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Yield potential of world wheat based on ARIMA model under global warming

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ABSTRACT

As the most important food crop across the world, with continuous increase in world population and steady declining farmlands, wheat has been attracting academic attention for improving its yield or potential in the future particularly under global warming. Therefore, analyzing the yield or potential of wheat at global level relevant to greenhouse gas effect is of great significance to direct future production of wheat in the world. However up to now, there are relatively few reports on potential yield of world wheat projected using 'time series' approach like ARIMA (Auto-regressive Integrated Moving Average) model. Thus in this paper, the crop potential yield of world wheat during 2019 to 2028 is projected using ARIMA model based on the yields from 1961 to 2018. Our results show that during 2019 to 2028, the average yields of world wheat are projected to increase from 3569 to 4257 kg ha^{-1} while top yields of world wheat from 9852 to 11246 kg ha^{-1}. Annual global mean temperatures are projected to increase from 15.05 to 15.31°C. Global warming exerts positive effect on average yield of world wheat while negative effect on the top yield in 1961 to 2018 and 2028. Our study concluded that for world wheat production in 2019 to 2028, the opportunities for improving production should be mainly dependent on the advantage of high-yield countries as the yield is still in low place before the turn-point of *S*-shaped curve in long-term trend affected partly by greenhouse gas effect.

Key words: World wheat; yield potential; ARIMA model; global warming.

As the most important food crop across the world, with continuous increase in world population and steady declining farmlands, wheat has been attracting academic attention for improving its yield or potential in the future particularly under global warming. Recent studies to determine the wheat yield and its potential through modelling have provided a number of important incites e.g. The accuracy and efficiency of optimization algorithms was done by comparing the POWELL and SCE-UA method to predict the regional winter wheat yield, the comparison shows that POWELL algorithm performs better than SCE-UA due to the high assimilation accuracy and much higher running efficiency (Tian *et al.,* 2013). The CERES-Wheat model which was used for estimating the regional production of wheat in Bihar of India, revealed the percentage deviation of +/- 4.0% of forecasted yield from the actual (Singh *et al.,* 2017). The impact of climate change on wheat yield in Myandoab of Iran was simulated by using SWAP, which showed that negative impact of temperature increase has dominated the positive impact of CO_2 concentration, hence decline in yield (Azad *et al.,* 2018). A linear mixed-effect model was presented to predict wheat yield in the northern grain-growing region of Australia, demonstrating moderate predictive accuracy at a field scale, with an average root mean square error (RMSE) of 0.79 Mg ha (Lai *et al.,* 2018). The DSSAT model, integrated with calibrated Hargreaves ET model and dynamic crop coefficient, was run with the generated weather data to predict the potential yield and crop water requirement of winter wheat in the Huang-Huai-Hai Plain in China; the models suggested that the spatial distribution of potential yield in the future was characterized by an increasing trend from the northwest inland to the southeast coast (Tang *et al.,* 2018). The APSIM model was parameterised for local soils and climate, furthermore calibrated for rice and wheat growth, phenology and yields in Pakistan by using experimental data sets; the study showed that farmers have currently achieved only 48% - 56% potential of wheat in Narowal and Gujranwala, respectively (Khaliq *et al.,* 2019). An improved Carnegie-Ames-Stanford approach (CASA) model was coupled with time-series satellite remote sensing