Improvement of GTAP Cropland Constant Elasticity of Transformation Nesting Structure

By

Liang Li, Farzad Taheripour, Paul Preckel, and Wallace E. Tyner

Authors' Affiliation

Liang Li is a Ph.D. student, Farzad Taheripour is Research Assistant Professor, Paul Preckel is Professor, and Wallace E. Tyner is James and Lois Ackerman Professor in the Department of Agricultural Economics at Purdue University.

Corresponding Author
Liang Li
Department of Agricultural Economics
Purdue University
403 West State St.
West Lafayette, IN 47907-2056
Fax: 765-494-9176
Email: liangli@purdue.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012

Improvement of GTAP Cropland Constant Elasticity of Transformation Nesting Structure

By

Liang Li, Farzad Taheripour, Paul Preckel, Wallace E. Tyner

Abstract

This paper suggests a new approach to econometrically estimate parameters of multi-level Constant Elasticity of Transformation (CET) functional forms which are widely used in developing Computable General Equilibrium (CGE) models. An illustrative CET functional form is estimated using the proposed method based on historical data taken from the U.S. economy for the time period of 1996-210 to evaluate the performance of the new method. The proposed estimation process may be used to improve the existing cropland frontier used in GTAP-BIO model. Currently, the cropland frontier in GTAP-BIO model supplies land to different crops using a simple one-level CET function due to the lack of empirically estimated more flexible functional forms. The proposed method provides an opportunity to estimate more flexible multi-level CET functional forms according to available historical data. This will help to change the land supply side of the GTAP-BIO model based on historical observations.

Key words: cropland allocation, CET, GTAP, land transformation elasticity, maximum likelihood estimation

1. Introduction

The economic modeling of land use and land use changes has been the focal point of many research studies in recent years. Explicit modeling of land use and land use changes is important to assess greenhouse gas emission reduction policies related to agricultural activities such as reduction in paddy rice production, managing livestock emissions, no till agriculture, forest carbon sequestration practices, and expansion in bioenergy crops and biofuel industry (Hertel, Rose, & Tol, 2008). In response to the demand for these types of analyses, many partial and general equilibrium models incorporated land into their framework.

The partial equilibrium models[1]usually consider land as an input in production functions of agricultural activities and assume that farmers maximize their profits for given input and output prices. These models typically follow land use activities and land management practices in detail. However, they miss the interactions between the land using industries and the rest of economic activities and often ignore resource constraints. The Computable General Equilibrium (CGE) models do not suffer from these deficiencies[2]. These models usually use Constant Elasticity of Transformation (CET) functional forms, originally introduced by Hertel and Tsigas (Hertel & Tsigas, 1988) to handle supply of land to its alternative uses. These CET functions use land transformation elasticities to accomplish this task. However, most of the existing CGE models use ad hoc elasticities due to the lack of reliable estimates in this area (Boeters, Veenendaal, van Leeuwen, & Rojas-Romagoza, 2008). In some cases a calibration process is used to retrieve land transformation elasticities from estimates for land supply elasticities

[1] Examples are: WATSIM (Kuhn, 2003); GTM (Sohngen, Mendelsohn, & Sedjo, 1999); and FASOM (Adams, Alig, Callaway, McCarl, & Winnett, 1996).

[2] Examples are: GTAP (Keeney & Hertel, 2009), ICES (Eboli, Parrado, & Roson, 2010), WorldScan (Boeters, Veenendaal, van Leeuwen, & Rojas-Romagoza, 2008).

(Ahmed, Hertel, & Lubowski, 2008). However, these calibrations cannot be used in many circumstances and the results are not satisfactory in many cases.

A CET land frontier allocates productivity adjusted land between its alternative uses using land transformation elasticities. In other words a CET function maps physical areas of land to a frontier which reflects productivity adjusted land. To econometrically estimate a CET land frontier one needs actual observations on land allocation, returns to alternative land uses, and total productivity adjusted areas of land. In practice, the productivity adjusted land is not observable. Because of this problem, no one has estimated a CET frontier directly from actual observations so far. This paper offers a new method to directly estimate a CET frontier using a maximum likelihood estimation process. Then it tests the proposed method and estimates an illustrative two-level nested CET cropland frontier using actual observations from the U.S. economy for the time period of 1996-2010.

The ultimate goal is to extend this work and estimate a flexible cropland frontier for the GTAP-BIO model. The model currently uses a simple one-level nested CET frontier to handle the supply of cropland among alternative crop industries. The method developed in this paper will be used to estimate a more flexible multi-level nested CET functional form for GTAP-BIO model.

