planting time representing the two cropping seasons of each crop (major/secondary or winter/spring), and year, respectively; $a0$, $a1$, and $a2$ are coefficients to be estimated; ΔT and ΔRN are the annual changes in the average temperature and precipitation, respectively; and Δy is the fluctuation in yield (unit yield) and the ratio of the calculated value as of year t to the actual value (3-year average) 1 to 3 years ago:

$$\triangle y_{i,g,s,t} = \frac{(y_{i,g,s,t} - y_{i,g,s,t-1})}{\frac{1}{3}\sum_{tt=t-1}^{t-3} y_{i,g,s,tt}} \times 100 \,. \tag{3}$$

The average grid-cell yield change, $\Delta\hat{y}_{i,g,t}$, over the two cropping seasons of each crop was computed using the average production in the 1990s during the different seasons as weights. For the national yield, $\Delta\hat{y}_{i,r,t}$ was computed by averaging $\Delta\hat{y}_{i,g,t}$ over each country represented by r, using the grid cell harvested area in 2000 as the weights. The estimation adopted a mosaic method that selected a single, best-performing GCM for each location and cropping season, based on the skill score of receiver operation characteristic curve (ROC score) for yield variability. Five GCMs [i.e., APCC by the APEC Climate Center, Korea; MSC-CANCM3 by the Meteorological Service of Canada; NCEP by the National Centers for Environmental Prediction, USA; NASA by the National Aeronautics and Space Administration, USA; and PNU by the Pusan National University, Korea] were selected (Min et al. 2014).

Using the crop model estimation, reliable seasonal forecasts, in which the ROC score was statistically significant at the 10% level, were obtained for many country-level yield fluctuations. The reliable national yield variability of seasonal forecasts 3 or 6 months ahead was estimated in 63, 71, 84, and 28 countries among 141 GTAP-based countries for rice, wheat, maize, and soybean, respectively. From the estimated yield change 3 and 6 months ahead ($\Delta\hat{y}3$ and $\Delta\hat{y}6$, respectively) the seasonal forecasts of crop yields 3 and 6 months ahead ($\hat{y}3$ and $\hat{y}6$, respectively) are calculated as follows:

$$\hat{y}3_{i,r,t} = y\_FAO_{i,r,t-1} + \Delta\hat{y}3_{i,r,t}\left(1/3\sum_{tt=t-1}^{t-3} y\_FAO_{i,r,tt}\right) \tag{4}$$

and

$$\hat{y}6_{i,r,t} = y\_FAO_{i,r,t-1} + \Delta\hat{y}6_{i,r,t}\left(1/3\sum_{tt=t-1}^{t-3} y\_FAO_{i,r,tt}\right). \tag{5}$$

4. Quasi-dynamic global CGE model

The price is forecasted by the quasi-dynamic global CGE model using the crop yields of major crops. The model is based on Lanz & Rutherford's (2017) global CGE model and has a similar structure to the GTAP CGE model.

The model is called quasi-dynamic because of the following treatments. In general, capital stocks ($K_{r,t}$) in region r in year t can be defined as follows:

$$K_{r,t} = (1-\delta_{r,t})K_{r,t-1} + I_{r,t} = (1-\delta_{r,t} + \alpha_{r,t})K_{r,t-1}\,, \tag{6}$$

where δ is the replacement rate of old capital stocks by the newly added investment I and α is the ratio of newly added investment to existing capital stocks as $I_{r,t} = \alpha_{r,t}K_{r,t-1}$. Here $\alpha_{r,t}$ changes every year to meet the macroeconomic constraints in which total investment equals total savings. Assuming that when the economy improves and the sales of firms increase, investment would increase and vice versa. In addition, during the period of increase in sales, firms would replace existing facilities that have not reached the end of their service life but are a little old. Meanwhile, during the decrease in sales, firms would find it difficult to invest; therefore, they would continue to use old facilities without replacement, and the replacement rate would be small. As the changes in δ and α are canceled out, $(1 - \delta_{r,t} + \alpha_{r,t})$ can be a constant rate in the long run, although it grows and varies from country to country. Moreover, assuming that $(1 - \delta_{r,t} + \alpha_{r,t})$ is proportional to the growth rate of products' demand that corresponds to the growth forecast of the sales value of the company and can grow according to population growth, $(1 - \delta_{r,t} + \alpha_{r,t}) = (1 + n_{r,t})$, the following relation is derived:[2]

$$\begin{aligned} K_{r,t} &= (1+n_{r,t})K_{r,t-1} \\ &= (1+n_{r,t})(1+n_{r,t-1})\cdots(1+n_{r,t_0+1})K_{r,t_0} = pop_{r,t}K_{r,t_0}\,, \end{aligned} \tag{7}$$

where $n_{r,t}$ is the growth rate of population in country r in year t and pop is the index of population level ($POPT$) referenced to the initial year t_0 as follows: $pop_{r,t} = (1+n_{r,t})(1+n_{r,t-1})\cdots(1+n_{r,t_0+1}) = POPT_{r,t} / POPT_{r,t_0}$. The capital stock of each industry is then allocated in proportion to the changes in productivity of each industry.

Similarly, labor inputs (L) are assumed to increase or decrease according to the population growth rate, and the following equation is derived:

$$L_{r,t} = pop_{r,t}\, L_{r,t_0}\,. \tag{8}$$

2 Here, the population growth is used as a proxy index for the growth rate of products' demand, but instead of the population growth, it can be possible to assume that for instance, the sales growth matches the growth forecast of the production values in each country. Such assumption does not make a big difference in the theoretical explanation of this part.

In contrast, land inputs (*LND*) are assumed to change in proportion to the changes in the cultivated land area (*LAND*) and natural resources, such as forest, mineral, and water, are constant:

$$LND_{r,t} = (LAND_{r,t} \,/\, LAND_{r,t_0})\, LND_{r,t_0} \tag{9}$$

$$RES_{i,r,t} = RES_{i,r,t_0}\,. \tag{10}$$

By assuming such a quasi-dynamic structure, it is easy to reproduce the past economic situation from the recent year as the initial condition and estimate the future situation without consecutively simulating the economic situation of each year.