images to estimate winter wheat yield in China, which presented that the estimated yield of winter wheat based on remote sensing images is consistent with the ground-measured yield, with R^2 of 0.56, RMSE of 1.22 t ha^{-1}, and an average relative error of -6.01% (Wang *et al.,* 2019). The impacts of climate change on wheat yield in the Huang-Huai-Hai Plain of China by 2099 was simulated by using DSSAT-CERES-Wheat model, which demonstrated that the effects of increasing thermal resources were counteracted by the aggravated water deficits caused by the increase in temperature (Qu *et al.,* 2019). Possible impacts of three climate variables on spring wheat yield in North Dakota of USA was assessed by building a regression model, which showed that the percentage deviation of error for the model is approximately +/- 30% in most of the years (Mistry and Bora, 2019). The impact of weather factors on the achieved wheat yields was analyzed by using a set of panel data on selected Serbian municipalities in 2000 to 2013, which displayed that the growth of water deficit by 0.1 mm in the period November 15 to April 1 resulted in 175 kg ha^{-1} lower yields while in the period April 1 to May 15 did in 45 kg ha^{-1} lower yields (Jelocnik *et al.,* 2019). The derived phenological metrics for vegetation indices (VIs) and surface reflectance's (SRs), namely peak, area under curve (AUC), and fitting coefficients from a quadratic function, were used for building empirical regression winter wheat models at a regional scale in Ukraine for three years (2016-2018), yielding a RMSE of 0.201 t ha^{-1} (5.4%) and coefficient of determination R^2 of 0.73 on cross-validation (Skakun *et al.,* 2019). Feng *et al.* (2019) developed a hybrid model by incorporating the APSIM model outputs and growth stage-specific ECEs indicators (i.e. frost, drought and heat stress) into the Random Forest (RF) model using multiple linear regression (MLR) model as a benchmark, and suggested that the APSIM + RF hybrid model could explain 81% of the observed yield variations in the New South Wales wheat belt of south-eastern Australia. The APSIM + RF hybrid model had a 33% improvement in modelling accuracy compared to the APSIM model alone and 19% improvement compared to the APSIM + MLR hybrid model. Zhang *et al.* (2019) investigated the applicability of the Simple Algorithm for Yield Estimate (SAFY) model for estimating winter wheat dry shoot biomass and grain yield in Guanzhong Plain of China, using two growing seasons field data from different irrigation scenarios, and pointed out that the leaf area index (LAI) could be reasonably well simulated, with a minimum RMSE of 0.11. DSSAT (decision support system for agro-technology transfer) was validated for predicting growth and yield of wheat in Iran under a diverse semi-arid climate (2 years with diverse climates) and different irrigation strategies, planting methods, and nitrogen rates, which indicated that water stress and inappropriate weather especially during the stem elongation influences the grain yield remarkably without noticeable effect on straw yield (Mehrabi *et al.,* 2019). A field study was conducted to estimate the regional wheat yield in Pakistan by integrating remotely sensed soil moisture index into CERES-Wheat model, reaching a good agreement between observed and simulated values of grain yield (RMSE = 284.8 kg ha^{-1}), which showed estimated mean yield of 2979 kg ha^{-1} being 5.2% higher than the yield reported by Crop Reporting Service in Punjab (Fahad *et al.,* 2019). A light use efficiency model (EC-LUE) was used for estimating winter wheat yield in Kansas of USA with 30-m spatial resolution Landsat data, which indicated that the EC-LUE model combined with wheat variety data can effectively capture the spatial variations of winter wheat yields, and specifically proposed method significantly improves model simulation performance for the inter-annual variation of yields during 2008-2017 and explains 82% of the inter-annual yield variation (Dong *et al.,* 2020); and so on.

