Analysis of the Effects of Soil Organic Matter (SOM) on Efficiency and Agricultural Productivity

(Implications for Cellulosic Ethanol)

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ABSTRACT

In an attempt to support the push for second generation biofuels in the United States, this research investigates the role that soil organic matter plays in explaining changes in technical efficiency and agricultural productivity across counties in Nebraska. We estimate optimum biomass harvest potentials for forty seven counties in Nebraska. These estimates reveal the percentage of biomass that can be harvested that would not negatively affect current levels of agricultural production. We also give an account of the status of inter-county changes in agricultural productivity in Nebraska. We use an output measure of technical efficiency from non-parametric data envelopment analysis to estimate technical efficiency measures. Total factor productivity change was estimated using an output-based Malmquist index approach. Biomass harvest potentials were obtained by shrinking/contracting only soil organic matter in our linear programming constraints. Results show that SOM does contribute to explaining changes in technical efficiency and total factor productivity across counties in Nebraska. Also, an average measure of TFP growth of 3.7% was obtained for the 41 years period, 99% of which was accounted for by technological change while the contribution of efficiency change was very minimal. 55% of counties in Nebraska have zero harvest potentials while only 45% of counties have excess biomass potentials for harvest. The highest average potential of 35% was reported for Lincoln, Cass, Gosper and Colfax counties.

1.1: Introduction

With reported increases in production levels of corn, soybeans and cattle (USDA 2010), coupled with favorable policies and socio-economic factors, there has been a rapid growth in the biofuel industry in Nebraska over the last seven years. While this production-pull effect creates a ready market for corn farmers, there are concerns over how sustainable and environmentally efficient are the more intensive farming practices that have ensued. These concerns have been directed mainly towards the sustainable growth of production. This issue has increasingly being debated upon lately particularly after studies have shown that the current mode of producing biofuels is not a panacea to the energy and environmental problems when compared to fossil fuels as had earlier been envisaged (Gorter H. et. al. 2009; U.S Energy Bill 2007). As a remedy to this problem and a possible complement to the current methods, researchers are exploring the possibility of using cellulose to produce ethanol (also called second generation biofuels). Increasing production of cellulosic ethanol would create a ready market for all biomass, including all post-harvest residues that are normally being reburied into the soil and contributes to the creation of SOM. Consequently, the question then becomes: what happens to agricultural productivity should biomass be commercially harvested for the purpose of cellulosic ethanol? This issue would not be contentious if SOM had no effect of agricultural productivity. The optimum thing then to do would be to grow and market as much biomass as profitable. However what if SOM really affects agricultural productivity? Then there would be every reason to establish that optimum threshold for which biomass can still be harvested but not at the expense of prevailing agricultural production levels. This study therefore aims at incorporating SOM characteristics when estimating agricultural performance across counties in Nebraska. The reasons for doing this are threefold:

i) Yields depend crucially on soil carbon content which is directly related to SOM, (FAO (2003))

ii) SOM provides insight into the ability for soils to sequester carbon which becomes very important when greenhouse gases and climate change are currently important issues (A.Picollo et.al (1capacity of soils which has implications for irrigation.

Obtaining a panel data set of SOM that goes far back as 1970 was one of the challenges faced by this research. This is because it has not been measured continuously for all these years and in multiple geographic regions. The most referred to data source is the soil survey geographic (SSURGO) database hosted by the United States Department of Agriculture's National Resource Conservation Service. The SOM values reported by SSURGO represent only current year projections (2009). Also, because of variations in soil types across counties, a standard way of comparing SOM levels across counties was required. Therefore the SOM panel was constructed using available literature on similar methodologies. These methodologies would be discussed later in the paper.

In this study we hypothesize that soil organic matter contributes to explaining changes in technical efficiency and total factor productivity. Based upon this hypothesis, the objective then becomes to confirm or provide evidence that refutes this hypothesis.

As the policy debate to increase the production of second generation biofuels heats up, the need to restrict the proportion of biomass harvested by regions would become very crucial. The following question then becomes what minimum level of crop residue and hence SOM should be maintained on and hence in the soil that would maintain a profitable level of crop production and at the same time provide an incentive for farmers to sell some crop residue for the production of cellulosic ethanol. This study also provides insights to this question.

1.2: Objectives of the study

This study therefore has three main objectives:

- Estimate technical efficiency of 47 counties across Nebraska to investigate whether SOM helps in explaining agricultural performance variation across counties.
- Estimate total factor productivity across counties in Nebraska to inquire the extent to which SOM explains variations in productivity growth in Nebraska.
- Calculate the optimum level of SOM needed to maintain the current levels of outputs.

2.0: Literature Review

In this section, we present a review of relevant literature for the study. Three main sections are considered; a brief review on efficiency measures; an attempt to understand SOM and an update on the state of county level agricultural performance in Nebraska.

2.1: Efficiency Measures

Theoretical and empirical methodologies for the estimation of efficiency across economic units have come through decades of development tracing far back as Farrell (1957). Here (Farrell, 1957), single output and multiple inputs efficiency measures were estimated. This methodology was criticized due to its extreme restrictive nature (Coelli, 2005). Some of the developments that have followed include the use of multiple outputs and multiple inputs in the estimation of efficiency; the estimation of scale efficiency; environmental efficiency; congestion under parametric, semi-parametric and non-parametric measure; the use of expenditure and revenue variables instead of the traditional input and output variables; to name a few. TE can be defined as the ability of a farm to produce maximum output from a given set of inputs, and allocative efficiency, the ability of a farm to optimize on the use of inputs given their respective prices. M. Graham (2004). There are several efficiency measures in use and are still being developed today. More generally and in a non-parametric context, efficiency is an estimation of the distance a given allocation is from the production frontier. Allocations on the frontier are considered as being perfectly efficient and the degree of efficiency decreases moving away from the frontier Färe, Grosskopff and Lovell (1996).

2.2: Parametric vs Non-Parametric

From the vast literature on methods of efficiency estimation, all the techniques that have been employed in the estimation of technical efficiency and productivity have fallen between these two extremes, parametric and non-parametric measures. The main differences between the two extremes depend on their stochasticity. The former is stochastic while the latter is deterministic (non-stochastic). This property has its advantages and disadvantages depending on the problem being analyzed. Parametric methods require the specification of a functional form while Non-Parametric measures don't. Given the need for functional specificity, parametric measures have been further divided into Primal and Dual Methods. Nonparametric measures assume that all deviations from the efficient allocation are due to inefficiency, while the stochastic parametric measures allow for statistical noise Coelli (1995). Therefore, a fundamental problem with non-parametric efficiency measures is that any measurement error, and any other source of stochastic variation in the dependent variable, is embedded in the one-sided component making the resulting TE estimates sensitive to outliers (Greene, 1993). Another characteristic of DEA methods is the potential sensitivity of efficiency scores to the number of observations as well as to the number of outputs and inputs (Nunamaker, 1985). As a way of correcting for the deterministic nature inherent in the non-parametric methods, there have been growing uses of mid-way solutions. Some of these include the use of bootstrapping methods on the Malmquist and technical efficiency estimates obtained from DEA to account for the power or level of significance off the Malmquist indices.

2.3: Soil Organic Matter (SOM) Measures

There has been considerable oversight on the role that soil structure plays in determining agricultural performance. The United Nations' Food and Agricultural Organization describes SOM as the key to drought-resistant soil and sustained food production. SOM is an important input in agriculture because it helps reduce soil erosion, maintain the constitution of soils and support physiological processes that improve soil productivity. A good soil should have a high soil carbon holding capacity. There is a linear relationship between SOM and soil carbon. Recent studies reveal a 2 to 1 conversion ratio between the two. This means dividing SOM by two yields the estimate of SOC (A. Liska 2011).

The extent to which carbon is released or absorbed by the soil depends on its structure. Organic matter enhances water and nutrient holding capacity of soils which improves soil structure. This enhances efficient management of soil carbon, improves yields and environmental quality, while at the same time reducing the severity and costs of natural phenomena, such as droughts, floods, and diseases. In addition, increasing soil organic matter levels can reduce atmospheric CO_2 levels that contribute to climate change (STATSGO Database). By emphasizing organic matter management technology, soil loss can be reduced on those lands that still suffer excessive erosion. Moderate erosion rates can harm air quality, water quality, and wildlife habitat.

There has been strong evidence of carbon sequestration potentials in forests over the last five years. Similarly for soil carbon sequestration, there is growing evidence of the potentials to sequester soil organic carbon in recent years when tillage practices are employed and crop residue being reintroduced into the soil through tillage (Rattan Lal et al. 2004). This study, though would not categorically provide relevant answers to the carbon sequestration question, it would provide some insights that would be helpful for future research on SOM and Soil Carbon.

2.4: Agricultural Productivity in Nebraska

There are very few studies that have been conducted on agricultural efficiency and productivity in Nebraska. The few available ones have either targeted the state level or firm level. None have looked at what the trends are at the county level. Three of these studies are discussed in the literature update. These include the following: Shaik and Perrin (1999); Azzam and Lopez (2004) and Shaik and Perrin (2001).

Shaik-Perrin (1999) - In this study, they directly estimate productivity changes non-parametrically using DEA, and also recover shadow prices of environmental impacts from this approach to modify the traditional indexing measure of productivity changes. Their results showed that parametric productivity methods provide unrealistic measurement of environmentally-adjusted productivity gains, but do offer shadow prices that seem to be plausible values for adjusting the standard productivity index approach.

Azzam - Lopez (2004) - This article they examine the role of imperfect competition in determining total factor productivity growth (TFPG) by bringing together a New Empirical Industrial Organization (NEIO) model and the TFPG model of Nadiri and Mamuneas (1998). Using data from 29 food processing industries revealed that changes in markups, economies of scale, and demand growth contributed positively to TFPG while the disembodied technical change was a negative contributor.

Shaik and Perrin (2001) - In this study they showed that Traditional TFP misrepresents the true change in agricultural productivity to the extent that environmental bads jointly produced with desirable outputs are unaccounted. Nonparametric productivity measures incorporating environmental bads are evaluated for Nebraska agriculture. The results indicate that prior to the

1980's the traditional TFP measures overstate productivity growth while it is underestimated afterwards, reflecting peak use of chemicals.