The basic structure of the model is the same as Lanz & Rutherford's. That is, the production part is formulated by the nested constant elasticity of substitution (CES) function, and the intermediate inputs are composed of the imported and domestic goods under a certain degree of substitutability according to Armington's assumption. The consumption sector considers the substitutability of domestic and imported products and is defined by a linear expenditure system (LES)-type function, where the total consumption of each good is divided into basic and variable consumption. Of these, variable consumption is determined according to the price of each good. Investment and government consumption are represented by a Leontief-type fixed-rate demand function. Furthermore, the closure of the model is the same as Lanz & Rutherford's as well as the GTAP CGE model.

5. Data for calibrating the CGE model's parameters

The World Social Accounting Matrix (SAM) of the GTAP10 database is used to calibrate the model parameters. To check the changes in the economic structure, we use SAMs from the years 2004 and 2014. The GTAP database consists of 65 industrial sectors and 151 countries/regions. These 65 sectors are merged into 15 sectors (Table 1)[3] and the 151 countries/regions are reduced to 87 countries and one merged region (ROW: the rest of the world) (Table 2) to save computational time. For the target countries, we select those where the domestic production and consumption of each crop are relatively large compared with the world average; furthermore, we consider the yield estimation feasibility of the crop model.

6. Simulation method

Three simulation cases are considered to evaluate the accuracy of the global CGE model with seasonal yield forecasts, and equilibrium prices are estimated from 1993 to 2015. The ACRs of crop prices are calculated from 1995 to 2015. In all cases, the exogenous variables related to the production factors are set according to Equations (7)-(10).

Based on Szewczyk et al. (2020), crop yields are assumed to change the total factor productivity (TFP) in the production function, and TFP changes the unit cost of the CGE model as follows:

$$c_{i,r,t} = \left(\sum_f \theta_{f,i,r} \cdot pf_{f,r,t}{}^{(1-\eta_i)} \right)^{1/(1-\eta_i)} / \, TFP_{i,r,t}\,, \tag{11}$$

where f shows the types of input factors comprising capital stocks (*cap*), labor (*lab*), land (*lnd*), and natural resources (*res*); $c_{i,r,t}$ is the unit cost at the value-added production level in sector i, region r, and year t; $pf_{f,r,t}$ is the factor price with taxes; $\theta_{f,i,r}$ is the cost share of each input factor calibrated from the base year data; and

[3] Maize is classified into "*gro*" and soybeans is classified into "*osd,*" but, to compare the simulation results with actual values, the simulation results of *gro* and *osd* are considered to represent only maize and only soybean, respectively.

Table 1. Industrial sectors analyzed

No.	Identifier	Industrial sectors	No.	Identifier	Industrial sectors
1	pdr	Paddy rice	9	omt	Meat products
2	wht	Wheat	10	vol	Vegetable oils and fats
3	gro	Other cereal grains	11	pcr	Processed rice
4	v_f	Vegetables fruit nuts	12	ofd	Other food products
5	osd	Oil seeds	13	man	Manufacture
6	ocr	Other crops	14	sev	Service
7	oap	Animal products	15	trp	Transportation
8	oxt	Resource & Energy			

Among the four major crops, maize is classified into "gro," including miscellaneous grains, and soybeans is classified into "osd," including rapeseed, based on the original GTAP database.

Table 2. Countries and regions analyzed

No.	Identifier	Regions	No.	Identifier	Regions	No.	Identifier	Regions
1	ARG[1,2,3,4]	Argentina	30	GHA	Ghana	60	NGA[4]	Nigeria
2	ARM	Armenia	31	GIN	Guinea	61	NIC	Nicaragua
3	AUS*[1,2,3,4]	Australia	32	GRC*	Greece	62	NLD*[1,4]	Netherlands
4	AUT*[2]	Austria	33	GTM	Guatemala	63	NPL	Nepal
5	AZE	Azerbaijan	34	HND	Honduras	64	PAK1	Pakistan
6	BEL*[1]	Belgium	35	HRV	Croatia	65	PAN	Panama
7	BGD	Bangladesh	36	HUN*[2,3,4]	Hungary	66	PER	Peru
8	BLR	Belarus	37	IDN[1]	Indonesia	67	PHL	Philippines
9	BOL	Bolivia	38	IND[1,2,3,4]	India	68	POL*[2,3,4]	Poland
10	BRA[1,3,4]	Brazil	39	IRL*	Ireland	69	PRT*	Portugal
11	BWA	Botswana	40	IRN	Iran	70	PRY[1,3,4]	Paraguay
12	CAN*[2,3,4]	Canada	41	ISR*	Israel	71	ROU[2,3,4]	Romania
13	CHE*	Switzerland	42	ITA*[1]	Italy	72	RUS[1,2,3,4]	Russia
14	CHL*[3]	Chile	43	JOR	Jordan	73	SAU	Saudi Arabia
15	CHN[1,4]	China	44	JPN*	Japan	74	SEN	Senegal
16	CIV	Cote d'Ivoire	45	KAZ[2,4]	Kazakhstan	75	SVN*	Slovenia
17	CMR	Cameroon	46	KEN	Kenya	76	SWE*	Sweden
18	COL*	Colombia	47	KGZ	Kyrgyzstan	77	TGO	Togo
19	CRI*	Costa Rica	48	KHM[1]	Cambodia	78	THA[1,3]	Thailand
20	DEU*[2,3,4]	Germany	49	KOR*	Korea	79	TUN	Tunisia
21	DNK*[3]	Denmark	50	LAO	Lao	80	TUR*	Turkey
22	DOM	Dominica	51	LKA	Sri Lanka	81	UKR[2,3,4]	Ukraine
23	ECU	Ecuador	52	LTU*[2]	Lithuania	82	URY[1,2,4]	Uruguay
24	EGY	Egypt	53	LVA*[2]	Latvia	83	USA*[1,2,3,4]	United States of America
25	ESP*[1]	Spain	54	MDG	Madagascar			
26	EST*	Estonia	55	MEX*[2]	Mexico	84	VEN	Venezuela
27	FRA*[2,3,4]	France	56	MNG	Mongolia	85	VNM[1]	Viet Nam
28	GBR*[2,3]	United Kingdom	57	MWI	Malawi	86	ZAF[1,3]	South Africa
			58	MYS	Malaysia	87	ZWE	Zimbabwe
29	GEO	Georgia	59	NAM	Namibia	88	XTW[1,2,3,4]	ROW

Identifiers are the same as GTAP countries/regions. Countries marked with "*" are members of OECD. Major exporters are indicated by superscripts "1," "2," "3," and "4" for paddy rice and processed rice, wheat, other cereal grains including maize, and oil seeds including soybean, respectively.

