Crop Yield Growth and Its Implication for the International Effects of US Bioenergy and Climate Policies (Draft)

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1 Introduction

In recent years, society has been placing greater demands on the agricultural sector making it a source of bioenergy with for example US corn usage for ethanol rising from 15.9 million tons (below 5%) to 104 million tons (about 26%) of the total crop in the last decade[1]. Furthermore agriculture is being considered as a possible source of climate change mitigation (see IPCC, 2007). The consequences of the demand expansion are multi-faceted. In the market, the bioenergy expansion coupled with other forces have caused crop prices to increase substantially (Trostle, 2008), resulting in food insecurity problems in developing countries (FAO, 2008). Simulated by higher prices production in the US has expanded by 40% in the past decade both due to changes in the intensive margin (e.g. using more fertilizer to increase yield) and the extensive margin (e.g., expansion of cropland via clearing of grassland, unprotected forest) (Melillo, et al., 2009). Beyond the market, such developments will inevitably have environmental consequences, notably increasing greenhouse gases emissions and fertilizer use. Expansion of production happens not only inside but outside a country's borders as well which can also have emissions stimulating and other environmental degradation implications (Fargione, et al., 2008, Murray, et al., 2004, Searchinger, et al., 2008). This makes the use of bioenergy, advocated for the benefit of climate change, less desirable than it appears. In the realm of climate change mitigation, it involves the problem of leakage which happens when mitigation policies reduce net GHG emissions in one context but increase prices that in turn cause emissions increases elsewhere.

[1] Data source: Earth Policy Institute (http://www.earth-policy.org/).

It is suggested in the literature (Baker, et al., 2010) that with rising price the market consequence will be modestly positive in the US as benefits to the producer outweighs the loss of consumers. However, this may not be true if the scope is broadened from a national analysis of a commodity exporter, i.e. US, to a global analysis. Even it may still be true, the loss may be unaffordable for some people in the developing world. Assessments on the international scale are often found in reports of international organizations, such as the FAO. A more frequently discussed issue in literature is the conceivably negative environmental consequences associated with the expansion of crop production—another layer that complicates policy implications (Fargione, et al., 2008, Searchinger, et al., 2008). However, there are some uncertainties clouding the magnitude of the consequences. Literature suggests that alternative assumptions regarding values on key parameters (such as crop yield, bilateral trade responses) and model assumptions (such as geographical scope) can lead to diverse estimations in policy assessments (Keeney and Hertel, 2009, Schneider and McCarl, 2006). For example, Searchinger et al. (2008) argues that promoting use of bioenergy will lead to large amount of forest clearance that would not have happen without the policy and the benefit can only be realized in the far future. In contrast, their finding is criticized for neglecting the price response of crop yield growth-- by using the low range of elasticity found in early literature, it is found that 30% of the marginal ethanol demand in 5 year term can be met by yield gains (Keeney and Hertel, 2009). Fundamentally, these two studies differ in assumption regarding how supply, the product of acreage and yield, catches up with growing demand. As there is an ultimate limit on acreage, it is worthy of investigating yield further in a time when sudden increase of demand intensifies scarcity.

Recent discussions on reductions in crop yield growth are seen both in the economics literature (Alston, et al., 2009, Villavicencio, 2010) and also in those of other subjects, such as biology (Arizen, et al., 2008). Studies in crop yield growth trend may arise for different reasons, such as to investigate whether climate or environmental change has exerted negative effects, to investigate whether change in priority of societal investment has had an unfavorable result. Some of these studies have argued that crop yield growth has slowed down. However, whether this is happening is complex. In particular such a finding could arise not only if it was occurring but also because of different

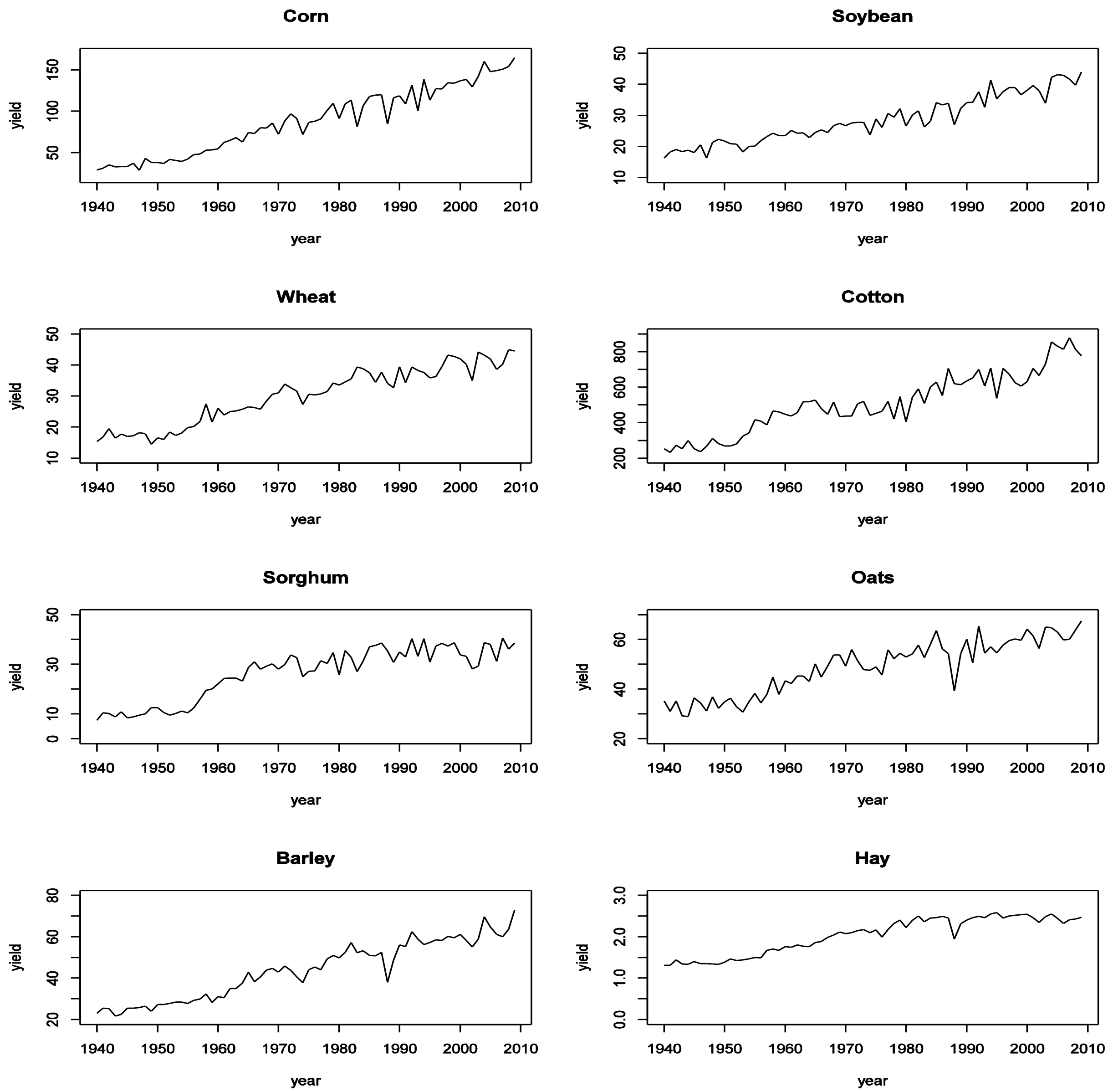
- measurement approaches — absolute growth vs. relative growth;
- time frame and
- functional form/estimation technique.

If one is to estimate the crop yield as a production function then it would have many factors as its arguments, notably climate conditions, soil type/characteristics, varieties and input use. If this were extended dynamically then research and extension expenditures would be included. Here rather than taking a production function approach this paper examines the more aggregate characteristics of crop yield growth with a time series technique using US data. Subsequently the results in the form of alternative yield growth scenarios up to the year 2030 will be used to investigate the effects on market prices, exports, and the international effects of U.S. bioenergy policies with a global agricultural sectoral model.

2 Examination of Historical Crop Yield Growth Trend of US

This study focuses on 8 major field crops at the national level in the US: 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 (http://www.nass.usda.gov/QuickStats/Create_Federal_All.jsp). The data are plotted in Figure 1.

Figure1 Yield Plots of 8 US Major Field Crops (1940-2009)



Now we turn attention to estimating the yield growth rate permitting it to change over time. To do this we examine the historical growth trend in a two step process: 1) we detrend the data to obtain residuals; 2) we examine the residuals to see if they are stationary[2] and if they exhibit correlation across time.

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[2] Time series data $\{X_t\}$ is strictly stationary if $(X_1,\ldots,X_n)$ and $(X_{1+h},\ldots X_{n+h})$ have identical joint distribution for all integers h and $n \geq 1$. Time series analysis typically works with weaker assumption that says the two random vector have the same first and second moments, i.e. their mean and covariance (Brockwell and Davis, 2002).

There are two ways of detrending the data: 1) a parametric way, such as finding the trend and/or seasonality function; and 2) a non-parametric way, such as differencing (the so-called Box-Jenkins method) until the resultant data is stationary (Brockwell and Davis, 2002). There is some subtle difference between these two methods[3] (Maddala and Kim, 1998). We follow the classical way to fit crop yield data with a time trend, which allows for greater flexibility in choosing time trend functions[4], easier detection of model misspecification[5] and also more straightforward interpretation.

The regression functions we consider use yield and/or its logarithm as the dependent variable with a linear time independent variable corresponding to linear and exponential growth processes respectively[6,7]. In view of the concern of crop yield growth reducing over time, we also allow for a possible break in the trend function and consider all the possible combinations of the trend functions pre and post the break, namely exponential trend followed by exponential trend, exponential trend followed by linear trend, linear trend followed by linear trend, and linear trend followed by exponential trend.

The best fit trend function is determined by the method of hold-out validation[8]. The procedure will be presented in detail in Section 2.1. After the best trend function is found, independence of residuals will be checked to see whether further modeling is needed.