3.0: Methodology

This study uses Data Envelopment Analysis to estimate technical efficiency and total factor productivity. This has the advantage of not having to make assumptions about a specific functional form. We develop an output-based Technical Efficiency measure using DEA for two outputs and four inputs. These include soybeans and corn as outputs and capital, labor, chemicals and SOM as inputs. Two types of SOM values were calculated and used in this study. The methods used in obtaining the respective SOM values are discuss in detail below. TFP is being estimated by a Malmquist index approach and disaggregated into Pure Technical Change (TC) and Efficiency Change (EC). These two analyses are carried out including SOM and excluding it to see clearly the contribution of SOM in explaining TFP and TE.

3.1: Data Structure

This section describes the nature of the data set used in the study. Some of the variables were constructed and the processes and steps are described in this section.

3.1.1: Constructing SOM Panels

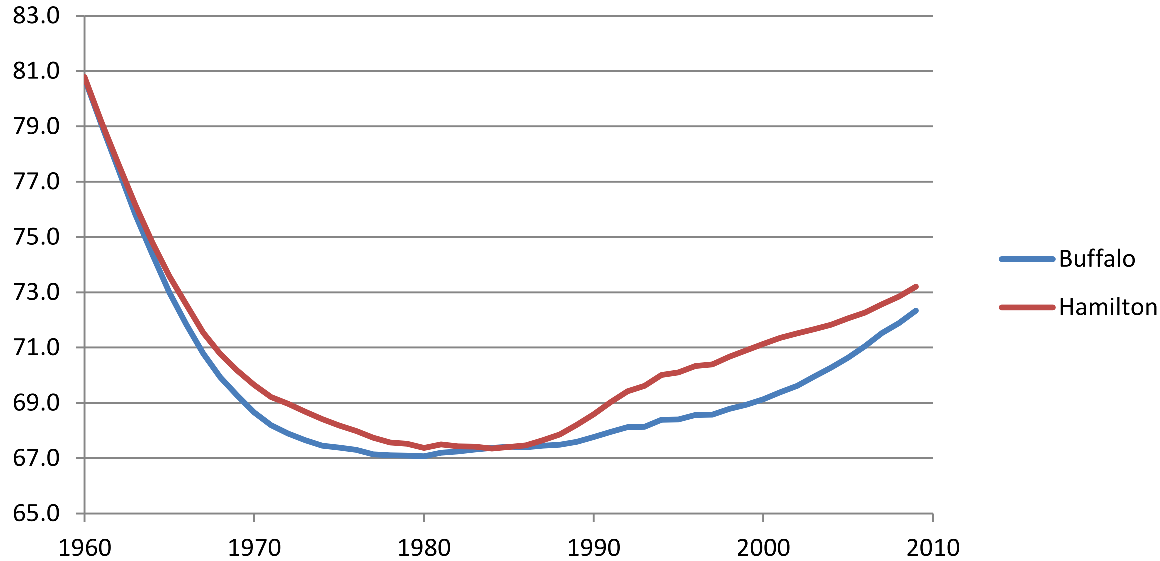
Obtaining a panel for SOM levels going far back as 1960 was a big challenge for the study. This is mainly because there are no inventories of surveys that actually took these estimates that far back in time. The closest that is available are point estimates from 1995 to 2003 that are not very useful when county level data in seeded. For the purpose of this study, we constructed SOM panels using three different methodologies. All three methodologies share a pattern of obtaining a stock level of SOM in period t (2009) and use various forms of discounting to obtain the t-n SOM stock values. Based on the pioneers, these methodologies are: A) Yang (1995)/Perrin (2010), B) Martellotto (2010)/M.Milner (2010), and C) A. Liska (2011)/M.Milner (2011). The last of these variables (Liska-Milner 2011) was excluded from this version of the study. We now describe in detail these methodologies one after another.

3.1.1.1: SOM Using H.S Yang (2000)/ R.Perrin (2010):

Yang (2000) developed a model for the mineralization of carbon from experimental data. Mineralization, as defined by Oxford refers to the breakdown of organic residues by oxidation to form soluble or gaseous chemical compounds which may then take part in further soil processes or be utilized by plant life. In his model, Yang treated organic matter as a single component. The logarithm of the average relative mineralization rate, K, or rate constant, of a substrate considered as a whole was found to be linearly related to the logarithm of time, t, provided prevailing soil conditions remained unchanged. The equation is: $\log K = \log R - S \log t$, or $K = R^{t-s}$, in which R (dimension t^{s-1}) represents K at t=1 and S (dimensionless, $1 >= S >= 0$) is a measure of the rate at which K decreases over time, also called the speed of aging of the substrate. The quantity of the remaining substrate, Y_t, is calculated by $Y_t = Y_0 \exp(-Rt^{1-s})$, where Y_o is the initial quantity of the substrate. The actual relative mineralization rate, k, at time t is proportional to K, according to $k=(1-S)K$.

Using Biomass data from National Agricultural Statistical Services database (NASS) 1960 to 2009, Yt, (SOM values in period t), were calculated. The graph below represents plots of the calculated SOM values for two counties Buffalo and Hamilton. Note that one key difference between this SOM value and the next one (SOM Milner/Martellotto) is that this one bottoms out around the mid-80s and have been increasing steadily afterwards.

Figure 1:
SOM VALUES CALCULATED FOR YANG AND PERRIN ESTIMATES FOR TWO REPRESENTATIVE COUNTIES

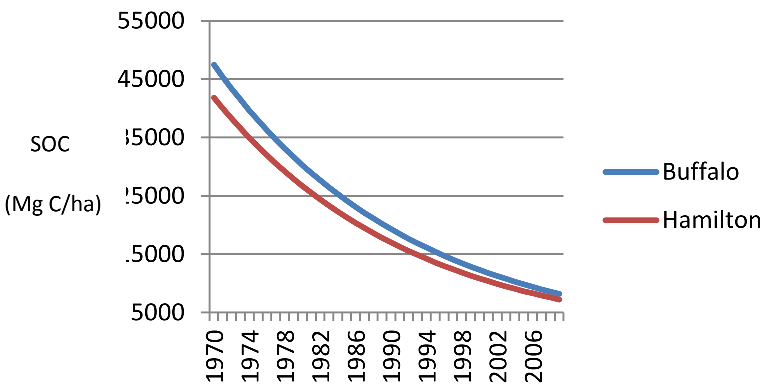


3.1.1.2: Martellotto (2010)/M.Milner (2010)

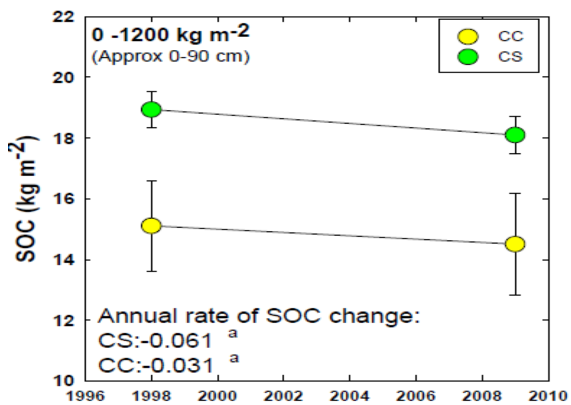
SOM stock levels for 2010 were obtained from the SSURGO database as described in Milner (2010) for 47 counties in Nebraska. A constant depreciation rate as defined by Martellotto (2010) was applied to all 2009 SOM values and traced backwards up to 1970. The average rate of SOC change used was 0.046 SOC for corn and soybeans. This is the average of corn and soybeans values as described in the graph to the right on figure two below. This rate was obtained from Martellotto (2010) who measured the rate of carbon change for corn and soybeans in Mead Nebraska. The results provide evidence of a declining trend in Soil carbon over the years. Different from the SOM values obtained in the previous case, here the SOM values do not bottom. This implies that these values predict a continuous decrease in net SOM levels for the coming years. The graphs below (left) show plots of SOM trends for two representative counties and SOC changes (right) from Martellotto 2010.

Figure 2: Graphs Showing SOM Change and Martellotto's SOC change

Change in SOM Milner/Martellotto: 1970 to 2009



Martellotto: Annual rate of SOC Change



From SSURGO database using Martellotto's average discount of 0.046

3.2: Descriptive Statistics

The other variables: corn and soybeans for outputs; fertilizer, chemicals and land; for inputs, are obtained from National Statistics (NASS) website. Table 1 gives a brief descriptive statistics of the variables.

Table 1.: Descriptive Statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
Corn (Tons)	1927	407916.02	271608.3	1000	1553924.46
Soy Beans (Tons)	1927	44010.53	50022.35	1000	241408.49
Hay All (Tons)	1927	66816.8	63760.27	1000	420620
Other (Tons)	1927	77581.06	118195.01	1000	1082112.1
Land(Acres) (Non-Irrigation)	1927	95335.17	68351.29	1000	299600
Land(Acres) (Irrigation)	1927	93825.46	73775.19	1000	332200
Fertilizer (Ratio)	1927	45211.82	25287.22	1000	143980.68
Chemicals (Ratio)	1927	24161.96	15340.18	1000	89700
TEMP (F)	1927	50.6054063	1.6753382	44.4422288	54.9829525
SOM Miln/Mart (Mg ha^{-1} C)	1927	23999.52	14615.54	5105.7	91168.06
SOM_Perrin (Mg ha^{-1} C)	1927	1781.9	269.6327987	779.2555281	2279.31

The descriptive statistics represents 40 years of data on annual production of corn and soy beans as outputs in tons and quantities of inputs, land, chemicals, fertilizer and SOMs. Given that other crops are being produced in other areas in varying amounts, our selection criteria on which crops to select were mainly based on dominance and highest representation.

