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Potential Yield of World Rice under Global Warming Based on the ARIMA-TR Model

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Abstract: As one of two most important cereals in the world, and with the continuous increase in population and demand for food consumption worldwide, rice has been attracting researchers' attention for improving its potential yield in the future, particularly as it relates to climate change. However, what will be the potential limit of world rice yield in the future, and how does global warming affect the yield of world rice? Therefore, analyzing the potential yield of world rice affected by global warming is of great significance to direct crop production worldwide in the future. However, by far, most modeled estimations of rice yield are based on the principle of production function from static biological dimension and at local or regional levels, whereas few are based on a time series model from a dynamic evolutionary angle and on global scale. Thus, in this paper, both average and top (national) yields of world rice by 2030 are projected creatively using the Auto-regressive Integrated Moving Average and Trend Regression (ARIMA-TR) model and based on historic yields since 1961; in addition, the impact of global warming on the yields of world rice is analyzed using a binary regression model in which global mean temperature is treated as the independent variable whereas the yield is expressed as the dependent variable. Our study concludes that between 2021 and 2030, the average yield of world rice is projected to be from 4835 kg/ha to 5195 kg/ha, the top yield from 10,127 kg/ha to 10,269 kg/ha, or the average yield ranging from 47.74% to 50.59% of the top yield. From 1961 to 2020, through to2030, global warming will exert a negative impact on the average yield of world rice less than that of the top yield, which partly drives the gap between these two yields and gradually narrowed; for world rice by 2030, the opportunities for improving global production should be dependent on both high and low yield countries as the average yield is approaching the turning point of an *S*-shaped curve in the long-term trend. These insights provide the academic circle with innovative comprehension of world rice yield and its biological evolution for global food security relating to global warming in the future.

Keywords: global warming; potential yield; world rice; ARIMA-TR model

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1. Introduction

As a staple food for nearly half of the world's population, rice constitutes about 20% of cereal grain produced globally and attracts researchers' attention for improving its potential yield in the future particularly as it relates to global warming. Recent studies on rice (potential) yield and its estimation through modelling have provided a number of important insights.

Most researchers microscopically explore rice yield from an agronomic angle mainly using experiments or trials. The Yongyou japonica/indica hybrids series (LMYS), especially late-maturity varieties with high yield potential, are widely planted in the lower reaches of the Yangtze River in China [1]. The yield advantage of hybrid rice was smaller than that of inbred varieties at medium and high yield levels, but the difference was larger at super high yield levels [2]. The erect panicle model of super rice can rationally convert solar energy into accumulated organic matter (biomass) to improve grain yield [3]. A survey of four representative agro-meteorological experimental stations in China found that the rice-wheat rotation system of farmers' yields were about 8101 kg/ha or 45.3% of potential yield, which have shrank from 1981 to 2009 [4]. The increased yield potential of super rice was mainly because of larger sink size due to larger panicles [5]. A rice cultivar developed and recommended by Embrapa for irrigated cultivation in Brazil—BRS Pampeira became famous for its high yield potential [6]. During the rainy seasons of 2009 and 2010, thirty-six upland rice genotypes collected from six provinces in northern and north-eastern Thailand along with one check variety (Sewmaejan) were evaluated at five locations, which showed that the genotype grain yield was greatly affected by location (59.90%), genotypes (G) x location (L) interaction (12.80%) and by genotype (6.79%) [7]. In major rice production regions of China, the yield gaps between actual yields and potential ones shrank [8].

It is well-known that light, temperature, water, fertilizer and gas each plays an essential role in the growth and yield of crop. Physical environment (such as climate and soil) and biological factors (such as insects and microbes) ultimately all have some influence on crops' growth and yield. However, crops produce dry matter basically through photosynthesis, part of which eventually becomes crop yield. Therefore, improving light use efficiency (LUE) is a critical factor in the improvement of potential crop yield. For example, taking into account the highest LUE in plant as the limitation, the maximum photosynthesis yield potential of rice is about 1.4 times that of existing levels in the world [9]. Daily average temperature and solar radiation throughout the growing period were significantly positively correlated with rice yield, total dry matter and harvest index [10].

Some scholars have put efforts in modelling to estimate rice potential yield. The correlation between twenty one years (1990–2010) of weather data and reported rice yield was used for simulating the yields in the districts of eastern and north-eastern regions of India under various management conditions, and compared with reported data there [11]. The ORYZA crop model was used for estimating the irrigated rice potential yield for two widely planted varieties (M-206 and CXL745) in three major U.S. rice-producing regions that collectively represent some of the highest-yielding regions in the world [12]. The target yield for super hybrid rice production could be determined by the average yield method or the regression model [13]. The area-weighted average yield potential (YP) levels of rice in Northeast China (NEC) estimated by the ORYZA-V3 crop model were 12,900 kg/ha for YP and 11,600 kg/ha for attainable YP [14]. The potential yields of hybrid rice in China under adequate irrigation and at reasonable fertilization levels in the Bangladesh, India and Myanmar (BIM) region in 2000 are estimated using the Environmental Policy Integrated Climate (EPIC) model showing 10,220 kg/ha and 11,330 kg/ha, respectively [15]. The potential impacts of climate change on the yield of T. aman rice variety in 12 representative areas of Bangladesh was estimated using the Decision Support System for Agrotechnology Transfer (DSSAT) 4.0 model, which indicated that an average yield of T. aman cultivars at selected sites in 2030, 2050 and 2070 are +5.04%, +6.06% and −32.43% compared to the baseline in 2008, respectively [16]. Based on key information derived from the crop growth model ORYZA and SAR, a rice yield estimation system was developed, which suggested that incorporating remote sensing data improves spatial distribution of yield estimates in south and south-east Asian countries [17]. Using an artificial neural network (ANN) and multiple linear regression (MLR) methods for modelling 'observed rice yield' and 'remotely sensed backscatter' in the eastern and western Godavari regions of Andhra Pradesh in India, it was revealed that the results of ANN models is better [18]. A satellite-based biophysical model was used for deriving actual yield (Y-a) in Northeast China (NEC) during the period from 2006 to 2017, which indicated the ability to provide reliable estimation of rice yields with a Root Mean Squared Error (RMSE) below 20% [19]. Sun et al. evaluated 14 rice growth models versus four heat treatments levels applied at different times after four years of flowering with phytotron experiments, and found that all models substantially underestimated the negative effects of heat on grain yield [20], and so on.