As discussed above, there are rich research reports on the crop yield or potential of wheat being modeled and partly related to climatic factor, but most are based on the theory of production function for wheat yield, of specific variety, from static biological dimension and at local or regional level, while few are based on (stationary) stochastic process for generic wheat from dynamic evolutionary dimension and at global level. Thus in this paper, we use 'time series' approach ARIMA (Auto-regressive Integrated Moving Average) model based on stationary stochastic process integrating global warming effect to estimate yield or potential of world wheat in the future basing the projections on historic performance, and aim to provide information on directing the production of wheat in the world facing global food insecurity deteriorated by the contradiction between the increase of human demand and the decrease of arable land.

MATERIALS AND METHODS

Datasets

Annual global mean temperature (°C), historic or statistical data of average and top yields (at national level) of world wheat from 1961 to 2018 is used for projecting and analyzing their futures under global warming.

As shown in Table 1, from 1961 to 2018: average

Table 1: Global mean temperature (°C), average and top yields of world wheat (kg ha^{-1}) from 1961 to 2018

Year	Global temp.	Average yield	Top yield	Country of top yield	Year	Global temp.	Average yield	Top yield	Country of top yield
1961	14.00	1089	4121	Denmark	1990	14.39	2563	8531	Ireland
1962	13.82	1206	4548	Netherlands	1991	14.24	2444	7865	Ireland
1963	13.93	1132	4196	Netherlands	1992	13.98	2540	8015	Netherlands
1964	13.52	1241	4706	Netherlands	1993	14.11	2544	8771	Netherlands
1965	13.55	1215	4457	Denmark	1994	14.26	2448	8067	Netherlands
1966	13.98	1408	4275	Denmark	1995	14.61	2515	8619	Netherlands
1967	13.65	1339	4791	Netherlands	1996	14.12	2577	8997	Ireland
1968	13.67	1453	4814	Denmark	1997	14.46	2702	7934	Belgium
1969	13.66	1417	4395	Ireland	1998	14.79	2706	8252	Luxembourg
1970	13.92	1494	4546	Netherlands	1999	14.59	2751	8767	Ireland
1971	13.67	1625	4969	Netherlands	2000	14.52	2722	9454	Ireland
1972	13.57	1605	4570	France	2001	14.61	2742	9060	Ireland
1973	14.02	1684	5255	Netherlands	2002	14.78	2755	8444	Ireland
1974	13.57	1616	5733	Netherlands	2003	14.61	2652	8744	Netherlands
1975	13.85	1570	5102	Denmark	2004	14.70	2943	9924	Ireland
1976	13.44	1791	5437	Netherlands	2005	14.81	2829	8593	Netherlands
1977	14.02	1672	5230	Netherlands	2006	14.72	2891	9154	Ireland
1978	13.77	1933	6567	Netherlands	2007	14.93	2815	8497	New Zealand
1979	13.98	1852	5938	Netherlands	2008	14.66	3062	9939	Zambia
1980	14.08	1855	6202	Netherlands	2009	14.69	3037	9465	Belgium
1981	14.23	1880	6701	Netherlands	2010	14.92	2971	8909	Netherlands
1982	13.86	1999	7390	Netherlands	2011	14.64	3164	9864	Ireland
1983	14.25	2126	7037	Netherlands	2012	14.78	3089	8925	New Zealand
1984	13.90	2220	7885	Netherlands	2013	14.72	3250	9105	New Zealand
1985	13.73	2172	6645	Netherlands	2014	14.80	3315	10014	Ireland
1986	14.01	2321	7998	Netherlands	2015	15.10	3317	10668	Ireland
1987	14.17	2290	7065	Ireland	2016	15.34	3405	9539	Ireland
1988	14.31	2293	7765	Ireland	2017	15.14	3541	10172	Ireland
1989	14.16	2373	7598	Netherlands	2018	14.96	3425	8960	New Zealand

Source: https://www.ncdc.noaa.gov/temp-and-precip/; http://www.fao.org/faostat/en/#data.

yields of world wheat rose more steadily than the top yields, annual global mean temperature increased in a slight fluctuation. 'Average yield' means average yield of world wheat worldwide while 'top yield' indicates top yield of specific country whose yield of wheat countrywide topped in the world in given year. For example, Danish yield of wheat countrywide topped in the world in 1961, so did New Zealand one in 2018, and so on.

ARIMA modelling

ARIMA model is a valuable approach used for projecting the futures of 'time series' variable, in which it is assumed that if a stochastic process has some numbers of unit root it can be converted to a stationary process of auto-regressive moving average after same times of differencing required for producing the stationarity of series. A simplified representation of the model is ARIMA (p,d,q), where p is the

Table 2: The equations of five basic models for fitting average yields of world wheat from 2009 to 2018

Model	Equation
ARMA (1,2)	$\ln ave_t = 0.019623 + 0.076314 \ln ave_{t-1} + 0.923686 \ln ave_{t-2} + \varepsilon_t + 0.469445\varepsilon_{t-1} - 0.483982\varepsilon_{t-2}$
ARMA (1,1)	$\ln ave_t = 0.019579 + 0.401460 \ln ave_{t-1} + 0.598540 \ln ave_{t-2} + \varepsilon_t - 0.042043\varepsilon_{t-1}$
AR (1)	$\ln ave_t = 0.019566 + 0.378403 \ln ave_{t-1} + 0.621597 \ln ave_{t-2} + \varepsilon_t$
MA (2)	$\ln ave_t = 0.019912 + \varepsilon_t - 0.683780\varepsilon_{t-1} + 0.202810\varepsilon_{t-2}$
MA (1)	$\ln ave_t = 0.019767 + \varepsilon_t - 0.562984\varepsilon_{t-1}$

Note: in the equations, 'ave' stands for 'average yield of world wheat'.