3.3: Representation of the Technology

Farmers are constrained by a production technology transforming a vector of *N* inputs x = (x_1, x_2 … x_N)$\in \Re_+^N$ into a vector of *M* outputs u = (u_1, u_2,…,u_M))$\in \Re_+^M$ Observed combinations of inputs used and outputs produced (x^j,u^j) are taken to be representative points from the feasible production technology. In this study we use DEA to infer the boundaries of the feasible technology set from the observed points, as outlined in Färe, et al.

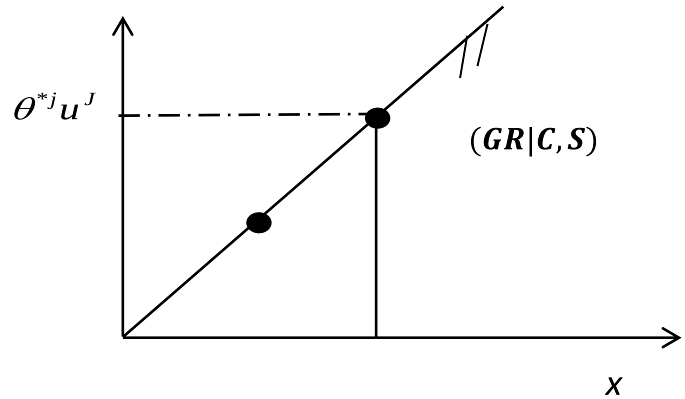
Observations from the technology consist of a sample of 47 DMUs producing outputs that have been categorized into four output variables (Corn, soybeans, hay and other) and using five conventional inputs in addition to SOM. These inputs are land (Irrigated and Non-Irrigated), fertilizer, chemicals, average annual temperature and the two types of SOM computed. The production technology can be represented by the graph denoting the collection of all feasible input and output vectors: *x* and *u*

$$GR = \{(x, u) \in \Re_+^{4+6}: x \in L(u)\}$$

Where *L(u)* is the input correspondence which is defined as the collection of all input vectors

$x \in \Re_+{}^N$ that yields at least the output vector $u \in \Re_+{}^M$

Figure 3: Graph Measure of TE with Constant Returns to Scale and Strong Disposability



3.4: Returns to Scale and Disposability

Throughout the literature, the choice of the prevailing returns to scale and disposability characteristics that represent the technology have always been dependent upon some knowledge that the researcher has about the technology set or for purposes of convenience in estimation. For this technology, we assume constant returns to scale mainly because there are no documented reasons why the size of a county affects the level of production obtained. We also assume strong disposability because there are no laws levying fines against farmers producing with less than stipulated amounts of biomass needed to produce soil organic matter. This means that there are no associated costs involved in the incorporation of SOM in the production process.

3.5: Technical Efficiency

There are several forms of TE measurements available in the literature. The version one uses depends on the type of data available and the particular problem investigated. For this analysis, we carry out an output based measure of TE as defined by Färe and Grosskopff. TE (output based), conditional on constant returns to scale technology and strong disposability can be defined using the following linerprogramming relationship:

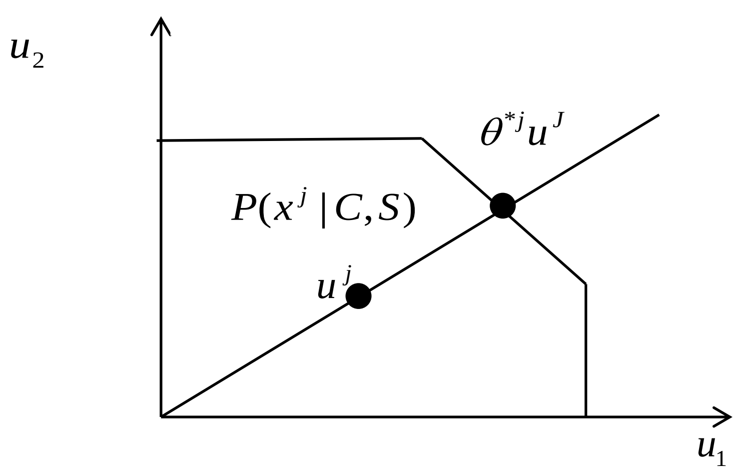
$$F_o(x^j, \delta u^j \mid C,S) = \delta^{-1} F_o(x^j, u^j \mid C,S), \delta \succ 0$$
$$F_o(x^j, u^j \mid C,S) = \max\{\theta : \theta u^j \in P(x^j \mid C,S)\}$$

for

j = 1, 2 …J

This measure, as illustrated in in Figure 4 is a piece-wise linear technology that measures the efficiency of u^j produced from x^j when the technology is assumed to satisfy constant returns to scale and strong disposability. It does so by radially expanding u^j as much as technologically possible and then by computing the ratio of the expanded to the observed output.

Figure 4: Output TE Measure



The properties of this output measure of technical efficiency are summarized below:

1) $F_o\left(x^j, \Theta u^j \middle| C, S\right) = \Theta^{-1} F_o\left(x^j, u^j \middle| C, S\right), \Theta > 0$

2) $F_o(\lambda x^j, u^j \mid C, S) = \lambda F_o(x^j, u^j \mid C, S), \lambda \succ 0$

3) $1 \leq F_o(x^j, u^j \mid C, S) \prec +\infty$

4) $u^j \in WEff\, P(x^j \mid C, S) \Leftrightarrow F_o(x^j, u^j \mid C, S) = 1$

5) $F_o(x^j, u^j \mid C, S)$ is independent of unit of measurement.

More explicitly, the output measure of technical efficiency is obtained by finding a solution to the problem:

$$F_o(x^j, u^j \mid C, S) = \underset{\theta, z}{Max}\ \theta$$

s.t.

$$\theta u^j \leq zM, x^j \geq zN and\ z \in \Re_+{}^j$$

3.6: Malmquist Productivity Index

This is an index number that is used to measure total factor productivity (TFP) growth of an industry, firm or any economic agent over time. It can be decomposed into two main sub categories which include technological change (TC) and efficiency change (EC).

The output based Malmquist index is used in this study and follows closely that developed by Färe and Grosskopff (1994) and Lindgren & Roos (1992). The two contributors above used as their basis the pioneering works of Farrell (1957) and, Christensen & Diewert (1982). Färe et al. (1992) merged efficiency theory as developed by Farrell (1957) with the Malmquist index of Caves et al. (1982) to propose a Malmquist index of productivity change that is now commonly used in the literature. Contrary to Färe et al. (1992), who considered an input based Malmquist index, we use an output based Malmquist index in the current paper.

We start by considering firms which use *n*-inputs to produce *m*-output. Denote $x \in R_+^n$ and $y \in R_+^m$ as, respectively, the input vector and output vector of those firms. The set of production possibilities of a firm at time *t* can be written as:

$$S^t = \{(x^t, y^t) \mid x^t \text{ can produce } y^t\}$$

Färe, Grosskopff, Norris & Zhang (1994) followed Shepherd (1970) to define the output distance function at time t as:

$$D_0^t(x^t, y^t) = \inf\{\theta \mid (x^t, y^t/\theta) \in S^t\} = (\sup\{\theta \mid (x^t, \theta y^t) \in S^t\})^{-1}$$

The subscript *o* is used to denote the output-based distance function. Note that, $D_0^t(x^t, y^t) \leq 1$ if and only if $(x^t, y^t) \in S^t$, and $D_0^t(x^t, y^t) = 1$ if and only if (x^t, y^t) is on the frontier of the technology.

To define the Malmquist index, Färe et al. (1994) defined distance functions with respect to two different time periods:

$$D_0^t(x^{t+1}, y^{t+1}) = \inf\{\theta \mid (x^{t+1}, y^{t+1}/\theta) \in S^t\}$$

and

$$D_0^{t+1}(x^t, y^t) = \inf\{\theta \mid (x^t, y^t/\theta) \in S^{t+1}\}$$

The distance function above measures the maximum proportional change in output required to make (x^{t+1}, y^{t+1}) feasible in relation to technology at time t. Similarly, the distances function in last equation above measures the maximal proportional change in output required to make (x^t, y^t) feasible in relation to technology at time *t + 1*. The output Malmquist TFP productivity index can then be expressed as:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}}$$

The term outside the brackets shows the change in technical efficiency while the geometric mean of the two ratios inside the brackets measures the shift in technology between the two periods *t* and *t + 1;* this could be called technological progress. Hence:

Efficiency change = $\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}$

Technical change = $\left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}}$

In each of the formulas above, a value greater than one indicates an improvement and a value smaller than one presents deteriorations in performance over time.

Optimum level of SOM

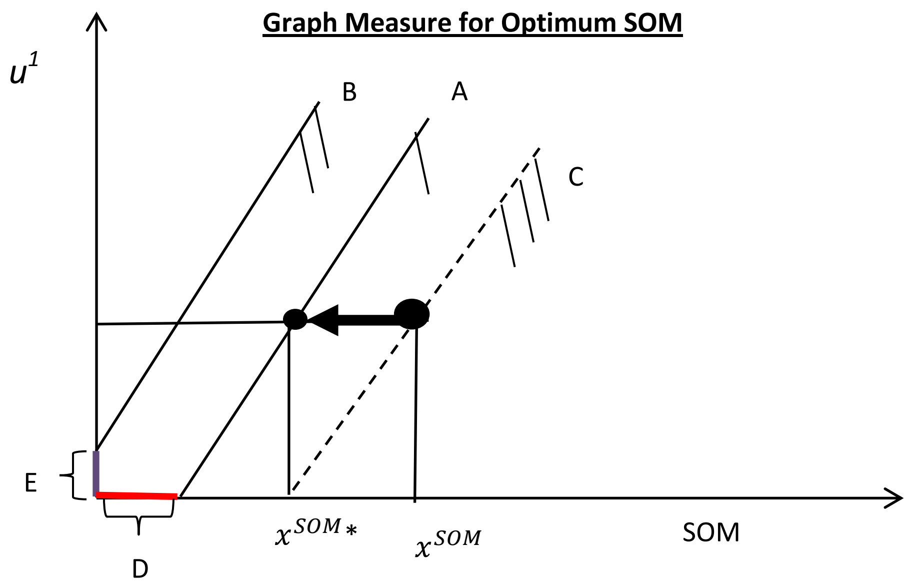
The main hypothesis of this paper is that soil organic matter contributes in explaining changes in technical efficiency and total factor productivity. Should the results fail to disprove this hypothesis, the following question then becomes, at what level of SOM would output levels be maintained? That is, what minimum level of SOM would ensure that production levels are maintained while some of the crop residue is being harvested for the production of cellulosic ethanol?