As discussed above, there are no lack of research reports on the potential yield of rice, which often adopt experimental methods and their modeled estimations partly considering climate change. As for the modelled estimation of rice yield, most are based on the principle of production function for specific varieties, from static biological dimension and at local or regional levels, whereas few are methodologically based on time series models for generic rice from a dynamic evolutionary angle and on a global scale. Thus in this paper, the Auto-regressive Integrated Moving Average and Trend Regression (ARIMA-TR) model is creatively used for projecting both average and top (national) yields of world rice by 2030 based on their historic performance since 1961; additionally, the impact of global warming on the yields of world rice during the same period is analyzed using a binary regression model in which global mean temperature is treated as the independent variable whereas the yield is treated as the dependent variable. Our purpose aims at offering information on directing the production of world rice for global food security considering climate change in the future.

2. Materials and Methods

2.1. Data

Global warming is the most important event in climate change and has an influence on the growth and yield of world rice. Therefore, average and top (national) yields of world rice from 1961 to 2020 are used for projecting future volumes by 2030, and their correlations with global mean temperature during the same period are analyzed.

As shown in Figure 1, from 1961 to 2020, global mean temperature gradually rose in fluctuation, and the average yield of world rice rose more steadily and faster than the top. 'Average yield' means average yield of world rice worldwide whereas 'top yield' refers to a specific country whose rice yield countrywide was at the top globally in the given year as follows: Puerto Rico in 1961, 1963 to 1964, 1970, 1972, and 1974 to 1983; Swaziland in 1984 to 1988 and 1990; Dominica in 1992; North Korea in 1993; Syria in 1994 to 1995; Egypt in 1996 to 1997, 2000, 2002, 2004 to 2009 and 2011 to 2012; Uzbekistan in 2003; and Australia in 1962, 1965 to 1969, 1971, 1973, 1989, 1991, 1998 to 1999, 2001, 2010 and 2013 to 2020.

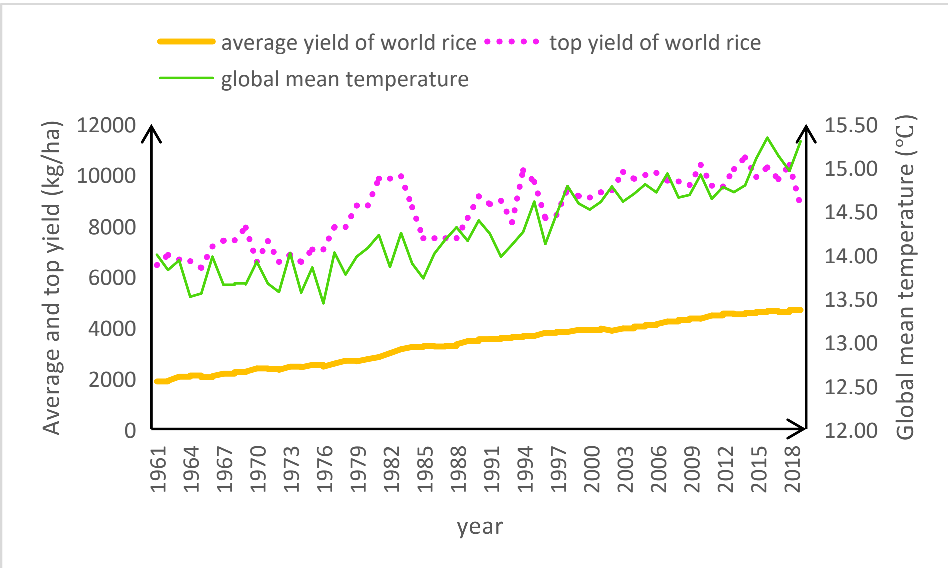

Figure 1. Global mean temperature (°C), average and top yields (kg/ha) of world rice from 1961 to 2020. Source: https://www.ncdc.noaa.gov/temp-and-precip/ (accessed on 1 March 2022); http://www.fao.org/faostat/en/#data (accessed on 1 March 2022).

2.2. Methods

2.2.1. ARIMA-TR Model

The ARIMA-TR model is the combination of the ARIMA (Auto-regressive Integrated Moving Average) model and the TR (Trend Regression) model.

(1) ARIMA model

The ARIMA model belongs to a time series approach based on the theory of stochastic process, whose complete representation is mathematically symbolized as Formula (1):

$$[1-\sum_{i=1}^{p}\varnothing_i L^i](1-L)^d X_t = [1+\sum_{i=1}^{q}\theta_i L^i]\varepsilon_t \tag{1}$$

In Formula (1), *p* refers to the number of auto-regressive parameters, whereas *d* is the order of differencing required for producing stationarity, *q* to the number of moving average parameters, *t* to the time unit, *L* to the lag operator, $\varnothing(L)$ to stationary auto-regressive operator, $\theta(L)$ to reversible moving average operator and $d \in z$ to target variable [21].

Both Auto-regressive and Moving Average models require stationary data, which means that the mean and variance of the time series are constant over time. The constant mean assumption implies that there are no cycles or trends in the data, whereas the constant variance assumption resembles the kind that is in the homogeneity-of-variance of linear regression. The order of differencing refers to the number of times that each previous observation is subtracted from the successive one until no systematic decrease or increase at the level of series remains while drifting. The noise in the time series drifts up and down across time.