η represents the substitution elasticity between input factors. The following simulation cases are set according to the different sources of crop yield changes.

Case 1 (estimation of the theoretical price): This case estimates the theoretical price, *P_T*, considering the supply and demand balance for four crops by putting actual yields published by FAO, y_FAO_i ($i \in pdr$, wht, gro, and osd), into the CGE model. *y_FAO* can change the TFP of each crop in each country as follows:

$$TFP_{i,r,t} = y\_FAO_{i,r,t} \,/\, y\_FAO_{i,r,t_0}, \quad (i \in pdr, wht, gro, osd) \,.(12)$$

Case 2 (estimation of the reproduced forecast price 3 months ahead): This case estimates the price of each crop in each country using the global CGE model. The crop yields are based on seasonal forecasts 3 months ahead ($\hat{y}3$) predicted by the crop model. TFP values are set as follows:

$$TFP_{i,r,t} = \hat{y}3_{i,r,t} \,/\, \hat{y}3_{i,r,t_0}, \quad (i \in pdr, wht, gro, osd) \,.(13)$$

By inserting Equation (13) in the CGE model, we obtain the reproduced forecasts 3 months ahead for agricultural prices, *P_ y3*.

Case 3 (estimation of the reproduced forecast price 6 months ahead): This case estimates crop prices using the global CGE model based on crop yields' seasonal forecasts 6 months ahead. Similar to Case 2, TFP is set with seasonal yield forecasts 6 months ahead ($\hat{y}6$) as follows:

$$TFP_{i,r,t} = \hat{y}6_{i,r,t} \,/\, \hat{y}6_{i,r,2014}, \quad (i \in pdr, wht, gro, osd) \,.(14)$$

Using Equation (14), we obtain the reproduced agricultural price forecasts 6 months ahead, *P_ y6*.

Substitution elasticities, income elasticities of demand, tariff rates, and other tax rates are set to be the same as in the GTAP database, except for substitution elasticities between export/import and domestic production. Generally, the shock from annual fluctuations is too short to adjust trading partners; hence, the flexibility of demand substitution between domestic and trading goods is not fully exhibited. To introduce such an inelastic situation for short-term adjustment, the transformation elasticities in exports and substitution elasticities between domestic and imported goods are set to 20% of the GTAP's original values.[4] These rates are the smallest numbers that provide a solution for the model.

Moreover, the analysis targets crops that can be stored to some extent, so that there can be a time lag between the time of harvest and the time when it is shipped to the market and reflected in the market price; such a time lag may differ by country. Given these situations, a 1-year time lag is considered if it is needed, when R and QW-κ are calculated between estimated and actual prices. In particular, these indices are calculated by matching the time points between the two targeted prices or shifting the time points by 1 year. Then, the larger index between the time-matched index and the time-lagged index is adopted. Therefore, we compare the index calculated by the theoretical and actual prices in year *t* with that of the theoretical value in year *t* and actual price in $t + 1$ year and then pick the larger one.

Results

1. Traceability of the global CGE model

Figure 1 shows the ACRs of actual, theoretical, and reproduced forecast prices for rice (Japan), wheat (France), and maize and soybean (USA). Usually, the price in the CGE model is relative to the numeraire goods. Therefore, for comparison, the price of each crop published in FAO statistics was divided by the gross domestic product (GDP) deflator of each country, similar to the study by Valenzuela et al. (2007). In this figure, the ACRs of the reproduced forecast price 3 or 6 months ahead, which will be explained later, were also plotted by the broken line.

Table 3 was calculated from the Case 1 simulation using 2014 GTAP SAM data. It shows the cross-sectional correlation between estimated and actual fluctuations measured by the standard deviation of price ACRs; the ratio of standard deviations between estimated and actual ACRs, similar to Valenzuela et al. (2007); the average R of ACRs during 1995-2015 among countries with available data; and the percentage of countries where R is more than statistically significant at the 10% significance level. Table 3 also includes the percentage of countries where QW-κ is more than 0.2, indicating "minimal concordance" (Landis & Koch 1977); the number of countries that can obtain price information in both FAO statistics and estimated crop yields; and the percentage of countries that meet the above criteria against a total number of countries.

As shown in Figure 1, first, the actual price fluctuated more than the theoretical price. Such tendency was measured by the ratio of standard deviations between estimated and actual ACRs in Table 3, indicating that this ratio was less than 1 for all crops and similar to the previous study (Valenzuela et al. 2007). Previous studies showed that actual agricultural prices were more affected by factors other than supply and demand, such as oil prices, exchange rates, and speculative money, which could not be considered in the theoretical price forecast (Headey & Fan 2008, Ueda & Kunimitsu 2020). These factors weakened the correlation between the actual and theoretical prices calculated by the CGE model. Moreover, the price itself changes daily and varies greatly depending on the timepoint at which the value is adopted in the statistics. As such, variations in the actual price include the effects of unexpected factors and statistical definition problems other than supply and demand conditions.

Second, the cross-sectional R between estimated and actual fluctuations were approximately 0.20-0.35 by crop. As revealed by Valenzuela et al. (2007), the usual GTAP CGE model can trace actual wheat prices at a similar R of 0.28 between actual price and estimated price fluctuations. They analyzed only wheat during 1990-2001 when crop prices were relatively stable. By contrast, our analytical period was 1995-2015, which included the global food price hike period in and around 2007. Considering such situations, the performance of our model is not inferior to that of the model used in the previous study.