The LP objective to solve this problem is given by the relationship below:

$$F_g\left(x^{all\prime}, x^{SOM}, u^j \middle| C, S\right) = \min_{\lambda,z} \lambda$$

St

$$u^j \leq zM, \quad zN_{SOM} \leq \lambda x^{SOM}, \quad zN_{all'} \leq x^{all'}, \; z \epsilon \Re_+^J$$



In the graph above, A represents the most feasible frontier. This is so because we believe there is nothing like zero level of SOM. There would always be some minimum level of SOM independent in the rate of depletion. This minimum level of SOM we represent as D on the graph. B represents a hypothetical frontier. Here we assume that zero levels of SOM is a possibility. This means that there would always be that minimum level of crop production that farmers can obtain in the absence of SOM in the soils. This we represent on the graph as E. C represents a policy effect. It is an indication of the percentage of SOM, hence biomass, that can be harvested by a given county that would not have any effect on current production levels. An efficiency ("*SOM Efficiency*") estimate of 0.7 represent a 30% SOM harvest potential by that county. Counties on the frontier represent those counties that need all their current levels of SOM to produce their prevailing levels of output. Their biomass harvest potential is thus zero. This analysis suggests that counties that are relatively *"SOM inefficient"* have higher biomass harvest potentials than those that are relatively *"SOM efficient"*.

4.0: Results and Discussions

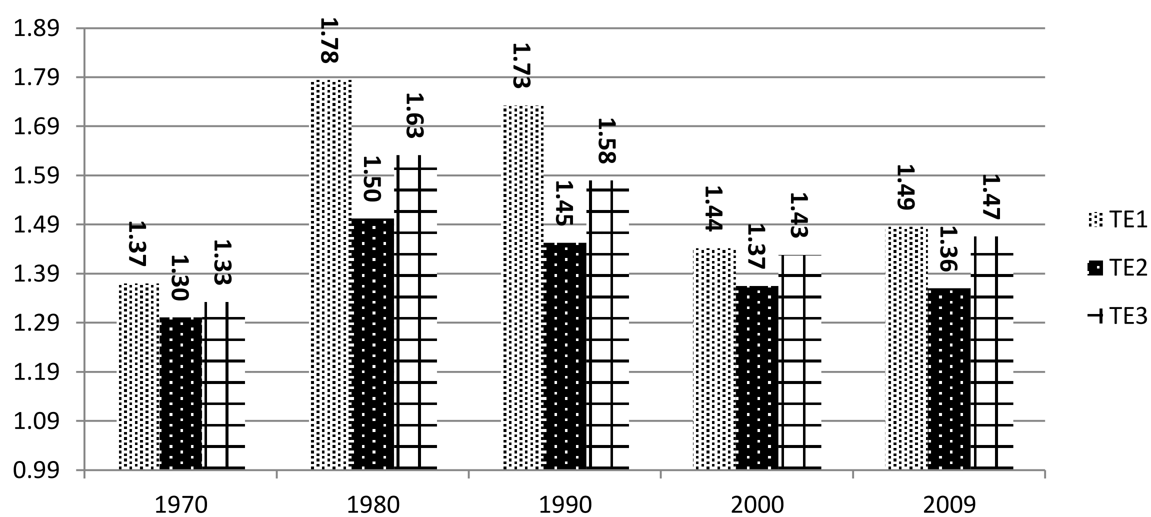
In this section we present results from the analysis carried out. These include TE and TFP estimates as described in the previous sections. We also present SOM efficiency estimates for 2010 for all 47 counties. The section is outlined in the following order: We first discuss the results from TE estimates revealing trends in Nebraska Agriculture and then showing the contributions of SOM to explaining TE. These are followed by TFP estimates also in the manner described above. Later we present SOM efficiency estimates.

4.1.1: Output Technical Efficiency

Output technical efficiency measures are bounded downwards by 1 and are open ended upwards.

4.1.1.1: Figure 5: Average Technical Efficiency Estimates for 28 counties in Nebraska (1970, 1980, 1990, 2000 and 2009)

Without SOM, With SOM - Milner/Martellotto and with SOM -Yang/Perrin



An output efficiency measure of 1 represents the optimum use of inputs to produce a given set of outputs.

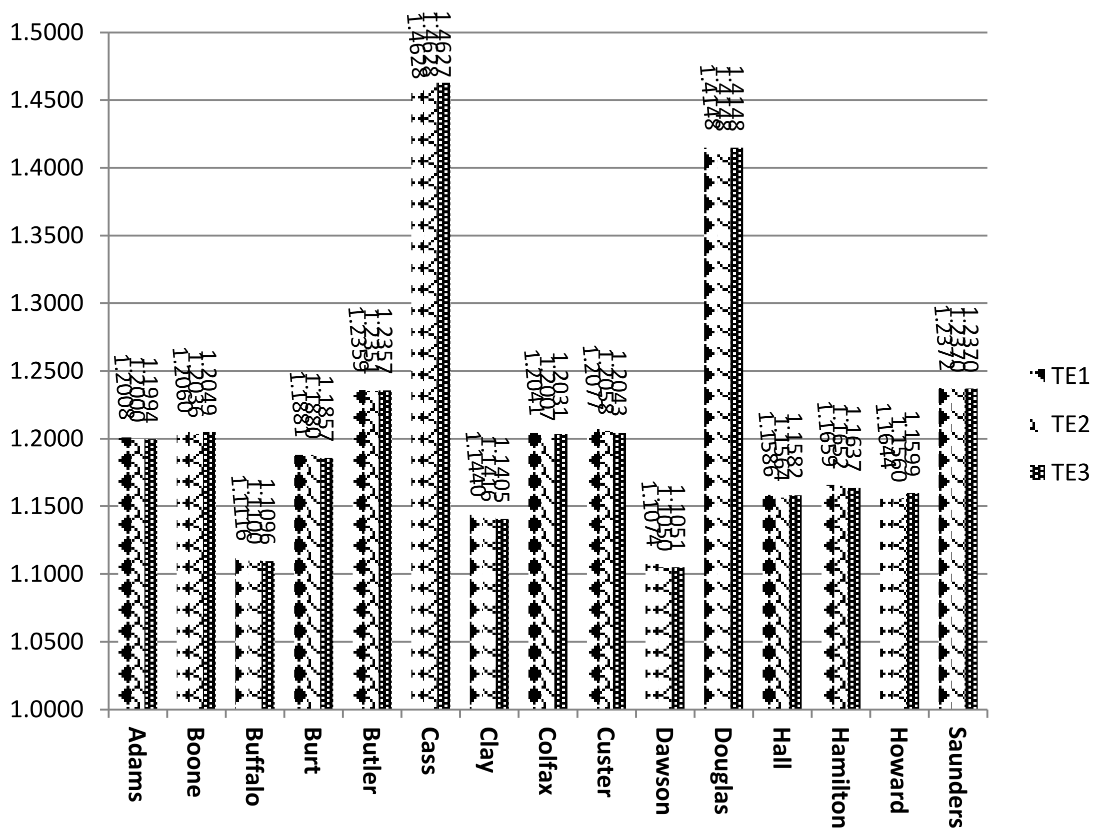
Deviation from one represent the percentage by which outputs can in increased given the same level of inputs. In our analysis, three output efficiency measures are estimated. TE1 represent technical efficiency in the absence of soil organic matter. TE2 represents technical efficiency when SOM (as defined by Milner/Martellotto) is included as an input. The third measure, TE3 is very similar to TE3 except that instead of using SOM from Milner/Martellotto, we use SOM from Yang/Perrin.

Figure 5 presents' average TE estimates for only 28 out of the 47 counties targeted for the years 1970, 1980, 1990, 2000 and 2009. For the respective years targeted, there had been an inefficient use of inputs to produce the given outputs. On average, there had been up to 49% potential increases in outputs in 2009 given the then prevailing inputs. Comparing the three TE measures, for all the years, the inclusion of either SOM helped in explaining performance for all the years. The highest contribution was in 1990 when SOM Yang/Perrin was included in the model as an input. The main implication of these results is that DMUs that appeared less efficient in the absence of SOM became even more efficient when SOM is included as an input. This effect was greatest in the 90s.

TE estimates were then computed across counties. For these estimates, a frontier was mapped for a given county over the 41 years. This was done for all 47 counties. The county averages are shown in figure 6. Similar to the previous case, three TE measures were estimated TE1, TE2 and TE3. All three measures are as described above.

All the counties targeted had technical efficiency estimates greater than one. This means that they all had huge room for improvements when averaged over the 41 years period. When compared across the three efficiency estimates. Very little changes were observed. TE2 and TE3 estimates tended towards a smaller measure than TE1. However these differences were very minute, particularly when compared to the change reported when the estimates were averaged over time as shown in the previous scenario.