Historic yields of world rice is considered a time series variable and can be estimated using the ARIMA model as it generally rises over time due to continuous improvement of the inputs into its production by scientific and technical means. In the application of this research, the following steps are undertaken to project world rice yields between 2020 and 2030, basing the projection on their historic performance since 1961. Firstly, to produce logarithmic values of world rice yields from 1961 to 2019 and to eliminate the heteroscedasticity, test the stationarity of the time series and establish a 'stationary series' through differencing if not stationary; secondly, empirically establish five such basic models as the ARMA(1,2) model, ARMA(1,1) model, AR(1) model, MA(2) model and MA(1) model to fit world rice yields from 1961 to 2019 and use RMSE for evaluating the fitness. Finally, select the optimal basic model used for ARIMA(*p*,*d*,*q*) modelling to project world rice yields between 2020 and 2030.

(2) TR model

In the TR model, the year (represented as ordinal number) is treated as the independent variable whereas the yield of world rice is treated as the dependent variable. The model with the highest R squared among such five trend-regressed models as Linear, Exponential, Logarithmic, Polynomial and Power, was used for projecting the futures between 2020 and 2030, basing the projection on their historic yields from 1961 to 2019.

(3) Combing the ARIMA model and TR model

Based on the comparison between different yields of world rice projected by using the ARIMA model and TR model, respectively, resulting yield was selected following RMSE as the estimated result of the ARIMA-TR model, and actual yield in 2020 was used for testing the projection.

2.2.2. Binary Regression Model

The effects of global warming on average and top yields of world rice from 1961 to 2020, and up to 2030 are respectively analyzed using the binary regression model, in which global mean temperature stands for the independent variable whereas the yield stands for the dependent variable.

3. Results

3.1. Descriptive Statistics of World Rice Yields and Global Mean Temperature from 1961 to 2020

The descriptive statistics of average and top yields of world rice and global mean temperature from 1961 to 2020 are shown in Table 1.

Table 1. Descriptive statistics of average and top yields of world rice and global mean temperature from 1961 to 2020.

Variable	Unit	Mean	Std. Dev.	Min	Max
Average yield of world rice	kg/ha	3380.767	885.8763	1869	4679
Top yield of world rice	kg/ha	8629.903	1302.228	6337	10,683
Global mean temperature	°C	14.29983	0.5134479	13.44	15.42

As shown in Table 1, the variation range of average yield of world rice from 1961 to 2020 is smaller than that of the top yield.

3.2. Seriess Stationarity and Auto-Correlation Tests of World Rice Yields and Global Mean Temperature from 1961 to 2020

The results of the series' stationarity test for average and top yields of world rice and global mean temperature from 1961 to 2020 are shown in Table 2.

Table 2. Results of series' stationarity test for average and top yields of world rice and global mean temperature from 1961 to 2020.

Series	T-Statistic	Test Critical Values			Prob.	Stationarity
		1%	5%	10%		
lnAYR	−1.218635	−4.121303	−3.487845	−3.172314	0.8973	No
lnTYR	−4.084024	−4.121303	−3.487845	−3.172314	0.0111	No
DlnAYR	−8.210128	−3.548208	−2.912631	−2.594027	0.0000	Yes
DlnTYR	−10.21046	−3.548208	−2.912631	−2.594027	0.0000	Yes
lnGMT	−6.843084	−4.121303	−3.487845	−3.172314	0.0000	Yes

Note: AYR refers to 'average yield of world rice' whereas TYR refers to 'top yield of world rice' and GMT to 'global mean temperature'.

As shown in Table 2, from 1961 to 2020, the logarithmic series of average yield of world rice became stationary only after first differencing, as does the top yield; the logarithmic series of global mean temperature is stationary.

The test results of the series' auto-correlation function (ACF) and partial auto-correlation function (PACF) for average and top yields of world rice and global mean temperature from 1961 to 2020 are shown in Figure 2.

As shown in Figure 2, all lag phases after the 8th in ACF and those after the 7th in PACF are in the confidence interval (viz. between the two dotted lines) for average yield of world rice from 1961 to 2020, whereas all lag phases after the 2nd in ACF and these after the 1st in PACF are in the confidence interval for the top yield, and all lag phases after the 2nd in both ACF and PACF are in the confidence interval for the global mean temperature. In other words, it is applicable to ARIMA(p,d,q) modelling in which 'p' is equivalent to 0 or 1 whereas 'q' is equivalent to 0, 1 or 2. These outputs are used to project average and top yields of world rice and global mean temperature by 2030, based on their historic performance since 1961.

