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Structural change in US crop yield growth

Siyi J. Feng
School of Biological Sciences, the Queen''s University of Belfast

Abstract

Crop yield growth is a key parameter in determining the future of agriculture—whether it can simultaneously meet our traditional demands and new demand derived from renewable energy production and climate change mitigation. At the same time, there is concern that crop yield growth has slowed down with changes in societal investment patterns and climate or environmental change. In this paper we investigate crop yield growth in the US for the past 70 years and develop the best possible estimates of likely future growth rates for 8 key crops, including corn, soybean, wheat, etc. We find that all crops investigated except for soybean have experienced slowdowns during the period of late 1960s to early 1980s. The reductions in crop yield growth rates are significant—most of the post-break growth rates are found to be lower than the pre-break growth rates by 50% or more. Furthermore, a linear growth model and an exponential growth model fit the post-break data equally well for corn and some other crops. This result suggests that long-term policy assessments would benefit from the inclusion of an optimistic scenario using the estimated exponential growth rates and a more pessimistic scenario in which the linear crop yield growth rates are used.

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Contact: Siyi J. Feng - fsy.joyce@gmail.com.
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1. Introduction

In recent years, crop yield growth rates have received renewed interest as society has been placing greater demands on the agricultural sector, making it not only a source of traditional food and fiber, but also a source of feedstocks for bioenergy and a possible way to sequester carbon to mitigate climate change (see IPCC, 2007). There is a driving force that these new demands share in common: attempt to reduce greenhouse gas (GHG) emissions. However, with the expansion of bioenergy production in recent years, crop prices worldwide have increased substantially, suggesting a tight supply and demand balance on the agricultural market. This in turn has raised concern of whether such policies would actually deliver the intended environmental benefits. This is because if new demands need to be met by converting forest into arable land (i.e. deforestation) they probably contribute to increase rather than reduction of GHG emissions and, as a result, undermine the policy objectives. Therefore, new policies that aim at expanding the role of agricultural sector in climate change mitigation need to be carefully assessed. There have been numerous studies on the potential future impacts of the emerging demands on the agricultural sector; but the results of these assessments vary widely depending on the modeling methods and the values of key parameters used. The rate at which yield per acre is expected to grow in the future is one of such key parameters, and future yield rates will play a critical role in determining how future demand will be met and, consequently, how serious the undesirable environmental consequences would be.

Recent studies have expressed concerns over reductions in crop yield growth in the past several decades (Alston, et al., 2009; Villavicencio, 2010). Possible explanations for this trend include changes in societal investment patterns and climate or environmental change. However, the studies that investigate the reasons for change in yield growth rates in the past are based on a structural approach in which useful information uncorrelated to the selected independent variables may be left in the error term, and therefore models used in these studies may not be well suited for the purpose of forecasting. In fact, average crop yield growth rates of different periods are calculated as an evidence of yield growth reduction— for example, the average rate between the 1940s and 2000s is greater than that between the 1970s and 2000s; however, a more systematic way of use of the non-structural time series techniques in the investigation of crop yield growths is absent. In view of the importance of forecasts of crop yield growth in policy assessments, in this paper we propose to systematically investigate crop yield growth in the US for the past 70 years and develop the best possible estimates of likely future growth rates for 8 key crops. Specifically, two questions are answered: What are the time trends of crop yield growths in the US? And, when did slowdowns in crop yield growth occur in the US?

2. The Models

There are two standard methods of estimating the time trend of crop yield growth: an approach based on the principal of moving averages and autocorrelation, and a classical model in which yield is regressed on time. In this paper both approaches are used to establish the best estimate of the growth rates.