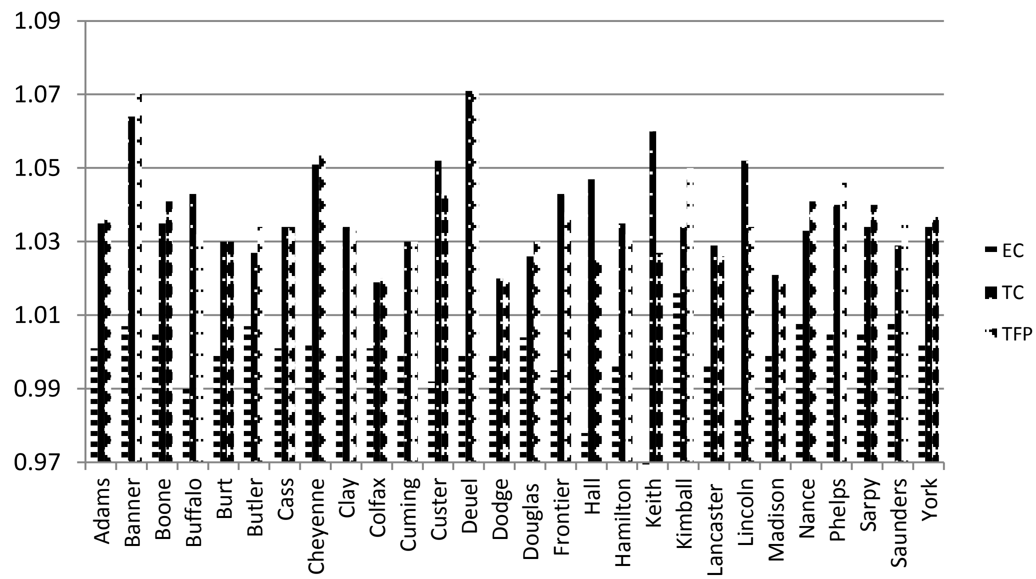
Figure-6: Technical Efficiency Estimates Averaged over 40 years for 15 Selected Counties out of 28 Counties



4.1.2: Malmquist Index Results

In this section, we report TFP estimates from the Malmquist indices computed. Most of the literature on inter-country productivity performance have attribute growth in TFP for the United States to technological change and had been on a positive growth trajectory over the years. Here we try to provide evidence of the drivers of TFP at the county level. For the most common prevailing technologies in agriculture, TFP estimates predominantly lie between zero and 1 and 1 to 2.

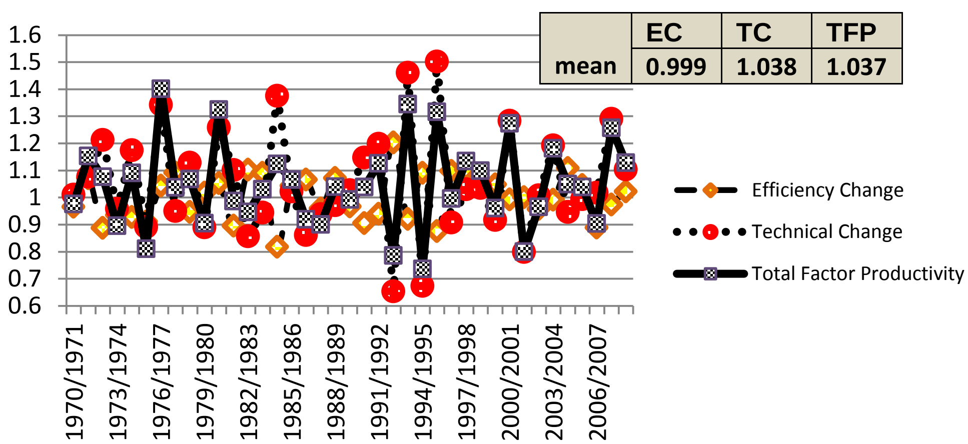
Figure 7: TFP ACROSS COUNTIES AND AVERAGED OVER 47 YEARS



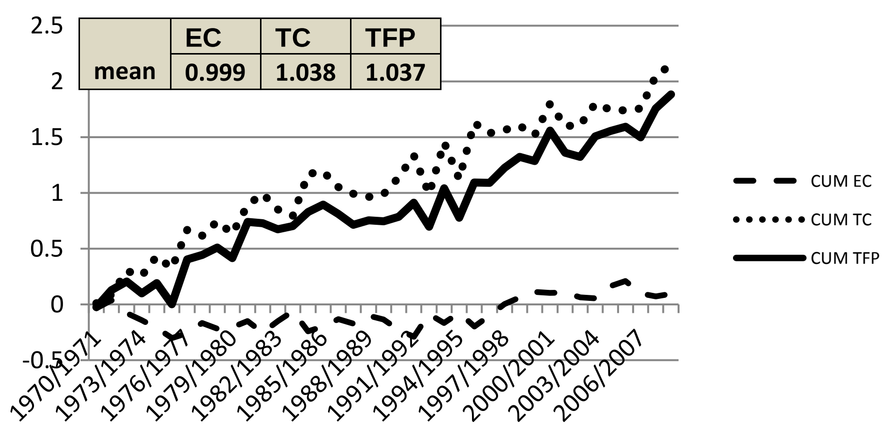
A value greater than one represents the percentage by which TFP increased and a value less than one represents a percentage decrease in TFP.

Figure 7 above shows TFP estimates for the 28 out of the 47counties and averaged over the 41 year interval. All TFP estimates were positive for all counties. This signifies that there has been an average increase in productivity growth for all counties over the period targeted. From the means reported, there was a TFP growth rate of about 3.7% for all counties and this growth was accounted mainly by Technological Change (3.8%) with Efficiency change accounting for a smaller proportion (-0.1%). From the counties considered, the most productive were Saunders, Cass and Bonne Counties.

Figure 8: TFP ACROSS COUNTIES AND AVERAGED OVER 41 YEARS



CUMULATIVE TFP, TC AND EC



4.1.3: Comparing Across Time

Figure 8 above presents TFP, EC and TC estimates averaged over all counties for the 41 years targeted. The first graph shows a plot of the Malmquist estimates while the second show the same estimates but cumulated. These further confirm that TFP have been growing in Nebraska over the years and this growth had been driven most significantly by TC.

4.1.4: Effects of SOM on TFP

Figure 9: Three TFP Measures Compared

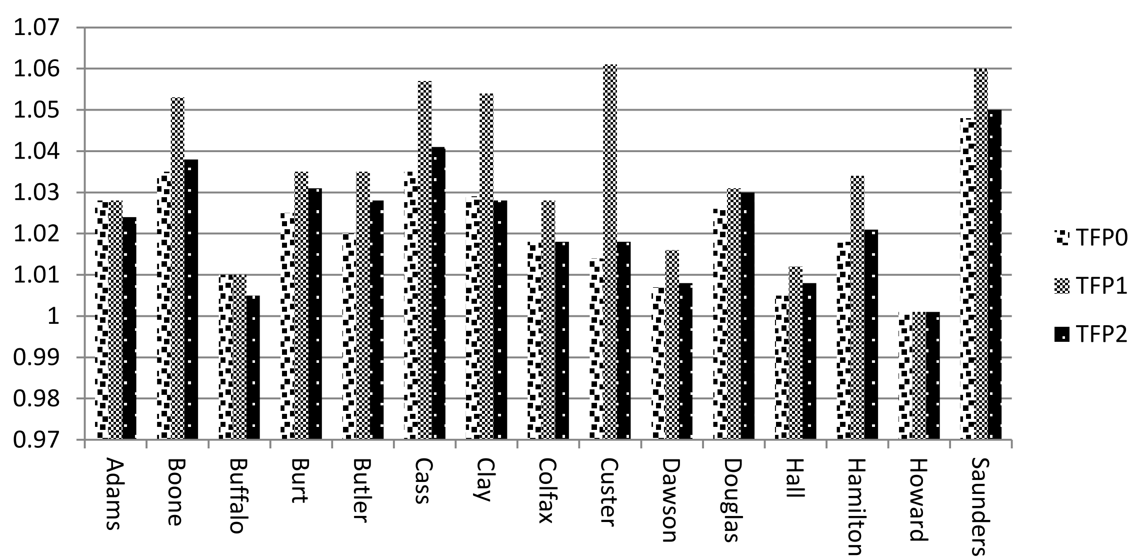


Figure 9 above presents TFP estimates for the three measures discussed above. TFP0 represents TFP estimates without SOM. TFP1 represents TFP estimates with SOM (Milner/Martellotto) while TFP2 represents TFP estimates with SOM (Perrin/Yang). For the counties the inclusion of SOM Milner/Martellotto as an input increased their TFP estimates. The same is true when SOM

Perrin/Yang was included except for Adams and Buffalo counties which reported a decrease. The Two graphs in appendix two try to determine which of TC and EC does SOM affect the most. They both confirm that the contribution of SOM has been more towards TC instead of EC. One may carefully infer then that SOM is TC enhancing and EC dis-enhancing.

All the discussions above on TE, and TFP were obtained from the tables in the appendix section. They can be useful for reference purposes.

4.1.5 Biomass Harvest Potentials

Table 2: SOM Efficiency, TE (2010) and Harvest Potentials for all counties

Counties	TE	SOM Efficiency	Harvest Potential	TFP
Adams	1.09	0.893	0.107	1.03
Banner	1	1	0	0.947
Burt	1	1	0	1.038
Butler	1	1	0	1.02
Cass	1.1	0.681	0.319	1.07
Chase	1.02	0.808	0.192	1.012
Cheyenne	1	1	0	0.95
Dawson	1	1	0	0.983
Deuel	1	1	0	0.969
Dodge	1	1	0	1.03
Hamilton	1	1	0	1.054
Hayes	1	1	0	0.983
Howard	1.07	0.778	0.222	0.978
Nance	1	1	0	1.004
Perkins	1.08	0.844	0.156	1.006
Phelps	1.07	0.848	0.152	1.043
Saunders	1.03	0.937	0.063	1.036
Scotts Bluff	1	1	0	1.007
Seward	1	1	0	1.028
York	1	1	0	1.059

Table 2 above shows parts of the results from the biomass harvest potentials obtained. The rest of the results can be viewed in the appendix section. As shown, 55% of the counties targeted have no biomass harvest potentials. The remaining 45% have varying potentials. One main inference that can be made from these results is that every county has its own unique biomass harvest potential. Therefore biomass harvest policy should be county specific and not state specific. The highest harvest potentials were reported in Lincoln, Gosper, Colfax and Cass counties. These counties have an average harvest potential of 35%.

5.0: Conclusion

This paper primarily tries investigates the contribution of SOM on explaining changes in TE and agricultural productivity across counties. It also tried to give an account of the status of inter-county agricultural productivity in Nebraska. These results are expected to give insight into the nature of the prevalent drivers of TFP growth. Obtaining biomass harvest potentials by county is crucial in order to ensure that agricultural productivity is not compromised at the expense of second generation biofuels. This paper proposes a methodology to obtain these estimates at the county level. These results would be useful to help make inferences on the future of cellulosic ethanol.