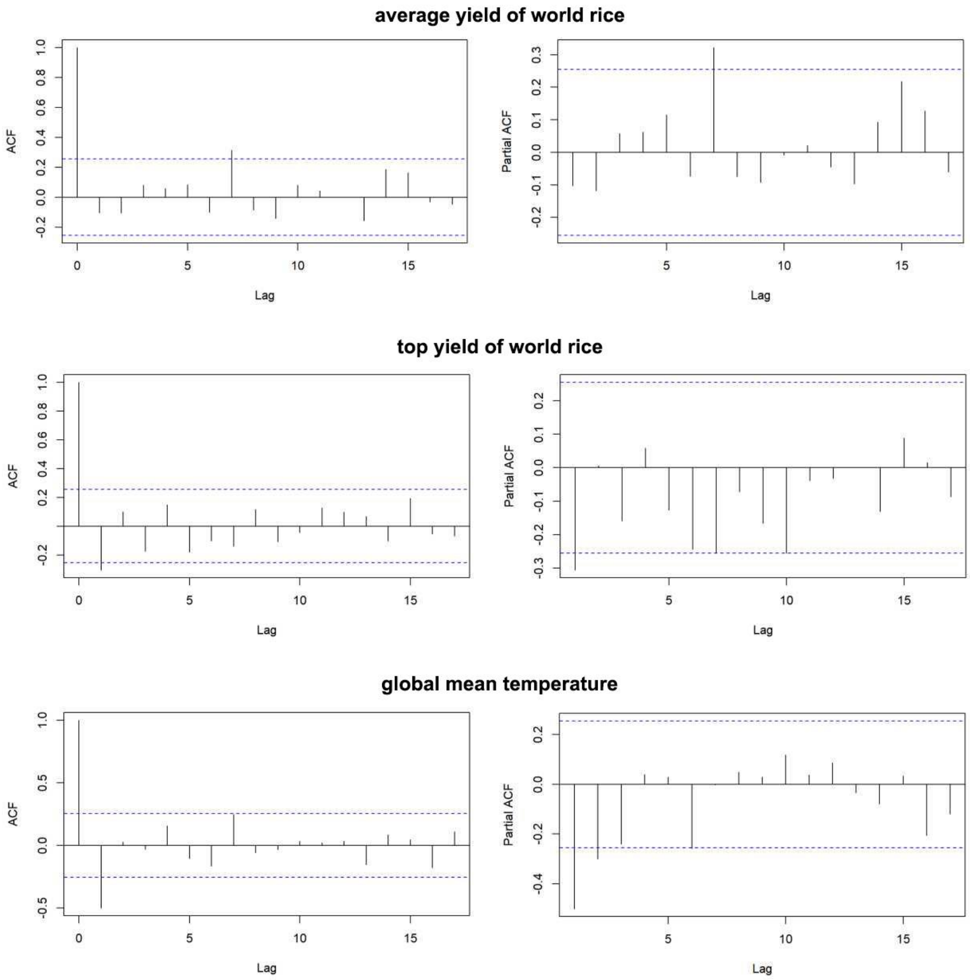

Figure 2. Test results of series' ACF and PACF for average and top yields of world rice and global mean temperature from 1961 to 2020.

3.3. Projecting Average Yields of World Rice between 2020 and 2030 Using ARIMA-TR Model

3.3.1. Projecting Average Yields of World Rice between 2020 and 2030 Using the ARIMA Model

The equations of five basic models for fitting average yields of world rice from 1961 to 2019 were established on the basis of its stationary 1st-differencing series and is shown in Table 3.

Table 3. Equations of five basic models for fitting average yields of world rice from 1961 to 2019.

Model	Equation
ARMA(1,2)	$\mathrm{lnayr}_t = 0.015700 + 0.182667\mathrm{lnayr}_{t-1} + 0.817333\mathrm{lnayr}_{t-2} + \varepsilon_t + 0.743222\varepsilon_{t-1} - 0.218335\varepsilon_{t-2}$
ARMA(1,1)	$\mathrm{lnayr}_t = 0.015851 + 0.502768\mathrm{lnayr}_{t-1} + 0.497232\mathrm{lnayr}_{t-2} + \varepsilon_t + 0.469079\varepsilon_{t-1}$
AR(1)	$\mathrm{lnayr}_t = 0.015820 + 0.873250\mathrm{lnayr}_{t-1} + 0.126750\mathrm{lnayr}_{t-2} + \varepsilon_t$
MA(2)	$\mathrm{lnayr}_t = 0.015688 + \varepsilon_t - 0.129004\varepsilon_{t-1} - 0.110087\varepsilon_{t-2}$
MA(1)	$\mathrm{lnayr}_t = 0.015786 + \varepsilon_t - 0.161670\varepsilon_{t-1}$

Note: '*ayr*' stands for 'average yield of world rice'.

The RMSE of each basic model used for fitting average yields of world rice from 1961 to 2019 is 349.2081 of ARMA(1,2) model, 328.9316 of ARMA(1,1) model, 348.8970 of AR(1) model, 349.5604 of MA(2) model and 344.8092 of MA(1) model, respectively. Thus, the basic model ARMA(1,1) best fitted among the five models, and was used for ARIMA(1,1,1) modelling to project average yields of world rice between 2020 and 2030.

In addition, the absolute values of the inverted AR root (−0.50) and inverted MA root (−0.47) of the ARIMA(1,1,1) are both below 1.00, which indicates the model is stationary and used for projecting average yields of world rice between 2020 and 2030.

Using the ARIMA(1,1,1) model, the average yields of world rice are projected to be 4785 kg/ha in 2020, 4861 kg/ha in 2021, 4939 kg/ha in 2022, 5018 kg/ha in 2023, 5098 kg/ha in 2024, 5179 kg/ha in 2025, 5262 kg/ha in 2026, 5346 kg/ha in 2027, 5431 kg/ha in 2028, 5518 kg/ha in 2029 and 5606 kg/ha in 2030, respectively.

3.3.2. Projecting Average Yields of World Rice between 2020 and 2030 Using TR Model

The equations of variation trends for average yields of world rice from 1961 to 2019 are shown in Table 4.

Table 4. Equations of variation trends for average yields of world rice from 1961 to 2019.

Trend	Equation	R Squared
Exponent	$y = 2006.6e^{0.016x}$	0.9678
Linear	$y = 50.883x + 1833.5$	0.9895
Logarithm	$y = 996.98\ln(x) + 585.75$	0.8252
Polynomial	$y = -0.1531x^2 + 60.072x + 1740$	0.9916
Power	$y = 1301.8x^{0.2915}$	0.8854

As shown in Figure 1 and Table 3, the average yield of world rice from 1961 to 2019 rises in a polynomial trend with the highest R squared among five trend-regressed models, which are used for projecting the yields between 2020 and 2030 and results in 4793 kg/ha in 2020, 4835 kg/ha in 2021, 4876 kg/ha in 2022, 4917 kg/ha in 2023, 4958 kg/ha in 2024, 4998 kg/ha in 2025, 5038 kg/ha in 2026, 5078 kg/ha in 2027, 5117 kg/ha in 2028, 5156 kg/ha in 2029 and 5195 kg/ha in 2030, respectively.