Third, in Figure 1, rice in Japan, wheat in France, and maize and soybean in the USA showed great traceability of *P_T* against actual prices. The average R among countries in Table 3 ranged from 0.13 to 0.26 by crop and the average of these for four crops was 0.19. Excluding countries where R was statistically insignificant, the regional average of R became over 0.38. Although there were differences in the average R among crops, such differences were not significant.

Fourth, the percentages of countries where R was beyond a statistically significant level ranged from 26.7% to 46.6% by crop and was 36.8% for the four crops on average. The percentage of countries, where QW-κ indicated better than minimal concordance, ranged from

[4] Valenzuela et al. (2007) proposed a transmission function between export/import and domestic prices to increases the price forecast accuracy of the CGE model. However, empirical estimations of the transmission function are difficult in many countries; therefore, rather than using the transmission function, we set the substitution elasticity of Armington's function to be less elastic.

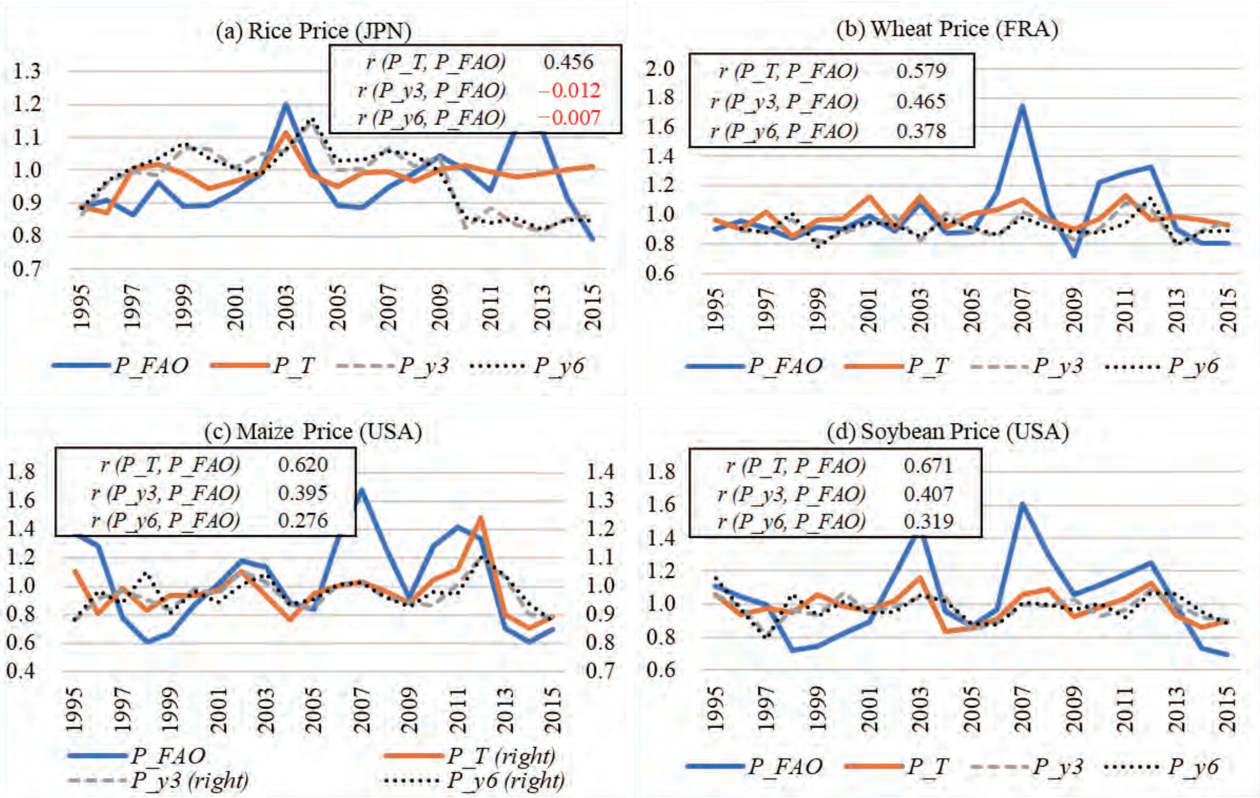

Fig. 1. Chronological changes in the prices of each crop regarding the statistical, theoretical, and reproduced forecast values

The numbers in the box indicate the correlation coefficient of *P_FAO* against *P_T*, *P_y3*, or *P_y6*.

Table 3. Accuracy of agricultural theoretical price fluctuations by the CGE model against actual price data (2014 SAM data)

Classifications	Rice	Wheat	Maize	Soybean	4 Crops
No. of available data	45	58	58	37	49.5
Standard deviation (*std*) by country					
ratio of average *std*	0.329	0.544	0.623	0.869	0.591
correlation coefficient of *std*	0.329	0.280	0.198	0.351	0.290
Correlation coefficient (R)					
average R	0.132	0.256	0.188	0.196	0.193
average R (only significant)	0.383	0.462	0.475	0.494	0.454
countries where R>=0.29	26.7%	46.6%	36.2%	37.8%	36.8%
QW-κ score					
average QW-κ	0.123	0.235	0.178	0.192	0.182
countries where QW-κ>=0.2	26.7%	56.9%	36.2%	35.1%	38.7%

The number of available data represents the number of countries where the data for both *P_FAO* and *P_T* are available among 87 countries, except for the rest of the world. The "standard deviation (*std*) by country" is calculated from the ACRs of actual (*P_FAO*) and theoretical price (*P_T*) by country, using the 2014 SAM data; the "ratio of average *std*" is calculated by dividing the average *std* of *P_FAO* by the average *std* of *P_T*; and "correlation coefficient of *std*" is the cross-sectional correlation that shows those relations. The correlation coefficient (R) and the quadratic weighted kappa score (QW-κ) are calculated for each country based on the ACRs of *P_FAO* and *P_T* from 1995 to 2015. Average R or QW-κ are calculated from those of each country between the ACRs of *P_FAO* and *P_T*. The value of "average R (only significant)" in the eighth row is the result of calculating the average value of R only for the countries where R is significant at the 10% level under the assumption that the distribution of ACR obeys normal distribution. The percentage numbers are the ratios of countries where R is greater than 0.29 or QW-κ is over 0.2. The threshold value of 0.29 means statistically significant at the 10% level and that of 0.2 on QW-κ indicates "minimal concordance" for "rising," "falling," and "remaining in status quo" on price change.