Table 3: The error between fitted values and actual average yields of world wheat from 2009 to 2018 (%)

Year	ARMA (1,2)	ARMA (1,1)	AR (1)	MA (2)	MA (1)
2009	-3.97	-3.35	-3.48	-5.23	-5.56
2010	+0.26	+0.73	+0.59	-1.19	-1.56
2011	-4.15	-3.55	-3.68	-5.35	-5.70
2012	+0.26	+0.74	+0.61	-1.10	-1.49
2013	-2.93	-2.35	-2.50	-4.10	-4.50
2014	-2.84	-2.36	-2.51	-4.08	-4.50
2015	-1.10	-0.49	-0.65	-2.24	-2.66
2016	-1.62	-1.15	-1.29	-2.82	-3.26
2017	-3.61	-3.08	-3.22	-4.69	-5.14
2018	+1.69	+2.19	+2.04	+0.53	+0.03
Mean	-1.80	-1.27	-1.41	-3.03	-3.43

Note: the error = 100%*(fitted value-actual average yield)/actual average yield.

number of auto regression parameters, *d* is the order of differencing required to produce stationarity, and *q* is the number of moving average parameters (Jensen, 1990). Both autoregressive and moving average models requires stationary data: mean and variance of the time series are constant over time. The constant mean assumption implies no cycles or trends in the data, and the constant variance assumption is similar to the homogeneity-of-variance assumption of linear regression. The order of differencing refers to the number of times each previous observation is subtracted from each successive observation until no systematic decrease or increase in the level of the series remains as it drifts. The noise in a time series drifts up and down across time. A complete representation of ARIMA model is mathematically written as formula (1):

$$\left[1-\sum_{i=1}^{p}\phi_i L^i\right](1-L)^d X_t = \left[1+\sum_{i=1}^{q}\theta_i L^i\right]\varepsilon_t \qquad (1)$$

In formula (1), besides *p*, *d* and *q* above explained, *t* refers to the time unit while *L* to the lag operator, $\phi(L)$ to stationary auto-regression operator, $\theta(L)$ to reversible moving average operator, and $d \in z$ to target variable.

The autoregressive model represents a process in which the observation at time *t* is a function of the previous observation *t-1*, while a Moving Average model represents a process in which an observation is a function of the previous random shock.

It is assumed that historic yields of world wheat be a 'time series' variable as it generally rises over time due to continuous improvement of inputs to its production through scientific and technical means. In other words, the rise of world wheat yield in a long run is of a stochastic process that hints some inevitable trend behind a large number of casual events. That is to say, potential yield of world wheat can be estimated (even only) by 'time series' approach instead of any model based on production function due to its too complicated influential factors. So ARIMA model can be used for projecting the yields of world wheat in 2019 to 2028 based on the yields from 1961 to 2018 in principle limiting the number of samples projected less than 15% of total samples. The more the samples are projected, the less reliable the projection will be; the wider the coverage is, the more accurate the projection will be. In application, the

Table 4: The regression result of ARIMA (1,1,1) model for average yields of world wheat in 2019 to 2028

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	0.019579	0.003306	5.923148	0.0000
AR(1)	-0.598540	0.164890	-3.629926	0.0006
MA(1)	-0.042043	0.211417	-0.198864	0.8431
R-squared	0.396882	Mean dependent var	0.018639	
Adjusted R-squared	0.374122	S.D. dependent var	0.052112	
S.E. of regression	0.041227	Akaike info criterion	-3.487375	
Sum squared resid	0.090081	Schwarz criterion	-3.378874	
Log likelihood	100.6465	Hannan-Quinn criter.	-3.445310	
F-statistic	17.43830	Durbin-Watson stat	1.961834	
Prob(F-statistic)	0.000002			
Inverted AR Roots	-0.60			
Inverted MA Roots	0.04			

Table 5: The equations of five basic models for fitting top yields of world wheat from 2009 to 2018