The first approach used in our study is the autoregressive-moving-average (ARMA) approach, which is widely used in the field of macroeconomics (see early discussion in Diebold

(1998)). In this approach, the variable of interest is regressed on its past history:

$$y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad [1]$$

where p is the order of the autoregressive part and q is the order of the moving average part of the model, both of which deal with how random shock at one period affects future periods. In equation (1), the variable y_t has to be stationary, i.e. does not trend either upward or downward. If a variable is increasing or decreasing over time, as is true for the crop yields in our study, then the data need to be first differenced before the regression, yielding an autoregressive-integrated-moving-average (ARIMA) model:

$$\Delta y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \,. \qquad [2]$$

Using the ARIMA model, the rate of change in y (i.e. Δy) is given by $c \Big/ \left(1 - \sum_{i=1}^{p} \varphi_i\right)$, namely $E(\Delta y_t) = c \Big/ \left(1 - \sum_{i=1}^{p} \varphi_i\right)$. For a series of data $\{y_t\}$, if a structural change occurs at time t, then the process can no longer be modeled with one constant C.[1] Instead, it needs to be modeled as:

$$\Delta y_t = c_1 + c_2 DU_t + \varepsilon_t + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \,, \qquad [3]$$

where DU_t is the dummy variable representing the shift in the rate of change in y, $E(\Delta y_t)$, namely $DU_t = 1$, if $t>T_B$, 0 otherwise with T_B denoting the occurrence of the change. If it is suspected that there is more than one break present in the data, then additional dummies can be added to model the shifts.

Structural change is present in the data if the coefficient c_2 in equation (3) is significantly different from zero. The traditional statistical test to test for the equivalence of two linear models (with versus without a break) is the Chow test, but it has been shown to be only applicable in the situation where the break date is exogenously known (see discussions in Hansen (2001)). A set of tests of structural change with unknown break date have been developed based on the ARIMA model. To test for a change in a crop yield growth rate when the break date is unknown, the procedure from Ben-David and Papell (1998) is used, which was originally developed to test for slowdowns in postwar GDP growth.

The Ben-David and Papell testing procedure involves two steps. The first step is to test the null hypothesis that the series $\{y_t\}$ is an integrated process (or random walk) against the hypothesis that the series is trend stationary with a possible one-time break in the trend function which occurs at an unknown time. The test is performed with model (4):

$$\Delta y_t = \mu + \theta DU_t + \tau t + \gamma DT_t + \delta D(T_B)_t + \rho y_{t-1} + \sum_{j=1}^{k} C_j \Delta y_{t-j} + \varepsilon_t, \forall t \in [\alpha T, \beta T] \,, \qquad [4]$$

where y_t is the logarithm of yield in our study, T denotes the sample size and T_B denotes the

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[1] Although $E(\Delta y_t)$ is determined by C and φ_i together, φ_i's represent the correlation between Δy_t and Δy_{t-i}. *Ceteris paribus*, a change in $E(\Delta y_t)$ implies a change in C. In this case, the process needs to be modeled with two constants C and C', and C corresponds to c_1 and C' corresponds to (c_1+c_2) in equation (3).

breakpoint year. Because estimations are only possible when both segments have enough observations, the interval of possible periods at which the change occurs is restricted and denoted by $[\alpha T, \beta T]$. As in equation (3), DU_t shifts the intercept such that, $DU_t = 1$ if $t>T_B$, 0 otherwise. The variable DT_t shifts the slope at time T_B, where $DT_t = t - T_B$ if $t>T_B$, 0 otherwise. Finally, and $D(T_B)_t = 1$ if $t=T_B+1$, 0 otherwise. The number of lags, k, is determined with a data dependent method: start with an upper bound k_{max} of k; if the last lag included in the regression is significant, then use $k= k_{max}$ otherwise reduce k_{max} by 1 and repeat. In this study, k_{max} is initially set at 5.

The second step in the Ben-David and Papell approach is to test for a structural break with model (5):

$$y_t = \mu + \theta DU_t + \tau t + \gamma DT_t + \sum_{j=1}^{k} C_j y_{t-j} + \varepsilon_t, \forall t \in [\alpha T, \beta T]. \qquad [5]$$

The hypothesis to be tested is H_0: $\theta=\gamma=0$, i.e. that there is no shift in the trend of y_t (or structural break) in the data. Ben-David and Papell (1998) use the "$\mathrm{SupF_t}$" test statistic. This statistic is two times the maximum over all possible trend breaks of the standard F-statistics for testing $\theta=\gamma=0$. The critical values are given in Vogelsang (1997). We also follow Bai and Perron (1998) to construct the SupF(l+1|l) test for the hypothesis of (l+1) breaks vs. l breaks. The SupF(l+1|l) is defined as:

$$F_T(l+1\,|\,l) = \{ S_T(\hat{T}_1,...,\hat{T}_l) - \min_{1\le i\le l+1} \inf_{\tau\in\Lambda_{i,\eta}} S_T(\hat{T}_1,...,\hat{T}_{i-1},\tau,\hat{T}_i...,\hat{T}_l)\} / \hat{\sigma}^2 \qquad [6]$$

where

$$\Lambda_{i,\eta} = \{ \tau; \hat{T}_{i-1} + (\hat{T}_i - \hat{T}_{i-1})\eta \le \tau \le \hat{T}_i - (\hat{T}_i - \hat{T}_{i-1})\eta \}$$

and $\hat{\sigma}^2$ is a consistent estimate of the variance of error term. When l equals 0, this test is equivalent to the one used in Ben-David and Papell (1998). If a break is found to be statistically significant, we further test the hypothesis of 1 break vs. 2 breaks with model (7):

$$y_t = \mu + \theta_1 DU1_t + \theta_2 DU2_t + \tau t + \gamma_1 DT1_t + \gamma_2 DT2_t + \sum_{j=1}^{k} C_j y_{t-j} + \varepsilon_t, \forall t \in [\alpha T, \beta T] \qquad [7]$$

where $DU1_t$ and $DU2_t$ are the dummy variables to model an intercept shift at time $T1_B$ and $T2_B$ respectively, and $DT1_t$ and $DT1_t$ are the dummy variables to model a slope shift at time $T1_B$ and $T2_B$ respectively.

The ARIMA method is favored over the classic method in which the variable in investigation or a variant of its transformation is regressed on the time variable, because it allows for, in addition to a deterministic time trend, a stochastic time trend (Stock and Watson, 1988). However, this method maintains a linear form,[2] implying that the assumption that the series is growing linearly or exponentially all the time has to be maintained. It does not, therefore, allow for the possibility of a switch from an exponential process to a linear process or vice versa. However, whether the variable being considered is growing linearly or exponentially is not always clear—in some cases, the data may be fitted equally well in both specifications. It may

[2] Extension to nonlinear models has also been developed but requires large data set and is mostly applicable with financial data (Diebold, 1998).

not make much difference, especially for short-term or intermediate-term forecasts (e.g., for the next 10 years), which is usually the case for macroeconomic studies. However, in climate change mitigation policy studies, forecast of key parameters for several decades are oftentimes necessary, so results are likely to be quite sensitive to whether the growth rate is linear or exponential. In the ARIMA model, we assume the crop yields are growing exponentially. We now turn to the classical time trend method, which admits greater flexibility in the choice of functional forms.

In the classical method, the variable of interest is regressed on the time variable:

$$y_t = a + bt + \varepsilon_t \,, \qquad [8]$$

where y_t is the original value or logarithm[3] of the variable at time period t and b gives the rate of change of y_t over time. To allow for potential structural change, the crop yield data are separated into two or more segments and regressed on time trend functions.[4] In general, no restrictions are imposed on whether each trend is linear or exponential or on whether the segments connect with each other. Assuming two segments, eight distinct specifications are possible as listed in Table 1. For models with structural change, the optimal breakpoint year is found by searching over all possible break point specifications, excluding the first and last few time periods. We first calculate for each specification the sum of squared errors (SSE) after converting all values to the same units.[5] Based on the mean of squared error (MSE), the set of candidate models is narrowed down from 8 to 3. Then hold-out validation is carried out by excluding the last 10 observations and evaluating the out-of-sample predictions of the estimated model. The final model from the set in Table 1 is chosen as the one with the smallest sum of squared out-of-sample prediction errors.

[3] The model estimated using a log transformation leads to a constant percentage rate of growth while the linear model yields a constant growth rate in yield per acre. Other transformations such as the Box-Cox transformation, are also possible. However, models estimated using a Box-Cox transformation resulted in only minor improvements in goodness of fit. Moreover, since the purpose of this analysis is to aid in the predicting of future yield growth rates, the Box-Cox results are not reported since this model is used in estimation but rarely in forecasting.

[4] Multiple l breaks can be modeled by further separating the data into $(l+1)$ segments. As noted below, we also reject the hypothesis that more than one structural break has occurred over the period. For ease of exposition, therefore, we present here only the case of a single break.