3.3.3. Average Yields of World Rice between 2020 and 2030 Estimated by ARIMA-TR Model

The RMSE of the basic model ARMA(1,1) is used for fitting the average yield of world rice from 1961 to 2019 is 328.9316 whereas that of the TR model is 79.815. Thus, average yields of world rice between 2020 and 2030 projected using the TR model are adopted as the estimated result of the ARIMA-TR model. Moreover, actual average yield of world rice in 2020 (4609 kg/ha) is 3.84% lower than its projection, which shows the robustness of validation. Namely, using the ARIMA-TR model average yield of world rice will be increased by 7.45% based on the projection in ensuing decades.

3.4. Projecting Top Yields of World Rice between 2020 and 2030 Using ARIMA-TR Model

3.4.1. Projecting Top Yields of World Rice between 2020 and 2030 Using ARIMA Model

The variation of top yields of world rice in the long-term is also deemed as a stochastic process. Therefore, top yields of world rice between 2020 and 2030 is projected using the ARIMA model, basing the projection on its historic performance since 1961. The equations of five basic models for fitting top yields of world rice from 1961 to 2019 are established on the basis of its 1st-differencing series, as shown in Table 5.

Table 5. Equations of five basic models for fitting top yields of world rice from 1961 to 2019.

Model	Equation
ARMA(1,2)	$\text{lntyr}_t = 0.005414 + 0.053938\text{lntyr}_{t-1} + 0.946062\text{lntyr}_{t-2} + \varepsilon_t + 0.673627\varepsilon_{t-1} - 0.209835\varepsilon_{t-2}$
ARMA(1,1)	$\text{lntyr}_t = 0.005255 + 0.208506\text{lntyr}_{t-1} + 0.791494\text{lntyr}_{t-2} + \varepsilon_t + 0.592135\varepsilon_{t-1}$
AR(1)	$\text{lntyr}_t = 0.005235 + 0.718797\text{lntyr}_{t-1} + 0.281203\text{lntyr}_{t-2} + \varepsilon_t$
MA(2)	$\text{lntyr}_t = 0.005815 + \varepsilon_t - 0.283615\varepsilon_{t-1} + 0.020142\varepsilon_{t-2}$
MA(1)	$\text{lntyr}_t = 0.005866 + \varepsilon_t - 0.284840\varepsilon_{t-1}$

Note: '*tyr*' stands for 'top yield of world rice'.

The RMSE of each basic model used for fitting top yields of world rice from 1961 to 2019 is 1059.049 of the ARMA(1,2) model, 1161.485 of ARMA(1,1) model, 1114.332 of AR(1) model, 1210.790 of MA(2) model and 1199.039 of MA(1) model, respectively. Thus, the basic model ARMA(1,2) best fitted among the five kinds and is used for ARIMA(1,1,2) modelling to project top yields of world rice between 2020 and 2030.

Moreover, theabsolute values of both the inverted AR root (−0.95) and inverted MA roots (0.23 and −0.91) of the ARIMA(1,1,2) are all below 1.00, which indicates the model is stationary and used for projecting top yields of world rice between 2020 and 2030.

Using the ARIMA(1,1,2) model, top yields of world rice between 2020 and 2030 is projected to be 31,600 kg/ha in 9282 kg/ha in 2020, 9337 kg/ha in 2021, 9383 kg/ha in 2022, 9438 kg/ha in 2023, 9486 kg/ha in 2024, 9541 kg/ha in 2025, 9589 kg/ha in 2026, 9645 kg/ha in 2027, 9694 kg/ha in 2028, 9749 kg/ha in 2029 and 9800 kg/ha in 2030, respectively.

3.4.2. Projecting Top Yields of World Rice between 2020 and 2030 Using TR Model

Likewise, the equations of variation trends for top yields of world rice from 1961 to 2019 are shown in Table 6.

Table 6. Equations of variation trends for top yields of world rice from 1961 to 2019.

Trend	Equation	R Squared
Exponent	$y = 6760.6e^{0.0077x}$	0.7073
Linear	$y = 63.661x + 6696.3$	0.7072
Logarithm	$y = 1157.8\ln(x) + 4984.9$	0.6419
Polynomial	$y = -0.6739x^2 + 104.09x + 6285.3$	0.7255
Power	$y = 5463.5x^{0.1415}$	0.6636

As shown in Figure 1 and Table 6, the top yield of world rice rises in a polynomial trend with top R squared among the five trend-regressed models, which are used for projecting the yields between 2020 and 2030 and results in 10,105 kg/ha in 2020, 10,127 kg/ha in 2021, 10,148 kg/ha in 2022, 10,168 kg/ha in 2023, 10,187 kg/ha in 2024, 10,204 kg/ha in 2025, 10,220 kg/ha in 2026, 10,234 kg/ha in 2027, 10,247 kg/ha in 2028, 10,259 kg/ha in 2029 and 10,269 kg/ha in 2030, respectively.

3.4.3. Top Yields of World Rice between 2020 and 2030 Estimated by ARIMA-TR Model

The RMSE of the basic model ARMA(1,2) is used for fitting top yield of world rice from 1961 to 2019 is 1059.049 whereas that of the TR model is 170.517. Thus, top yields of world rice between 2020 and 2030 projected using the TR model are adopted as an estimated result of the ARIMA-TR model as the actual top yield (10,031 kg/ha) in 2020, which is only 0.73% lower than the projection. That is to say, the top yield of world rice in ensuing decades will increase by only 1.40%, as estimated using the ARIMA-TR model, which indicates that the increase range of the top yield is much smaller than that of the average yield during the same period. The top (national) yield of world rice is considered a potential limit of the average because the latter will 'chase after' but never approach the former.

