

US Maize Yield Growth Implications for Ethanol and Greenhouse Gas Emissions

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During the past half century, per-acre maize yields have increased due to improved cultivars, better management, and favorable weather. Recent US biofuel legislation, e.g., revised Renewable Fuel Standard, has increased the demand for biofuel and added competition for available cropland. Growth in maize yield may alleviate the potential impacts, including greenhouse gas effects, of rising food, feed, and fuel demand. Using 1960-2009 maize yields for the United States and top maize-producing states, we test for structural breaks and develop yield trend and growth forecasts for 2030. Depending on the forecasting model, US maize yield ranges from 205 to 242 bushels per acre in 2030. Holding maize production constant at the 2009 level, 16-25 million acres could be shifted to other crop production. Maize yield forecasts are sensitive to model choice (linear trend vs. growth rate) and time period (short- vs. long-run trends). Ultimately, maize yield growth and trends have important impacts on greenhouse gas emissions.

Key words: biofuel, cropland use, greenhouse gas emissions, maize yield growth rates, maize yield trends, nitrogen use, structural breaks.

Introduction

Growing concerns about greenhouse gas (GHG) emissions from maize ethanol production have recently been manifested in the 2007 Energy Independence and Security Act (EISA) through the revised Renewable Fuels Standard (RFS2). Maize ethanol from new plants must reduce life-cycle GHG emissions by 20% and cellulosic ethanol by 60% relative to the life-cycle GHG emissions from 2005 conventional fuel. Further, the cellulosic biofuel mandate increases demand for biofuel feedstock and cropland on which the feedstock is produced. Increased competition for cropland between food, feed, and biofuel feedstock will increase commodity prices and ultimately food prices faced by consumers (Alexander & Hurt, 2007; Babcock & Fabiosa, 2011; Hayes et al., 2009; Rathmann, Szklo, & Schaeffer, 2010; Tokgoz et al., 2007). Significant shifts in land allocation or agricultural production practices (e.g., tillage, rotations) driven by increased food, feed, and biofuel demand could result in adverse GHG effects. Yet, actual land-use change and market adjustments are highly uncertain. A major determinant of biofuel market impacts will be technological progress in biofuel and commodity crop production, especially maize production. Improved technology in commodity crop production (e.g., yield growth) will help alleviate potential market impacts of meeting biofuel mandates even if food and feed demand continue to increase. Likewise, improved efficiency in input use, such as nitrogen fertilizer input, could further

reduce GHG emissions associated with maize ethanol production.

During the past half century, per-acre maize yield has experienced a continuous and substantial increase. US maize yield increases have been attributed to breeding of improved cultivars, better crop management practices, and favorable weather conditions (Crosbie et al., 2006; Tannura, Irwin, & Good, 2008a, 2008b). If maize yields continue to increase at a higher trend or growth rate, the impact of increasing feedstock demand on commodity market prices will be decreased. First, less acreage will be needed to satisfy food and feed demand with higher maize yields, thus freeing land for dedicated biofuel crop production (i.e., perennial crops) or expanded commodity crop production. Second, higher maize yields provide higher stover yields, increasing the quantity of sustainably harvestable stover for biofuel.

Most efforts to model the impacts of biofuel expansion rely on long-run trend yields for major commodity crops that may underestimate future production and overestimate future commodity prices and GHG impacts. We take a closer look at US and state-level maize yield increases in both the short- and long-run based on statistically identified structural breaks. We use both linear trend and autoregressive growth models, and if statistically appropriate, fit short- and long-run models to forecast future US aggregate and state-level maize yields. Although US yield forecasts provide a useful approximation of future US maize yields, US

Table 1. 2009 US and top maize-producing states' production.

State	2009 maize production (thousand bushels)	% of 2009 US production
United States	13,110,062	100
Iowa	2,438,800	18.6
Illinois	2,053,200	15.66
Nebraska	1,575,300	12.02
Minnesota	1,244,100	9.49
Indiana	933,660	7.12
South Dakota	706,680	5.39
Kansas	598,300	4.56
Ohio	546,360	4.17
Wisconsin	448,290	3.42
Missouri	446,760	3.41
Michigan	309,320	2.36
Texas	254,800	1.94
North Dakota	200,100	1.53
Kentucky	189,750	1.45
Colorado	151,470	1.16
Pennsylvania	131,560	1

Source: http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats_1.0/

average yields are based on total production over total acreage. Considering maize yield trends and growth rates at the state level for the major maize-producing states provides a more in-depth and disaggregated picture of yield trends and growth rates. Some states may be early adopters of new maize technology and have a disproportionate impact on future US average yields. Other states may have lower maize productivity and lower opportunity cost cropland, thus dedicated biomass crops may compete more effectively for cropland if the local climatic conditions are appropriate. State-level yield forecasts may provide important insights into yield increase patterns, implications for future cropland uses, and GHG emission impacts relative to aggregate US analyses.

US maize production and acreage data for 1960-2009 from the National Agricultural Statistics Service (NASS) are used for this analysis. In addition to aggregate US data, the 16 top maize-producing states (TMPS), each with more than 1% of the 2009 US production (Table 1), are included. US and state data are first used to test for structural breaks in yield trends and growth rates. Based on statistical tests for linear-trend structural breaks, we identify the US and state short- and long-run maize yield trends and use these models to forecast yields to 2030. The same procedure is used to

identify yield growth structural breaks within autoregressive models and forecast short- and long-run yield growth to 2030.

Next, we calculate the amount of maize cropland needed with 2030 yield forecasts to produce the 2009 maize crop. Depending on the yield forecast used, 16 to 25 million fewer maize acres will be needed to produce the 2009 maize crop in 2030. Finally, we combine the 2030 yield forecasts with state nitrogen (N) use forecasts to estimate nitrogen-use savings from producing the 2009 maize crop on 2030 acreage. The N-use savings are converted to potential GHG savings and provide a lower-bound GHG savings based only on forecasted N use to produce the 2009 maize crop under 2030 production conditions (e.g., yield, acreage, N efficiency).