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[3] If the data follows the process: $y_t = a + bt + \varepsilon_t, \varepsilon_t \text{ is } i.i.d.$, then its first difference $\Delta y_t = b + \varepsilon_t - \varepsilon_{t-1}$ which has a non invertible error term. If the data follows the process $\Delta y_t = b + \varepsilon_t, \varepsilon_t \text{ is } i.i.d.$, then it implies $y_t = a + bt + \sum_t \varepsilon_t$ the error term of which follows random walk.

[4] If the differencing procedure were used, it would impose implicit assumptions on the growth process. Differencing in original data implies an assumption of linear growth while differencing in logarithm of the original data assumes exponential growth. If the process grows in a mixed way, the derived data will not be stationary, which might jeopardize the following analysis.

[5] If the data should be first differenced but they are modeled with time trend, the residual will follow random walk as discussed in Footnote 3 (and thus is non-stationary) -- this situation will be revealed by stationary test after the regression.

[6] For linear trend, yield=a+b*year, implying ever decreasing growth rate, that is $GrowthRate = \frac{a+b*Year}{a+b*(Year-1)} - 1 = \frac{b}{a+b*(Year-1)}$ and $\frac{\partial GrowthRate}{\partial Year} = -\frac{b^2}{\left(a+b*(Year-1)\right)^2} < 0$

For exponential trend, $yield = e^{a_1+b_1*Year}$, implying $GrowthRate = \frac{e^{a_1+b_1*Year}}{e^{a_1+b_1*(Year-1)}} - 1 = e^{b_1} - 1$ which is constant over time.

[7] We have also tried the quadratic time trend; however, our result indicates that it is highly sensitive to the specific data set used-- even though it sometimes provides good estimate of the trend, it performs poor in validation.

[8] http://research.cs.tamu.edu/prism/lectures/iss/iss_l13.pdf

Following the time trend estimation, we then test statistically the hypothesis that there is structural break in the crop yield growth process. The structural break test employed here contains a large number of competing specific tests which can be classified by different criteria, notably whether the test assumes the break date is known or not. When the break date is assumed to be known, the classical Chow test (Hansen, 2001) can be applied. When the break date is assumed to be unknown the tests typically have higher critical value leading to the null hypothesis that there is no structural break being rejected less frequently. However, there is hardly a clear cut answer to this question in that investigators typically have some a prior but not complete knowledge regarding the occurrence of the change (Hansen, 2001, Maddala and Kim, 1998). In fact, research like ours is motivated an observation that technical progress has slowed down but we do not exactly know when the change occurred. Identification of the break point in our case will be data driven. Therefore, we will use both types of the test.

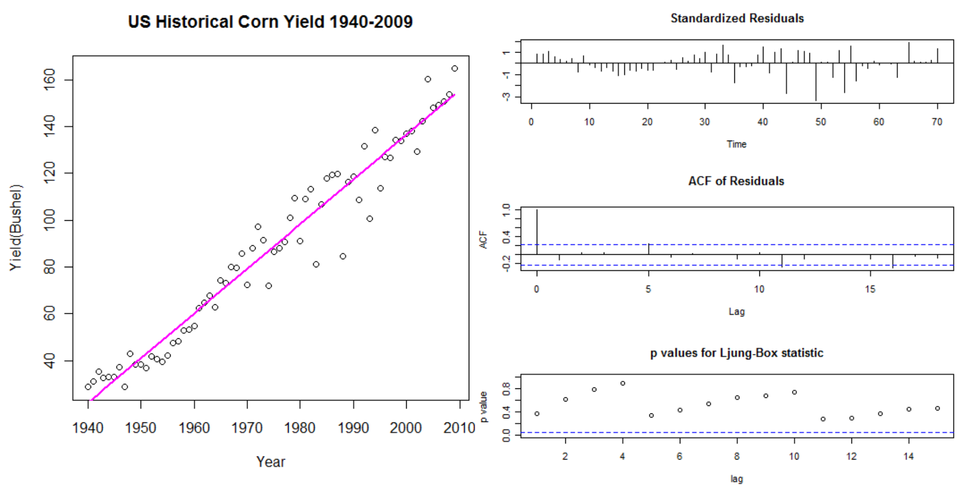
2.1 Estimating yield growth trends for US Crops

Let us begin with corn which is the most prevalent crop in US agriculture. The left panel of Figure 2 shows the average corn yield in the United States from 1940-2009, with a fitted linear model passed through it where $y = a + b * t, with\ a = -3681\ and\ b = 1.91$. The estimated slope on the year variable suggests the yield is growing at 1.91 bushels/year, equivalent to a 6.57% increase in 1940 but only 1.15% in 2009 where the yields in those periods average 28.9 bushel and 164.7 bushel respectively.

There are more to be said if the residual plot of the fitted linear model (Figure 2) is observed Firstly, residuals of the model are spanning out—variance is increasing with time, which is no surprise since the yield has increased by 3 folds over the whole period. More importantly, the standardized residual plot (the first panel on the right) does not seem to be random, especially for the first three decades. Fitted values of the model tend to persistently underestimate the yield data for the first 10 years and overestimate the next 10. Then the residuals become and remain positive for another decade with only 1 or 2 exceptions. This pattern suggests nonlinear yield growth. However, the null hypothesis that the residual is random using the Ljung-Box test[9] (the last panel on the right) cannot be rejected, suggesting that the deterministic part of the data has been captured and the corn yield is growing linearly in this period. Since this pattern occurs only in a segment of the data and does not recur, the Ljung-Box test, when applied to the residual of the whole period, may not have the power to reject the null. Therefore, the model selection section does not stop here, and two more classes of models will be estimated.

[9]Ljung-Box test is defined as $Q = T(T+2)\sum_{k=1}^{s}\frac{r_k^2}{T-k}$.It is used to test whether the autocorrelations of a time series are different than zero. The null hypothesis is that the data is random. And the alternative hypothesis is that the data is not random.

Figure 2 US Historical Corn Yield 1940-2009 with Fitted Linear Model



Careful examination of figure 2 seems to indicate that the yield grows at a different rate up until about 1970 than after that. Consequently we adopted an estimation procedure that fit 2 functions of potentially different forms (exponential and linear) with a break point (a year like 1970) at where the estimation can change parameters. There are 2 parameters in the time trend function: the intercept and the slope. The models are called unrestricted models when both coefficients are allowed to change--these models will have the most freedom to fit data but are very likely to have jumps in the two segments of fitted regressions. The models in which segments must connect with each other are called restricted models. The restriction has cost the models one degree of freedom in choosing parameters, i.e. only the slope coefficient can change freely. In other words, the restricted versus unrestricted is referring to whether the absolute level of crop yield is allowed to change (as a result of a shock). To do this I fit eight models and determined a breakpoint where the functional forms switched (Table 1).

Table 1 Models with Two Segments

Model 1 (Exponential + Linear-unrestricted)	$\log(y) = a_1 + b_1 * t, t = 1940, \ldots, i$ $y = a_2 + b_2 * t, t = i+1, \ldots, 2009$
Model 2 (Exponential + Exponential-unrestricted)	$\log(y) = a_1 + b_1 * Year, Year = 1940, \ldots, i$ $\log(y) = a_2 + b_2 * Year, Year = i+1, \ldots, 2009$
Model 3 (Linear + Exponential-unrestricted)	$y = a_1 + b_1 * Year, Year = 1940, \ldots, i$ $\log(y) = a_2 + b_2 * Year, Year = i+1, \ldots, 2009$
Model 4 (Linear + Linear-unrestricted)	$y = a_1 + b_1 * Year, Year = 1940, \ldots, i$ $y = a_2 + b_2 * Year, Year = i+1, \ldots, 2009$
Model 5 (Exponential + Linear-restricted)	$\log(y) = a_1 + b_1 * t, t = 1940, \ldots, i$ $y = a_2 + b_2 * t, t = i+1, \ldots, 2009$ *Subject to* $\exp(a_1 + b_1 * (t_i + 1)) = a_2 + b_2 * (t_i + 1)$
Model 6 (Exponential + Exponential-restricted)	$\log(y) = a_1 + b_1 * Year, Year = 1940, \ldots, i$ $\log(y) = a_2 + b_2 * Year, Year = i+1, \ldots, 2009$ *Subject to* $\exp(a_1 + b_1 * (t_i + 1)) = \exp(a_2 + b_2 * (t_i + 1))$
Model 7 (Linear + Exponential-restricted)	$y = a_1 + b_1 * Year, Year = 1940, \ldots, i$ $\log(y) = a_2 + b_2 * Year, Year = i+1, \ldots, 2009$ *Subject to* $a_1 + b_1 * (t_i + 1) = \exp(a_2 + b_2 * (t_i + 1))$
Model 8 (Linear + Linear-restricted)	$y = a_1 + b_1 * Year, Year = 1940, \ldots, i$ $y = a_2 + b_2 * Year, Year = i+1, \ldots, 2009$ *Subject to* $a_1 + b_1 * (t_i + 1) = a_2 + b_2 * (t_i + 1)$

These models imply that the trend function of the data changes once during the whole period. No restrictions on 1) whether the growth process is linear or exponential and 2) whether the restriction is imposed that the two segments connect with each other. Furthermore in the estimation we search for the best break point (year) over the period [1959,1988] (i.e. for i in the above equations), excluding the possibility that the change happens in the first or last 20 years. The break point is chosen at the point associated with the smallest mean squared error for the entire model. The estimated result is shown in Table 2.