Model	Equation
ARMA (1,2)	$\ln top_t = 0.017079 + 1.801354 \ln top_{t-1} - 0.801354 \ln top_{t-2} + \varepsilon_t - 1.775870\varepsilon_{t-1} + 0.913188\varepsilon_{t-2}$
ARMA (1,1)	$\ln top_t = 0.014675 + 0.690251 \ln top_{t-1} + 0.309749 \ln top_{t-2} + \varepsilon_t - 0.540504\varepsilon_{t-1}$
AR (1)	$\ln top_t = 0.014105 + 0.411273 \ln top_{t-1} + 0.588727 \ln top_{t-2} + \varepsilon_t$
MA (2)	$\ln top_t = 0.014427 + \varepsilon_t - 0.967721\varepsilon_{t-1} + 0.338629\varepsilon_{t-2}$
MA (1)	$\ln top_t = 0.014740 + \varepsilon_t - 0.671608\varepsilon_{t-1}$

Note: in the equations, ‘top’ stands for ‘top yield of world wheat’.

projection of world wheat yields is undertaken following these steps: firstly, to produce logarithmic values of world wheat yields from 1961 to 2018 to eliminate heteroscedasticity, to test the stationarity of ‘time series’ and establish ‘stationary series’ through differencing if not stationary; secondly, to establish such five basic models as ARMA(1,2), ARMA(1,1), AR(1), MA(2) and MA(1) to fit world wheat yields from 2008 to 2017 in principle equating the number of fitted samples to that of projection, and compare fitted values with actual yields to evaluate the fitness; finally, to validate and select optimum basic model used for ARIMA (p,d,q) modelling to project world wheat yields in 2019 to 2028.

RESULTS AND DISCUSSION

To Project average yields of world wheat in 2019 to 2028

Average yields of world wheat in 2019 to 2028 is projected using ARIMA model based on the yields from 1961 to 2018.

Through testing it is shown that logarithmic series of average yields of world wheat from 1961 to 2018 is not stationary (t-statistic value is -1.837562 but ADF unit root test critical value at 1% level is -4.130526) while it becomes stationary after being once differenced (t-statistic value is -15.54040 and ADF unit root test critical value at 1% level is -3.552666). Thus, five basic models used for fitting average yields of world wheat from 2009 to 2018 are established on the basis of once differenced series of the yields’ logarithmic values. Their equations and fitness are shown in Table 2 and Table 3, respectively.

As shown in Table 3, ARMA(1,1) basic model is used for ARIMA (1,1,1) modelling to project average yields of world wheat in 2019 to 2028 because its fitness with mean error (ME) of -1.80% is the best among five kinds.

ARIMA modelling to project average yields of world wheat in 2019 to 2028

The regression result of ARIMA (1,1,1) model is shown in Table 4. Absolute values of both inverted AR root (-0.60) and inverted MA root (0.04) are all below 1.00, which shows the ARIMA (1,1,1) model is stationary. Therefore,

Table 6: The error between fitted values and actual top yields of world wheat from 2009 to 2018 (%)

Year	ARMA (1,2)	ARMA (1,1)	AR (1)	MA (2)	MA (1)
2009	-12.01	-10.20	-12.15	-8.00	-6.63
2010	-4.91	-3.18	-5.35	-0.84	+0.67
2011	-12.63	-11.26	-13.29	-9.14	-7.73
2012	-1.78	-0.47	-2.81	+1.89	+3.50
2013	-2.07	-1.00	-3.37	+1.31	+2.95
2014	-9.42	-8.66	-10.89	-6.54	-5.00
2015	-13.51	-12.99	-15.17	-10.99	-9.49
2016	-1.60	-1.25	-3.78	+0.99	+2.72
2017	-6.14	-6.03	-8.49	-3.92	-2.25
2018	+8.39	+8.26	+5.37	+10.66	+12.62
Mean	-5.57	-4.68	-6.99	-2.46	-0.86

Note: the error = 100%*(fitted value-actual top yield)/actual top yield.