Top (national) yields of world rice with corresponding countries of intensity ranges represented as a time (year) number from 1961 to 2020 were labeled using ArcGIS map to show their spatial distribution worldwide, as seen in Figure 3.

As shown in Figure 3, from 1961 to 2020, the top (national) yields of world rice were seen in the following countries with corresponding number of distribution-years, respectively: Puerto Rico in fifteen years; Swaziland in six years; Dominica, North Korea and Uzbekistan in one year each; Syria in two years; Egypt in twelve years; and Australia in twenty-two years. The nations with the top (national) yields of world rice are classified into four hierarchic clusters—over 21 years, 11 to 15 years, 6 to 10 years, and 1 to 5 years, among which Australia topped with harvested areas ranging from 2318 hectares in 2008 (minimum) to 176,576 hectares in 2001 (maximum). Intuitively, the map of top yields of world rice from 1961 to 2020 showed stochastic distribution worldwide. These countries with the top yields represent certain conditions—climate, soil and agronomy, under which the population of rice plants grows best at the national level, and an inevitable law limits the average yield of the crop worldwide approaching its top.

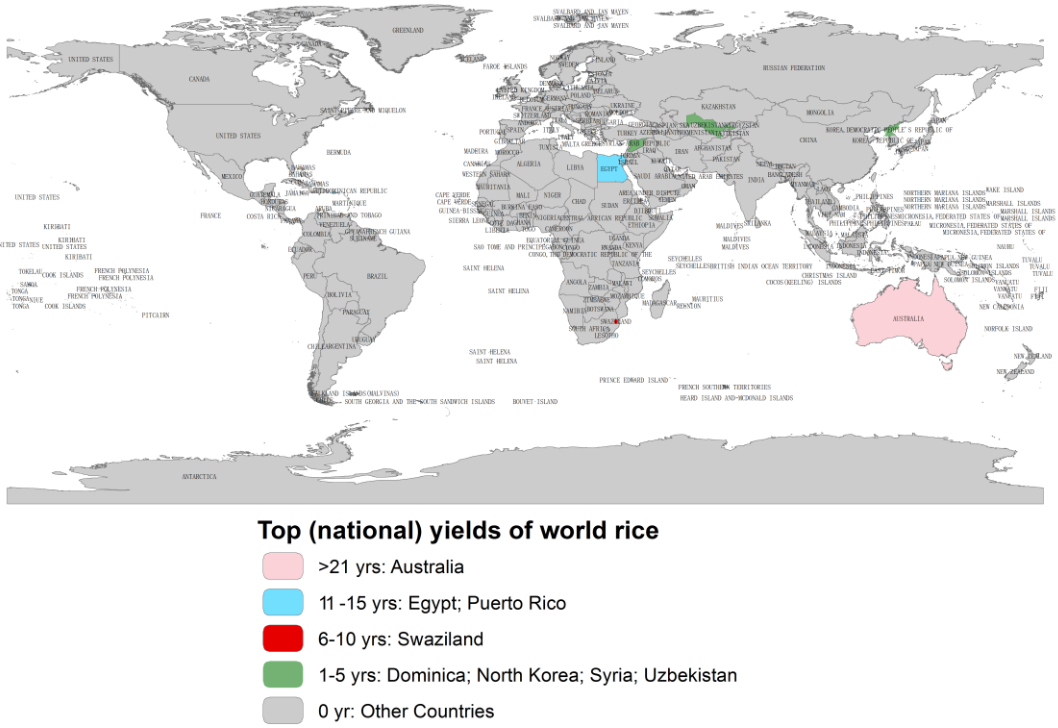

Figure 3. Distribution of top (national) yields of world rice from 1961 to 2020.

3.5. Variation Trends for Average and Top Yields of World Rice from 1961 to 2020 up to 2030

The variation trends for average and top yields of world rice from 1961 to 2020 and up to 2030 are shown in Figure 4.

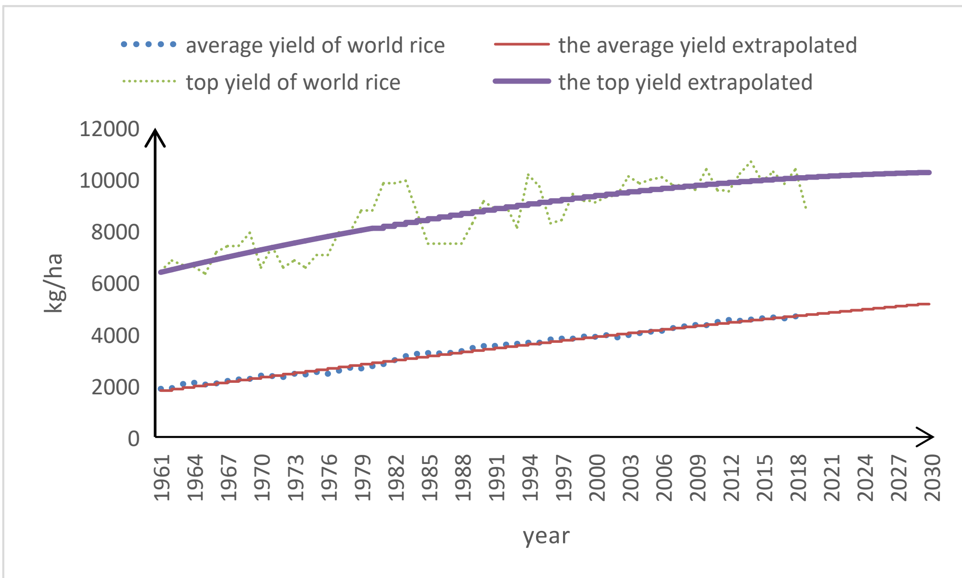

Figure 4. Average and top yields of world rice from 1961 to 2020 and up to 2030.