Table 2 Estimation of Models with Two Segments

Model	Estimation Result	Break Year	Ljung-Box Test	Implied Growth Rate	SSE/MSE
Simple Linear Model – No break point	a=-3681, b=1.91	--	Fail to Reject	6.57% at Year 1940 1.15% at Year 2009	SSE=4956.25 MSE=72.89
Model 1 (Exp. + Linear-unrestricted)	a_1=-67.03 b_1=0.03627	1973	Fail to Reject	3.67%	SSE=4526.58 MSE=68.58
	a_2=-3910.6 b_2=2.02		Fail to Reject	2.21% at Year 1973 1.23% at Year 2009	
Model 2 (Exp. + Exp-unrestricted)	a_1=-67.03 b_1=0.03627	1973	Fail to Reject	3.67%	SSE=4470.05 MSE=67.72
	a_2=-29.86 b_2=0.01736		Fail to Reject	1.75%	
Model 3 (Linear + Exp.-unrestricted)	a_1=-2829.9 b_1=1.47	1964	Reject	5% at Year 1940 2.3% at Year 1964	SSE=4628.58 MSE=70.13
	a_2=-28.59 b_2=0.017		Fail to Reject	1.7%	
Model 4 (Linear + Linear-unrestricted)	a_1=-3791 b_1=1.96	1987	Fail to Reject	6.78% at Year 1940 1.63% at Year 1987	SSE=4630.25 MSE=70.16
	a_2=-5113.7 b_2=2.62		Reject	3% at Year 1988 1.59% at Year 2009	
Model 5 (Exponential + Linear-restricted)	a_1= -65.90 b_1=0.0358	1968	Reject	3.64%	SSE=4782.90 MSE=71.39
	a_2=-3667 b_2=1.9		Fail to Reject	2.5% at Year 1969 1.28% at Year 2009	
Model 6 (Exp + Exp-restricted)	a_1=-66.03 b_1=0.0357	1971	Fail to Reject	3.64%	SSE=4566.12 MSE=68.15
	a_2=-27.73 b_2=0.01632		Fail to Reject	1.64%	
Model 7 (Linear + Exponential-restricted)	a_1=-3680.11 b_1=1.91	1980	Reject	7.5% at Year 1940 1.9% at Year 1980	SSE=5010.05 MSE=74.78
	a_2=-27.05 b_2=0.01598		Reject	1.6%	
Model 8 (Linear + Linear-restricted)	a_1=-3647.31 b_1=1.89	1989	Fail to Reject	9.7% at Year 1940 1.6% at Year 1989	SSE=5135.40 MSE=76.64
	a_2= -3931.51 b_2=2.03		Reject	1.8% at Year 1990 1.3% at Year 2009	

Note: SSE stands for Sum of Squared Error. MSE stands for Mean Squared Error. And Year is the year when the data is separated.

Model 2 (Exponential+Exponential-unrestricted) is the best model in terms of MSE. Furthermore, the Ljung-Box test cannot reject the null hypothesis of random residuals for both segments. This model implies that a break occurred at the year 1973 both to the growth rate and to the yield level, i.e. $b_1 > b_2$ and $\exp(a_1 + b_1 * i) > \exp(a_2 + b_2 * i)$. The yield growth rate fell by more than 50% from 3.67% to 1.75%. Such change implies yield gains was approximately half of what it would have been without the change the first year after the change and dropped to a quarter the next year and $(\frac{1}{2})^n$ n years after. Two other models are worth noting: Model 1 (Exponential+Linear-unrestricted) and Model 6 (Exponential+Exponential-restricted). They have slightly larger MSE but give similar break point (Year 1973). Together, these three models suggest that the trend of corn yield growth of year 1940-1973 is exponential but that of year 1974-2009 is not as clear -- fitted with either linear time trend or exponential time trend the residual can pass the Ljung-Box test. In view of this, we will proceed to the model validation with all three models.

To further compare the models, hold-out validation is used, i.e. the previous steps are repeated twice with the last 5 and 10 observations excluded from the model estimation and used for validation. Namely, the simple linear model, Model 1 (Exponential+Linear-unrestricted), Model 2 (Exponential+Exponential-unrestricted) and Model 6 (Exponential+Exponential-restricted) will be estimated again with the data of 1940–2004 and 1940–1999, and used to predict the yields of 2005–2009 and 2000–2009. Estimation result along with the prediction error is reported in Table 3.

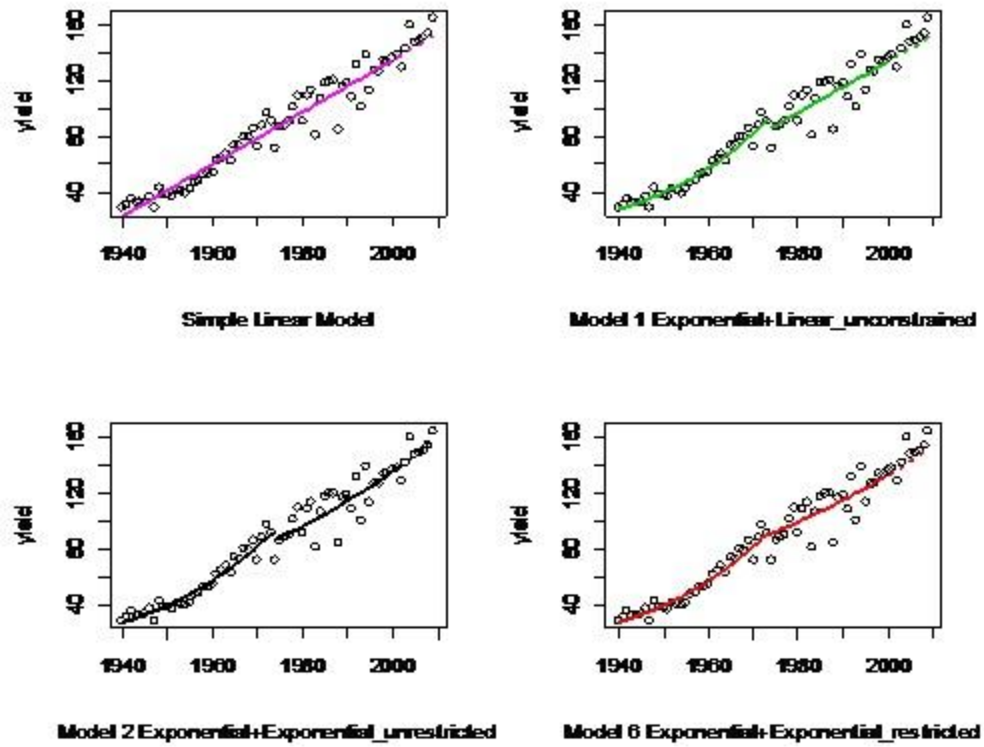
Table 3 Model Validation- Estimation and Prediction

Model	Estimation Result-0	Estimation Result-5	Out of sample Prediction Error-5	Estimation Result-10	Out of sample Prediction Error-10
Simple Model $y = a + b * Year$	SSE=4956.25 MSE=72.89 a=-3681, b=1.91	SSE=5033.63 MSE=79.90 a=-3629, b=1.88	179.43	SSE=4622.88 MSE=79.70 a=-3588, b=1.86	652.52
Model 1 (Exponential + Linear-unrestricted)	SSE=4526.58 MSE=68.58 Year=1973	SSE=4415.04 MSE=72.38 Year=1973	148.78	SSE=4003.21 MSE=71.49 Year=1973	747.46
	a_1=-67.03 b_1=0.036	a_1=-67.03 b_1=0.036		a_1=-67.03 b_1=0.036	
	a_2=-3910.55 b_2=2.02	a_2=-3746.17 b_2=1.94		a_2=-3521.62 b_2=1.82	
Model 2 (Exponential + Exponential-unrestricted)	SSE=4470.05 MSE=67.72 Year=1973	SSE=4419.17 MSE=72.45 Year=1973	50.52	SSE=4072.20 MSE=72.72 Year=1973	397.43
	a_1=-67.03 b_1=0.036	a_1=-67.03 b_1=0.036		a_1=-67.03 b_1=0.036	
	a_2=-29.69 b_2=0.01736	a_2=-29.80 b_2=0.01736		a_2=-29.52 b_2=0.01722	
Model 6 (Exponential + Exponential-restricted)	SSE=4566.12 MSE=68.15 Year=1971	SSE=4512.27 MSE=72.78 Year=1971	55.39	SSE=4148.86 MSE=72.79 Year=1972	668.76
	a_1=-66.03 b_1=0.0357	a_1=-66.03 b_1=0.0357		a_1=-67.10 b_1=0.036	
	a_2=-27.73 b_2=0.01632	a_2=-2751 b_2=0.01621		a_2=-23.62 b_2=0.01425	

Note: "-5" denotes 5 latest observations (2005–2009) removed from estimation. "-10" denotes 10 latest observations (2000–2009) removed from estimation.

Although Model 2 (Exponential+Exponential-unrestriced) does not always have the smallest MSE, it is the best among the three in terms of giving the smallest out of sample prediction error. In fact, all except Model 2 under predict all the yields of 2005–2009 or 2000–2009 (Figure 3). Furthermore, both the simple linear model and the unrestricted Exponential+Linear model (Model 1) have increasing estimations of the slope coefficient (in their linear parts) when more observations are added in, suggesting that the absolute annual growth in recent years are actually increasing which agrees with the exponential growth process to some extent. Therefore, Model 2 (the unrestricted Exponential+Exponential model) is determined to be the best model for the corn data. After detrending corn data with Model 2, the null hypothesis that the residuals are random cannot be rejected and there is no need to further model the residuals.

Figure 3 Model Validation with Prediction (2000-2009)



The same procedure is applied to all 8 crops to find out their yield growth trends. Summary of the results is presented in Table 4. It is found that:

(1) Soybean is the only crop that can be fitted well with out a break point;
(2) Hay yield grows exponentially until 1982, and then yield growth becomes zero since then;
(3) All other crops can be modeled by an Exponential + Exponential model implying that the best fit involves a break point. Furthermore after that break point the growth rates are 50% or more lower than the growth rate before that break. Among them, corn and cotton can be better modeled with the unrestricted model which suggests there was shift in level along with the growth rate; and
(4) The break dates are different across crops.

Table 4 Result Summary of Crop Yield Growth Trend

	One trend	Model 2 Exponential+Exponential_unrestricted		Model 6 Exponential+Exponential_restricted				
Crop	Soybean	Corn	Cotton	Wheat	Sorghum	Barley	Oats	Hay
Yield Growth Rate of 1st Period	1.28%	3.67%	3.4%	2.3%	5%	2%	1.8%	1.6%
Break Year		1973	1965	1972	1969	1979	1969	1982
Yield Growth Rate of 2nd Period		1.75%	1.5%	0.9%	0.5%	0.9%	0.65%	0

Finally we proceed to test randomness of residual of the above best fitted trend functions with Ljung-Box test. Only the autocorrelation of wheat at lag 1 is statistically significantly different than zero, which will be only useful for one step ahead forecast[10] and therefore the result will not be incorporated into our simulation model the step of which is 10 years.