26.7% to 56.9% by crop and that for four crops was 38.7% on average. Although the QW-κ captured relatively extreme price changes, the percentage of reproducible countries by QW-κ was only slightly higher than that marked by R over the threshold level. Overall, the CGE model associated with the crop model could reproduce actual price fluctuations in approximately 30% of the targeted countries.[5]

For reference, a similar table was created for the production value (Table 4). When compared with the price, R and percentage numbers regarding production were markedly higher, showing that the CGE model could estimate quantitative variables, such as production, with higher accuracy than price. However, there were some errors between the theoretical and actual values even in production because the actual harvested areas were different from the theoretical values, which were estimated under the optimization behavior of producers.

2. Regional differences in the traceability of the global CGE model

Figure 2 shows the differences in the average R by classified region. The developed liberal countries in the Organization for Economic Co-operation and Development (OECD) marked a higher traceability of the CGE model than in non-OECD countries; however, the t-statistics on the difference in the average R were not so high. In contrast, the results classified into major exporters and others showed different tendencies by crop in the regional average R.

Regarding the estimated price of wheat by the CGE model, the traceability to the actual price was significantly higher in the exporting country than in the importing country, which is consistent with the results of previous studies (Valenzuela et al. 2007); however, rice and soybeans tended to be the opposite of wheat. Overall, the difference in R between OECD and non-OECD countries showed more consistent tendencies in the four crops than the difference between major exporters and other countries in each agricultural product.

3. Reproducibility of price forecasts months ahead by the global CGE model

Table 5 shows the results that compare the actual and reproduced forecast prices 3 and 6 months ahead that were estimated in Cases 2 and 3. Each value was calculated using the ACR index, which indicates the annual variation after detrending. In other words, this table demonstrates the reproducibility of forecasts several months ahead of the actual price changes. The following points are evident.

First, the percentages of countries, where R between *P_FAO* and *P_ y3* or *P_ y6* was statistically significant at the 10% level, ranged from 17.0% to 27.8% by crop. These percentages were lower than those in Table 3, which shows a correlation between *P_T* and *P_FAO*. Comparing the percentages of countries with significant R of *P_ y3*, for example, Case 2 was lower by 18% [= (1 − 22.0 / 26.7) × 100], 52% [= (1 − 22.4 / 46.6) × 100], 53% [= (1 −

[5] To check the influences of economic structural changes, the same simulation as that shown in Table 3 was conducted with the 2004 SAM data (Table A1 in Appendix A1). Tables 3 and A1 show similar values, indicating the limited influence of economic structural changes during 2004-2014. In addition, R and QW-κ were calculated by changing the analysis period to the 2000s to determine the stability of the estimation results (Table A2 in Appendix A2). Almost the same tendencies were found between Tables 3 and A2. Thus, changes in the analytical period had little influence on the estimation results, and the results in Table 3 seemed to be robust.

Table 4. Accuracy of the fluctuations in theoretical agricultural production (*Y_T*) by the CGE model against actual production data (*Q_FAO*) (2014 SAM data)

Classifications	Rice	Wheat	Maize	Soybean	4 Crops
No. of available data	61	70	79	60	67.5
Standard deviation (*std*) by country					
ratio of average *std*	0.342	0.522	0.182	0.159	0.301
correlation coefficient of *std*	0.342	0.227	0.517	0.565	0.413
Correlation coefficient (R)					
average R	0.537	0.529	0.585	0.336	0.497
average R (only significant)	0.669	0.686	0.678	0.574	0.652
countries where R>=0.29	80.3%	78.6%	84.8%	61.7%	76.3%
QW-κ score					
average QW-κ	0.439	0.432	0.446	0.312	0.407
countries where QW-κ>=0.2	73.8%	77.1%	77.2%	60.0%	72.0%

All values calculated based on ACRs of the statistical production quantities (*Q_FAO*) and the theoretical production values (*Y_T*) from 1995 to 2015, using 2014 SAM data. Other remarks are the same as in Table 3 but regarding production rather than price.

17.0 / 36.2) × 100], and 27% [= (1 − 27.8 / 37.8) × 100], for rice, wheat, corn, and soybeans, respectively. In other words, replacing crop yields from actual to seasonal forecast values reduced the estimation accuracy in some countries. As both reproduced forecasts and theoretical values were estimated by the CGE model with the same structure, the low percentage of countries with statistically significant R did not result from the CGE model but rather from the low reproducibility of meteorological conditions by the GCMs themselves or the low reproducibility of the crop model.

Second, regarding QW-κ, the percentage of countries with QW-κ over 0.2 was approximately 20%, which is similar to the percentage R. Therefore, approximately 20% of the targeted countries can reproduce the actual annual price fluctuations by the CGE model associated with the crop model even in the case of forecasting several months ahead.

Third, comparing indices for both prices in Table 5, the percentage values of R and QW-κ between *P_ y3* and *P_FAO* were almost the same as those between *P_y6* and *P_FAO*, and were therefore different from our intuition. Slight differences in the performance of reproduced forecasts between 3 and 6 months ahead were also observed in Figure 1, which plots the chronological tendencies in ACRs of prices, but these differences were not clear.