The next two sections review background of land supply in CGE modeling and highlight the current limits in this area. Then historical data on US cropland evolution is examined to learn how cropland allocation has changed in this economy in recent years and then a nesting structure will be proposed in the data section.

2. Supply of land in CGE modeling

Many CGE models use the CET function to allocate land among its alternative uses. These models usually disaggregate land supply by physical characteristics such as length of growing period, soil type, and climate conditions. Darwin et al. used this approach and introduced disaggregated land into the FARM model (Darwin, 1998). Following this initial work, Burniaux introduced disaggregated land supply into the GTAP modeling framework and defined competition for land among crops in this model (Burniaux & Truong, 2002). Then Lee et al. improved this approach and introduced land by 18 Agro Ecological Zones (AEZs) into the GTAP modeling framework (Lee, Hertel, Rose, & Avetisyan, 2008). The GTAP-BIO model and many other CGE models which follow GTAP adopted this framework.

In GTAP-BIO model, land is assumed to be transformable among uses of cropland, pasture, and forest in each AEZ. Land allocation among land cover types is governed by a Constant Elasticity of Transformation (CET) function. Then cropland is allocated among crops using a one-level CET function as well. Today many CGE models still follow this structure.

A representative CGE model that is quite different from GTAP is MIT-IGSM-EPPA. At first, the model used economic accounting of inputs of land, where annual land service available is represented by the total rental value of land and did not explicitly allow for competition among different land uses. In an extended version of this model, land is modeled as a renewable resource with five land types: cropland, pasture, harvested forest land, natural grass land, and natural forest land. The crop sectors and the two biomass sectors compete for cropland. Pasture land and harvested forest land are assumed to be used exclusively in the livestock sector and forest sector respectively. Natural grass land and natural forest land enters directly into the utility of the representative agent for value of biodiversity (Gurgel, Reilly, & Paltsev, 2008).

Another characteristic CGE model is USAGE (U.S. Applied General Equilibrium model). USAGE has recently been updated and modified for agriculture and energy sector study to enhance its utility in agricultural and biofuels analysis. In this model the demand for land is modeled using a CRESH (constant ratio of elasticity of substitution, homothetic) functional form, and a CRETH (constant ratio of elasticity of transformation, homothetic) function is used to model the supply side of the land market. There are 72 (9 Farm Resource Regions × 8 Land Capability Classes) land types in fixed supply. The allocation decision is governed by a CRETH function, characterized by the transformation possibilities among uses. (Ashley & Winston, January 2009)

3. Current GTAP land allocation and its limitation

As mentioned earlier in this paper, the GTAP-BIO model handles land allocation in two steps. It first uses a one-level CET to allocate a fixed endowment of land among forest, grassland and cropland. Then it uses another one-level CET to allocate cropland among crop industries. In this paper we concentrate on the cropland frontier used in this model. A simple one-level CET functional form is as follows:

$$F(x) = \alpha\left[\sum_{i=1}^{n} \beta_i {x_i}^{\rho}\right]^{1/\rho} = \alpha[\beta_1 {x_1}^{\rho} + \beta_2 {x_2}^{\rho} + \dots + \beta_n {x_n}^{\rho}]^{1/\rho}$$

Where α and β_i are positive constants parameters and $\rho > 1$. A CET function is strictly increasing in its arguments (x_is), homogenous degree one and convex. The relationship between the elasticity of transformation (σ) and the constant ρ is:

$\sigma = \frac{1}{1-\rho}$ or $\rho = 1 - \frac{1}{\sigma}$

Note that Constant Elasticity of Substitution functions (CESs) share the same functional form with CETs, the only difference is the constraint on ρ. The value range ρ can take on for

CES is $(-\infty, 0) \cup (0,1)$. In the limiting case where ρ approaches zero and σ approaches 1, this function approaches the Cobb-Douglas. Another limiting case used often in economics is where $\sigma = 0$ and ρ approaches negative infinity, which gives the Leontief function (Preckel, 2010). As mentioned above for the simple CET functional form represented above, ρ should be strictly greater than 1.

Due to nice mathematical properties and information availability, the CET function was first introduced to constrain the land stock and determine the responsiveness of land supply to changes in relative yields and prices by Hertel and Tsigas (Hertel & Tsigas, 1988), where an aggregate endowment of land is transformed across alternative uses, subject to some transformation parameters. Then CET is used by GTAP to handle land transformation across and within sectors. The problem with CET is that it does not keep track of physical hectares across uses. Instead, CET function constrains the land rental share-weighted sum of hectares to equal to the total value of endowment of land, which are believed to constrain the effective hectares in aggregate (Hertel, Rose, & Tol, 2008).