Table 7: The regression result of ARIMA (0,1,1) model for top yields of world wheat in 2019 to 2028

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	0.014740	0.003448	4.275444	0.0001
MA(1)	-0.671608	0.104856	-6.405074	0.0000
R-squared	0.395847	Mean dependent var	0.012109	
Adjusted R-squared	0.384659	S.D. dependent var	0.095615	
S.E. of regression	0.075004	Akaike info criterion	-2.307493	
Sum squared resid	0.303781	Schwarz criterion	-2.235159	
Log likelihood	66.60980	Hannan-Quinn criter.	-2.279449	
F-statistic	35.38133	Durbin-Watson stat	2.246638	
Prob(F-statistic)	0.000000	/		
Inverted MA Roots	0.67	/		

average yields of world wheat in 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 2027 and 2028, are projected using the ARIMA(1,1,1) model and resulted with 3569, 3640, 3712, 3785, 3860, 3936, 4014, 4094, 4175 and 4257 kg ha^{-1}, respectively.

To project top yields of world wheat in 2019 to 2028

Though wheat in different countries has its own climatic condition differing from the others, but those that enjoyed top yields of world wheat in some given years, represent various casual events behind which an inevitable law limits average yield meeting the top. In this case, the variation of top yields of world wheat in long term is deemed as stochastic process. This study does not aim to reveal the effect of climatic factors on the growth of wheat in any specific country owning top yield in the world, but to explore general trend of top yields of wheat on global scale. Thus similarly, top yields of world wheat in 2019 to 2028 can be projected using ARIMA model based on the yields from 1961 to 2018.

To establish and test basic models used for fitting top yields of world wheat from 2009 to 2018

Through testing it is shown that logarithmic series of top yields of world wheat from 1961 to 2018 is not stationary (t-statistic value is -0.465786 but ADF unit root test critical value at 1% level is -4.140858) while it becomes stationary after being once differenced (t-statistic value is -14.06732 and ADF unit root test critical value at 1% level is -3.555023). Thus, five basic models used for fitting top yields of world wheat from 2009 to 2018 are established on the basis of once differenced series of the yields' logarithmic values, whose equations and fitness are respectively shown in Table 5 and Table 6.

Table 8: Model Summary and Parameters of global warming effect on the average yield from 1961 to 2018

Equation		Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.793	214.986	1	56	0.000	-15802.517	1269.394		
Logarithmic	0.793	214.454	1	56	0.000	-45903.582	18142.430		
Inverse	0.792	213.275	1	56	0.000	20478.934	-258956.435		
Quadratic	0.793	105.583	2	55	0.000	-13410.136	934.611	11.699	
Cubic	0.793	105.583	2	55	0.000	-13410.136	934.611	11.699	0.000
Compound	0.724	147.185	1	56	0.000	0.603	1.777		
Power	0.726	148.327	1	56	0.000	7.043E-7	8.227		
S	0.727	149.126	1	56	0.000	15.946	-117.577		
Growth	0.724	147.185	1	56	0.000	-0.506	0.575		
Exponential	0.724	147.185	1	56	0.000	0.603	0.575		
Logistic	0.724	147.185	1	56	0.000	1.659	0.563		

Table 9: Model Summary and Parameters of global warming effect on the top yield from 1961 to 2018

Equation		Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.712	138.233	1	56	0.000	-41322.602	3413.511		
Logarithmic	0.714	140.040	1	56	0.000	-122541.947	48890.046		
Inverse	0.717	141.550	1	56	0.000	56447.880	-699298.853		
Quadratic	0.723	71.791	2	55	0.000	-229529.489	29750.673	-920.353	
Cubic	0.723	71.909	2	55	0.000	-168294.561	16742.218	0.000	-21.686
Compound	0.669	113.238	1	56	0.000	6.453	1.634		
Power	0.673	115.080	1	56	0.000	5.383E-5	7.036		
S	0.676	116.724	1	56	0.000	15.935	-100.719		
Growth	0.669	113.238	1	56	0.000	1.865	0.491		
Exponential	0.669	113.238	1	56	0.000	6.453	0.491		
Logistic	0.669	113.238	1	56	0.000	0.155	0.612		

As shown in Table 6, the ARIMA (0,1,1) model used for projecting top yields of world wheat in 2019 to 2028, is established on the basis of MA(1) basic model because of its best fitness with ME of -4.68% among five kinds. Noticeably, the top yields is not as well fitted as the average yields from 2009 to 2018 according to their ME because it fluctuated more than the average.