To observe this tendency in detail, a scatter plot was

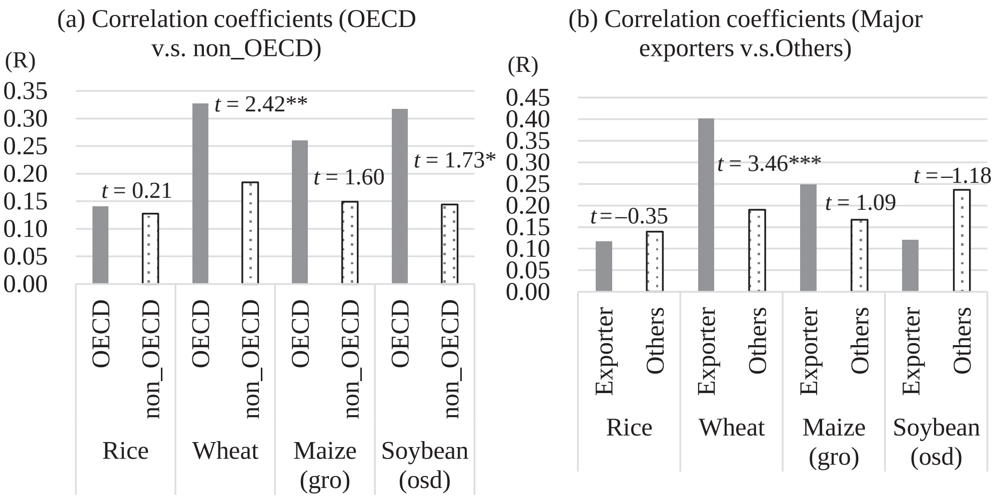

Fig. 2. Difference in the traceability of regional CGE model to real price measured by the correlation coefficient

Major food-exporting countries are the top 20 countries in 2014 by the export value of each crop in the GTAP10 database. *t* is the *t*-value, indicating that ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Table 5. Reproducibility of price fluctuations by the CGE model using seasonal yield forecast three and six months ahead (2014 SAM data)

Classifications	Rice	Wheat	Maize	Soybean	4 Crops
No. of available data	41	58	53	18	42.5
Countries where R>=0.29					
(a) P_y3 : P_FAO	22.0%	22.4%	17.0%	27.8%	22.3%
(b) P_y6 : P_FAO	22.0%	24.1%	22.6%	22.2%	22.7%
(b) / (a)	1.00	1.08	1.33	0.80	1.02
Countries where QW-κ>=0.2					
(c) P_y3 : P_FAO	31.7%	25.9%	18.9%	11.1%	21.9%
(d) P_y6 : P_FAO	26.8%	36.2%	18.9%	27.8%	27.4%
(d) / (c)	0.85	1.40	1.00	2.50	1.25

Correlation coefficient (R) and quadratic weighted kappa score (QW-κ) are calculated from the ACRs of *P_FAO* and *P_y3* (or *P_y6*), using 2014 SAM data. Other remarks are the same as in Table 3.

drawn for each crop, with the R of *P_ y3* and *P_FAO* on the horizontal axis and that of *P_y6* and *P_FAO* on the vertical axis (Fig. 3). In Figure 3, the approximate line and equations of the approximate line, showing the relation between the two kinds of R in each axis, are indicated. The vertical index is the same as the horizontal index if the slope of the approximate line is 1.

As shown in Figure 3, the slopes of the approximate line were less than 1 for all four crops, indicating that the values of R on the vertical axis tended to be smaller than that on the horizontal axis. When the change rate was calculated by (1 − slope) × 100, it was found that extending the forecast period by 3 months decreased R by 26.2% for rice, 17.6% for wheat, 22.5% for maize, and 0.4% for soybean. For soybean, these percentages became small due to a small number of available price data. On average, for the four crops, the influence of the 3-month extension of the forecast period exhibited a 16.7% decrease in R.

Discussion and policy implications

Based on the analytical results, the following aspects can be discussed, and some policy implications can be highlighted. First, the reproducibility of the model was not high, but we must consider the difficulty in estimating functions with detrended fluctuation data used in this study. So long as the possibility of price forecasting is not zero, these results provide hope for improving the GCM, crop, and even economic models. To improve the accuracy of these models, data and statistics are critical. Changing the measurement unit of statistics in agricultural production and economics from the national level to a smaller regional unit and making the network of meteorological observation data more detailed will contribute to the improvement of models in these fields.

Second, the high performance of the CGE model may be related to the degree of regulation in each country's market, as the developed liberal countries in