[5] To compare regressions using the original data and those using their logarithm, SSE is calculated based on the original scale of the data. For regressions implemented with logarithms of the data, fitted values are converted into their inverses using the exponential function before residuals are computed.

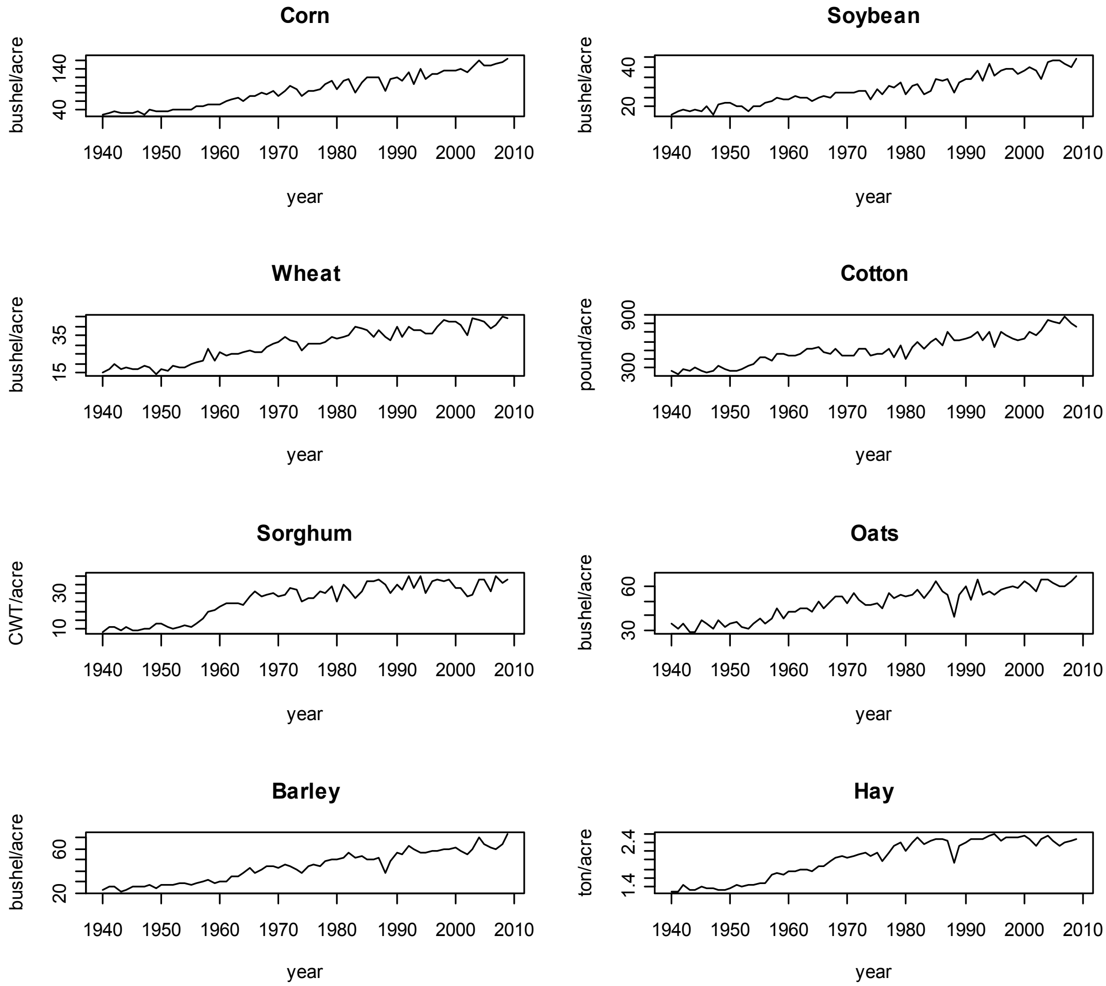
Table 1: Time Trend Models with Breakpoint at Year *i*