In the GTAP-BIO model, cropland is distributed across different crops using a simple one-level CET function, as shown in figure 1. The allocation of cropland in this version of GTAP depends on a single value for the land transformation elasticity of σ. One value of land transformation elasticity for one level CET function signifies the same level of ease of land transformation among all crops. In practice, the ease of switching from one crop to another one is not the same for all pairs of crops. A more flexible multi-level CET frontier provides the opportunity to bundle crops with respect to the ease of switching among them. Clearly, a more flexible framework would allow σ to varying across different crop bundles. To introduce more flexible functional forms in GTAP, we need to define a nesting structure which represents recent patterns in allocation of cropland among its alternative uses and empirically estimate its associated land transformation elasticities. The next section proposes a new method to estimate such a CET function.

4. A new approach to estimate a nested CET frontier

To build up a more flexible structure for cropland frontier, two alternative functional forms are usually considered. The first one is the CRETH (Constant Ratio of Elasticities of Transformation, homothetic) functional form. It is possible to define a CRETH for the case of cropland cover frontier as well. The flexibility advantages of a CRETH functional form lies in the fact that the values of the Allen-Uzawa elasticities of substitution can vary along isoquants and differ between pairs of factors but the Allen-Uzawa elasticities of substitution will remain the same for the same pair of factors everywhere (Hanoch, 1971). While a CRETH functional form provides more flexibility, empirical estimation of this type of functional form is difficult in any event and more so given the available data and variability in that data (Vincent, Dixon, & Powell, 1980).

Another approach which can bring more flexibility into the land allocation model is a multi-level nested CET functional form. Many CGE models have used CET functions to allocate land among its alternative uses. But they usually use ad hoc land transformation elasticities. Few attempts[3] have been made to calibrate or estimate these elasticities for cropland frontiers.

To introduce more flexibility in easiness of land transformation among alternative crops, a nesting structure is proposed in this paper. At this point, we consider a general functional form with *n* types of crops defined by $f(L_1,...,L_n)$. In general the land allocation problem can then be reformulated as:

[3] Examples are: (Laborde, 2011) and (Palatnik, Kan, Rapaport-Rom, Ghermandi, Eboli, & Shechter, 2011).

$$\text{Max} \;:\; \sum_{i=1}^{n} NR_i L_i - C(TPL)$$

$$\text{s.t.} \quad f(L_1,...,L_n) \leq TPL : \pi$$

where TPL stands for the total available productivity adjusted cropland; *C(TPL)* stands for the conversion cost due to the crop switching activity; NR_i stands for the per unit of land net revenue generated to grow crop i, L_i is the amount of land allocated to crop i and π represents the shadow value of cropland. In this optimization problem, the conversion cost is considered to be a function of total productivity adjusted cropland. The land constraint in this optimization problem represents a CET cropland frontier which governs land allocation. The physical land constraint is not included due to the fact that the constraint is always binding by construction of the data. Hence, imposing a physical land constraint is redundant in this optimization model.

The Lagrangian function for this optimization problem at time t is:

$$L_t = \sum_{i=1}^{n} NR_{it} L_{it} - C(TPL_t) - \pi_t [\, f(L_{1t},...,L_{nt}) - TPL_t \,]$$

Acreage decisions and total productivity land are choice variables (when acreage decision of an individual crop is free to change, the total productivity adjusted land is also able to change with appropriate adjustment of capital and labor). And First Order Conditions (F.O.C.s) would be:

$$\frac{\partial L_t}{\partial L_{it}} = NR_{it} - \pi_t \frac{\partial f(L_{1t},...,L_{nt})}{\partial L_{it}} = 0 \qquad \forall i = 1,2,...,n; t = 1,2,...,T \qquad (1),$$

$$\frac{\partial L_t}{\partial TPL_t} = \frac{-\partial C(TPL_t)}{\partial TPL_t} + \pi_t = 0 \qquad \forall t = 1,2,...,T \qquad (2),$$

$$\frac{\partial L_t}{\partial \pi_t} = f(L_{1t},...,L_{nt}) - TPL_t = 0 \qquad \forall t = 1,2,...,T \qquad (3).$$

Thus, we will have a system of first order conditions for all the crops (i=1,…,n) and all time periods (t=1,…, T).