From the analysis carried out, the following conclusions can be made: SOM does help in explaining variations in TE across counties in Nebraska. The inclusion of either SOM in the model made all counties look at least better off than their efficiency estimates without SOM. SOM also helps in explaining productivity growth across counties. However the effects on TE are greater than the effects on productivity growth. Over the years, counties in Nebraska have enjoyed a growth in TFP of 3.7%. The main driver of this growth in TFP as revealed by the Malmquist index decomposition was technological change. Technological change accounted for 3.8% while efficiency change accounted for only -0.1%. This is in consonant with the broad literature of inter-country level total factor productivity estimates for the United States. Most of these studies report that US agriculture relative to other countries in the world is driven by TC rather than EC. These results therefore suggest that the commercial harvest of biomass for cellulosic ethanol should be done at minimal levels that would still leave enough crop residues for conversion to SOM. In the vain, the most important conclusion is that biomass harvest potentials vary considerably across counties. Therefore policy targets should be county specific instead of state specific. On average, 55% of the counties in Nebraska have zero biomass harvest potentials. Only the remaining 45% should be granted the rights to harvest biomass for cellulosic ethanol purposes.

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Appendix

Technical Efficiency Estimates for 1970, 1980, 1990, 2000 and 2009 for 28 counties

Counties	1970			1980			1990			2000			2009		
	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3
Adams	1.45	1.4	1.4	2.43	2.22	2.28	1.76	1.7	1.7	1.2	1.2	1.22	1.39	1.38	1.39
Banner	1.86	1.9	1.86	1.54	1.54	1.54	1.57	1.6	1.57	1.6	1.6	1.6	1.41	1.41	1.41
Boone	1.63	1.5	1.6	2.77	1.6	2.5	2.37	1.3	2.07	1.4	1.3	1.38	1.3	1.1	1.29
Buffalo	1.11	1.1	1.09	2.13	1.4	1.68	1.7	1.3	1.53	1.7	1.6	1.6	1.67	1.58	1.66
Burt	1.06	1.1	1.05	1.11	1.11	1.05	1.09	1.1	1.09	1.1	1.1	1.04	1.05	1.05	1.05
Butler	1.53	1.5	1.53	1.54	1.43	1.53	1.51	1.3	1.51	1.2	1.2	1.15	1.17	1.12	1.17
Cass	1.03	1	1.03	1	1	1	1	1	1	1	1	1	1	1	1
Cheyenne	1.48	1.5	1.48	1.48	1.03	1	2.16	1.1	1	1	1	1	1.34	1	1
Clay	1.32	1.2	1.27	1.69	1.28	1.61	1.42	1	1.4	1.1	1	1.03	1.38	1.22	1.36
Colfax	1.17	1.2	1.17	1.09	1.09	1.09	1.19	1.2	1.19	1.1	1.1	1.11	1.14	1.14	1.14
Cuming	1.11	1.1	1.07	1.3	1.3	1.3	1.23	1.2	1.2	1.2	1.2	1.22	1.1	1.1	1.1
Custer	1.86	1	1.64	2.52	1	1.89	2.39	1	1.86	2.5	1.4	2.48	2.58	1.01	2.55
Deuel	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Dodge	1	1	1	1.21	1	1.21	1.26	1	1.17	1	1	1.01	1.04	1	1.04
Douglas	1.32	1.3	1.32	1.36	1.36	1.36	1.43	1.4	1.43	1	1	1	1.13	1.13	1.13
Frontier	1.9	1.8	1.87	2.67	2.67	2.67	3.06	3.1	3.06	2.6	2.6	2.61	2.29	2.27	2.29
Hall	1.13	1.1	1.1	2.57	2.32	2.07	2.29	2.2	2.04	1.9	1.9	1.91	2.63	2.63	2.63
Hamilton	1.24	1	1.01	2.64	1.43	1.9	2.05	1.2	1.56	1.1	1.1	1.08	1.37	1.24	1.36
Keith	1	1	1	1.97	1.97	1.97	2.94	2.9	2.94	3.6	3.6	3.61	3.5	3.46	3.5
Kimball	2.32	2.3	2.32	1.41	1.41	1.41	1.14	1.1	1.14	1.6	1.2	1.59	1.26	1	1.16
Lancaster	1	1	1	1	1	1	1	1	1	1.1	1.1	1.12	1.12	1.12	1.12
Lincoln	1.34	1.3	1.29	2.35	1.85	2.34	2.94	2	2.75	2.4	2.2	2.4	2.68	2.1	2.65
Madison	1.13	1.1	1.13	1.52	1.51	1.48	1.37	1.4	1.37	1.2	1.2	1.14	1.18	1.18	1.18
Nance	1.85	1.8	1.84	2.8	2.76	2.8	2.33	2.3	2.33	1.5	1.5	1.49	1.34	1.34	1.34
Phelps	1.51	1.4	1.43	2.44	1.78	1.85	2.19	1.6	1.73	1	1	1	1.22	1.22	1.22
Sarpy	1.22	1.2	1.22	1.26	1.26	1.26	1.23	1.2	1.23	1.1	1.1	1.05	1	1	1
Saunders	1.36	1.4	1.36	1	1	1	1.21	1.1	1	1	1	1	1	1	1
York	1.45	1.3	1.23	2.17	1.76	1.89	1.69	1.3	1.38	1.2	1.2	1.16	1.31	1.29	1.31

	1970			1980			1990			2000			2009		
	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3
Average	1.37	1.3	1.33	1.78	1.5	1.63	1.73	1.45	1.58	1.44	1.37	1.43	1.49	1.36	1.47

Technical Efficiency Estimates for Selected Counties over 40 years

Years	Adams			Banner			Boone		
	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3
1970	1.16	1.16	1.16	2.59	2.59	2.59	1.12	1.12	1.12
1971	1.17	1.17	1.17	2.73	2.73	2.73	1.17	1.17	1.17
1972	1	1	1	4.34	4.34	4.34	1	1	1
1973	1.15	1.15	1.15	3.48	3.48	3.48	1.07	1.03	1.03
1974	1.15	1.15	1.15	6.36	6.36	6.36	1.37	1.37	1.37
1975	1.09	1.09	1.09	4.61	4.61	4.61	1.01	1.01	1.01
1976	1	1	1	4.45	4.45	4.45	1.19	1.19	1.19
1977	1.01	1	1	2.49	2.49	2.49	1.02	1.02	1.02
1978	1	1	1	2	2	2	1.03	1.03	1.03
1979	1	1	1	2.06	2.06	2.06	1.09	1.08	1.08
1980	1.31	1.31	1.31	2.33	2.33	2.33	1.38	1.38	1.38
1981	1.06	1.06	1.06	2.37	2.37	2.37	1	1	1
1982	1.16	1.16	1.16	1.89	1.89	1.89	1.16	1.15	1.15
1983	1.3	1.3	1.3	2.07	2.07	2.07	1.25	1.25	1.25
1984	1.19	1.19	1.19	1.58	1.58	1.58	1.03	1.03	1.03
1985	1.1	1.1	1.1	1.91	1.91	1.91	1	1	1
1986	1.17	1.17	1.17	1.38	1.38	1.38	1.12	1.11	1.11
1987	1.08	1.08	1.08	1	1	1	1.15	1.14	1.15
1988	1.12	1.12	1.12	1.4	1.4	1.4	1.22	1.22	1.22
1989	1.13	1.13	1.13	1.45	1.45	1.45	1.14	1.14	1.14
1990	1.05	1.05	1.05	1.74	1.74	1.74	1.08	1.06	1.07
1991	1	1	1	1.24	1.24	1.24	1.17	1.14	1.15
1992	1.04	1.04	1.04	1	1	1	1.02	1	1
1993	1.56	1.56	1.56	1.7	1.62	1.61	1.3	1.27	1.27
1994	1.1	1.1	1.1	1.23	1.19	1.18	1	1	1
1995	1.19	1.19	1.19	2.18	2.16	2.13	1.42	1.42	1.42
1996	1	1	1	1.47	1.44	1.42	1	1	1
1997	1.14	1.12	1.09	1.5	1.41	1.38	1.2	1.2	1.19
1998	1.11	1.07	1.04	1.07	1.03	1.03	1.03	1.02	1.03
1999	1.09	1.07	1.05	1	1	1	1.16	1.13	1.12
2000	1.11	1.09	1.07	1.55	1.51	1.48	1.28	1.26	1.26
2001	1	1	1	1.25	1.25	1.24	1	1	1
2002	1.08	1.05	1.06	2.44	2.41	2.39	1.14	1.11	1.12
2003	1.01	1	1.01	2.44	2.41	2.39	1.13	1.09	1.1
2004	1.01	1.01	1.01	1.78	1.76	1.75	1.1	1.06	1.07
2005	1.01	1.01	1.01	1.55	1.54	1.53	1.05	1.04	1.04
2006	1	1	1	1.67	1.64	1.64	1.02	1.02	1.02
2007	1	1	1	1	1	1	1.03	1	1
2008	1.02	1.02	1.01	1	1	1	1.08	1.08	1.08
2009	1	1	1	1	1	1	1	1	1