2.2 Testing for structural break in US Crop yields growth trend

In this section, we are going to test statistically whether there is structural change in the crop yield data. As explained in the beginning of this session, both tests assuming known break date and unknown break date will be used.

2.2.1 Test with known break date

If the assumption that the break date is known were to be made, the Chow test[11] for linear models can be applied to test for a structural break in our data[12]. For the 7 crops that were found

[10] When the autocorrelation (ACF) of a stationary time series (ε_t) is statistically significantly different than zero at lag 1 and the partial autocorrelation (PACF) of ε_t is not statistically significantly different than zero at all lags, it is recommended that ε_t be modeled with MA(1), namely $\varepsilon_t = z_t + az_{t-1}, where\ \{z_t\}\ is\ white\ noise\ with\ mean\ 0\ and\ variance\ \sigma^2$. Let P denote the prediction of ε_t, then $P(\varepsilon_{t+1}) = P(z_{t+1}) + aP(z_t), where\ P(z_{t+1}) = 0\ and\ P(z_t)\ can\ be\ calculated\ with\ the\ observed\ data$ and $P(\varepsilon_{t+2}) = P(z_{t+2}) + aP(z_{t+1}), where\ P(z_{t+2}) = P(z_{t+1}) = 0$ (Brockwell and Davis, 2002).

.[11]Chow test is a test of whether coefficients of different linear regression are equal. Suppose the data is {(x1, y1),...,(xT, yT)} and the break date is TB which separate the data into two sub-samples: $\{(x_1, y_1),...,(x_{TB}, y_{TB})\}$ and $\{(x_{TB+1}, y_{TB+1}),...,(x_T, y_T)\}$. To test whether the two sub-samples can be modeled by the same model, first run three regressions: 1) yt=a+bxt, t=1,...,T; 2) yt=a1+b1xt, t=1,...,TB; and 3) yt=a2+b2xt, t=TB+1,...,T and let SSE0, SSE1 and SSE2 denote their sum of squared error respectively. Then the test is defined as $\frac{(RSS_0-RSS_1-RSS_2)/2}{(RSS_1+RSS_2)/(n-4)}$, and under the null hypothesis (a_1=a_2, b_1=b_2), the test follows F distribution with degree of freedom (2,n-4).

to be better modeled with a break point, the null hypothesis of no structural change is rejected at the 1% significance level (Table 5).

Table 5 Chow Test Result of Structural Change in Crop Yield

Crop	Assumed Break Year	Test Value ($F_{0.01}(2,66)=4.942$)
Corn	1973	36.29951
Cotton	1965	23.71622
Wheat	1972	22.88726
Sorghum	1969	72.94017
Barley	1979	16.06635
Oats	1969	13.44144
Hay	1982	73.0562

2.2.2 Test with unknown break date

To test for a slowdown in crop yield growth when the break date is unknown, this study adopts the procedure used in Ben-David and Papell (1998), which was developed to test for slowdowns in postwar GDP growth. The testing procedure includes two steps: 1) test whether the time series possesses a unit-root, the result of which determines the use of different sets of critical value of the test for structural break; 2) test for a structural break.

Ben-David and Papell's (1998) procedure is as follows:

Let T denote the sample size and T_B denote the time of break. Then $T_B \in [\alpha T, \beta T]$, where $[\alpha T, \beta T]$ denotes the interval of possible periods at which the change occurs. α and β are called the trimming parameters and we use the value of 0.25 and 0.75 to correspond the time period during which we search for break point in Section 2.1. Step 1 and 2 involve sequential regression of Equation [1] and [2] respectively.

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

$$y_t = \mu + \theta DU_t + \tau t + \gamma DT_t + \sum_{j=1}^{k} C_j y_{t-j} + \varepsilon_t, \forall t \in [\alpha T, \beta T] \quad [2]$$

[12] The application is facilitated by the fact that no mixed model (half exponential and half linear) appears among our best models.

where in Ben-David and Papell(1998) y_t is the logarithm of GDP per capita and will be replaced with yield in this study, $DU_t = 1, if\ t > T_B$, $0\ otherwise$, $DT_t = t - T_B, if\ t > T_B, 0\ otherwise$ and $D(T_b)_t = 1, if\ t = T_B + 1, 0\ otherwise.$

Essentially, DU_t and DT_t allows a post break shift in the intercept and the slope in the regression which are captured by (θ-γ*TB) and γ respectively. k, the number of lags, 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 by 1. In this study, k_{max} is set at 10.

For Step 1 unit root test, let t-stat denote the minimum, over all possible trend breaks, of the t-statistics on ρ. The null hypothesis (H_0) is that the data follows a unit root process and the alternative (H_1) is the data is stationary. Then H_0 will be rejected if t-stat<critical value at the given significance level. The test is developed in Perron (1994), which also provides the critical value.

For Step 2 structural break test, let $SupF_t$ denote the maximum, over all possible trend breaks, of two times the standard F-statistics for testing θ=γ=0. The null hypothesis (H_0) is that there is no structural break in the data and the alternative (H_1) is there exists a break. The H_0 is rejected if $SupF_t$ > critical value at given significance level. And $TB = \underset{t}{arg}\, SupF_t$ gives the estimation of the break date. The test is developed in Vogelsang(1997), which also provides the critical value.

The result of test assuming the break date is unknown agrees with the Chow-test result (Table 6). All the crops in our study, except soybean, exhibit a slowdown in their yield growth.

Table 6 Test with Unknown Break Date Result of Structural Change in Crop Yield

Crop	Stage1 t-stat	Unit Root	Stage2 $SupF_t$	Break	Year of $SupF_t$	Initial Intercept μ	Intercept Shift θ- γ*TB	Initial Slope T	Slope Shift γ

Soybean	-8.20	No	5.90	No	--	--	--	--	--
Corn	-9.51	No	73.45	Yes	1972	-80.65	51.172	0.043	-0.026
Cotton	-6.79	No	38.13	Yes	1965	-83.40	60.635	0.046	-0.031
Wheat	-6.29	No	21.76	Yes	1968	-77.54	51.278	0.042	-0.026
Sorghum	-6.75	No	27.16	Yes	1966	-102.71	96.249	0.054	-0.049
Barley	-5.54	No	15.72	Yes	1982	-58.34	31.632	0.032	-0.016
Oats	-7.74	No	37.66	Yes	1971	-44.49	33.407	0.025	-0.017
Hay	-6.32	No	20.94	Yes	1982	-22.67	21.772	0.012	-0.011

2.3 Conservative Estimation of the Yield Growth Rates

For the purpose of policy analysis, we also derive a conservative estimation of the estimation of the crop yield growth rate, i.e. a growth rate that can be reached with probability of 0.9. With the break point identified, the time trend function for the period 1940-2009 can be written in the following form:

$$y_t = a_1 + (a_2 - a_1)D_T + \ b_1 t(1 - D_T) + b_2 t D_T \quad [3]$$

$$y_t = a_1 + \ b_1[D_T T_0 + t(1 - D_T)] + b_2(t - T_0)D_T \ [4]$$

Equation [3] and [4] are for the unrestricted and restricted model respectively. y_t is the logarithm of crop yields. T_0 is the break year and $D_T=0$ if $t \le T_0$ and $D_T=1$ if $t>T_0$. b_1 and b_2 are the annual increase of logarithm of yield for the first period and second period respectively. By estimating Equation [3] and [4],we obtain the estimated standard error of b_2 $\hat{\sigma}$. Then based on the delta method, the conservative estimation of crop yield growth rate is

$$ConservativeGrowthRate = \left(e^{\widehat{b_2}} - 1\right) - 1.28\sqrt{\hat{\sigma}^2 \left(\frac{\partial (e^{b_2 - 1})}{\partial b_2}\right)^2} \ [5]$$

The numeric result of the major crops is shown in Table7.

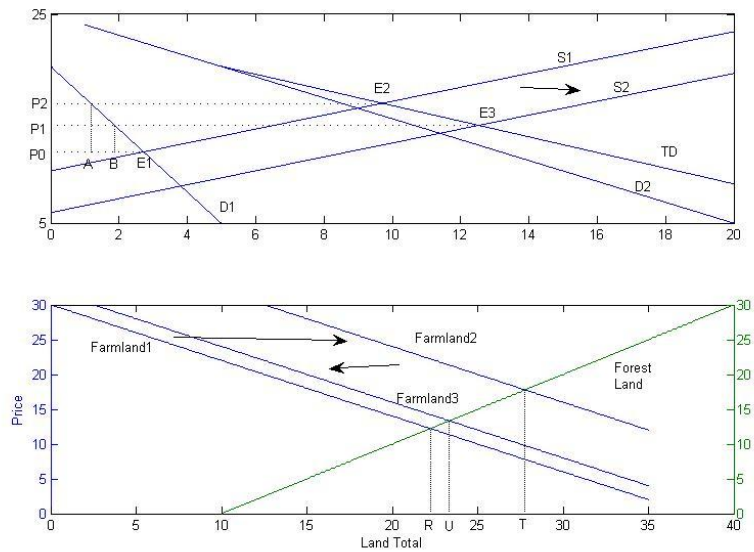
Table 7 the Conservative Estimation of Crop Yield Growth Rate

Crop	Soybean	Corn	Cotton	Wheat	Sorghum	Barley	Oats	Hay
Conservative Estimation	1.22%	1.54%	1.32%	0.8%	0.34%	0.8%	0.5%	0%

3 Exploration of the Policy Implication of Slowdown in Yield

The importance of technology progress can be shown with a simple graphic analysis.