Since equations 2 and 3 are not observable, we will only be able to estimate equations defined in (1) of the above system. More specifically, we can econometrically estimate the following equations:

$$NR_{it} - \pi_t \frac{\partial f(L_{1t},...,L_{nt})}{\partial L_{it}} + \varepsilon_{it} = 0 \quad \forall i = 1,2,...,n; t = 1,2,...,T$$

Where ε_{it} is the vector of residuals and assumed to distribute independently across observations as a multivariate normal as $N\ (0, \Omega)$ and Ω is a n×n finite covariance matrix and

$$E(\varepsilon_{it}\varepsilon'_{js}) = \begin{cases} \Omega, \mathrm{t} = \mathrm{s} \\ 0, t \neq s \end{cases}.$$

To examine the proposed method in details, we consider a two-level nested CET functional form including corn, soybeans, and wheat shown in Figure 1 and the following equation:

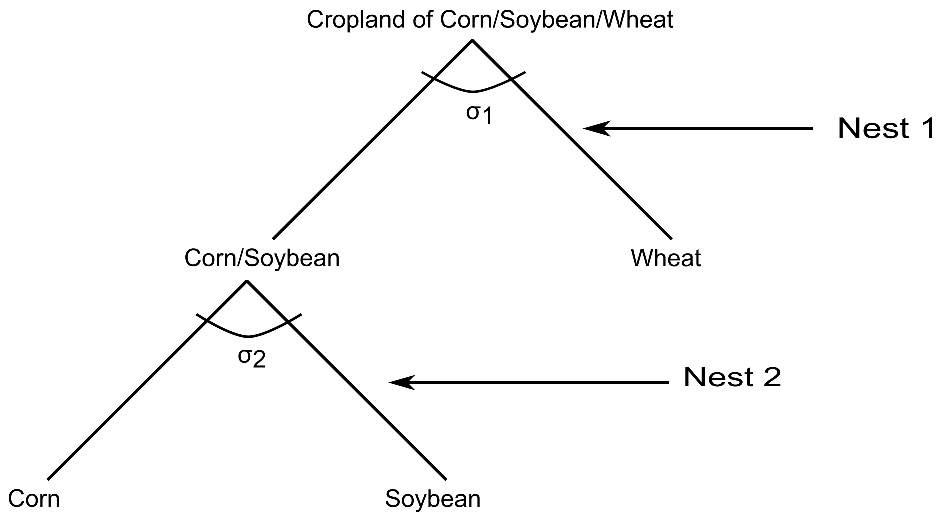

Figure 1. Nesting Structure for Cropland Allocation for the simple case

$$f(L_{1t},\ldots,L_{nt})=\left[\lambda_2\left[\left[\lambda_1 L_{1t}{}^{\rho_2}+(1-\lambda_1)L_{2t}{}^{\rho_2}\right]^{\frac{1}{\rho_2}}\right]^{\rho_1}+(1-\lambda_2)L_{3t}{}^{\rho_1}\right]^{\frac{1}{\rho_1}}.$$

In the rest of this paper, we work with this illustrative case. For this simple case, we need to estimate the following system of equations:

$$NR_{corn,t}-\pi_t*\frac{\partial f(\boldsymbol{L_{corn,t}},\boldsymbol{L_{soybean,t}},\boldsymbol{L_{Wheat}})}{\partial L_{corn,t}}+\varepsilon_{corn,t}=0 \qquad \forall t=1,2,\ldots,T$$

$$NR_{soybean,t}-\pi_t*\frac{\partial f(\boldsymbol{L_{corn,t}},\boldsymbol{L_{soybean,t}},\boldsymbol{L_{Wheat}})}{\partial L_{soybean,t}}+\varepsilon_{soybean,t}=0 \quad \forall t=1,2,\ldots,T$$

$$NR_{wheat,t}-\pi_t*\frac{\partial f(\boldsymbol{L_{corn,t}},\boldsymbol{L_{soybean,t}},\boldsymbol{L_{Wheat}})}{\partial L_{wheat,t}}+\varepsilon_{wheat,t}=0 \qquad \forall t=1,2,\ldots,T$$

Where $\varepsilon_{corn,t}, \varepsilon_{soybean,t}, \varepsilon_{wheat,t}$ are multi-normally distributed as $N\ (0,\Omega)$.