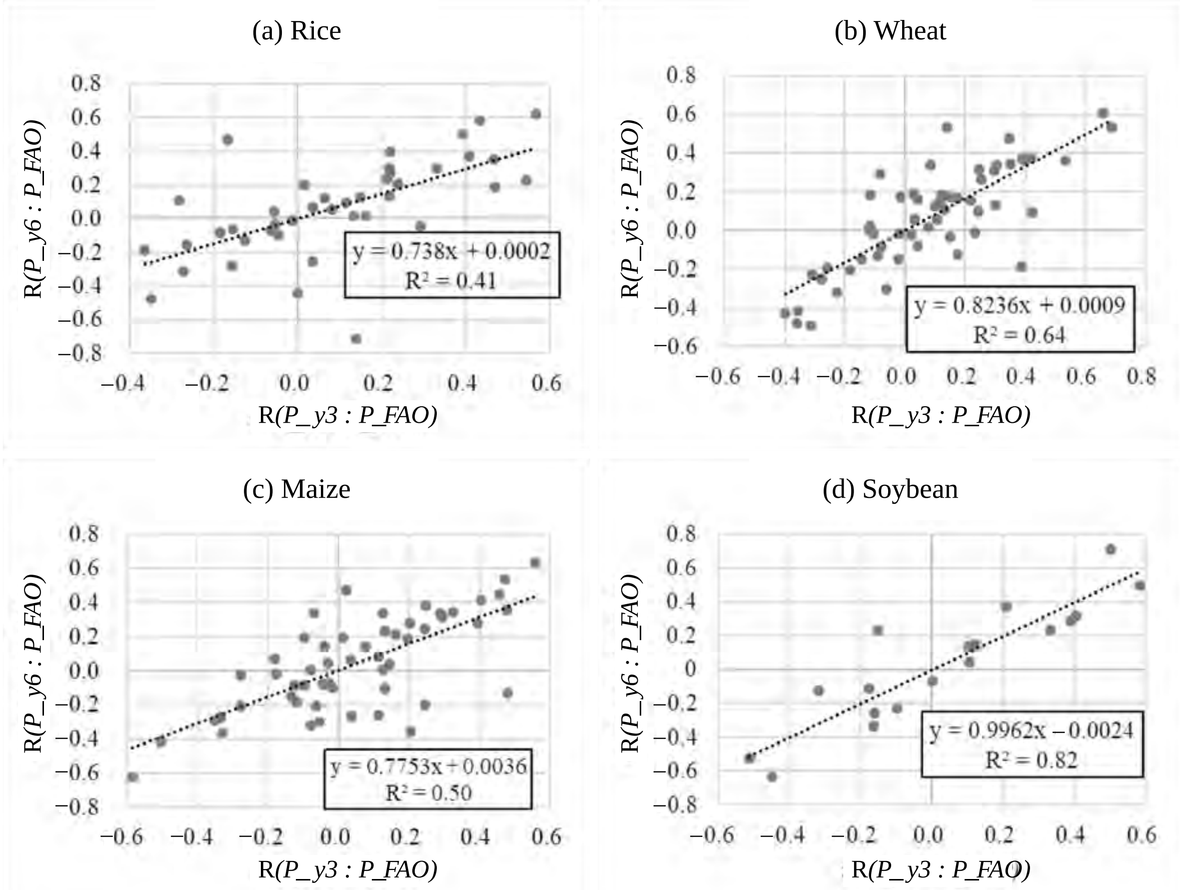

Fig. 3. Scatter plot of the target countries by two kinds of correlation coefficients

The horizontal axis shows the correlation coefficient between *P_y3* and *P_FAO*. The vertical axis represents the correlation coefficient between *P_y6* and *P_FAO*. The equation in each figure shows the relation of both axes; this is represented by the approximate line (broken line).

OECD exhibit relatively high correlation between actual and theoretical prices. Countries with a dictatorship or countries that adopt populism policies may control food prices to stabilize domestic political conditions. Consequently, their markets are less susceptible to supply and demand factors, and real prices may deviate from theoretical prices. Nevertheless, for such countries, forecasting international agricultural prices can be an important policy information to prepare for price controls.

The third important policy implication is the handling of price forecast information. A hike in agricultural prices will likely cause market disturbances, such as buying up products for speculation. In particular, if forecast information is restricted to limited people, it may encourage speculation. As the models for forecasting price changes become more accurate, more people would like to monopolize such forecast information for commercial purposes. The current forecasting accuracy of agricultural prices has not reached the commercial level, but it is necessary to establish a system that discloses information on price forecasts so that anyone can access it.

Fourth, agricultural price forecasts have the potential to stabilize the incomes of farmers in developing countries that are most vulnerable to meteorological disasters. However, regardless of the accuracy of the forecast level, the risk of the forecast failure cannot be reduced to zero. If farmers in developing countries do not use information on price forecasts due to fear of such risks, the problem of poverty cannot be addressed. Hence, it is necessary to enhance the insurance system for meteorological disasters and expand the safety net for risk aversion. Furthermore, under future global climate change, providing consistent price forecasts in all countries worldwide increases the potential for optimizing agricultural production globally.

Summary and conclusions

Global warming will accelerate meteorological disasters, such as droughts, heatwaves, and floods, which may lead to soaring food prices and induce political and economic turmoil worldwide. To avoid such turmoil and minimize climate risks, this study attempted to forecast agricultural prices several months ahead using the quasi-dynamic large-scale global CGE model, which comprised 88 countries/regions and 15 sectors associated with the results of the crop model and GCMs. Furthermore, this study evaluated the accuracy of the CGE model and the reproducibility of forecasted price fluctuations 3 and 6 months ahead by comparing the annual fluctuations of actual and estimated prices.

As a result, first, the accuracy of the model to trace the actual price fluctuations of crops, measured by the regional average of correlation coefficients during 1995-2015, ranged from 0.13 to 0.26 by crop. Judging by the correlation coefficient above the threshold of 10% significance level and the QW-κ above the level of "minimal concordance," the CGE model can reproduce actual price fluctuations in approximately 30% of the targeted countries worldwide. These simulations were robust against changes in economic structure during 2004-2014 and changes in simulation periods.

Second, the traceability of the model, measured by correlation coefficients, tended to be higher in the developed liberal countries in OECD than the non-OECD countries. Although the difference between these groups had low statistical significance, the tendency of such differences was more consistent among the four crops than those between major exporters and other countries of each agricultural product mentioned by the previous study (Valenzuela et al. 2007).

Third, when these forecasts and estimations were compared with actual price fluctuations, the reproducibility of the forecasted price fluctuations 3 or 6 months ahead was found to be lower than the theoretically estimated price fluctuations. However, approximately 20% of the targeted countries were still able to reproduce the actual annual price fluctuations using the CGE model associated with the results of the crop model.

Fourth, comparing the reproduced forecasts 3 and 6 months ahead, a 3-month extension of the forecast period reduced the reproducibility of agricultural price fluctuations by 16.7% in the correlation coefficient.

Overall, the reproducibility of forecasting agricultural prices several months ahead is not particularly high, with only a small portion of the fluctuations in actual statistical data being reproduced. However, some of the 88 countries showed high reproducibility of forecasts. The existence of such countries demonstrates some possibilities in which forecasting prices by the CGE model associated with the results of the crop model and GCM can be used as a forecasting index in the agricultural market as well as a preparation for meteorological disasters.

Future studies should i) compare the reproducibility of agricultural price forecasts with other macroeconomic models and economic forecasting methods, ii) update seasonal forecast data for climate prediction and crop yield prediction as well as statistical data, and iii) evaluate the reproducibility of price forecasts several months ahead for crops other than the four discussed in this study.

Acknowledgements

This study was supported by the Grants-in-Aid for Scientific Research 16KT0036, 20K06269, and 21H02294 (the Japan Society for the Promotion of Science). We are grateful to Katsuhiro Saito (University of Tokyo) for invaluable information and discussion and Editage (www.editage.jp) for language editing. All possible errors are our own.