In Figure 4, the ratio between the extrapolated average and top yields of world rice between 2021 and 2030 based on the estimations of the ARIMA-TR model are: 47.74% in 2021, 48.05% in 2022, 48.36% in 2023, 48.67% in 2024, 48.98% in 2025, 49.30% in 2026, 49.61% in 2027, 49.93% in 2028, 50.26% in 2029 and 50.59% in 2030, respectively. Namely, the average yield of world rice projected to be increasingly reaching around 50% of potential limit by 2030 is based on the estimated result of the ARIMA-TR model. In other words, the gap between average and top yields of world rice will continuously narrow in ensuing decades as the average rises faster than the top. The role that global warming plays is explored as follows using the binary regression model.

3.6. Effects of Global Warming on World Rice Yields Based on Binary Regression Model

It is acknowledged worldwide that annual global mean temperature has been rising in slight fluctuations over time since the industrial revolution. As analyzed above, both the average and top yields of world rice rose from 1961 to 2020 and will rise up to 2030 in general. Theoretically, there must exist certain inner correlations between annual global mean temperature and the yields of world rice because temperature is an essential factor for rice growth and yield. Though all climatic factors such as sunlight, temperature, precipitation and gases each make a respective contribution to the growth and yield of world rice, only the variation (viz. rise) of annual global mean temperature is observed and proven to be the result of higher CO_2 concentrations in the atmosphere. Generally speaking, world rice yield is dependent mainly on climatic factors at global or macroscopic levels and primarily on nutritional conditions on a local or microscopic scale. At a global or macroscopic level in climate change, sunlight and gases have changed but have also contributed to the yields of world rice primarily in the form of global warming effect because they cause the decrease or increase of global mean temperature directly or indirectly. Furthermore, the variation of annual precipitation over time on a global scale does not show any trend of increase or decrease. Therefore, theoretically, and for the sake of simplification, the contribution of sunlight, precipitation and gases yearly on a global scale can be treated as constant in modelling when it comes to the yields of rice worldwide.

Thus, taking global mean temperature as the independent (X) and world rice yield as the dependent variable (Y), the effects of global warming on average and top yields of world rice from 1961 to 2020 are, respectively, regression-modeled with constants and shown in Formulas (2) and (3).

$$Y = -52887.984 - 5.736X^3 \tag{2}$$

In Formula (2), R squared = 0.819 and F = 129.355 at a great significance level.

As shown in Formula (2), global warming exerts a negative impact on average yield of world rice from 1961 to 2020 with a Cubic function better simulated, having one of the two highest R squared values than 0.814 of Linear, 0.816 of Logarithmic, 0.817 of Inverse, 0.762 of Compound, 0.766 of Power, 0.769 of S, 0.762 of Growth, 0.762 of Exponential and 0.762 of Logistic, and higher F value than Quadratic (F = 129.125) sharing R squared.

$$Y = -152274.561 + 1580.727X - 22.257X^3 \tag{3}$$

In Formula (3), R squared = 0.675 and F = 59.320 at a great significance level.

As shown in Formula (3), global warming also exerts a negative impact on the top yield of world rice from 1961 to 2020 with a Cubic function better simulated, having one of the two highest R squared values than Linear with 0.637, Logarithmic with 0.642, Inverse with 0.647, Compound with 0.627, Power with 0.633, S with 0.638, Growth with 0.627, Exponential with 0.627 and Logistic with 0.627, and a higher F value than 59.125 of Quadratic with same R squared.

According to different values of b3 coefficients in in Formulas (2) and (3), the average yield of world rice from 1961 to 2020 was negatively affected by global warming less than the top, which partly drives the gap between these two yields and was gradually shrunk in the past.

To see further global warming effects on the yields of world rice in 1961 to 2020 and to 2030, the ARIMA(p,d,q) model is similarly applied for projecting global mean temperatures in the future. Concretely, the ARIMA(1,0,2) model is established using a stationary logarithmic series of annual global mean temperature and the ARMA(1,2) basic model with the lowest RMSE of 0.176178 between fitted values and actual temperatures from 1961 to 2019 among the five kinds, as shown in Table 7.

Table 7. Equations of five basic models for fitting global mean temperature from 1961 to 2019.

Model	Equation
ARMA(1,2)	$\text{lngmt}_t = 0.002127 + 1.768495\text{lngmt}_{t-1} - 0.768495\text{lngmt}_{t-2} + \varepsilon_t - 1.875406\varepsilon_{t-1} + 0.881251\varepsilon_{t-2}$
ARMA(1,1)	$\text{lngmt}_t = 0.001942 + 1.033052\text{lngmt}_{t-1} - 0.033052\text{lngmt}_{t-2} + \varepsilon_t - 0.960579\varepsilon_{t-1}$
AR(1)	$\text{lngmt}_t = 0.001572 + 0.480270\text{lngmt}_{t-1} + 0.519730\text{lngmt}_{t-2} + \varepsilon_t$
MA(2)	$\text{lngmt}_t = 0.001900 + \varepsilon_t - 0.891965\varepsilon_{t-1} - 0.064221\varepsilon_{t-2}$
MA(1)	$\text{lngmt}_t = 0.001891 + \varepsilon_t - 0.955289\varepsilon_{t-1}$

Note: '*gmt*' stands for 'average yield of world rice'.

The stationary ARIMA(1,0,2) model with an inverted AR Root of 0.77 and inverted MA Roots of 0.94 + $\sqrt{0.04}$ is used for projecting annual global mean temperature resulting from 15.18 °C in 2021 to 15.48 °C in 2030.

Meanwhile, the variation trend of global mean temperature from 1961 2019 is shown in Table 8.