Unrestricted models: trend lines may not be continuous	
Model 1 (Exponential + Linear-unrestricted)	$\log(y_t) = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $y_t = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$
Model 2 (Exponential + Exponential-unrestricted)	$\log(y_t) = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $\log(y_t) = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$
Model 3 (Linear + Exponential-unrestricted)	$y_t = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $\log(y_t) = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$
Model 4 (Linear + Linear-unrestricted)	$y_t = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $y_t = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$
Restricted models: continuity of trend lines is imposed	
Model 5 (Exponential + Linear-restricted)	$\log(y_t) = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $y_t = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$ s.t. $\exp(a_1 + b_1 \cdot (t_i + 1)) = a_2 + b_2 \cdot (t_i + 1)$
Model 6 (Exponential + Exponential-restricted)	$\log(y_t) = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $\log(y_t) = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$ s.t. $\exp(a_1 + b_1 \cdot (t_i + 1)) = \exp(a_2 + b_2 \cdot (t_i + 1))$
Model 7 (Linear + Exponential-restricted)	$y_t = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $\log(y_t) = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$ s.t. $a_1 + b_1 \cdot (t_i + 1) = \exp(a_2 + b_2 \cdot (t_i + 1))$
Model 8 (Linear + Linear-restricted)	$y_t = a_1 + b_1 \cdot t + \varepsilon_t, \quad t = 1940,\ldots,i$ $y_t = a_2 + b_2 \cdot t + \varepsilon_t, \quad t = i+1,\ldots,2009$ s.t. $a_1 + b_1 \cdot (t_i + 1) = a_2 + b_2 \cdot (t_i + 1)$

3. Data and Results

This study focuses on the national level US average yields per acre for eight major field crops: corn, soybean, wheat, cotton, sorghum, oats, barley and hay. Their yield data for the years 1940-2009 are collected from the Quick Stats data set developed by the National Agricultural Statistics Service of US Department of Agriculture. This amounts to a sample size of 70 for each series. The data are plotted in Figure 1.

Figure1: National Average of Yield of 8 major US crops of 1940-2009



We first present the results of test with one unknown structural break in crop yield growth in Table 2. A statistically significant break in the yield growth rates is found for all crops but soybean, most in the late 1960s or early 1970s. With the break years, the pre-break and post-break growth rates of crop yield per acre based on the ARIMA model are also estimated. For six out of the seven crops a structural break is found with estimated growth rates after the break 50% or less than the growth rates before the break. The yield growth rate for hay drops to almost zero after 1982.

In Table 3 we further test the null hypothesis of one break vs. the alternative hypothesis of a second break. For all of the crops investigated, we find that the null hypothesis cannot be rejected at the 90% confidence level.

Table 2: Test with One Unknown Break $SupF_t$ Date in Crop Yield

Crop	$SupF_t$	Break	Year of $SupF_t$	Initial Intercept μ	Intercept Shift θ- γ*T_B	Initial Slope τ	Slope Shift γ	Growth Rate Pre-Break	Growth Rate Post-Break
Soybean	5.90	No	--	--	--	--	--	1.26%	1.26%
Corn	28.49	Yes	1974	-88.76	53.90	0.047	-0.027	3.95%	1.69%
Cotton	14.81	Yes	1966	-54.32	39.17	0.030	-0.020	4.39%	1.44%
Wheat	16.23	Yes	1973	-38.36	27.21	0.021	-0.014	2.82%	0.94%
Sorghum	15.92	Yes	1967	-75.41	70.51	0.039	-0.035	6.57%	0.58%
Barley	12.16	Yes	1962	-0.137	0.90	0.008	-0.0004	1.29%	1.22%
Oats	20.36	Yes	1973	-44.49	33.41	0.020	-0.013	2.0%	0.70%
Hay	20.94	Yes	1982	-22.67	21.77	0.012	-0.011	1.73%	0.09%
Critical values at the 90%, 95% and 99% level are 11.25, 13.29 and 17.51 respectively.									

Table 3: Test with Two Unknown Breaks vs. One Unknown Break SupF(2|1) in Crop Yield

Crop	$SupF_t$	Year of 1st Break	Year of 2nd Break
Corn	9.32	1974	1957
Cotton	5.07	1966	1980
Wheat	4.59	1973	1956
Sorghum	5.28	1967	1956
Barley	0.64	1962	1983
Oats	6.87	1973	1956
Hay	3.19	1982	1966
Critical values at the 90%, 95% and 99% level are 12.79, 14.50 and 17.98 respectively.			