References

Food and Agriculture Organization (FAO) (2021) World food situation. http://www.fao.org/worldfoodsituation/foodpricesindex/en/. Accessed on 2 August 2021.

Furuya, J. et al. (2015) Climate change effects on long-term world-crop production: incorporating a crop model into long-term yield estimates. *JARQ*, **49**, 187-202.

Gaupp, F. et al. (2020) Changing risks of simultaneous global breadbasket failure. *Nat. Clim. Change*, **10**, 54-57.

Headey, D. & Fan, S. (2008) Anatomy of a crisis: the causes and consequences of surging food prices. *Agric. Econ.*, **39**, 375-391.

Iizumi, T. et al. (2018) Global crop yield forecasting using seasonal climate information from a multi-model ensemble. *Clim. Serv.*, **11**, 13-23.

Intergovernmental Panel on Climate Change (IPCC). (2019) Food security. *In* IPCC special report: Climate change and land, chapter 5. https://www.ipcc.ch/srccl/. Accessed on 20 December 2020.

Jha, G. K. & Sinha, K. (2014) Time-delay neural networks for time series prediction: an application to the monthly wholesale price of oilseeds in India. *Neural Comput. Appl.*, **24**, 563-571.

Kalliovirta, L. et al. (2019) Forecasting milk prices with VAR Models—application to farm gate price in Finland. *SSRN*, Available https://ssrn.com/abstract =3473862, Accessed on 20 November 2021.

Kundel, H. L. & Polansky, M. (2003) Measurement of observer agreement. *Radiology*, **228**, 303-308.

Kunimitsu, Y. et al. (2020) Systemic risk in global agricultural markets and trade liberalization under climate change: synchronized crop-yield change and agricultural price volatility. *Sustainability*, **12**, 10680.

Landis, J. R. & Koch, G. G. (1977) The measurement of observer agreement for categorical data. *Biometrics*, **33**, 159-174.

Lanz, B. & Rutherford, F. T. (2017) GTAP in GAMS: multiregional and small open economy models. *J. Global Econ. Anal.*, **1**, 1-77.

Li, N. et al. (2017) Modeling regime-dependent agricultural commodity price volatilities. *Agric. Econ.*, **48**, 683-691.

Min. Y.-M. et al. (2014) Assessment of APCC multimodel ensemble prediction in seasonal climate forecasting: retrospective (1983-2003) and real-time forecasts (2008-2013). *J. Geophys. Res. Atmos.*, **119**, 132-150.

Szewczyk, W. et al. (2020) Economic analysis of selected climate impacts, *JRC Technical Report*, EUR 30199 EN, Publications Office of the European Union, Luxembourg.

Tigchelaar, M. et al. (2018) Future warming increases probability of globally synchronized maize production shocks. *PNAS*, **115**, 6644-6649.

Ueda, T. & Kunimitsu, Y. (2020) Interregional price linkages of fossil-energy and food sectors: evidence from an international input-output analysis using the GTAP database. *Asia-Pac. J. Reg. Sci.*, **4**, 55-72.

Valenzuela, E. et al. (2007) Assessing global CGE model validity using agricultural price volatility. *Am. J. Agric. Econ.*, **89**, 383-397.

Wang, B. J. et al. (2018) Research on hybrid model of garlic short-term price forecasting based on big data. *Comput. Mater. Contin.*, **57**, 283-296.

Wang, D. et al. (2021) Economic impacts of climate-induced crop yield changes: evidence from agri-food industries in six countries. *Clim. Change*, **166**, 30.

Wang, L. Y. et al. (2020) Agricultural product price forecasting methods: research advances and trend. *Br. Food J.*, **122**, 2121-2138.

Watson, J. et al. (2015) Comparing the effects of calibration and climate errors on a statistical crop model and a process-based crop model. *Clim. Change*, **132**, 93-109.

Wright, B. D. (2011) The economics of grain price volatility. *Appl. Econ. Perspect. Policy*, **33**, 32-58.

Table A1. Accuracy of the fluctuations in theoretical agricultural price (*P_T*) by the CGE model against actual price data (*P_FAO*), but using 2004 SAM data

Classifications	Rice	Wheat	Maize	Soybean	4 Crops
No. of available data	45	57	58	36	49.0
Standard deviation (*std*) by country					
ratio of average *std*	0.308	0.495	0.573	0.722	0.525
correlation coefficient of *std*	0.308	0.316	0.155	0.361	0.285
Correlation coefficient (R)					
average R	0.120	0.256	0.185	0.200	0.190
average R (only significant)	0.377	0.491	0.481	0.500	0.462
countries where R>=0.29	24.4%	45.6%	32.8%	38.9%	35.4%
QW-κ score					
average QW-κ	0.116	0.236	0.177	0.183	0.178
countries where QW-κ>=0.2	24.4%	50.9%	36.2%	36.1%	36.9%

Same as in Table 3, except for using 2004 SAM data

Table A2. Accuracy of the fluctuations in theoretical agricultural price (*P_T*) by the CGE model against actual price data (*P_FAO*) using 2014 SAM data, with simulation period of 2000-2015

Classifications	Rice	Wheat	Maize	Soybean	4 Crops
No. of available data	45	58	58	37	49.5
Correlation coefficient (R)					
average R	0.144	0.274	0.182	0.226	0.207
average R (only significant)	0.466	0.547	0.546	0.551	0.528
countries where R >=0.34	24.4%	41.4%	31.0%	37.8%	33.7%
QW-κ score					
average QW-κ	0.130	0.244	0.204	0.257	0.209
countries where QW-κ>=0.2	31.1%	58.6%	39.7%	59.5%	47.2%

The threshold of 0.34 indicates R with a significance level of 10% (number of data = 16 years) and QW-κ = 0.2 represents minimal concordance between ACR of *P_T* and ACR of *P_FAO*. Other remarks are the same as in Table 3, except for the simulation period.