Maize Yield Models

To identify historical per-acre maize yield patterns, we consider two model specifications: a linear trend (LT) model and an autoregressive (AR) model. Reilly and Fuglie (1998) analyzed yield trends for 11 major crops in the United States for the 1939-1994 period in order to detect evidence of a yield plateau based on the assumption that yield growth is linear and the assumption that yield growth is a constant average exponential rate. Unlike models that incorporate additional factors such as climate and soil characteristics and therefore require explicit specification of relationships between these factors and yield (Deschenes & Greenstone, 2007; Huang & Khanna, 2010; Schlenker & Roberts, 2006, 2009), the LT model and AR model require little information to forecast yield increases. Greene (2008) notes that a simple model describing the behavior of a variable in terms of past values (e.g., AR model)—without the benefit of a well-developed theory—may prove quite satisfactory for forecasting purposes. We describe the theoretical foundation and underlying assumptions for the LT and AR models and then fit both models using 1960-2009 maize yield data (bushels/acre) for the entire United States and 16 TMPS.

Linear Trend Model

The LT model is a linear regression of yield (y) on time (t), which can be written as

$$y_t = \alpha_{LT} + \beta_{LT}t + \varepsilon_{t,LT}, \quad (1)$$

where α_{LT} is the intercept parameter, β_{LT} is the (slope) coefficient of time, and $\varepsilon_{t,LT}$ is a mean zero error term.

Table 2. AR model optimal and model lag length.

State	Optimal lag length		Modeled
	AIC	BIC	
United States	4	4	4
Iowa	4	4	4
Illinois	4	4	4
Nebraska	2	2	2
Minnesota	7	4	4
Indiana	8	4	4
South Dakota	4	1	4
Kansas	3	1	3
Ohio	5	5	5
Wisconsin	4	2	4
Missouri	7	5	5
Michigan	3	3	3
Texas	3	1	3
North Dakota	3	2	3
Kentucky	4	4	4
Colorado	1	1	1
Pennsylvania	7	2	2

Taking the first difference from Equation 1, it is easy to show that the LT model assumes a constant expected yield increment over time (β_{LT}).

$$E(y_t - y_{t-1}) = E(\alpha_{LT} + \beta_{LT}t + \varepsilon_{t,LT}) - E[\alpha_{LT} + \beta_{LT}(t-1) + \varepsilon_{t-1,LT}] = \beta_{LT} \quad (2)$$

The expected yield increment over time is our parameter of interest and, given annual data, β_{LT} can be interpreted as the annual yield trend (bushels/acre/year).

Autoregressive Model

The autoregressive (AR) model estimates the rate of yield increase as a function of its past values. The general form for an AR(p) model, where the dependent variable is a function of its past p values, can be written as

$$dly_t = \alpha_{AR} + \sum_{k=1}^p \beta_{k,AR} dly_{t-k} + \varepsilon_{t,AR}, \quad \varepsilon_{t,AR} \sim i.i.d.N(0, \sigma^2), \quad (3)$$

where dly_t is the difference in log yield over time [i.e., $dly_t = \ln(y_t) - \ln(y_{t-1})$], α_{AR} is the intercept parameter, $\beta_{k,AR}$ is the coefficient for the k^{th} previous value, and $\varepsilon_{t,AR}$ is a mean zero error term. Fitting an AR model using dly_t (a measure of the percentage change in per

acre yield) instead of y_t avoids the issue of “random walk versus structural change” when testing for structural breaks (Hansen, 2001). Taking the expectation of Equation 3 and assuming the process is covariance-stationary with mean value μ [i.e., the mean of annual yield increase rates is constant over time at $\mu = E(dly_t) = E(dly_{t-k})$], we obtain

$$E(dly_t) = E(\alpha_{AR} + \sum_{k=1}^p \beta_{k,AR} dly_{t-k} + \varepsilon_{t,AR})$$

$$\mu = \alpha_{AR} + \sum_{k=1}^p \beta_{k,AR} \mu, \text{ where } \mu = E(dly_t) = E(dly_{t-k})$$

$$\alpha_{AR} = \mu \{1 - \sum_{k=1}^p \beta_{k,AR}\}. \quad (4)$$

Substituting Equation 4 into Equation 3 and rearranging, the AR model becomes

$$dly_t = \mu + \sum_{k=1}^p \beta_{k,AR} \{dly_{t-k} - \mu\} + \varepsilon_{t,AR}, \quad \varepsilon_{t,AR} \sim i.i.d.N(0, \sigma^2). \quad (5)$$

Unlike the LT model, which assumes a constant expected annual yield *increment*, the covariance-stationary AR model assumes a constant expected annual yield *growth rate* (μ).

Optimal lag length (p) is determined by the lag length that minimizes the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Table 2 lists the optimal lag length for the United States and each state for both the AIC and BIC. Both criteria identified an optimal lag length of 4 for the aggregate US yield data. For states where the AIC and BIC do not agree on the optimal lag length, we use the lag length closest to the US optimal lag of 4. For example, the AIC and BIC identified an optimal lag length of 4 and 1 for South Dakota, respectively, and therefore the lag length used for South Dakota was 4.

Testing for Structural Breaks

Given advances in technology over the past half-century, we formally test the dataset for structural breaks over that period. We evaluate whether the estimated LT model parameters (yield trend) and AR model parameters (yield growth) are significantly different when estimated on subsets of the data. For the LT model, we use the method outlined in Greene (2008) for testing structural breaks in linear regression models with unequal variances. For the AR model, we follow the method used by McConnell and Perez-Quiros (2000) to analyze structural breaks in an AR(1) model of US GDP

Table 3. US and top maize-producing states' long- and short-run linear trend periods.

State	Long-run	Short-run
United States	1970-2009*	--
Iowa	1970-2009^	1995-2009
Illinois	1970-2009	1995-2009*
Nebraska	1974-2009*	1995-2009*
Minnesota	1974-2009*	1988-2009**
Indiana	1970-2009	--
South Dakota	1977-2009	1994-2009*
Kansas	1987-2009	2000-2009**
Ohio	1970-2009	--
Wisconsin	1970-2009^	--
Missouri	1970-2009	--
Michigan	1970-2009	--
Texas	1971-2009	--
North Dakota	1973-2009*	1998-2009*
Kentucky	1970-2009	--
Colorado	1971-2009	1992-2009
Pennsylvania	1970-2009	--

Note: ^ denotes states where the 1970 break was also identified within the state-level analysis

* denotes significance only at the 5%; ** denotes significance only at 10%

between 1953 and 1999. For a range of potential break dates, McConnell and Perez-Quiros (2000) and Dejong, Liesenfeld, and Richard (2003) assume the smallest dataset should contain at least 15% of the observations in the dataset. Using this rule of thumb with our dataset of 49 data points (1960-2009), the minimum sub-dataset to test for structural breaks consists of seven data points. We use this restriction when testing for structural breaks in the LT and AR(1) models, resulting in testing for structural breaks between 1967 and 2002. For any AR(*p*) model with *p* greater than 1, we increase the minimum data points by (*p*-1). For example, the optimal autoregressive model using US yields is an AR(4) model, and therefore we test for structural breaks between 1970 and 1999.