ARIMA modelling used for projecting top yields of world wheat in 2019 to 2028

The regression result of ARIMA (0,1,1) model is shown in Table 7.

As shown in Table 7, absolute value of inverted MA root (0.67) are below 1.00, which shows the ARIMA (0,1,1) model is stationary. Thus, the top yields of world wheat in 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 2027 and 2028, projected using the ARIMA(0,1,1) model, are to be 9852, 9998, 10146, 10297, 10449, 10604, 10761, 10920, 11082 and 11246 kg ha^{-1}, respectively.

The effects of global warming on the yields of world wheat

It is worldwide acknowledged that annual global mean temperature has been rising over time since industrial evolutionary. As above-analyzed, both average and top yields of world wheat rise over time in general. Theoretically, there must exist certain inherent relationship between annual

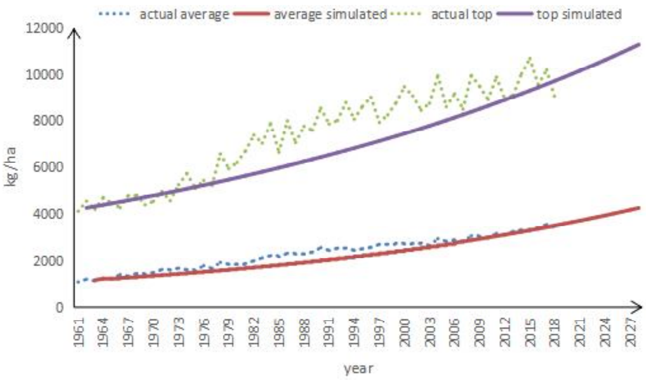

Fig. 1: Average and top yields of world wheat in 1961 to 2028

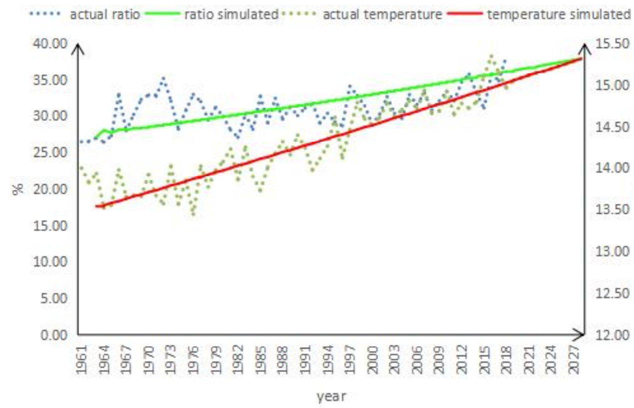

Fig. 2: The ratio (%) of average to top of yield and annual global mean temperature (°C) in 1961 to 2028

Note: ratio simulated = 100*average yield simulated/ top yield simulated.

global mean temperature and the yields of world wheat because temperature is one of essential factors for wheat growth and yield. Though all climatic factors such as sunlight, temperature, precipitation and gases have their respective influences on the growth and yield of world wheat, but only the variation (rise) of annual global mean temperature is observed. Therefore, the contribution of sunlight, precipitation and gases each year at global level can be considered as constant (in modelling), to the yield of world wheat including both spring and winter varieties worldwide.

In empirical analyses: it is causality-tested that there exist Granger causalities between annual global mean temperature and average yield (with P of 0.0093 and F-Statistic of 6.18295) and top yield (with P of 0.0499 and F-Statistic of 3.30424) of world wheat from 1961 to 2018; and it is co-integration-tested that there are long-run equilibrium relationships between annual global mean temperature and average yield (P = 0.0000 while t-Statistic = 76.09989) and top yield (P = 0.0434 while t-Statistic = 2.068827) of world wheat from 1961 to 2018. Thus, taking annual global mean temperature as independent while world wheat yield as dependent, the effect of global warming on the yields from 1961 to 2018 is respectively regression-modeled with constant and shown as in Table 8 and Table 9.

As shown in Table 8, the effect of global warming on average yield of world wheat from 1961 to 2018 is positive with coefficient b1 of 18142.430 and linear function best simulated citing the highest R squared of 0.793 and F of 214.986.