Figure 4 Graphic Analysis of Commodity and Land Market



In Figure 4, the upper panel represents the commodity market and the lower panel represents the land market. The land market representation is adopted from (Mendelsohn and Dinar, 2009). Bioenergy policy exposes positive demand shock while climate mitigation policy exposes negative supply shock to the commodity market. To make the graphical analysis clear, we use a positive demand shock (D2). D1 represents the traditional crop demand; total demand TD is the horizontal sum of D1 and D2. The market equilibrium is E1 without D2. Adding in D2 without increasing supply moves the market equilibrium to E2. Price increases from P0 to P2, traditional demand decrease by AE1. On the land market (lower panel), farmland acreage increases from OR to OT. If at the same time there is increase in supply shifting S1 outwards to S2 to counteract the demand increase, then raise in market price and reduction in traditional demand would be less by P1P2 and AB and conversion of forest land can be avoided by UT. B and U could be on the other side (opposing to A and T) of E1 and R if the shift in supply is large enough; however, the shift required to make BE1 to be zero is very likely to be different than that required to make UT to be zero.

Viewing the process in a dynamic way, then S1 represents supply under current technology in each period and S2 represents the supply with higher yield growth rate induced by technology progress. Furthermore, the distance between S1 and S2 will increase over time; or in other words, S2 is moving away from S1. However, how fast and how far S2 moves in the real world cannot be determined in this highly abstract graphic. And we proceed to quantity the effects with a global agricultural simulation model.

3.1 Models Used

The global agricultural simulation model is the integration of the US FASOM (Forest and Agricultural Sector Optimization Model) and GLOBIOM (Global Biomass Optimization Model). The integrated model is a recursive dynamic, nonlinear programming model of the global forest and agricultural sector. The model is a bottom-up model. It maximizes the sum of producer's profit and consumer surplus of all regions, subject to supply demand balance and a set of resource constraints and technology constraints of each region. This method is essentially based on the First Fundamental Theorem of Welfare Economics (see detailed discussion in McCarl and Spreen (1980)). Its solution is a Pareto Optimal market equilibrium when the market is perfectly competitive. Natural resources (such as land and water) are essential inputs in agriculture. And their allocations are also endogenously determined in the model. Therefore, the model is utilized in our research to assess the international market and environmental impacts of US agricultural policies.

3.2 Scenario setup

We use the projection of Annual Energy Outlook 2009 (AEO) by US Energy Information Administration as our baseline and the Renewable Fuel Standard as our reference policy scenario. The major difference between AEO 2009 and RFS is that the demand for conventional ethanol is 2 billion gallons less each year in the AEO projection. Our simulation period is from 2000 to 2030. We will simulate three technical progress scenarios and see what effect they have with and without the RFS. In addition to the continuation of current (post break point) growth (Current Tech) and the pre break point high growth (Hi Tech) scenarios, we also include the conservative scenario (Low Tech)[13]. The differences of crop yield growth rates across scenarios are substantial: crop yield growth rates in Low Tech are 0.1%~0.2% lower than those under the Current Tech most of which are less than 50% of those in Hi Tech except for soybeans.

3.3 Simulation results

3.3.1 General Results on Price, Production and Welfare

Under the Low Tech and Current Tech scenarios, prices of 6 crops (except for wheat and oats) increase at the beginning of the simulation period. Among them, prices of corn and soybean rise to 3 dollar/bushel and 6 dollar/bushel and return to lower level at 2020 and price of barley shows similar trend but begins to drop earlier. Prices of the rest three crops increase and stay high—at 2030 cotton price is around 35% higher and sorghum and hay are more than double. Under the Hi Tech scenarios, no crop has higher price at 2030 than at the beginning—corn and barley experience price increase in the first period (2000-2010) and their prices drop afterwards;

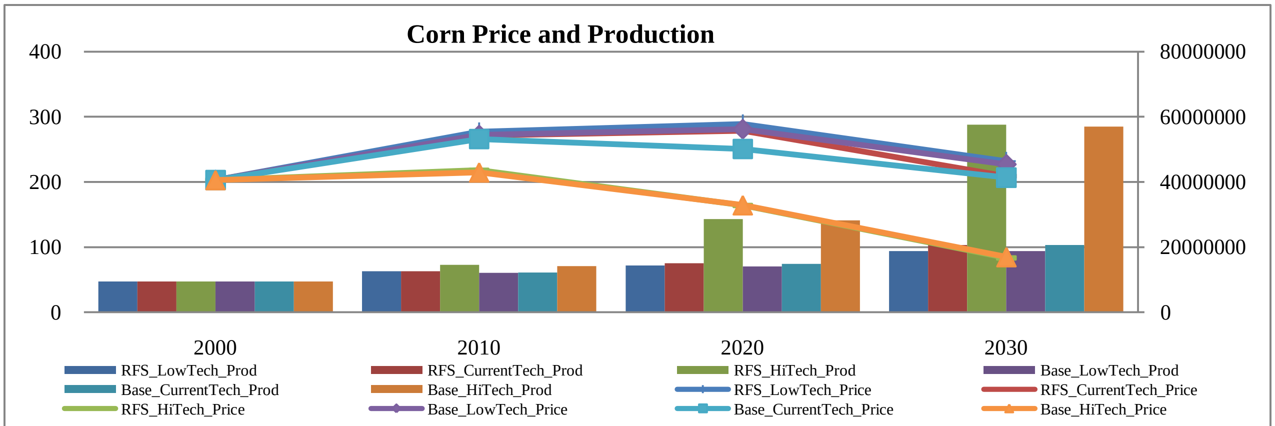
[13] Crop yield growth rates estimated in Section 2 are used for the US, for rest of the world, crop yield rates are set at 0.5% per year.

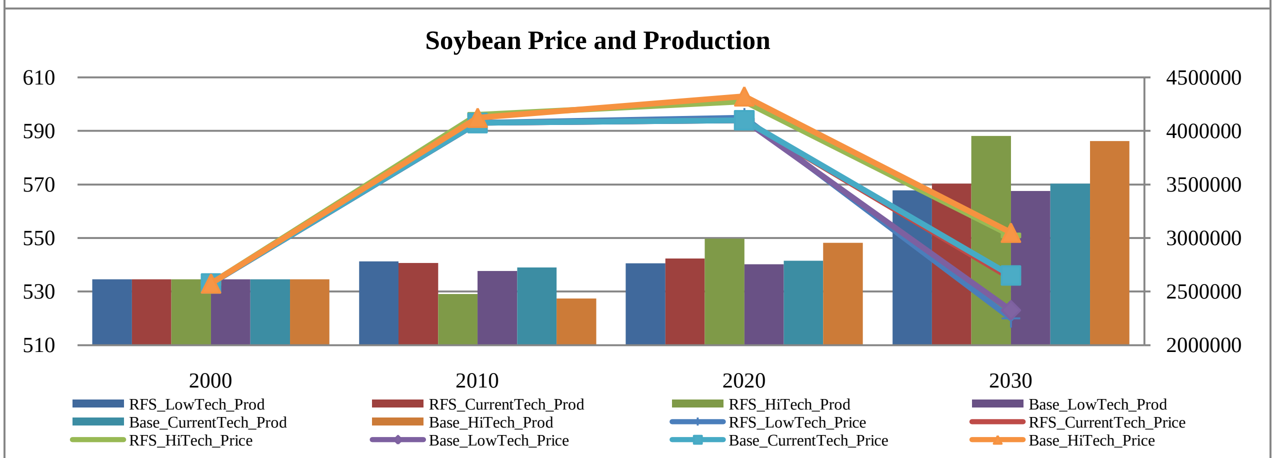
soybean has similar price trend but price does not start to decrease until 2020; rest of the crops show flat or decreasing price trend.

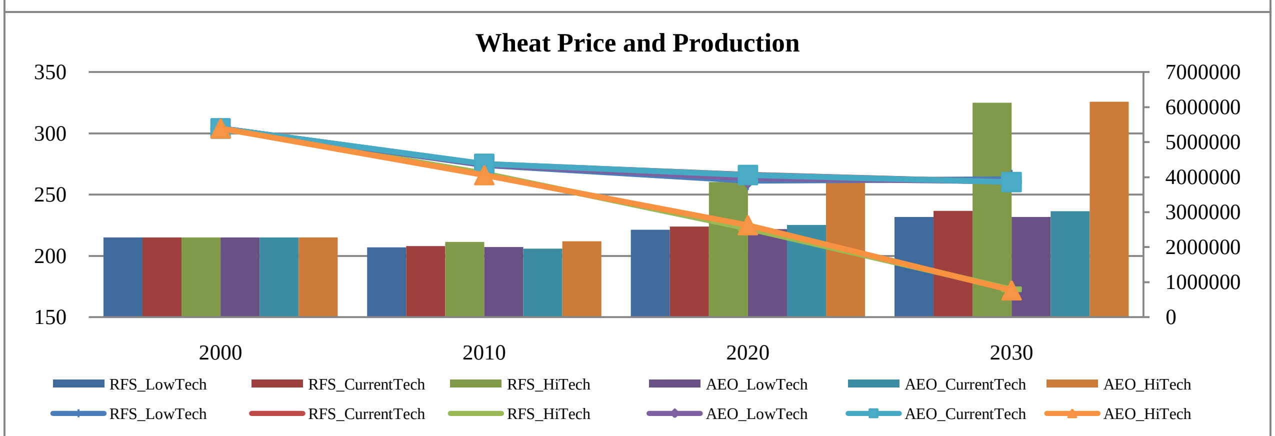
With the same crop yield growth, the RFS policy causes crop price to be higher (except for soybean). Especially, with Current Tech, high corn price persists longer—price starts to decline after 2010 without the policy but does not decline until 2020 with the policy.