To find the most recent structural break and identify the “short-run” trend, we use the following break identification process. In the first round, we test for structural breaks within the complete dataset (1960-2009). For each τ in {1967, 1969, ..., 2002}, we test for significant parameter differences between the data subset 1960-(τ -1) and the data subset τ -2009 (i.e., 1960-1966 vs. 1967-2009; 1960-1967 vs. 1968-2009; etc.).¹ The value of τ that yields the largest Wald statistic provides evidence of a structural break (denoted as τ^*) and is

compared to the Andrews (1993) critical values to test for significance.² If the break at τ^* is not significant, our identification process is finished with no evidence of a short-run trend/growth rate period. If a significant τ^* is found prior to 1990, we repeat the structural break testing process over the subset of data τ^* -2009 (i.e., data points after first structural break). If necessary, this process is repeated until the most recent significant structural break is identified. Similarly, if a significant τ^* is found after 1990, we repeat the structural break testing process over the subset of data 1960- τ^* (i.e., data points before the first structural break identified) to identify the appropriate long-run trend/growth rate period.

Linear Trend Model Structural Breaks

For the LT model, the Wald test statistic used to test for structural breaks between data subset 1 and 2 is calculated as (Greene, 2008, p. 123)³

$$W = (\hat{\theta}_1 - \hat{\theta}_2) (\hat{V}_1 - \hat{V}_2)^{-1} (\hat{\theta}_1 - \hat{\theta}_2), \tag{6}$$

where $\hat{\theta}_i$ is the parameter estimates vector and \hat{V}_i is the covariance matrix from a regression using data subset *i*. Table 3 provides the long- and short-run time periods based on structural break testing in the LT model for both the United States and TMPS.

Using aggregate US data for all states, we find a structural break in 1970 and calculate the long-run trend based on a linear regression over the 1970-2009 period. State-level analysis was used to identify state long-run trend periods. If structural break tests did not identify a state long-run trend, the state long-run trend was estimated using the US long-run time period of 1970-2009, as opposed to the complete 1960-2009 dataset. For the aggregate US yield data, a short-run break in the linear trend was not identified, and therefore a short-run US linear trend was not estimated. Similarly, state short-run trends were only estimated for states where an identified structural break was significant at the 10% level.

1. In the AR model, the set of potential break dates varies based on the optimal number of lags.
2. Since the true break date is a priori unknown, Hansen (2001) claims that an obvious candidate for a break date is the date that yields the largest Wald statistic.
3. The Wald test is used instead of the regular Chow test since the disturbance variance may not be the same in both (or all) regressions (Greene, 2008).

Table 4. US and top maize-producing states' long- and short-run autoregressive periods.

State	Long-run	Short-run
United States	1970-2009	1999-2009*
Iowa	1970-2009 [^]	1995-2009 ^a
Illinois	1970-2009	1999-2009
Nebraska	1970-2009 [^]	1995-2009**
Minnesota	1971-2009	1981-2009**
Indiana	1972-2009	1999-2009**
South Dakota	1970-2009	--
Kansas	1970-2009	--
Ohio	1972-2009	--
Wisconsin	1970-2009 [^]	1999-2009
Missouri	1970-2009	--
Michigan	1970-2009	--
Texas	1970-2009	1994-2009
North Dakota	1973-2009*	1999-2009
Kentucky	1970-2009 [^]	--
Colorado	1970-2009	--
Pennsylvania	1970-2009	--

Note: [^] denotes states where the 1970 break was also identified within the state-level analysis; * denotes significance only at the 5%; ** denotes significance only at 10%

^a Initially, 1993 was estimated as a structural break year for Iowa and Nebraska using both the LT and AR models, but 1993 was an anomaly with serious flooding and extremely low yields in the Midwestern maize states. For Iowa, using 1993 as the break year leads to phenomenal maize yield increases and growth rates from the short-run model, likely not a reliable forecast of future yield growth. Thus, we arbitrarily selected 1995 as the break year to be consistent with the break identified in the linear trend model for Iowa.

Autoregressive Model Structural Breaks

To identify structural breaks in the AR(*p*) model, we estimate the following equation.

$$dly_t = \alpha_{1,AR} D_1 + \alpha_{2,AR} D_2 + D_1 \sum_{k=1}^p \beta_{k,AR} dly_{t-k} + D_2 \sum_{k=1}^p \beta_{k,AR} dly_{t-k} + \varepsilon_{t,AR}, \tag{7}$$

where *D*₁ (*D*₂) is a dummy variable that takes the value of 1 if *t* < τ (*t* ≥ τ) and 0 otherwise and test jointly for a break in the constant and AR coefficients. Table 4 presents long- and short-run time periods based on structural break testing in the AR model for both the United States and TMPS.

As in the LT model, the US AR(4) long-run period is identified as 1970-2009. Unlike the LT model, which found no evidence of a short-run trend, we found a structural break in the US data for the AR(4) model in

1999. Therefore, we estimate the short-run US growth rate using an AR(4) model over the 1999-2009 period. Similarly, state short-run growth rates were only estimated for states where an identified structural break was significant at the 10% level using the lag lengths reported in Table 2.

Maize Yield Model Estimates

Using the short- and long-run time periods identified from the structural break analysis, maize yield trends for long- and short-run periods are derived by fitting Equation 1 to NASS maize yield data for the United States and the TMPS.⁴ Based on US average maize yield data for the 1970-2009 long-run time period, the “long-run” expected annual yield increment ($\hat{\beta}_{LT}$) is 1.92 bushels/acre/year. This long-run trend coefficient would forecast a 2030 maize yield of 205 bushels/acre. The results of using LT models to forecast 2030 US and state maize yields are reported in Table 5.

