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# CALIBRATED MODELS FOR AGRICULTURAL PRODUCTION AND ENVIRONMENTAL ANALYSIS

by
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# Calibrated Models for Agricultural Production and Environmental Analysis

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# Calibrated Models for Agricultural Production and Environmental Analysis

## Introduction

Models of production agriculture have invariably fallen into the two broad classifications of Econometric models and Programming models. Econometric models combine the two tasks of estimation and model building, and are usually characterized by an absence of inequality constraints on the productive system. In contrast, programming models almost exclusively use inequality constraints to model the production possibilities, and the underlying technology. At the extreme, econometric models can be characterized as all first orders conditions and no inequality constraints, while programming models are all constraints and no first order conditions.

Both approaches have shortcomings for modelling the detailed use of agricultural inputs, production, and the resulting environmental impacts. In addition, for cases where agricultural production is influenced by government support programs, or a transition from administered pricing to market pricing is occurring, the ability to use a mix of inequality constraints and first order conditions in the model is a distinct advantage.

The generally acknowledged ideal approach to production model building would be to use a time series, cross section data set that was rich enough to estimate the production technology and behavioral responses, subject to the appropriate resource and policy constraints. Methods have been developed to accomplish this for both primal and dual specifications (Just et. al., 1983; Chambers and Just, 1989). However, the number of econometric multi-output production models that have been estimated over the past ten years is surprisingly small, no doubt due to the difficulty of obtaining sufficiently rich data sets. Some authors (Just, Zilberman, Hochman, and Bar-Shira 1990; Zilberman, 1989) have also raised doubts about the precision of predictions of input use based solely on econometric estimates of production functions. Aggregate econometric production models produce robust estimates of the central parameters of the system in the form of the elasticity of supply, marginal productivity and elasticity of substitution. However, for disaggregated production models, there is additional region specific information to be used in the form of resource limits and policy constraints. This extra information can improve the short run regional level predictions of the model.

Programming models have a serious shortcoming in the inflexible normative basis for the usual linear or piecewise linear production technology that underlies LP and QP models. The normative technology specification introduces difficulties in calibrating the model against empirical data, while the Leontieff, or piecewise Leontieff technology usually restricts the ability of the model to show significant substitution of inputs. Since a shift in the environmental impacts of agriculture, or a change in agricultural efficiency under input price changes are currently important policy questions, the ability of the model technology to accurately portray input substitution is an important asset.

This paper advances a production modelling approach that calibrates to a specific cross section realization of regional agricultural production and input use, but specifies a production technology that accommodates input substitution where appropriate, and satisfies the known and measurable constraints on the productive system. The calibration approach has strong parallels in the CGE model calibration methods (Shoven and Walley, 1984), and only differs in the way that inequality constraints and factor demand conditions are combined, and the method used to calculate the calibrated coefficients. The resulting model uses econometric estimates of the available parameters, but calibrates the disaggregated model to a single set of cross section data, rather than estimating an aggregate specification.

The paper continues with an explanation of the calibration approach and its limitations. The next section outlines a twelve region, five input, Cobb Douglas model of the U.S. crop sector and the modelling of participation in government commodity price support programs.

We conclude with a brief review of the characteristics and developments of the calibration approach to agricultural production models.

## Calibration Methods in Agricultural Models

Programming models have a long history of use in the quantitative analysis of agricultural resources. In terms of the number of applications to regional and national resource problems, programming models are probably still the dominant method of analysis. Reasons for this tenacity despite more sophisticated methodological advances in other areas has to be attributed to more than tradition. Programming models are often better suited to the available data on resource problems, and their ability to incorporate a wealth of physical structural detail is often appealing, where the physical structure dominates or strongly influences the behavioral response.

Programming models have their origin in normative farm management models, where the modeler assumed that they knew the correct technological parameters, and derived the behavioral response by imposing normative optimizing behavior on a detailed structure of constraints. With regional and national models of production and resource use, programming modelers have used a variety of methods, with varying success, to move away from the normative origins of the method and incorporate more positive behavior in the models, while retaining the structural detail that gives much of the explanatory power to the models.

Like the ex ante simulation model, programming models of resource allocation are oriented around crop acreage allocations. Invariably, the production technology is specified as a Leontieff fixed proportion to land acreage. This enables model construction from a minimal data base, but causes severe problems if production cost functions are also linear. The ability to define empirical inequality constraints on regional resource use is a major advantage of programming models for resource policy. In addition, many resource policies for production agriculture are defined in terms of physical inequality constraints rather than prices. Notable examples of this are the programs for Conservation Reserve, Paid Land Diversion, Set Aside, Commodity Program base acreage, and water quantities in many Bureau of Reclamation projects.