Estimation results of the classical method are presented in Table 4. Generally, crop yield growths can be modeled well with exponential process. With the exception of barley, the estimated break dates are within four years of the ones estimated using the ARIMA method; all but two break dates are within two years. Yield growth rate estimates are different because autocorrelation is taken into account in the ARIMA method but not in the classical method. However, differences in post-break yield growth rate estimations are qualitatively quite small.

Table 4: Result Summary of Estimated Crop Yield Growth Rates

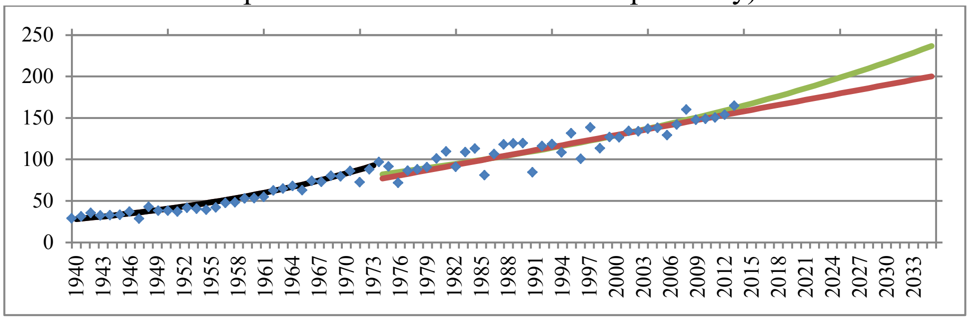
	Exponential growth, no breakpoint	Model 2 Exponential+Exponential_unrestricted with breakpoint		Model 6 Exponential+Exponential_restricted with breakpoint				
Crop	Soybeans	Corn	Cotton	Wheat	Sorghum	Barley	Oats	Hay
Yield Growth Rate Before breakpoint	1.28%	3.67%	3.4%	2.3%	5%	2%	1.8%	1.6%
Break Year		1973	1965	1972	1966	1979	1969	1984
Yield Growth Rate after breakpoint		1.75%	1.5%	0.9%	0.5%	1.0%	0.65%	0.07%

Although the Exponential+Exponential model has been identified as the best model for most of crops in the validation stage, it should be noted that when the whole series of data is used for estimation, the Exponential+Linear model performs just as well and gives the same break date estimation for corn, wheat, sorghum, oats and hay. In Table 5, yield growth forecasts using both methods are presented for these crops. As differences in forecasts resulting from the two models increase with time, crop yield gains will be much smaller in the far future were they growing linearly. Figure 2 shows the difference in corn yield forecast in 2035 between the exponential model and the linear model. They may well have opposite implications in terms of the environmental impacts of the bioenergy and climate change mitigation policies. Hence, we recommend that long term policy assessments include the linear growth case as a pessimistic scenario.

Table 5 Annual Yield Growth Forecasts (Exponential Growth vs. Linear Growth)

	Corn	Soybean	Wheat	Sorghum	Oats	Hay
Exponential Growth	1.75%	1.28%	0.9%	0.5%	0.65%	0.07%
Linear Growth	2.02 bushel/acre	0.36 bushel/acre	0.37 bushel/acre	0.20 CWT/acre	0.35 bushel/acre	0.003 ton/acre

Figure 2 Corn Yield Forecast to 2035(green line and red line denote forecasting based on the exponential and linear model respectively)



4. Conclusion

This paper has examined the yield growth trend of 8 major US crops using both the ARIMA method and the classical method. We found that all but soybean have experienced slowdowns during the period of late 1960s to early 1980s. The reductions in crop yield growth rates are statistically significant—most of the post-break growth rates are found to be lower than the pre-break growth rates by 50% or more. In particular, the annual growth rate for corn, the most important crop in the nation, has fallen from 3.67% to 1.75%.

Yield growth rate estimates obtained using the two different methods do not differ greatly, especially the post-break rates. Furthermore, a linear growth model fits the post-break data equally well for some of the crops. In view of the tight supply demand balance of the agricultural market, we believe that long-term policy assessments would benefit from the inclusion of an optimistic scenario using the estimated exponential growth rates and a more pessimistic scenario in which the linear crop yield growth rates are used.

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