The long-run linear trend estimate for Iowa, the largest maize-producing state, was 2.12 bushels/acre/year with a 2030 yield forecast of 227 bushels/acre. The short-run trend period for Iowa begins in 1995 and has a significantly higher trend yield (3.63 bushels/acre/year). Assuming the short-run trend continues to 2030, Iowa maize yield would reach almost 260 bushels/acre. Illinois, the second-largest maize-producing state, shows a similar short-run trend pattern with a 1995-2009 short-run yield trend of 3.86 bushels/acre/year and a 2030 forecast yield of 255 bushels/acre/year. Nebraska, Minnesota, South Dakota, and Kansas also had structural breaks in linear trend yields in the late 1980s or early 1990s with higher short-run yield trends than long-run trends. Two smaller maize-producing states, North Dakota and Colorado, had short-run linear yield trends (forecasts) that were lower than their long-run yield trends (forecasts).

To fit the AR model for the entire United States and each state, we first compute annual yield-increase rates (*dly*_{*t*}). As previously noted, we tested for optimal lag lengths using the AIC and BIC selection criteria. Both selection criteria suggest four years as the optimal lag length for the US average yield data. Therefore, we estimate Equation 3 with four lags for the United States and use the optimal lag structure for each state reported in Table 2. Using the 1970-2009 US maize yield data, the

4. See http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats_1.0/ for details about the dataset used in our analysis.

Table 5. US and top maize-producing states' linear yield trend estimates and 2030 yield forecasts.

State	Long-run			Short-run	
	2009 yield (bu/ac)	Trend (bu/ac/yr)	2030 yield (bu/ac)	Trend (bu/ac/yr)	2030 yield (bu/ac)
United States	165	1.92	205	--	--
Iowa	182	2.12	227	3.63	258
Illinois	174	1.93	214	3.86	255
Nebraska	178	2.08	222	3.15	244
Minnesota	174	2.55	227	3.36	245
Indiana	171	1.81	209	--	--
South Dakota	151	2.29	199	2.41	202
Kansas	155	0.39	163	2.15	200
Ohio	174	1.72	210	--	--
Wisconsin	153	1.62	187	--	--
Missouri	153	1.89	193	--	--
Michigan	148	1.71	184	--	--
Texas	130	1.01	151	--	--
North Dakota	115	1.94	156	0.69	129
Kentucky	165	1.84	204	--	--
Colorado	153	1.2	178	0.69	168
Pennsylvania	143	1.14	167	--	--

Table 6. US and top maize-producing states' autoregressive yield growth estimates and 2030 yield forecasts.

State	Long-run			Short-run	
	2009 yield (bu/acre)	Growth rate (per year)	2030 yield (bu/acre)	Growth rate (per year)	2030 yield (bu/acre)
United States	165	1.62%	231	1.85%	242
Iowa	182	1.51%	249	1.89%	270
Illinois	174	1.56%	241	2.12%	270
Nebraska	178	1.76%	257	2.08%	274
Minnesota	174	1.89%	258	1.84%	255
Indiana	171	1.45%	231	1.88%	253
South Dakota	151	2.45%	251	--	--
Kansas	155	1.45%	210	--	--
Ohio	174	1.62%	248	--	--
Wisconsin	153	1.29%	200	0.87%	183
Missouri	153	1.75%	220	--	--
Michigan	148	1.56%	205	--	--
Texas	130	2.54%	220	1.04%	161
North Dakota	115	2.00%	174	0.55%	129
Kentucky	165	1.87%	244	--	--
Colorado	153	1.10%	192	--	--
Pennsylvania	143	1.20%	184	--	--

expected annual yield growth rate is 1.62%/year, with a 2030 yield forecast of 231 bushels/acre/year.⁵ After 1999, US yield growth was above the long-run growth rate. Using 1999-2009 data, the US short-run expected

growth rate is 1.85%/year, resulting in a 2030 US yield forecast of 242 bushels/acre/year. Table 6 provides growth-rate estimates from the US and state AR models along with 2030 maize yield forecasts.

Table 7. US and top maize-producing states' 2030 maize yield forecasts (bu/acre) by model.

State	Linear trend		Autoregressive	
	Long-run	Short-run	Long-run	Short-run
United States	205	--	231	242
Iowa	227	258	249	270
Illinois	214	255	241	270
Nebraska	222	244	257	274
Minnesota	227	245	258	255
Indiana	209	--	231	253
South Dakota	199	202	251	--
Kansas	163	200	210	--
Ohio	210	--	248	--
Wisconsin	187	--	200	183
Missouri	193	--	220	--
Michigan	184	--	205	--
Texas	151	--	220	161
North Dakota	156	129	174	129
Kentucky	204	--	244	--
Colorado	178	168	192	--
Pennsylvania	167	--	184	--

Using state AR models, long-run annual growth rates range from 1.1%/acre/year in Colorado to 2.5% in Texas. Several states had structural breaks in the AR model, providing support for short-run growth rates to make yield forecasts. Iowa, Illinois, Nebraska, and Indiana had higher short-run than long-run growth rates for the state. Using the estimated long-run yield growth rate, the 2030 Iowa maize yield forecast is 249 bushels/acre/year. Given the short-run yield growth rate for Iowa, the 2030 forecast is 270 bushels/acre/year. Likewise, Illinois' long-run yield growth forecast for 2030 is 241 bushels/acre/year, while the short-run yield growth forecast is 270 bushels/acre/year. Lower short-run than long-run growth rates in Minnesota, Wisconsin, Texas, and North Dakota indicate slowing yield growth forecasts.⁶

A comparison of the 2030 US and state maize yield forecasts for the alternative models considered in our analysis is provided by Table 7.