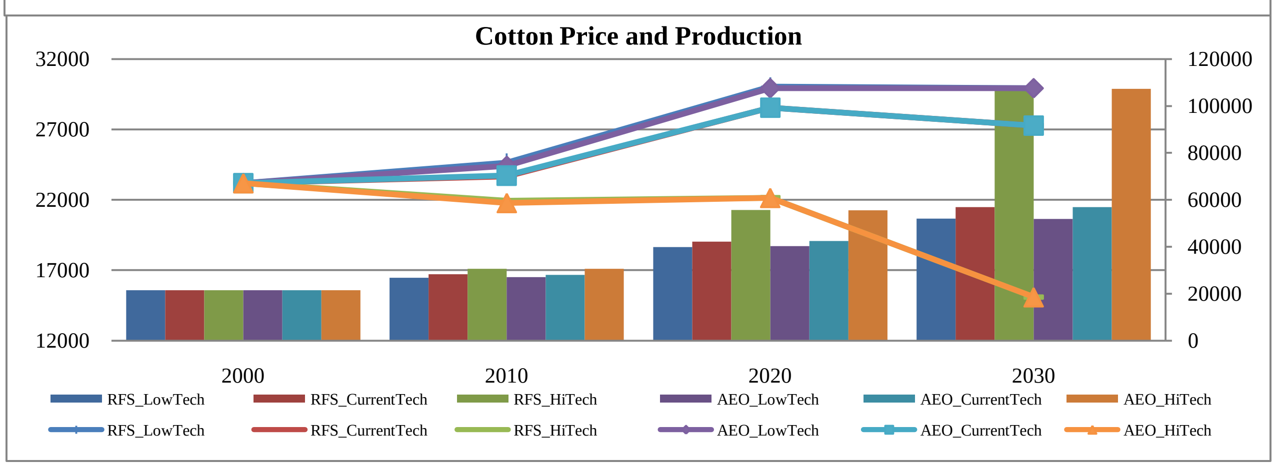
Production consistently increases with higher yield growth rates. Differences in corn production quantities widens with time. With Low Tech, annual production doubles from 9 billion bushels to 18 billion bushels. With Current Tech, annual production will be more than 20 billion bushels by the year 2030. Production in Hi Tech scenario is almost double as that in Current Tech scenario in 2020 and triple in 2030. Production of other crops show diverse tendencies for the period 2010- soybean and sorghum increase only in the Hi Tech scenarios, wheat, barley and hay decrease slightly, and the rest increase. For the further future, production generally increases with time.

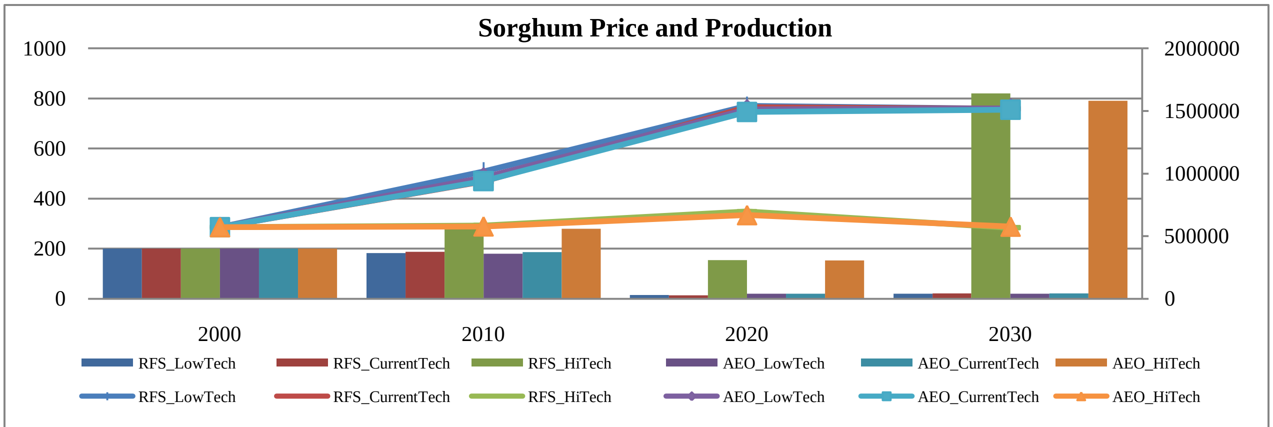
Figure 5 Equilibrium Price and Production of Corn, Soybean, Wheat and Other Crops in the US

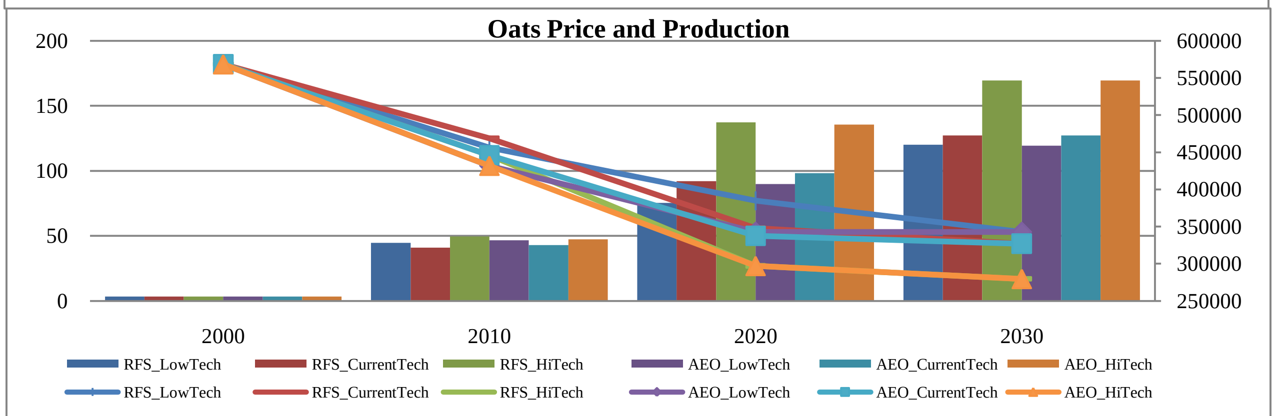

Corn Price and Production
400
300
200
100
0
80000000
60000000
40000000
20000000
0
2000
2010
2020
2030
RFS_LowTech_Prod
RFS_CurrentTech_Prod
RFS_HiTech_Prod
Base_LowTech_Prod
Base_CurrentTech_Prod
Base_HiTech_Prod
RFS_LowTech_Price
RFS_CurrentTech_Price
RFS_HiTech_Price
Base_LowTech_Price
Base_CurrentTech_Price
Base_HiTech_Price

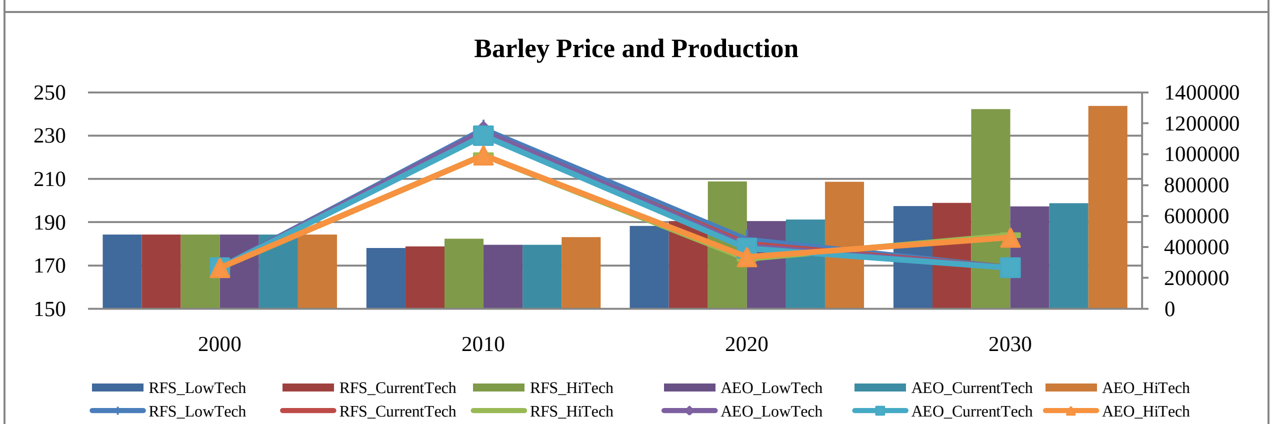

Soybean Price and Production
610
590
570
550
530
510
4500000
4000000
3500000
3000000
2500000
2000000
2000
2010
2020
2030
RFS_LowTech_Prod
RFS_CurrentTech_Prod
RFS_HiTech_Prod
Base_LowTech_Prod
Base_CurrentTech_Prod
Base_HiTech_Prod
RFS_LowTech_Price
RFS_CurrentTech_Price
RFS_HiTech_Price
Base_LowTech_Price
Base_CurrentTech_Price
Base_HiTech_Price

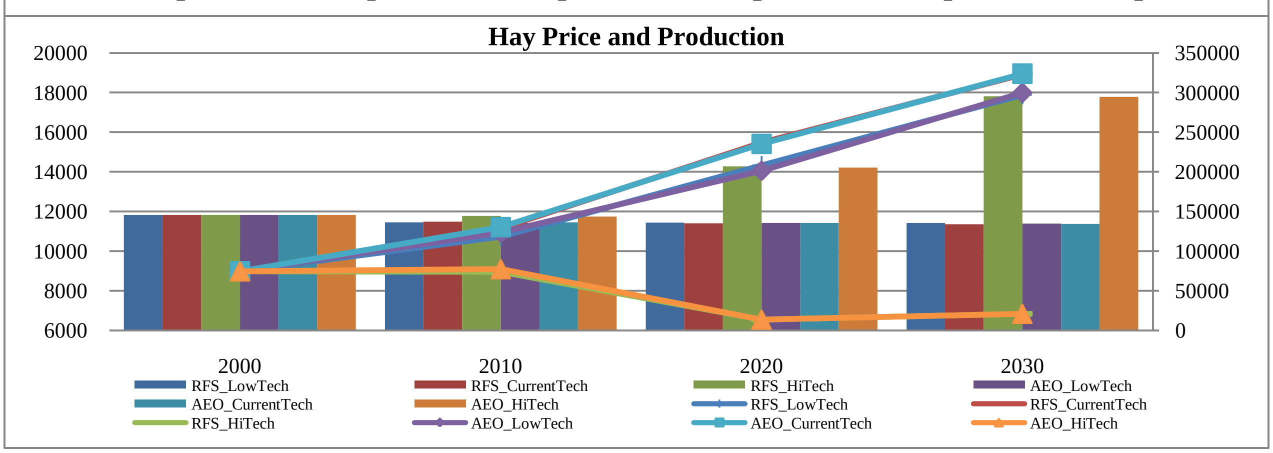

Wheat Price and Production
350
300
250
200
150
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
2000
2010
2020
2030
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech


Cotton Price and Production
32000
27000
22000
17000
12000
120000
100000
80000
60000
40000
20000
0
2000
2010
2020
2030
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech


Sorghum Price and Production
1000
800
600
400
200
0
2000000
1500000
1000000
500000
0
2000
2010
2020
2030
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech


Oats Price and Production
200
150
100
50
0
600000
550000
500000
450000
400000
350000
300000
250000
2000
2010
2020
2030
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech


Barley Price and Production
250
230
210
190
170
150
1400000
1200000
1000000
800000
600000
400000
200000
0
2000
2010
2020
2030
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech


Hay Price and Production
20000
18000
16000
14000
12000
10000
8000
6000
350000
300000
250000
200000
150000
100000
50000
0
2000
2010
2020
2030
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech
RFS_LowTech
RFS_CurrentTech
RFS_HiTech
AEO_LowTech
AEO_CurrentTech
AEO_HiTech

Total US domestic welfare shows 70 billion loss if crop yields were growing at the conservative rates and over 300 billion gain if crop yields were resumed to historical high (Table 9) over the whole simulation period. This holds with and without the RFS policy. RFS policy will result in minor gains for the US.