The detailed expressions of the partial derivative of this simple case are available in appendix 1. Since the derivatives of this system are highly nonlinear, there are no closed-form expressions of $L_i s$. Let us denote the implicit system as $h(NR_{it},\rho_1,\rho_2,\lambda_1,\lambda_2,\pi_t)+\varepsilon_{it}=0$. We can see that $h(NR_{it}, \rho_1, \rho_2, \lambda_1, \lambda_2, \pi_t)$ is a continuously differentiable function of parameters. In addition we assume strict exogeneity of the independent variables. This means that:

$$E[\varepsilon_{it} \mid h(NR_{it}, \rho_1, \rho_2, \lambda_1, \lambda_2, \pi_t)] = 0,$$

$$E[\varepsilon_{it}\varepsilon_{it}' \mid h(L_{it}, \rho_1, \rho_2, \lambda_1, \lambda_2, \pi_t)] = \sigma_{it}{}^2 I.$$

To estimate this system we also assume that the disturbances are uncorrelated across observations but correlated across equations. Which means:

$E[\varepsilon_{it}\varepsilon_{js} \mid h(L_{it}, \rho_1, \rho_2, \lambda_1, \lambda_2, \pi_t)] = \text{cov}(\varepsilon_{it}, \varepsilon_{js})$ if s = t and 0 otherwise. (Greene, 2008)

For this simple illustrative case there are T+4 parameters to be estimated. These parameters are: $(\rho_1, \rho_2, \lambda_1, \lambda_2, \pi_1, ...\pi_T)$. With 3 crops and T time observations the total number of observations will be about 3T. The degrees of freedom are 2T-4.

This system can be estimated using the maximum likelihood method. Given the multivariate normal nature of the error structure for the system, the log likelihood function for error vector of time t is:

$$\ln L(\varepsilon_{i,t}^{'}) = -\frac{n}{2}\ln(2\pi) - \frac{\ln(|\Omega|)}{2} - \frac{\varepsilon_{i,t}\Omega^{-1}\varepsilon_{i,t}^{'}}{2} \quad \forall t = 1,2,...,T.$$

Where Ω is the covariance matrix of the errors, which was specified earlier (Greene, 2008) (pp. 530). By summing the log of density of $\varepsilon_{i,t}$ over all T observations, the log likelihood function for the system can be obtained. The log of the likelihood function can be concentrated in terms of the elements of Ω and be expressed as (Greene, 2008) (pp.533):

$$L(\rho_{1-4}, \pi_t, \lambda_{1-4}) = -\frac{n \times T}{2}(\ln(2\pi) + 1) - \frac{T}{2}\ln(|\hat{\Omega}|)$$

Where $\hat{\Omega}$ is the estimate of Ω and $\hat{\Omega}_{ij} = T^{-1}\sum_{i=1}^{T} \varepsilon_{i,t}\, \varepsilon_{j,t}$. Since T, n are scalars, the maximum likelihood boils down to minimizing $\ln(|\hat{\Omega}|)$. If $\hat{\Omega}$ has full row rank, then $\hat{\Omega}$ can be decomposed according to $\hat{\Omega} = R^t R$, where R is an upper triangular matrix of conformable dimension. Thus $|\hat{\Omega}| = |R^t||R|$, which means $|\hat{\Omega}| = (\prod_{i=1}^{n} r_{ii})^2$, where $r_{ii}s$ are the diagonal elements of R. After further simplifying the objective to minimize $|\hat{\Omega}| = (\prod_{i=1}^{n} r_{ii})^2$ by taking the logarithm on both sides, the problem boils down to minimize $(\prod_{i=1}^{n} r_{ii}{}^2)$. For estimation purpose, $\varepsilon_{i,t}$ is replaced by its estimate $\hat{\varepsilon}_{i,t}$, which is in turn calculated by $\hat{\varepsilon}_{i,t} = L_{it} - L\hat{}_{it}$. Given that $\hat{\Omega}_{ij} = T^{-1} \sum_{i=1}^{T} \varepsilon_{i,t}\, \varepsilon_{j,t} = T^{-1} \sum_{k}^{n} r_{ki} r_{kj}$, then the system can be estimated to obtain the unknown parameters using the maximum likelihood, similar to dissertation work of Cranfield (Cranfield, 1999).

5. Data

To estimate the illustrative CET functional form proposed in the previous section, we take data from the U.S. agriculture. Figure 2 represents changes in the U.S. harvested areas for corn, soybean, and wheat during the past two decades. This figure shows that during the past two decades the harvested areas of corn and soybean have followed increasing trends, and the harvested areas of wheat took a decreasing path. To estimate the illustrative CET from, we rely on this data for the time period of 1996-2010. Price, yield, harvested acreages and production for the crops are obtained from U.S. census and USDA-NASS. Production cost data is collected from ERS. Price, yield and production cost are used to calculate the net revenue of land dedicated to different crops. Then the dataset that contain the net revenue and harvested acreages of the crops are available for analysis.