The time period (short- vs. long-run), as well as the model specification (LT vs. AR), impact potential 2030 maize production and state maize-yield rankings. These yield forecasts provide an indication of the sensitivity of yield forecasts to forecasting model, time period analyzed (i.e., identification of breakpoints), and underlying technology assumptions. As an illustration, consider the differences in forecasted 2030 yield for the United States and Iowa, the largest maize-producing state. For the United States, the 2030 yield forecast ranges from 205 bushels/acre/year based on the long-run LT model to 242 bushels/acre/year based on the short-run AR model (Figure 1a). Holding maize acreage constant at the 2009 US harvested acreage (79.6 million acres), the 37 bushel/acre/year difference between the high and low yield forecast in 2030 corresponds to a 3 billion bushel difference in US maize production. Likewise, the high and low 2030 yield forecasts for Iowa differ by 43 bushels/acre/year (Figure 1b) or 0.6 billion bushels of production based on the 2009 Iowa maize acreage (13.4 million acres). From our analysis, we are not necessarily trying to determine the "best yield forecast." Rather, we hope to illustrate how misleading yield forecast assumptions may be when used in policy analysis—in particular, policy prescriptions designed to reduce GHG emissions such as LCFS and biofuel mandates.

Two recent studies (Alston, Beddow, & Pardey, 2010; Feng, McCarl, & Havlik, 2011) provide an indication of how different yield forecasts can be when different breakpoints are used. We estimate annual US maize yield growth rates of 1.82%/acre/year for 1999-2009 and 1.65%/acre/year for 1970-2009. Alston et al. (2010) arbitrarily select 1990 as their breakpoint for a comparative yield growth analysis and estimate an annual US growth rate of 1.45%/acre/year for the 1990-2007. Feng et al. (2011) test for structural breaks and fit both linear-trend and growth-rate models but use a conservative US maize yield growth rate of 1.5%/acre/year for 1973-2010 in their modeling analysis. Neither of these studies considers state-level yield growth patterns. These yield growth discrepancies will not only have significant yield forecast impacts, but also market implications for supply, prices, land-use change, and policy assessments. These results indicate the importance of carefully select-

5. Closer examination of the data reveals that 1960-1969 was a period of unprecedented yield growth with an estimated annual growth rate of 4.2%/acre/year. Therefore, focusing on the post-1970 period removes this period of rapid growth and provides a more representative estimation of a long-run trend (Crosbie et al., 2006).

6. These results are not necessarily surprising. In general, it may only indicate that high-productivity corn states are gaining further comparative advantage over other states. Possibly, new corn-producing technologies are more readily adopted in these states given expected returns and yield response to climatic conditions.

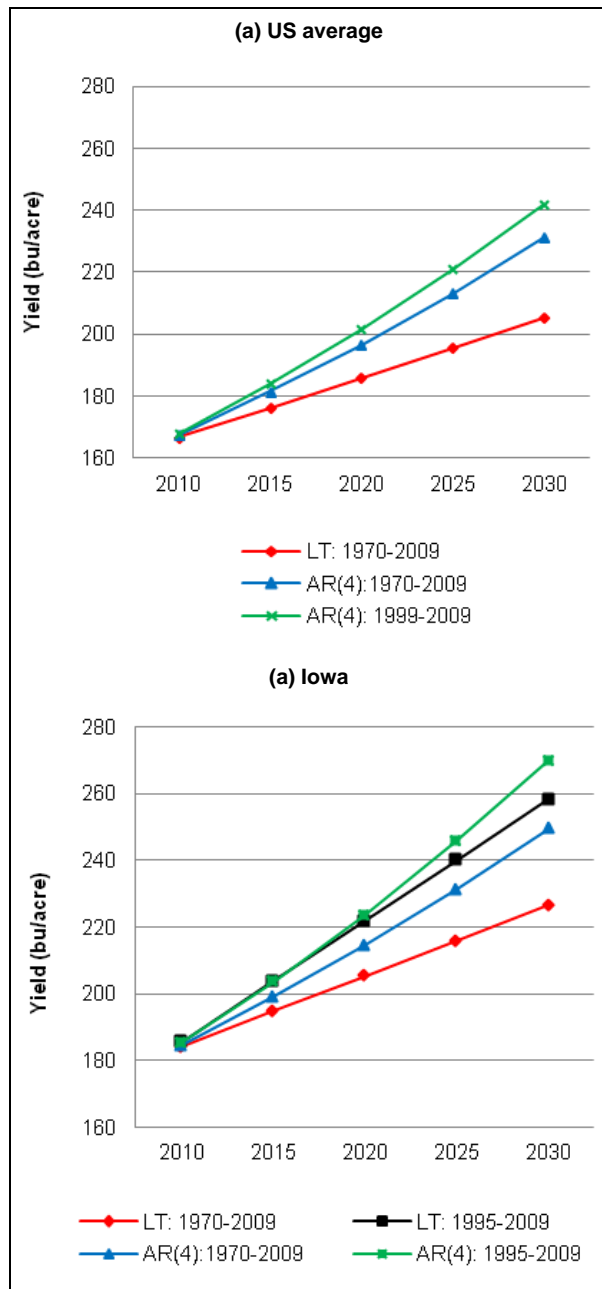


Figure 1. 2030 maize yield forecasts for United States and Iowa models.

ing yield trend and growth rate breakpoints, especially when using yield forecasts for policy analysis.

Yield Potential, Growth Forecasts, and Nitrogen-Use Efficiency

Are maize yield forecasts for 2030 realistic from an agronomic point of view? This question is related to the

agronomic concepts of potential yields, actual yields, and yield gaps. Phillips (2010) proposes alternatives for breaking yield barriers; Lobell, Cassman, and Field (2009) discuss options for reducing the gap between potential and actual yields; and Fischer, Byerlee, and Edmeades (2009) take a more pragmatic look at the concepts and include enhancing the genetic pool as an option. Yield potential as used in this context is fixed at a point in time. Current yield potential is based, at least in part, on the current genetic pool or resource stock. The yield gap, or difference between potential yield and actual yields, is largely due to weather and crop-management practices. If the genetic pool is held constant over the next 20 years, then yields can increase by no more than the current yield gap. Alternatively, if we anticipate that the genetic pool will be enhanced over the next 20 years (e.g., Crosbie et al., 2006; Jauhur, 2006), then so will potential yields.⁷ Thus, we assume that 2030 yield forecasts will not be constrained by current potential yields (or barriers).

Interestingly, not only have we seen at least five decades of increasing maize yields, but nitrogen (N) use/acre/year has been increasing at a slower rate than yields, if at all. As a result, maize grain weight divided by N applied, i.e., nitrogen use efficiency (NUE), has been increasing over time.⁸ Although Good, Shrawat, and Muench (2004) discuss possible genetic and transgenic breeding options for modifying plant physiology to improve NUE, none have been reported in the commercial seed industry.