Table 8. Equations of variation trends for global mean temperature from 1961 to 2019.

Trend	Equation	R Squared
Exponent	$y = 13.505e^{0.0018x}$	0.8343
Linear	$y = 0.0264x + 13.489$	0.8349
logarithm	$y = 0.40761\ln(x) + 13.005$	0.5482
Polynomial	$y = 0.0003x^2 + 0.0081x + 13.675$	0.8608
Power	$y = 13.054x^{0.0285}$	0.5506

Note: x stands for the year (ordinal number) and y for global mean temperature.

As shown in Figure 1 and Table 8, global mean temperature from 1961 to 2019 rises in a polynomial trend with the highest R squared among the five trend-regressed models. In addition, the RMSE of the TR model for fitting global mean temperature from 1961 to 2019 is 0.033064, which is lower than that of the ARIMA(1,0,2) model. Therefore, the TR model is used for projecting global mean temperature between 2020 and 2030 and resulted in 15.24 °C in 2020, 15.29 °C in 2021, 15.33 °C in 2022, 15.38 °C in 2023, 15.42 °C in 2024, 15.47 °C in 2025, 15.52 °C in 2026, 15.56 °C in 2027, 15.61 °C in 2028, 15.66 °C in 2029and 15.71 °C in 2030, which is adopted as the estimated result of the ARIMA-TR model. Moreover, actual global mean temperature in 2020 is 15.42 °C, being only 1.18% higher than that projected, which indicates a good validation of the projection.

Similarly, different regression models are used for simulating the dependence of world rice yields on annual global mean temperature from 1961 to 2030, which reveals that the average yield of world rice negatively goes with global warming in a Cubic function (Formula (4)), and so does the top (Formula (5)).

$$Y = -51344.450 + 4947.778X - 5.460X^3 \tag{4}$$

In Formula (4), R squared = 0.879 while F = 244.272 at 0.1% level.

$$Y = -176499.617 + 18397.428X - 26.565X^3 \tag{5}$$

In Formula (5), R squared = 0.688 and F = 73.839 at 0.1% level.

As shown in Formulas (4) and (5), global warming exerts a negative impact on the average yield of world rice less than the top from 1961 to 2030, which indicates that the gap between these two kinds of yield will be further narrowed in ensuing decades in accordance with different values of b3 coefficients in the Cubic equations. This result is consistent with the scenario from 1961 to 2020 in terms of the trend that narrows the gap between average and top yields of world rice, in which the difference between 1961–2020 and 1961–2030 is from the variation of three variables with more fluctuation during the former period than that during the latter one.

4. Discussion

Crop models are efficient tools for assisting research and development efforts towards achieving maximum production potential especially in developing countries as it predicts the phenology and yield of crops, taking into consideration the factors affecting growth and development [22]. Furthermore, crop models are usually developed using a test set of data and simulations representing some combination of factors including environment, soil, management and genotype [23]. Rather than most existing studies that estimate the yield of rice using models based on the principle of production function, in which various contributors are respectively taken into account, this research estimates the yields of world rice creatively using the ARIMA-TR model based on the theory of (stationary) stochastic process in which the contribution of all influential factors is integrated into certain variation trends over time. The advantage of a time series model over the others lies in its simplification and integration of complicated linkages working in the growth of crop to yield, being particularly applicable to macroscopic and dynamic scenarios in which the variable varies on a large scale and in the long term, similar to the variation of world rice yield over time. This time series approach follows mega data law: the wider as well as longer the coverage is, the more precise the estimation will be. In addition, the TR model performs better than the ARIMA model generally but not absolutely. For example: the area-weighted average YP of rice in NEC estimated by the ORYZA-V3 crop model was 11,600 kg/ha attainable [14], which is 11.47% higher than top yield of world rice in 2030 estimated using the ARIMA-TR model. Yılmaz et al. compared ARIMA methodology and harmonic regression to forecast monthly average temperatures and monthly average precipitation in Turkey, and found that harmonic regression performs better than the classical methodology in both time series [24]. On the contrary, those models based on the theory of production function are more applicable to microscopic and static scenarios, in which the smaller the coverage is, the more precise the estimation will be. These two categories of methodology do not contradict but complement each other.

As for the effects of global warming on rice yielding, there exists either a positive or negative story in different regions in the world, which mainly depends on climatic condition of specific variety grown. However, this research does not explore the effect of global warming on any concrete variety grown in specific conditions but generic rice planted in all seasons worldwide.

Theoretically, the long-term variation of any crop yield over time shows some tendency of an S-shaped curve, where it is positively accelerated before the middle turn-point and negatively afterwards towards final limitation [25]. Therefore, to optimize the global production of crop, priority should be given to these as follows: to the crop in high-yield countries with good conditions and high efficiency when average yield is still in low part before the turn-point of S-shaped curve, and to the crop in low-yield countries with poor conditions and high input for output when average yield is in a high place after the turn-point of an S-shaped curve, and to the crop in both high and low yield countries with moderate conditions and integrated efficiency when the average yield is in main body of an S-shaped curve, respectively.

5. Conclusions

From our study, it is concluded that in the ensuing decades, the average yield of world rice will be estimated using the ARIMA-TR model, resulting in an increase by 7.45% and the top yield by 1.40%, or the average will be increasingly 'chasing after' the top; for world rice, the priority to improving global production should be given to both high and low yield countries as the average yield is approaching half of the top- the turn-point of *S*-shaped curve in the long-term trend of biological evolution. Since 1961, global warming has been exerting a negative effect on the average yield of world rice less than on the top one, which partly drives the former to rise faster than the latter and then the gap between these two yields gradually shrinks. This insight provides the academic circle with an innovative comprehension of rice yielding in the world and could direct crop production worldwide when considering global warming for global food security in the future.

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