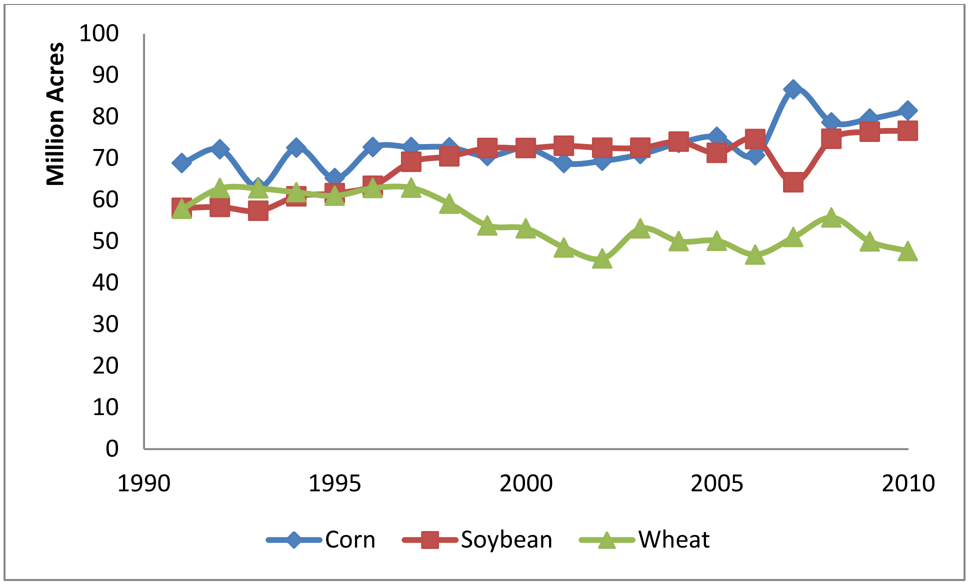

Figure 2. 1991-2010 Observed Harvested Acreages of Major Crops in the U.S.
Source: US Census, The 2012 Statistical Abstract, Agriculture, Crops
http://www.census.gov/compendia/statab/cats/agriculture.html

Table 1 shows the summary of statistics of the dataset used for estimation. There are 15 observations for each variable from 1996-2010. The net revenues are the independent variables and the harvested acreages are the dependent variables. The variations in net revenue of land for different crops are relatively large, indicating fast changes of net revenues of land dedicated to different crops over the time frame. On the other hand, the harvested acres for the crops are relatively stable. This combination suggests a rather inelastic change of harvested acres due to changes of net return of land. Based on the dataset, the system of equations listed above will be estimated using maximum likelihood estimation.

Table 1. Summary of Statistics for Independent and Dependent Variables

Variable	Mean	Std Dev	Minimum	Maximum
Corn net return ($/acre)	209.18	133.15	86.60	549.54
Soybeans net return ($/acre)	184.68	87.76	91.62	377.06
Wheat net return ($/acre)	85.66	46.46	35.86	178.74
Corn harvested acre (10^6 acres)	74.35	5.02	68.77	86.52
Soybean harvested area (10^6 acres)	71.82	3.85	63.35	76.62
Wheat harvested area (10^6 acres	52.66	5.38	45.82	62.84

6. Estimation Results and Analysis

Table 2 shows the maximum likelihood estimates of the parameters for a two level nested CET frontier. The estimation is implemented in General Algebraic Modeling System (GAMS) and solved using the CONOPT solver. The estimated ρ_1 for nest 1 is 9.341 and ρ_2 for nest 2 is 5.999. Those correspond to elasticities of transformation of -0.12 and -0.2 for nest 1 and nest 2, respectively.

The results of the bootstrap simulation are also presented. As shown in table 2 the estimated parameters are statistically significant based on the t-statistics obtained based on a bootstrap approach. The estimated parameters under second column are treated as the data generating process in the bootstrap simulations. 600 pseudo harvested acreage observations for corn, soybean and wheat were generated. In table 2, the mean, standard deviation for the bootstrap estimates of the parameters are also presented. The means of $\rho 2$ and $\lambda 2$ are close in value to the actual estimates while the means of $\rho 1$ and $\lambda 1$ are not. This is probably due to the fact that there is not too much variation in data of harvested acreages for wheat and the group of corn and soybean. More data or data with more variation should resolve the discrepancy between the maximum likelihood estimates of ρ1 and λ1 and their bootstrap means. The standard deviation measures the spread of an estimate about its mean and the low values of all the standard deviations for all the parameters signify a low measure of variability of the bootstrap estimates. The results of Lagrangian multipliers from the optimization problem are reported in appendix 2.