Maize breeding improvements have been an important source of improved NUE. Fischer et al. (2009) report Iowa maize yield growth from 1996-2007 compared with small yield declines in France and Italy over the same period. These authors inferred that Iowa's maize yield growth may be due to the introduction of biotech traits (along with other plant-breeding advances) in modern maize varieties in Iowa beginning in 1996. In

7. The US maize seed industry assumes that about half of recent increases in maize yields is attributable to plant breeding.
8. It is important to note that we are not referring to a static production environment for a given maize variety, holding all other things equal. In a given area, increasing applications of N to increase maize yield would be expected to result in decreasing nitrogen use efficiency. But we are not conducting an agronomic experiment where we can hold all other things constant. Instead, we use a statistical approach that lets all factors vary simultaneously over time, including plant varieties, N use rates, production environments, and location—a more dynamic, multivariate experiment.

Table 8. 2030 US maize production using 2009 acreage with alternative yield forecasts and potential acreage reduction.

Year	Maize production ^a (billion bushels)	2030 acreage needed to produce 2009 maize crop of 13.1 billion bushels (million acres)	Potential acreage reduction (million acres)
2009	13.1	79.6	--
2030			
LT – LR	16.3	63.9	15.7
AR – LR	18.4	56.8	22.8
AR – SR	19.3	54.2	25.4

^a Maize acreage held constant at 2009 allocation.

addition to direct yield response to biotech traits, important physiological changes are occurring in modern corn varieties. For example, biotech traits improve maize root-system resistance to pests. Crosbie et al. (2006) indicate that modern corn breeding and biotech traits have resulted in an improved root system, which facilitates the uptake of nutrients and water more efficiently relative to previous hybrid corn varieties. Modern information technologies (e.g., precision farming, guidance systems, and variable rate applications) and improved crop management systems are enhancing input-use efficiency as well. These biotech traits produce even larger impacts in developing countries characterized by more risky production environments and less sophisticated crop management systems (Sexton & Zilberman, 2010).

We applied the same statistical approach used to forecast 2030 maize yields to forecast N application rates (lbs/acre) to 2030 for the United States and TMPS. Using NASS nitrogen application rates between 1970 and 2003 for the United States and TMPS, we were unable to identify any structural breaks in the fertilizer data. Therefore, we used the long-run linear trend model, which provided the best statistical fit to the fertilizer data to forecast N use rates to 2030 for the United States and TMPS.

Implications of Yield Growth for Land-Use Change and Nitrogen-Use Efficiency

To consider the implications of 2030 yield forecasts for cropland and nitrogen use, we first establish a 2009 maize-production baseline for the United States and TMPS. Second, given the 2030 US and TMPS yield forecasts, we calculate potential 2030 maize production on 2009 US and TMPS maize acreage. Third, we estimate the maize acreage needed in 2030 to produce the 2009 crop, assuming the highest yielding (or most productive) cropland is used in 2030. Fourth, we use forecasts of 2030 fertilizer application rates for the United States and TMPS and multiply the application rate by the US and TMPS acres needed in 2030 to produce the

2009 maize crop. Finally, total N used to produce the 2009 crop in 2030 is subtracted from total N used in 2009 to achieve the same maize production in order to determine the potential N savings from increased yields and NUE.

Maize Yield Growth and Cropland Use

If we hold US maize production constant at the 2009 level and use alternative maize yield forecasts for 2030, we can estimate the US cropland needed to produce the 2009 crop in 2030 and the cropland no longer needed to produce the 2009 maize crop. It is not possible to estimate how much of this land would be available to produce alternative crops because maize demand is expected to increase significantly between 2009 and 2030 due to domestic and global feed and food demand. These estimates for cropland reduction need to be interpreted as an upper bound on the amount of land available for alternative uses.

Table 8 reports potential US maize production, acreage needed to produce the 2009 crop in 2030, and potential maize acreage reduction in 2030 using alternative yield-forecasting models. Holding total US maize production constant at the 2009 crop (13.1 billion bushels), 16 million acres could become available for alternative uses if the long-run linear trend persists to 2030. Based on the AR model yield forecasts, there is an even greater potential reduction in maize acreage by 2030 (23 to 25 million acres).

Assuming that lower productivity maize cropland (e.g., lower opportunity cost cropland) has the highest probability of being transitioned into alternative uses, using average yield for all US maize acres may overestimate the acreage needed to produce the US 2009 maize crop. Presumably, the land released from corn production will begin with the least productive acres first. From Table 7, states with lower expected 2030 maize yields—such as North Dakota, Pennsylvania, Texas, Colorado, and Kansas—may see significant acreage shifts from commodity crops like maize to other grain

Table 9. Top maize-producing states' 2030 production using 2009 acreage with alternative yield forecasts and potential acreage reduction.

Year		Maize production (billion bushels)	Acreage needed to produce 2009 maize crop of 12.2 billion bushels (million acres)	Potential acreage reduction (million acres)
2009		12.2	73	--
2030	LT – LR	15.1	56.2	16.9
	LT – SR	16.5	50.1	23
	AR – LR	17.4	48.9	24.1
	AR – SR	18.1	45.8	27.2

Table 10. Potential reduction in GHG emissions from producing 2009 maize crop in the top maize-producing states using 2030 yield and nitrogen use forecasts.

	2009 nitrogen use (million metric tons)	2030 nitrogen use (million metric tons)	Nitrogen savings (2009 use—2030 use) (million metric tons)	GHG reductions from nitrogen savings ^a (mmt CO ₂ -eq)
LT – LR	4.7	4.1	0.6	7.3
LT – SR	4.7	3.7	1	12.6
AR – LR	4.7	3.5	1.2	14.6
AR – SR	4.7	3.3	1.4	17.5

^a Assuming that 4% of nitrogen fertilizer is released as N₂O with a GHG impact of 310 CO₂-eq per unit.