Malmquist Index Results Without SOM – Averaged over Counties

Period	Efficiency Change	Technical Change	Total Factor Productivity
1970/1971	0.966	1.01	0.976
1971/1972	1.071	1.077	1.153
1972/1973	0.887	1.213	1.076
1973/1974	0.935	0.958	0.896
1974/1975	0.928	1.175	1.091
1975/1976	0.911	0.891	0.811
1976/1977	1.044	1.343	1.402
1977/1978	1.092	0.95	1.038
1978/1979	0.947	1.128	1.068
1979/1980	1.017	0.89	0.905
1980/1981	1.053	1.258	1.325
1981/1982	0.896	1.101	0.987
1982/1983	1.103	0.857	0.946
1983/1984	1.091	0.944	1.03
1984/1985	0.818	1.375	1.124
1985/1986	1.043	1.022	1.066
1986/1987	1.066	0.862	0.919
1987/1988	0.959	0.938	0.9
1988/1989	1.072	0.971	1.04
1989/1990	0.967	1.027	0.993
1990/1991	0.905	1.148	1.039
1991/1992	0.94	1.198	1.126
1992/1993	1.203	0.654	0.786
1993/1994	0.921	1.461	1.345
1994/1995	1.091	0.674	0.736
1995/1996	0.876	1.502	1.316
1996/1997	1.098	0.908	0.996
1997/1998	1.102	1.03	1.135
1998/1999	1.062	1.035	1.099
1999/2000	1.048	0.917	0.961
2000/2001	0.993	1.283	1.274
2001/2002	1.001	0.799	0.8
2002/2003	0.957	1.008	0.965
2003/2004	0.992	1.192	1.182
2004/2005	1.108	0.946	1.049
2005/2006	1.046	0.994	1.039
2006/2007	0.889	1.017	0.904
2007/2008	0.974	1.291	1.257
2008/2009	1.022	1.104	1.128
mean	0.999	1.038	**1.037**

Malmquist Index Results With SOM Milner/Martellotto- Averaged over Counties			
Period	**Efficiency Change**	**Technical Change**	**Total Factor Productivity**
1970/1971	0.986	1.034	1.02
1971/1972	1.052	1.097	1.154
1972/1973	0.893	1.227	1.096
1973/1974	0.938	0.969	0.909
1974/1975	0.955	1.168	1.116
1975/1976	0.92	0.919	0.845
1976/1977	1.067	1.34	1.429
1977/1978	1.126	0.947	1.066
1978/1979	0.963	1.144	1.102
1979/1980	1.003	0.917	0.919
1980/1981	1.063	1.261	1.341
1981/1982	0.871	1.154	1.005
1982/1983	1.038	0.838	0.87
1983/1984	1.139	0.994	1.133
1984/1985	0.849	1.352	1.148
1985/1986	1.082	0.978	1.058
1986/1987	1.007	0.921	0.927
1987/1988	0.963	0.97	0.933
1988/1989	1.081	0.991	1.071
1989/1990	0.991	1.05	1.041
1990/1991	0.93	1.162	1.081
1991/1992	0.973	1.186	1.154
1992/1993	1.093	0.711	0.777
1993/1994	0.943	1.521	1.434
1994/1995	1.053	0.702	0.739
1995/1996	0.917	1.518	1.392
1996/1997	1.064	0.959	1.02
1997/1998	1.07	1.064	1.139
1998/1999	1.02	1.074	1.095
1999/2000	1.023	0.939	0.961
2000/2001	1.014	1.254	1.272
2001/2002	0.994	0.815	0.811
2002/2003	0.988	1.019	1.006
2003/2004	0.997	1.215	1.211
2004/2005	1.08	0.977	1.055
2005/2006	1.028	1.021	1.05
2006/2007	0.892	1.06	0.945
2007/2008	1.006	1.209	1.216
2008/2009	1.013	1.132	1.148
Mean	1	1.057	**1.056**

Malmquist Index Results With SOM Perrin/Wang – Averaged Over Counties

Period	Efficiency Change	Technical Change	Total Factor Productivity
1970/1971	0.995	1.03	1.025
1971/1972	1.046	1.1	1.151
1972/1973	0.872	1.264	1.102
1973/1974	0.932	0.966	0.901
1974/1975	0.946	1.162	1.099
1975/1976	0.911	0.91	0.829
1976/1977	1.077	1.325	1.428
1977/1978	1.12	0.937	1.049
1978/1979	0.953	1.154	1.1
1979/1980	0.999	0.914	0.913
1980/1981	1.048	1.265	1.326
1981/1982	0.89	1.114	0.991
1982/1983	1.074	0.831	0.893
1983/1984	1.123	0.978	1.098
1984/1985	0.823	1.369	1.126
1985/1986	1.07	0.981	1.049
1986/1987	1.037	0.876	0.909
1987/1988	0.945	0.968	0.914
1988/1989	1.077	0.977	1.053
1989/1990	0.995	1.016	1.011
1990/1991	0.9	1.17	1.053
1991/1992	0.959	1.172	1.124
1992/1993	1.123	0.689	0.773
1993/1994	0.936	1.474	1.38
1994/1995	1.084	0.674	0.73
1995/1996	0.877	1.517	1.331
1996/1997	1.099	0.918	1.009
1997/1998	1.075	1.051	1.13
1998/1999	1.051	1.037	1.09
1999/2000	1.045	0.913	0.954
2000/2001	0.989	1.279	1.265
2001/2002	1.002	0.804	0.806
2002/2003	0.975	1.009	0.984
2003/2004	0.993	1.201	1.193
2004/2005	1.108	0.95	1.053
2005/2006	1.038	1.009	1.048
2006/2007	0.878	1.029	0.904
2007/2008	0.98	1.276	1.25
2008/2009	1.024	1.102	1.128
mean	0.999	1.045	**1.044**

<u>Malmquist Index Results Without SOM – Averaged over Years</u>

Counties	Efficiency Change	Technical Change	Total Factor Productivity
Adams	1.001	1.035	1.036
Banner	1.007	1.064	1.072
Boone	1.006	1.035	1.041
Buffalo	0.99	1.043	1.032
Burt	1	1.03	1.03
Butler	1.007	1.027	1.034
Cass	1.001	1.034	1.034
Cheyenne	1.003	1.051	1.054
Clay	0.999	1.034	1.033
Colfax	1.001	1.019	1.02
Cuming	1	1.03	1.03
Custer	0.992	1.052	1.043
Deuel	1	1.071	1.071
Dodge	0.999	1.02	1.019
Douglas	1.004	1.026	1.03
Frontier	0.995	1.043	1.038
Hall	0.978	1.047	1.025
Hamilton	0.997	1.035	1.032
Keith	0.968	1.06	1.027
Kimball	1.016	1.034	1.05
Lancaster	0.997	1.029	1.026
Lincoln	0.982	1.052	1.034
Madison	0.999	1.021	1.019
Nance	1.008	1.033	1.041
Phelps	1.005	1.04	1.046
Sarpy	1.005	1.034	1.04
Saunders	1.008	1.029	1.037
York	1.003	1.034	1.037

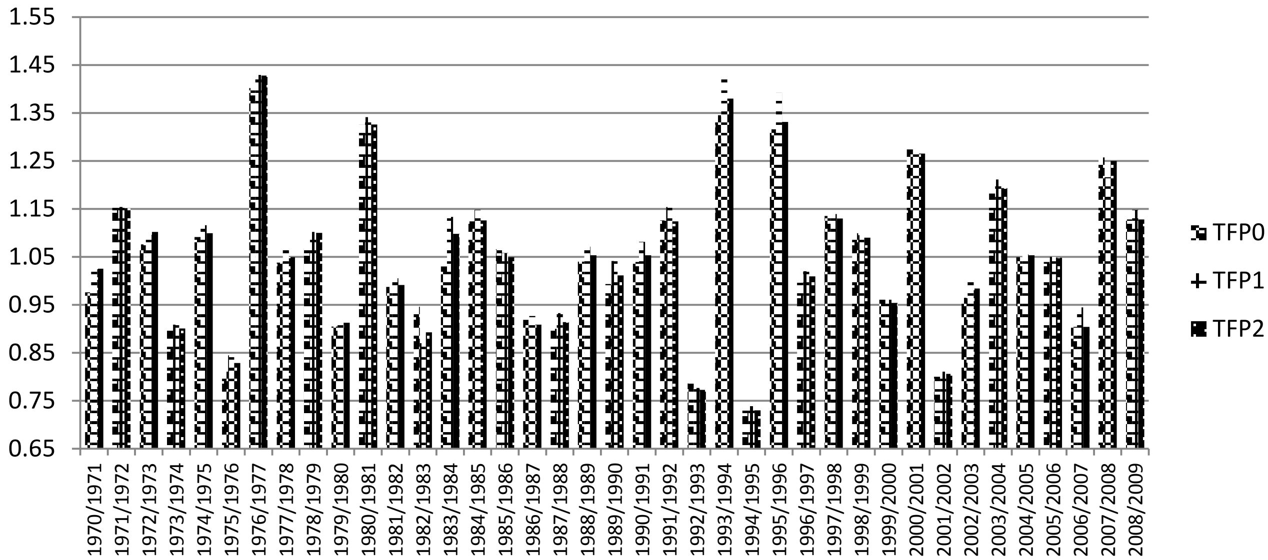
Malmquist Index Results with SOM Milner/Martellotto- Averaged over Years