Table 2. Maximum Likelihood Estimates of Parameters and Bootstrap Summary Statistics

		Bootstrap Summary Statistics		
Parameter	Estimated value	Mean	Standard Deviation	t-ratio
ρ_1	9.431	7.236	1.420	5.096
ρ_2	5.999	6.006	0.171	32.123
λ_1	0.316	0.538	0.075	7.173
λ_2	0.882	0.850	0.026	32.692

7. Conclusion

The CET structure proposed in the paper provides an alternative method to re-construct the cropland allocation process in GTAP. The approach is unique in that it models the land transformation among crops based on real aggregate behavior of landowners which is revealed by the empirical observations of harvested acres and net return of cropland. The estimates of land transformation elasticities in the paper are within expected ranges.

There are two main kinds of extensions can be done to model land supply in a way that is closer to reality. We know that land transformation process is determined by land quality and crops. One kind of extension is to further disaggregate the analysis unit. For example, in terms of the extension for U.S. cropland allocation structure, the analysis units can be the nine Farm Resource Regions, defined by ERS. The nine Farm Resource Regions share important similarities of the farm characteristics. Each region will have their own cropland allocation structure of a particular set of crops and adopt different values of land transformation elasticities. Another kind of extension is to apply the practice to EU, Brazil etc. Then more flexible frameworks of land allocation can be established for other GTAP countries and regions which will improve the policy analysis like biofuel policies.

The empirical results provided in this paper are quite preliminary and are provided simply to illustrate the approach. More work is needed with a wider range of crops and probably with pseudo-data.

References

Adams, D., Alig, R., Callaway, J., McCarl, B., & Winnett, S. (1996). *The forest and agricultural sector optimization model (FASOM): model structure and policy applications.* Washington, D.C.: USDA Forest Service Pacific Northwest Research Station Research Paper.

Ahmed, S., Hertel, T., & Lubowski, R. (2008). *Calibration of a land cover supply function using transition probabilities.* West Lafayette, IN: GTAP.

Ashley, R., & Winston, P. (January 2009). *Enhancing Agriculture and Energy sector Analysis in CGE Modelling: An Overview of Modifications to the USAGE Model.* Clayton, Australia: Centre of Policy Studies, Monash University and U.S. International Trade Commission.

Boeters, S., Veenendaal, P., van Leeuwen, N., & Rojas-Romagoza, H. (2008). *The Potential for Biofuels alongside the EU-ETS.* CPB Netherlands Bureau for Economic Policy Analysis.

Burniaux, J., & Truong, T. (2002). *GTAP-E: an energy-environmental version of the GTAP model.* West Lafayette, Indiana: Center for Global Trade Analysis.

Cranfield, J. (1999). Aggregating non-linear consumer demands: A maximum entropy approach. *Ph.D. Dissertation*. West Lafayette: Agricultural Economics, Purdue University.

Darwin, R. F. (1998). *FARM: A Global Framework for Integrated Land Use/Cover Modelilng.* Canberra: Center for Resource and Environmental Studies-Ecological Economics Program, The Australian National University.

Eboli, F., Parrado, R., & Roson, R. (2010). Climate-change feedback on economic growth: explorations with a dynamic general equilibrium model. *Environment and Development Economics*, 515-533.

Greene, W. H. (2008). *Econometric Analysis (6 Edition).* Upper Saddle River, NJ: Pearson Prentice Hall.

Gurgel, A., Reilly, J., & Paltsev, S. (2008). *Potential land use implications of a global biofuels industry.* Cambridge, MA (USA): MIT Joint Program on the Science and Policy of Global Change.

Hanoch, G. (1971). CRESH Production Functions. *Econometrica*, 695-712.

Hertel, T. W., & Tsigas, M. E. (1988). Tax Policy and U.S. Agriculture: A General Equilibrium Analysis. *American Journal of Agricultural Economics*, 289-302.

Hertel, T., Rose, S., & Tol, R. (2008). Land Use in Computable General Equlibrium Models : An Overview. *GTAP Technical Paper*.

Keeney, R., & Hertel, T. (2009). The indirect land use impacts of United States biofuel policies: the importance of acreage, yield, and bilateral trade responses. *American Journal of Agricultural Economics*, 895-909.

Kuhn, A. (2003). *From world market to trade flow modelling-the re-designed WATSIM model.* Bonn, Germany: WATSIM AMPS-Applying and Maintaining the Policy Simulation Version of the World Agricultural Trade Simulation Model. Final Report.

Laborde, D. (2011). *Assessing the Land Use Change Consequences of European Biofuel Policies.* Final Report prepared for the European Commission DG Trade. Implementing Framework Contract No TRADE/07/ A.