[Note: For our analysis, we assume a fixed value of 4% for all application rates and locations. Li, Narayanan, and Harriss (1996) found an emissions factor for N₂O of 3.1% to 4.5% when applying 100 and 150 kg N per hectare for maize production, respectively. Rosas, Babcock, and Hayes (2011) used field data to derive the N₂O emissions response to nitrogen fertilizer and found that at the economic optimum maize application rate, each unit of nitrogen applied released 4.6% as N₂O.]

crops, dedicated biofuel feedstock crops, or retired to non-crop activities. Table 9 provides the potential 2030 maize production for the TMPS using 2030 yield forecasts and 2009 acreage (Column 2), the potential maize acreage needed to produce the 2009 maize crop in 2030 within the TMPS assuming acreage is released from the lowest yielding states (Column 3), and the potential acreage reduction within the TMPS using alternative yield forecasting models (Column 4). Holding acreage constant at the 2009 allocation in each state, maize production within the TMPS could increase from 12.2 billion bushels in 2009 to between 15.1 and 18.1 billion bushels depending on the forecasting model used. There is little doubt that the impact on maize prices from the increase in maize production would be significant. Alternatively, if acreage is released from states with the lowest 2030 yield forecast, 17-27 million acres of land used for maize production in 2009 would not be needed to produce the 2009 crop in 2030. Since state yield analyses are only done for the TMPS (12.2 billion bushels), state acreage reductions in Table 9 are not comparable with acreage reductions in Table 8 based on total US production (13.1 billion bushels).

These results indicate a possible limitation of using only US long-run LT yield forecasts to evaluate future economic and environmental impacts of bioenergy policies and biofuel expansion. If structural breaks are

occurring (and yield improvement patterns vary spatially across states), projecting US-level yields in agricultural programming and competitive general equilibrium (CGE) models to simulate bio-energy policy shocks may overstate (or seriously distort) the negative economic welfare impacts and food security implications of these models. Further, when such models are extended to estimate land-use change and GHG emission impacts “attributable” to these biofuel policies, the results may seriously distort the impacts of particular policy choices and environmental consequences.

GHG Illustration and Implications

Given maize yield and nitrogen application forecasts in 2030 for the TMPS, we estimate the reduction in N used to produce the 2009 maize crop in a 2030 production environment. Because we are only illustrating the importance of yield growth and related plant-breeding improvements for potential GHG emissions reduction, we only consider GHG emissions attributable to N fertilization and do not attempt a full life-cycle analysis.⁹ Not only is nitrous oxide (N₂O) a far more potent GHG

9. Essentially, this is assuming that other inputs and production practices do not change per unit output, providing a lower bound estimate of potential GHG reductions.

than CO₂,¹⁰ it is also the major source of GHG emissions in maize ethanol production.

First, we use long-run linear trend forecasts for N-use rates in the TMPS to establish the 2009 amount of N used to produce the 2009 maize crop in the TMPS (12.2 billion bushels; Table 10, Column 2). Second, we calculate the total N needed in 2030 to produce the 2009 maize crop (12.2 billion bushels), assuming production occurs in the highest yielding states and using the 2030 N-use rate forecasts for the states that remain in production (Table 10, Column 3). N savings are determined by subtracting the N use forecast to produce the 2009 crop in 2030 from the total N used in 2009 to achieve the same maize production. Estimated N savings are between 0.6 and 1.4 million metric tons (mmt) of N, depending on the yield forecast model used (Table 10, Column 4). Finally, total N savings for each forecast is multiplied by the GHG coefficient for N₂O emissions in order to get estimates of the net change in GHG emissions within the TMPS. The GHG emissions savings (reported in the last column in Table 10) range between 7.3 and 17.5 mmt CO₂-equivalent (CO₂-eq), depending on the forecasting model used.

The GHG reductions reported in Table 10 are only a first approximation of GHG savings based on a partial analysis. Due to increased yields, an estimated 17 to 27 million fewer acres will be needed within the top 16 maize states to produce the 2009 maize crop if production occurs on the highest yielding acreage (states). Since we do not know how this acreage—which is no longer needed to produce the 2009 maize crop—will be used, we did not consider the potential GHG implications from the “released” land in our GHG analysis. It could remain in maize production, if that is the most profitable alternative, or shift to biomass crop production (e.g., switchgrass) if that is more profitable, or transition out of crop production. Therefore, since we only consider the GHG impacts attributable to nitrogen fertilization on land remaining in maize production in 2030 to meet the 2009 crop, our GHG estimates can be thought of as lower-bound estimates. A more comprehensive life-cycle accounting of all sources of GHG emissions in maize production may indicate a more substantial reduction than is appropriate based on our maize yield forecasts.

10. Nitrous oxide is estimated to have a global warming potential 310 times more potent than CO₂ per ton (US EPA, 2011).

Conclusions

We used NASS maize yield data from 1960 to 2009 in order to identify and estimate long- and short-run yield trends and growth rates for the United States and 16 major maize-producing states. The yield model estimates (trends and growth rates) were used to forecast maize yields out to 2030. Based on short- and long-run yield forecasts, the acreage needed to meet 2009 maize production with forecasted 2030 maize yields was estimated for the United States and the TMPS (assuming 2009 production is satisfied by higher productivity states). The 2030 maize acreage needed was then subtracted from 2009 maize cropland to derive an estimate (upper bound) of cropland available for other uses, such as growing additional maize or a biofuel feedstock.

Based on statistical tests for structural breaks, the US long-run maize yield trend began in 1970 for both the linear trend and autoregressive models. Using the long-run US linear trend (1.92 bushels/acre/year) for 2030, 16 million fewer cropland acres would be needed for 2009 maize production. Using the long-run US AR forecast for 2030 (231 bushels per acre), 23 million fewer acres would be needed to meet 2009 production. The short-run (1999-2009) AR forecast for 2030 (242 bushels per acre) released 25 million acres for other uses. The state yield trend and growth forecasts illustrate the importance of considering high yielding, large maize-producing states, as opposed to US averages in evaluating land-use change and GHG emissions impacts. In general, these results also indicate potential limitations of extrapolating long-run yield trends into the future when modeling land-use change and impacts of biofuel expansion.

Finally, we provide a first approximation of potential GHG savings from higher trend yields or growth rates attributing these savings solely to forecast N use rates and improved NUE in 2030 maize production. A significant reduction in GHG emissions in maize production is achievable with improved yield trends/growth rates and NUE.