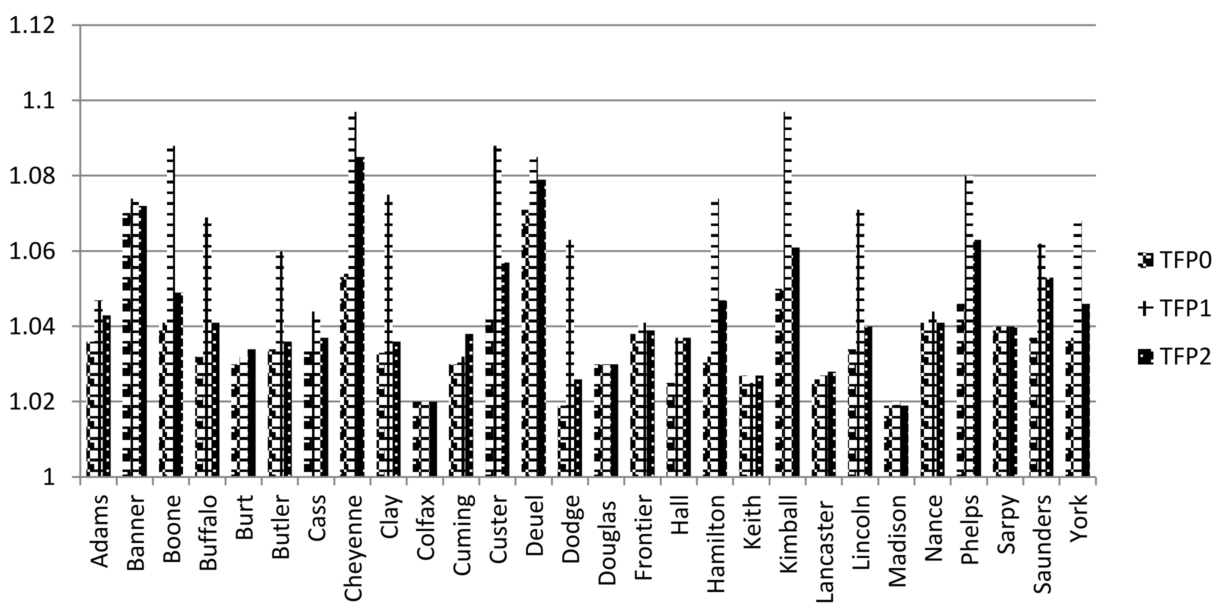
Counties	Efficiency Change	Technical Change	Total Factor Productivity
Adams	1	1.047	1.047
Banner	1.007	1.066	1.074
Boone	1.007	1.081	1.088
Buffalo	0.991	1.079	1.069
Burt	1	1.032	1.032
Butler	1.008	1.052	1.06
Cass	1.001	1.043	1.044
Cheyenne	1.01	1.086	1.097
Clay	0.999	1.076	1.075
Colfax	1.001	1.019	1.02
Cuming	1	1.032	1.032
Custer	1	1.089	1.088
Deuel	1	1.085	1.085
Dodge	1	1.063	1.063
Douglas	1.004	1.026	1.03
Frontier	0.995	1.047	1.041
Hall	0.978	1.06	1.037
Hamilton	0.995	1.08	1.074
Keith	0.969	1.058	1.025
Kimball	1.022	1.074	1.097
Lancaster	0.997	1.03	1.027
Lincoln	0.988	1.084	1.071
Madison	0.999	1.021	1.02
Nance	1.008	1.036	1.044
Phelps	1.004	1.075	1.08
Sarpy	1.005	1.034	1.04
Saunders	1.008	1.054	1.062
York	1	1.069	1.068

Malmquist Index Results With SOM Perrin/Wang – Averaged Over Years

Counties	Efficiency Change	Technical Change	Total Factor Productivity
Adams	1	1.042	1.043
Banner	1.007	1.064	1.072
Boone	1.005	1.043	1.049
Buffalo	0.989	1.053	1.041
Burt	1	1.034	1.034
Butler	1.007	1.029	1.036
Cass	1.001	1.037	1.037
Cheyenne	1.01	1.074	1.085
Clay	0.998	1.038	1.036
Colfax	1.001	1.019	1.02
Cuming	0.999	1.038	1.038
Custer	0.989	1.069	1.057
Deuel	1	1.079	1.079
Dodge	0.999	1.027	1.026
Douglas	1.004	1.026	1.03
Frontier	0.995	1.045	1.039
Hall	0.978	1.061	1.037
Hamilton	0.992	1.055	1.047
Keith	0.968	1.061	1.027
Kimball	1.018	1.043	1.061
Lancaster	0.997	1.03	1.028
Lincoln	0.982	1.059	1.04
Madison	0.999	1.02	1.019
Nance	1.008	1.033	1.041
Phelps	1.004	1.059	1.063
Sarpy	1.005	1.034	1.04
Saunders	1.008	1.045	1.053
York	0.998	1.048	1.046

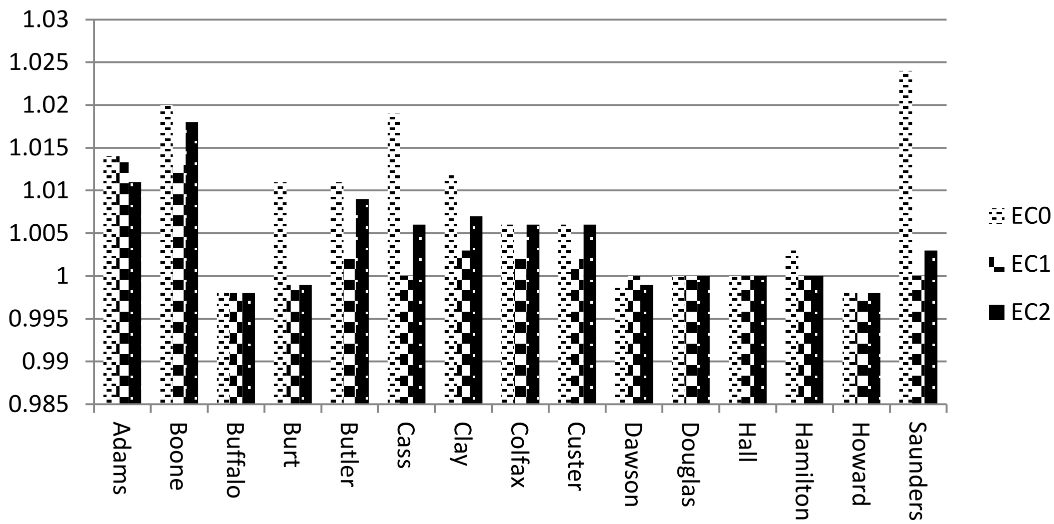
Effects of SOM on TFP. Over Time and Counties





Technical Change and Efficiency Change for Three levels of SOM

Efficiency Change



Technical Change

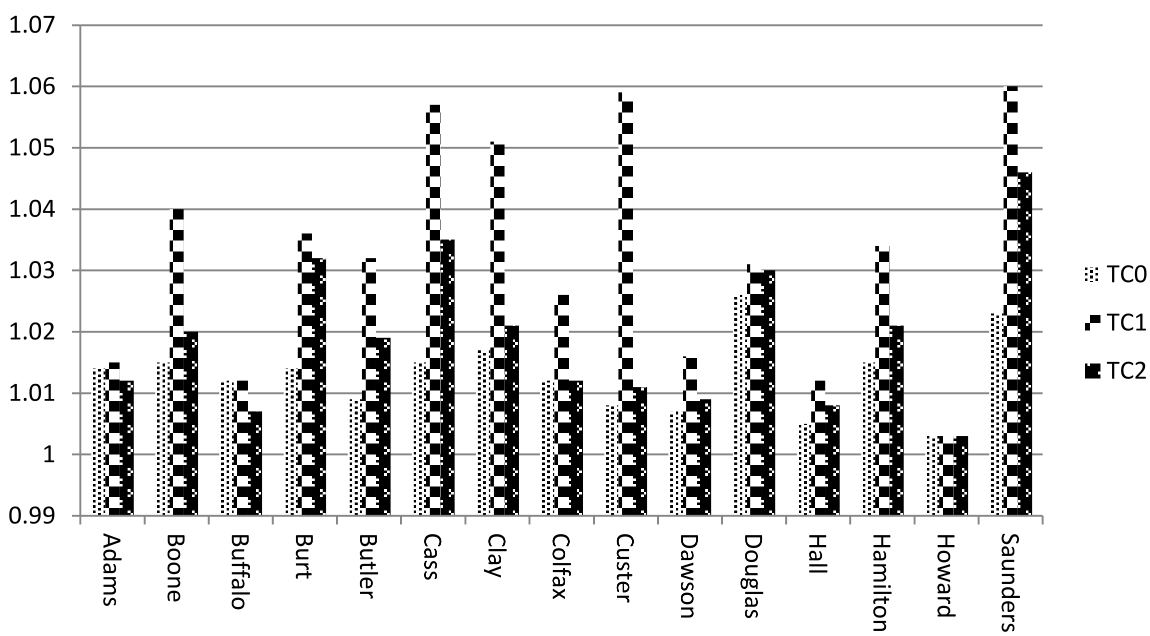


Table 10: SOM Efficiency, TE (2010) and Harvest Potentials for all counties

Counties	TE (2010)	SOM Efficiency (2010)	Harvest Potential (2010)	TFP(Average)
Adams	1.09	0.893	0.107	1.03
Banner	1	1	0	0.947
Boone	1	1	0	1.006
Buffalo	1	1	0	1.004
Burt	1	1	0	1.038
Butler	1	1	0	1.02
Cass	1.1	0.681	0.319	1.07
Chase	1.02	0.808	0.192	1.012
Cheyenne	1	1	0	0.95
Clay	1	1	0	1.038
Colfax	1.25	0.675	0.325	1.009
Cuming	1	1	0	0.999
Custer	1.02	0.949	0.051	0.988
Dawson	1	1	0	0.983
Deuel	1	1	0	0.969
Dodge	1	1	0	1.03
Douglas	1.11	0.863	0.137	1.017
Fillmore	1	1	0	1.05
Frontier	1.01	0.91	0.09	0.995
Gosper	1.03	0.658	0.342	1.012
Greeley	1	1	0	0.994
Hall	1	1	0	1.025
Hamilton	1	1	0	1.054
Hayes	1	1	0	0.983
Howard	1.07	0.778	0.222	0.978
Kearney	1.04	0.888	0.112	1.03
Keith	1	1	0	0.991
Kimball	1.03	0.94	0.06	0.957
Lancaster	1	1	0	0.98
Lincoln	1.39	0.671	0.329	0.989
Madison	1.02	0.954	0.046	0.939
Merrick	1.18	0.756	0.244	1.022
Nance	1	1	0	1.004
Perkins	1.08	0.844	0.156	1.006
Phelps	1.07	0.848	0.152	1.043
Platte	1.13	0.785	0.215	1.025
Polk	1.2	0.776	0.224	1.025
Saline	1.08	0.878	0.122	1.003
Sarpy	1.15	0.835	0.165	1.07
Saunders	1.03	0.937	0.063	1.036
Scotts Bluff	1	1	0	1.007
Seward	1	1	0	1.028
Sherman	1	1	0	0.973
Stanton	1	1	0	0.99
Valley	1	1	0	0.997
Washington	1	1	0	0.996
York	1	1	0	1.059