Lee, H., Hertel, T., Rose, S., & Avetisyan, M. (2008). *An integrated global land use data base for CGE analysis of climate policy options.* West Lafayette, IN: GTAP.

Palatnik, R., Kan, I., Rapaport-Rom, M., Ghermandi, A., Eboli, F., & Shechter, M. (2011). Land transformation analysis and application.

Preckel, P. (2010). Quantitative Economic Analysis via Mathematical Programming. West Lafayette, IN: Department of Agricultural Economics, Purdue University.

Sohngen, B., Mendelsohn, R., & Sedjo, R. (1999). Forest management, conservation, and global timber markets. *American Journal of Agricultural Economics*, 1-13.

Vincent, D. P., Dixon, P. B., & Powell, A. A. (1980). The Estimation of Supply Response in Australian Agriculture : The CRESH/CRETH Production System. *International Economic Review*, 221-242.

Appendix 1

For the system of land allocation among corn, soybean and wheat governed by the two level nested CET function

$$f(L_1,...,L_n) = \left[\lambda_2 \left[\left[\lambda_1 L_1^{\rho_2} + (1-\lambda_1) L_2^{\rho_2} \right]^{\frac{1}{\rho_2}} \right]^{\rho_1} + (1-\lambda_2) L_3^{\rho_1} \right]^{\frac{1}{\rho_1}},$$

The detailed partial derivatives of the F.O.Cs in the estimation system are as follows:

$$\frac{\partial f(L_1,...,L_n)}{\partial L_1} = \left[\lambda_2 \left[\left[\lambda_1 L_1^{\rho_2} + (1-\lambda_1) L_2^{\rho_2} \right]^{\frac{1}{\rho_2}} \right]^{\rho_1} + (1-\lambda_2) L_3^{\rho_1} \right]^{\frac{1}{\rho_1}-1} \times \lambda_2 \left[\left[\lambda_1 L_1^{\rho 2} + (1-\lambda_2) L_2^{\rho_2} \right]^{\frac{1}{\rho 2}} \right]^{\rho_1 - 1}$$
$$\times \left[\lambda_1 L_1^{\rho_2} + (1-\lambda_1) L_2^{\rho_2} \right]^{\frac{1}{\rho_2}-1} \times \lambda_1 L_1^{\rho_2 - 1}$$

$$\frac{\partial f(L_1,...,L_n)}{\partial L_2} = \left[\lambda_2 \left[\left[\lambda_1 L_1^{\rho_2} + (1-\lambda_1) L_2^{\rho_2} \right]^{\frac{1}{\rho_2}} \right]^{\rho_1} + (1-\lambda_2) L_3^{\rho_1} \right]^{\frac{1}{\rho_1}-1} \times \lambda_2 \left[\left[\lambda_1 L_1^{\rho 2} + (1-\lambda_2) L_2^{\rho_2} \right]^{\frac{1}{\rho 2}} \right]^{\rho_1 - 1}$$
$$\times \left[\lambda_1 L_1^{\rho_2} + (1-\lambda_1) L_2^{\rho_2} \right]^{\frac{1}{\rho_2}-1} \times (1-\lambda_1) L_2^{\rho_2 - 1}$$

$$\frac{\partial f(L_1,...,L_n)}{\partial L_3} = \left[\lambda_2 \left[\left[\lambda_1 L_1^{\rho_2} + (1-\lambda_1) L_2^{\rho_2} \right]^{\frac{1}{\rho_2}} \right]^{\rho_1} + (1-\lambda_2) L_3^{\rho_1} \right]^{\frac{1}{\rho_1}-1} \times (1-\lambda_2) L_3^{\rho_1 - 1}$$

Appendix 2

Table 3. Maximum Likelihood Estimates of Time Varying Lagrangian Multipliers and Bootstrap Summary Statistics

	Maximum Likelihood	Bootstrap Summary Statistics	
Parameter	Estimates	Mean	Standard Deviation
π_1996	4.018	3.947	0.023
π_1997	3.566	3.560	0.031
π_1998	2.761	2.741	0.017
π_1999	2.341	2.323	0.014
π_2000	2.389	2.372	0.015
π_2001	2.535	2.492	0.014
π_2002	3.653	3.599	0.020
π_2003	4.439	4.383	0.025
π_2004	3.961	3.926	0.024
π_2005	3.295	3.302	0.028
π_2006	5.219	5.106	0.030
π_2007	9.067	8.892	0.051
π_2008	7.945	7.808	0.046
π_2009	6.937	6.871	0.044
π_2010	11.193	10.923	0.067