References

- Alexander, C., & Hurt, C. (2007). *Biofuels and their impact on food prices* (BioEnergy ID-346-W). West Lafayette, IN: Purdue University, Purdue Extension.
- Alston, J.M., Beddow, J.M., & Pardey, P.G. (2010). Global patterns of crop yields and other partial productivity measures and prices. In J.M. Alston, B.A. Babcock, & P.G. Pardey (Eds.), *Shifting patterns of agricultural production and productivity worldwide* (CARD-MATRIC Electronic Book).

- Ames, IA: Center for Agricultural and Rural Development (CARD).
- Andrews, D. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, 61(4), 821-856.
- Babcock, B., & Fabiosa, J. (2011). *The impact on ethanol and ethanol subsidies on corn prices: Revisiting history* (CARD Policy Brief 11-PB 5). Ames, IA: CARD.
- Crosbie, T., Eathington, S., Johnson, G., Edwards, M., Reiter, R., Stark, S., et al. (2006). Plant breeding: Past, present and future. In K.R. Lamkey & M. Lee (Eds.), *Plant breeding: The Arnel R. Hallauer international symposium* (pp. 3-50). Ames, IA: Blackwell Publishing.
- DeJong, D., Liesenfeld, R., & Richard, J. (2003, July). *A structural break in U.S. GDP?* (SSRN Working Paper). Rochester, NY: Social Science Research Network (SSRN). Available on the World Wide Web: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=428664.
- Deschenes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *The American Economic Review*, 97(1), 354-385.
- Feng, S.J., McCarl, B.A., & Havlik, P. (2011, July 24). *Crop yield growth and its implications for the international effects of US bioenergy and climate policies (Draft)*. Paper presented at the 2011 Agricultural & Applied Economics Association (AAEA) Annual Meeting, Pittsburgh, Pennsylvania.
- Fischer, R., Byerlee, D., & Edmeades, G. (2009, June 24). Can technology deliver on the yield challenge to 2050? In *Proceedings of the expert meeting on how to feed the world in 2050*. Rome: Food and Agriculture Organisation of the United Nations (FAO).
- Good, A., Shrawat, A. & Muench, D. (2004). Can less yield more? Is reducing nutrient input into the environment compatible with maintaining crop production? *TRENDS in Plant Science*, 9, 1360-1385.
- Greene, W. (2008). *Econometric analysis*. Upper Saddle River, NJ: Prentice Hall.
- Hansen, B. (2001). The new econometrics of structural change: Dating breaks in U.S. labor productivity. *Journal of Economic Perspectives*, 15, 117-128.
- Hayes, D., Babcock, B., Fabiosa, J., Tokgoz, S., Elobeid, A., Yu, T., et al. (2009). *Biofuels: Potential production capacity, effects on grain and livestock sectors, and implications for food prices and consumers* (Working Paper 09-WP 487). Ames, IA: CARD.
- Huang, H., & Khanna, M. (2010, July 25). *An econometric analysis of U.S. crop yield and cropland acreage: implications for the impact of climate change*. Paper presented at the 2010 Agricultural & Applied Economics Association (AAEA) Annual Meetings, Denver, Colorado.
- Jauhur, P. (2006). Modern biotechnology as an integral supplement to conventional plant breeding: prospects and challenges. *Crop Science*, 46, 1841-1859.
- Li, C., Narayanan, V., Harriss, R. (1996). Model estimates of nitrous oxide emissions from agricultural lands in the United States. *Global Biogeochemical Cycles*, 10(2), 297-306.
- Loell, D., Cassman, K., & Field, C. (2009). Crop yield gaps: Their importance, magnitudes, and causes. *Annual Review of Environment and Resources*, 34, 179-204.
- McConnell, M., & Perez-Quiros, G. (2000). Output fluctuations in the United States: What has changed since the early 1980's? *The American Economic Review*, 90(5), 1464-1476.
- Phillips, R. (2010). Mobilizing science to break yield barriers. *Crop Science*, 50, S-99-S-108.
- Rathmann, R., Szklo, A., & Schaeffer, R. (2010). Land use competition for production of food and liquid biofuels: An analysis of the arguments in the current debate. *Renewable Energy*, 35, 14-22.
- Reilly, J., & Fuglie, K. (1998). Future yield growth in field crops: What evidence exists? *Soil & Tillage Research*, 47, 275-290.
- Rosas, F., Babcock, B., & Hayes, D. (2011, April). *A nonlinear offset program to reduce nitrous oxide emissions induced by excessive nitrogen application* (Working Paper 11-WP 521). Ames, IA: CARD. Available on the World Wide Web: <http://www.card.iastate.edu/publications/synopsis.aspx?id=1158>.
- Schlenker, W., & Roberts, M. (2006). Nonlinear effects of weather on corn yields. *Review of Agricultural Economics*, 28(3), 391-398.
- Schlenker, W., & Roberts, M. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 106(37), 15594-15598. Available on the World Wide Web: <http://www.pnas.org/content/106/37/15594.full.pdf+html>.
- Sexton, S., & Zilberman, D. (2010). Agricultural biotechnology can help mitigate climate change. *ARE Update*, 14(2), 1-4.
- Tannura, M., Irwin, S., & Good, D. (2008a). *Are maize trend yields increasing at a faster rate?* (Marketing and Outlook Briefs). Urbana-Champaign: University of Illinois at Urbana-Champaign, Department of Agricultural and Consumer Economics.
- Tannura, M., Irwin, S., & Good, D. (2008b). *Weather, technology, and maize and soybean yields in the U.S. maize belt* (Marketing and Outlook Briefs). Urbana-Champaign: University of Illinois at Urbana-Champaign, Department of Agricultural and Consumer Economics.
- Tokgoz, S., Elobeid, A., Fabiosa, J., Hayes, D., Babcock, B., Yu, T., et al. (2007). *Emerging biofuels: Outlook of effects on U.S. grain, oilseed, and livestock markets* (Staff Report 07-SR 101). Ames, IA: CARD.
- US Environmental Protection Agency (EPA). (2011, April). *Inventory of greenhouse gas emissions and sinks: 1990-2009* (EPA 43-R11-005). Washington, DC: Author. Available on

the World Wide Web: <http://www.epa.gov/climatechange/emissions/usinventoryreport.html>.

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