Result on rest of the world tells similar story: prices decrease with higher US crop yield growth rates and they are higher with RFS than without the policy. Total welfare is also higher under the with policy scenarios (Table 8).

Table 8 Total US Agricultural Sector Welfare (In Billion US Dollar)

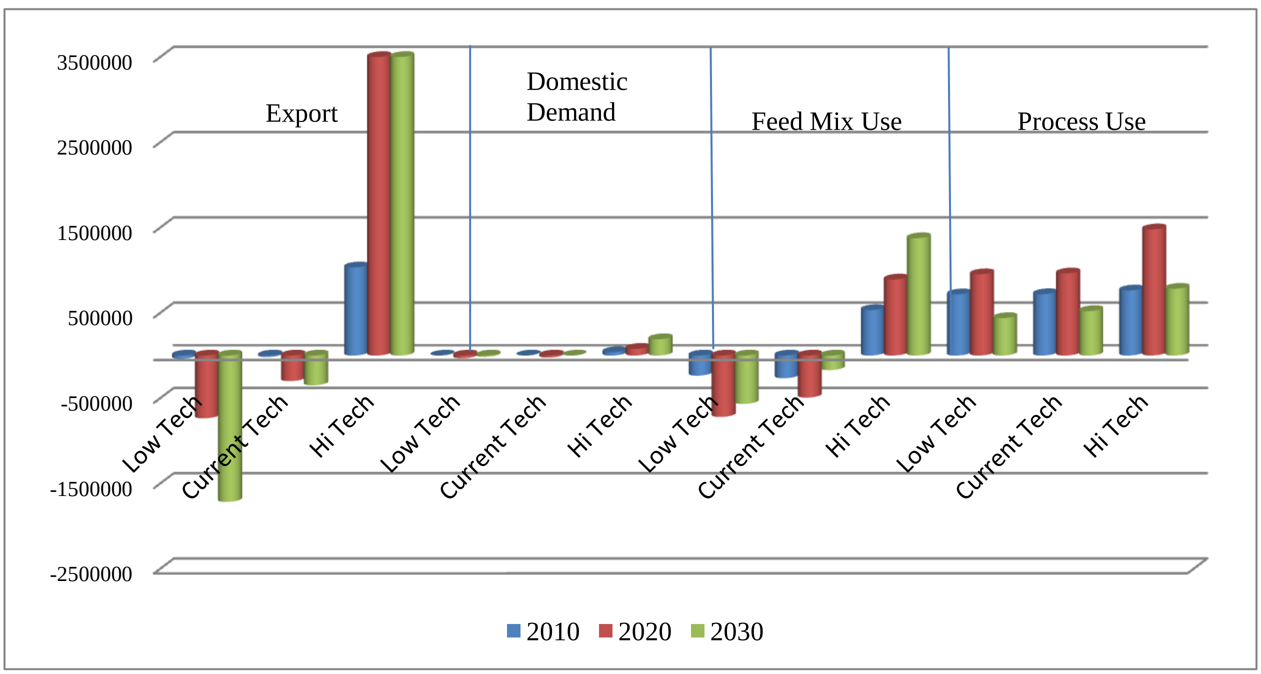
			Total			Difference from Current Tech Scenario			Difference from CurrentTech_Baseline		
			2010	2020	2030	2010	2020	2030	2010	2020	2030
World Total	Baseline	Low Tech	36560.1	40333.5	43099.8	-0.2	-21.4	-60.0			
		Current Tech	36560.3	40354.9	43159.8						
		Hi Tech	36568.3	40447.6	43427.8	7.9	92.6	268.1			
	RFS	Low Tech	36561.7	40337.0	43103.8	-0.3	-21.7	-60.1	1.4	-17.9	-55.9
		Current Tech	36562.0	40358.7	43163.9				1.7	3.8	4.2
		Hi Tech	36570.3	40452.4	43432.6	8.3	93.7	268.7	9.9	97.5	272.8
US	Baseline	Low Tech	1636.1	1860.7	2068.9	0.5	-16.8	-53.5			
		Current Tech	1635.6	1877.5	2122.4						
		Hi Tech	1641.8	1961	2355.6	6.2	83.5	233.2			
	RFS	Low Tech	1637.1	1863.5	2072.9	0.5	-17.6	-53.6	1.5	-14.0	-49.5
		Current Tech	1636.6	1881.1	2126.5				1.0	3.6	4.1
		Hi Tech	1643	1965.6	2359.6	6.4	84.5	233.1	7.4	88.1	237.2
Rest of the World	Baseline	Low Tech	34924.0	38472.8	41030.9	-0.7	-4.6	-6.5			
		Current Tech	34924.7	38477.4	41037.4						
		Hi Tech	34926.5	38486.6	41072.2	1.7	9.1	34.9			
	RFS	Low Tech	34924.6	38473.5	41030.9	-0.8	-4.1	-6.5	-0.1	-3.9	-6.4
		Current Tech	34925.4	38477.6	41037.4				0.7	0.2	0.1
		Hi Tech	34927.3	38486.8	41073.0	1.9	9.2	35.6	2.5	9.4	35.6

3.3.2 What would be improved when yield growth were high

3.3.2.1 In the Market

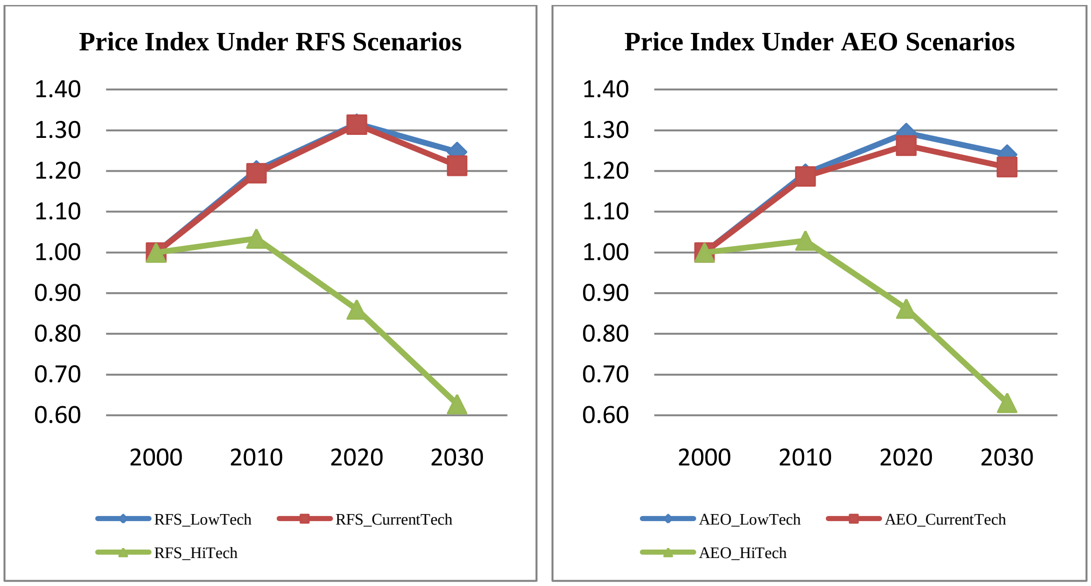
Were yield growing fast, the sudden increase in demand caused by the RFS policy would be met by gain in yield growth without diverting corn for other purposes. Our results show that this would not happen if crops continue to grow at their current rates. Figure 6 shows the differences in corn usage for different purposes between the RFS_Low Tech, RFS_Current Tech, RFS_Hi Tech and the Baseline_Current Tech scenarios. Under the Low Tech and Current Tech scenarios, the implementation of RFS decreases corn quantity for feed mix use and export use and increases process use (which includes making ethanol); while under the Hi Tech scenario, corn for all usages are higher under the RFS scenario.

Figure 6 Difference in Categories of Corn Demand in US (RFS- AEO) in Thousand Bushels



The Fisher price index for the US composed of the eight crops is shown in Figure 7. The RFS does cause prices to be higher but the effects do not last long. Price increase caused by demand shock can be mitigated by increase in supply.

Figure 7 US Crop Price Index under Alternative Yield Scenarios 2000-2030



That crop usage in consumption and feed-mix decreases with RFS in place under current yield growth rates happens not only in the US but in rest of the world as well (Table 9). If crop yields were growing at the historical high level, excess supply from the US would increase even with RFS compared to the Current Tech_Baseline scenario. Price changes resemble that in the US but the magnitude is much smaller.