As shown in Table 9, the effect of global warming on top yield of world wheat from 1961 to 2018 is negative with cubic function (coefficient b3 = -21.686) showing one of two highest R squared values (0.723) among 11 kinds and higher F of 71.909 than the other (71.791).

To see further global warming effects on the yields of world wheat in 1961 to 2028, ARIMA (1,0,1) model is established with stationary logarithmic series of annual global mean temperature (t-statistic value = -6.996297 while ADF unit root test critical value at 1% level = -4.127338) and ARMA (1,1) basic model with the lowest ME of -0.08% between fitted values and actual temperatures from 2009 to 2018 among five kinds. The ARIMA (1,0,1) model is used for projecting annual global mean temperature resulted with 15.05, 15.08, 15.11, 15.14, 15.16, 15.19, 15.22, 15.25, 15.28 and 15.31°C in 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 2027 and 2028, respectively. Then different regression models are used for simulating the dependence of world wheat yields on annual global mean temperature, which reveals that global warming exerts positive effect on average yield of world wheat with a quadratic function (coefficient b2 = 314.531 as R^2 = 0.873) while negative effect on the top yield with cubic function (coefficient of b3 = -11.733 as R^2 = 0.798). The result is consistent with the scenario from 1961 to 2018 in terms of the trend.

The ratio of average to top of world wheat yields and annual global mean temperature in 1961 to 2028

As previous-discussed, the 'top yield' is considered potential limit of the 'average yield' because the latter will chase after but never meet the former. Just as projected in this research, average yields of world wheat in 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 2027 and 2028 are 36.23%, 36.41%, 36.59%, 36.76%, 36.94%, 37.1%, 37.30%, 37.49%, 37.67% and 37.85% of the top ones, respectively. As shown in Fig.1, top yield of world wheat fluctuated more than the average in rise from 1961 to 2018, average yield simulated rises almost in linear trend while the top simulated does in smooth curve one in 1961 to 2028.

As shown in Fig. 2, actual ratio of average to top of world wheat yields from 1961 to 2018 rose in fluctuation ranging from 38.23% (in 2018) to 26.37% (in 1964) while the ratio simulated in 1961 to 2028 almost rises in linear trend; annual global mean temperature from 1961 to 2018 fluctuated in slight rise while the temperature simulated in 1961 to 2028 almost rises in linear trend. In the future, the average yield will increasingly approach the top partly due to positive effect on the average while negative effect on the top, of global warming.

From the years, researchers have been working hard for seeking quality yield of food crop especially staple one like wheat. Through different techniques like variety cultivation and genetic engineering techniques, the yield of wheat can be improved. Genetic engineering is regarded as the most effective way for improving the yield potential of wheat. Improving seeds through breeding and advanced cultivation should be simultaneously used to maximize wheat yields. However, no matter what seed improving approaches (for example cloning) or cultivation technology (for example controllable temperature) are used, there is evidence that any given crop’s yield is limited due to the solar radiation limit. Unfortunately, ‘low yield’ and ‘high quality’ is often ‘bundle-sold’, which represents an indissoluble link e.g. when attempting to maximize wheat production means accepting an inevitable decrease in its quality. It is undeniable that under special conditions, wheat top yields can be maximized, however this will not be sustained for a long period of time. Thus in a long run, any crop’s yield over time theoretically shows a trend of logistic curve (i.e. *S*-shaped curve), where the crop’s yield is positively accelerated before the turn-point, while negatively accelerated after that until the acceleration stopped eventually. For the crop whose current average yield is in low place before the turn-point of such *S*-shaped curve, the opportunities for improving global production should be mainly dependent on raising the crop yield potential in high-yield countries with high efficiency; for those in high place after the turn-point of such *S*-shaped curve, the opportunities should be mainly dependent on low-yield countries through the amelioration of arable land as top yield rises increasingly difficult over time; and for those in middle place around the turn-point of such *S*-shaped curve, the opportunities should be dependent on both high-yield and low-yield countries with integrated efficiency.

CONCLUSION

Global warming exerts positive effect on average yield of world wheat while negative one on the top yield; as for world wheat production in 2019 to 2028, the opportunities for improving production should be mainly dependent on the advantage of high-yield countries as the yield is still in low place before the turn-point of *S*-shaped curve in long-term trend affected partly by greenhouse gas effect.

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