Table 9 Demand and Feed-mix Use of Selected Crops in Rest of the World

(With policy scenarios minus Baseline under Current Tech in thousand tones)

		Demand			Feedmix		
		2010	2020	2030	2010	2020	2030
Corn	Low Tech	-209.8	-1090.4	-1804.7	-1249.4	-4628.6	-28269.7
	Current Tech	-71.3	-634.0	-17.5	-776.2	-622.9	-3995.5
	Hi Tech	822.6	5420.8	11728.1	10200.2	186120.9	550363.6
Soybean	Low Tech	1.2	2.4	401.1	-953.6	-3134.2	-15218.8
	Current Tech	0.0	7.0	47.4	-451.0	-794.3	-5528.2

	Hi Tech	-137.1	-238.6	-869.3	4994.8	40402.0	95538.1
Wheat	Low Tech	-48.5	-59.2	-1061.9	-323.2	-2623.0	-2007.0
	Current Tech	0.0	-6.1	-71.9	-178.0	-668.5	-231.3
	Hi Tech	80.5	1793.0	1443.8	2262.5	32460.6	93432.7

3.3.2.2 Leakage

Under Current Tech Scenario, the RFS policy causes total cropland acreage in rest of the world to increase by 2555 thousand hectares, which come from conversion of grassland, natural land and deforestation. If crop yield growth rates were resumed to historical rates, more than 95% of the deforestation would be avoided. Leakage in the form of natural land reversion is negative.

(Thousand Ha)	2010	2020	2030	Total
CurrentTech_RFS-CurrentTech_AEO				
Cropland Increase	254.4	2065.4	236.0	2555.7
Grassland Increase	-21.8	-574.9	-777.1	-1373.9
Plantatation Forest Increase	3.3	1.5	-55.6	-50.8
Primary Forest Decrease	128.3	682.7	-159.6	651.3
Natural Land Decrease	126.5	806.0	-427.4	505.1
HiTech_RFS-CurrentTech_AEO				
Cropland Increase	-1519.7	-19020.0	5216.6	-15323.2
Grassland Increase	20.2	1520.7	5568.2	7109.2
Plantatation Forest Increase	157.3	-131.7	-66.8	-41.2
Primary Forest Decrease	-1671.9	-2903.7	4615.4	39.8
Natural Land Decrease	-13.1	-14689.4	6763.7	-7938.8

3.3.3 What would be cost of the high yield growth

We have examined what policy impacts in the market and on the environment would be if crop yield growth rates were resumed to its historical high level. And our results suggest consumer would gain from the higher growth rates and leakage would be much less. However, this alternative set of yield growth rates are not proportional increase of the current rates for different crops and therefore regional comparative advantages are different under alternative yield growth scenarios. Notably under the Hi_Tech scenarios soybean is relatively more expensive to produce in the US and its soybean acreage is smaller. World supply of soybean comes more from South America region and deforestation with the region exacerbates (Table 10).

Table 10 Deforestation in Brazil and Rest of South America

(HiTech_RFS minus CurrentTech_RFS in thousand Hectares)

Brazil	
cropland net increase	5229.654
grassland net increase	-781.391
natural land net decrease	1584.505
plantation forest net increase	-7.73706
primary forest net decrease	2856.022
Rest of South America	
cropland net increase	5209.138
grassland net increase	-141.042
natural land net decrease	1724.695
plantation forest net increase	-269.953
primary forest net decrease	3073.447

Production reallocation may also cause producers in certain regions to incur losses with higher yield growth. In the US, such regions include Lake States, and Western US. Their losses can be higher than 50% from Current Tech to Hi Tech (Table 11).

Table 11 Regional Producers' Surplus under RFS (million dollars)

Regions that gain with increase in crop yield growth					Regions that lose with increase in crop yield growth				
		2010	2020	2030			2010	2020	2030
Corn belt	Low Tech	7426.2	20910.3	21774.9	Lake states	Low Tech	2201.7	6297.1	7699.1
Corn belt	Current Tech	7457.7	21629.3	21977.9	Lake states	Current Tech	2286.5	6391.7	7994.5
Corn belt	Hi Tech	6272.9	22393.0	24101.9	Lake states	Hi Tech	1708.5	4769.9	5849.8
Plains	Low Tech	2461.9	18898.4	21953.2	Western US	Low Tech	2034.9	5435.0	8665.5
Plains	Current Tech	2225.4	19771.4	23101.5	Western US	Current Tech	2044.8	5608.5	8659.9
Plains	Hi Tech	1935.5	72136.7	199960.4	Western US	Hi Tech	1768.0	3169.2	3549.3
Southern US	Low Tech	1706.6	7935.2	9669.3					
Southern US	Current Tech	1749.3	7812.1	9225.6					
Southern US	Hi Tech	1843.2	14572.2	33083.2					
North East	Low Tech	272.7	364.6	375.7					

North East	Current Tech	271.9	364.6	364.7				
North East	Hi Tech	290.7	510.6	811.6				
Grand Total	Low Tech	11867.4	48108.5	53773.1	Low Tech	4236.6	11732.1	16364.6
	Current Tech	11704.4	49577.4	54669.6	Current Tech	4331.3	12000.2	16654.4
	Hi Tech	10342.3	109612.5	257957.1	Hi Tech	3476.5	7939.1	9399.1

4 Conclusion

This paper has examined the yield growth trend of 8 major US crops and found that all but soybeans has experienced slowdown during the period of late 1960s to early 1980s. In particular corn has fallen from 3.67% to 1.75%. We further test statistically whether there was structural break to the yield growth. And the test result agrees with our estimation.

We use the estimation results to investigate the international effect of the US bioenergy policy (the Reusable Fuel Standard) under alternative yield scenarios. The policy has been subject to criticism as it competes with traditional demand and entails high price and undesirable environmental consequences, notably land use changes. We have found that if US crop yield growth rates were resumed to the historical high level, policy shocks could be largely smoothed out. If US crop grows at the current rate, the bioenergy policy causes reallocation of corn usage in the domestic market -- corn use for domestic feed mix reduce by 0.3 million bushel in 2010 and 0.5 million bushel in 2020 and they are the biggest reduction among all the usages. The policy also causes high prices to persist longer. Under the Current_Tech scenario, the policy causes cropland increase in rest of world by 2.6 million hectares—0.65 and 0.5 million hectares come from deforestation and come from natural land reversion and the rest half come from grassland.

If crop yield growth rates were resumed to historical high level in the US, new demand from bioenergy would be met without decreasing crop usage for other purposes. Furthermore, 95% of the deforestation would be avoided and leakage in the form of natural land reversion would be negative. Although the historical high level of crop yield growth rate leads to higher welfare and less undesirable land use change, it does not represent a parallel out shifting of the production frontier and thus changes comparative advantages and relative prices among crops resulting in producers of certain regions to lose and increase of forest clearance in specific regions.

Reference

Alston, J. M., J. M. Beddow, and P. G. Pardey. "Agricultural Research, Productivity, and Food Prices in the Long Run." *Science* 325, no. 5945(2009): 1209-1210.

Arizen, M. A., L. A. Garibaldi, S. A. Cunningham, and A. M. Klein. "Long-Term Global Trends in Crop Yield and Production Reveal No Current Pollination Shortage but Increasing Pollinator Dependency." *Current Biology* 18, no. 20(2008): 1572-1575.

Baker, J. S., B. A. McCarl, B. C. Murray, S. K. Rose, R. J. Alig, D. Adams, G. Latta, R. Beach, and A. Daigneault. "Net Farm Income and Land Use under a U.S. Greenhouse Gas Cap and Trade." *Policy Issues* (April 2010): 17.

Ben-David, D., and D. H. Papell. "Slowdowns and Meltdowns: Postwar Growth Evidence from 74 Countries." *The Review of Economics and Statistics* 80, no. 4(1998): 561-571.

Brockwell, P. J., and R. A. Davis. *Introduction to Time Series and Forecasting*: Taylor & Francis, 2002.

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. "Land Clearing and the Biofuel Carbon Debt." *Science* 319, no. 5867(2008): 1235-1238.

Food and Agriculture Organization of the United Nations (2008) The State of Food Insecurity in the World 2008. Rome, Italy.

Hansen, B. E. "The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity." *The Journal of Economic Perspectives* 15, no. 4(2001): 117-128.

IPCC (2007) Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, ed. S. Solomon, et al. Cambridge, United Kingdom and New York, NY, USA, Cambridge University Press.

Keeney, R., and T. W. Hertel. "The Indirect Land Use Impacts of United States Biofuel Policies: The Importance of Acreage, Yield, and Bilateral Trade Responses." *American Journal of Agricultural Economics* 91, no. 4(2009): 895-909.

Maddala, G. S., and I.-M. Kim. *Unit Roots, Cointegration, and Structural Change*. themes in modern econometrics. Cambridge, United Kingdom: Cambridge University Press, 1998.

McCarl, B.A. and T.H. Spreen. *Applied Mathematical Programming Using Algebraic Systems*. 2007.Book released through Web at http://agecon2.tamu.edu/people/faculty/mccarl-bruce/mccspr/newb.pdf.

Melillo, J. M., J. M. Reilly, D. W. Kicklinghter, A. C. Gurgel, T. W. Cronin, S. Paltsev, B. S. Felzer, X. Wang, A. P. Sokolov, and C. A. Schlosser. "Indirect Emissions from Biofuels: How Important?" *Science* 326, no. 5958(2009): 1397-1399.

Mendelsohn, R., and A. Dinar. "Land Use and Climate Change Interactions." *The Annual Review of Resource economics* 1, no. 2009(2009): 309-32.

Murray, B. C., B. A. McCarl, and H.-C. Lee. "Estimating Leakage from Forest Carbon Sequestration Programs " *Land Economics* 80, no. 1(2004): 109-124.

Perron, P. (1994) Further Evidence on Breaking Trend Functions in Macroeconomic Variables, University of Mnotreal.

Schneider, U. A., and B. A. McCarl. "Appraising Agricultural Greenhouse Gas Mitigation Potentials: Effect of Alternative Assumptions." *Agricultural Economics* 35(2006): 277-287.

Searchinger, T., R. Heimilich, R. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T. Yu. "Use of U.S. Croplands for Biofuels Increases Greenhouse Gases through Emissions from Land-Use Change." *Science* 319, no. 5867(2008): 1238-1240.

Trostle, R. (2008) Fluctuating Food Commodity Prices: A Complex Issue With No Easy Answers, ed. U. S. D. o. Agriculture. Washington D.C.

Villavicencio, X. A. "Essays on the Effect of Climate Change on Agriculture and Forestry." Texas A&M University, 2010.

Vogelsang, T. J. "Wald-Type Tests for Detecting Breaks in the Trend Function of a Dynamic Time Series." *Econometric Theory* 13, no. 6(1997): 818-849.