Most of the proposed environmental regulations that are pending for U.S. agriculture are formulated as physical constraints on the type or method of input use. While an ex ante simulation can incorporate any of these constraints, the important question is whether the constraints were incorporated as information in estimating the model parameters. Except on a macro scale, unconstrained estimates of agricultural resource technology are bound to contain a greater or lesser degree of misspecification.

The set of constraints in programming models enables the model builder to impose physical relationships on the production processes. The most common type of constraint is a rotation between activities. While many agricultural systems have some crops with identifiable rotations, too often, they are used to impose arbitrary constraints on the model which help it calibrate to the base year.

Constraints are very convenient for embedding physical relationships within an economic model. Concepts of water use, salinization, erosion, and crop rotations, to mention a few examples. This greatly helps when resource economists have to work in interdisciplinary projects.

Another widespread use of constraints is to model the institutional structure of agricultural resources. Policy institutions that use input constraints are mentioned above. Other constraints on property rights or market access can be modeled explicitly in the constraint structure.

### Calibration Procedures in Programming Models.

One of the principle problems that has plagued programming models of agricultural resources is the difficulty of getting models that are linear in the profit (objective) function to calibrate to the base data set, without excessively constraining them. In most cases, the number of production activities that are observed in the base year for a given region, exceeds the number of binding constraints that can be empirically justified. Since the number of activities in a linear system cannot exceed the binding constraints, the model builder is faced with the dilemma of adding dubious constraints, or having a model that doesn't represent the base year data.

There are several methods to overcome the calibration problem. One method that begs the problem, is to divide the model into many subregions, each of which can be considered homogeneous with respect to production. Resource constraints are also subdivided into these regions. The individual subregions will have the same problems of overspecialization, but if reported in larger aggregate regions, the results will show more heterogeneity of production.

A more transparent method of regional calibration is to use flexibility constraints to control the deviation of the model results from some base average value. These constraints are ironically named, since the one thing that they prevent is flexibility of the solution. If used extensively, flexibility constraints can control the set of policy responses that are obtainable from the model. At an extreme, flexibility constraints which are tightly binding, can reduce a resource model to an accounting model that largely adds up resource use. In short, flexibility constraints blur the extent to which these models can represent competitive behavior.

McCarl (1982) advocates a data based approach to model constraint specification. The linear models should be replete with as much detail on operational constraints as possible. Rotations are not defined as simple alternatives, but as a set of historical alternative rotations that have been observed. This is a substantial advance over flexibility constraints, but has the drawback that it restricts the model outcomes to linear combinations of past cropping patterns. In the case of a new production technology or an innovative policy design, the model may be unduly restricted to the past to reflect the new competitive solution.

The Positive Programming (Howitt 1991) approach overcomes the calibration problem by taking a more econometric view of model building, and hypothesizing that the unconstrained input allocations result from first order conditions. The simplest cost function which would result in these conditions is one that is quadratic in land allocated to a given activity. PMP uses the dual results from an initially constrained run to derive the quadratic cost coefficients that calibrate the model to the base data. The resulting model has a quadratic cost function calibrated for each nonzero regional activity in the base data. The resulting models calibrate precisely, but are free to respond to changes in competitive equilibrium induced by policy or resource changes. PMP models have a significant constraint on the production technology, in that the quadratic cost is associated with land allocations to crops, with other inputs being allocated in fixed Leontieff proportion to the land.

Computable General Equilibrium (CGE) models have long been calibrated against a known data set using more flexible Cobb Douglas or CES technologies. A full CGE model is usually developed by specifying the functional form of the set of equations in the model, and then using the data in the base year social accounting matrix to derive a deterministic calibration of the parameters in the functions which satisfy the base data set. Usually, exogenous estimates of key parameters are used in the calibration. Elasticity of substitution and demand are normally specified to complete the calibration of parameters with the more flexible functional forms, such as Constant Elasticity of Substitution (CES) production functions.

The partial or complete use of econometric estimates for the production or expenditure function parameters is possible, but rare in practice.

Functional forms for these production and expenditure relations range over the simpler forms that show some degree of flexibility. Cobb Douglas, CES, and linear forms are widely used.

As would be expected with general models, there are several different methods and viewpoints on calibration methods, trade specification, and model closure. The deterministic calibration is usually done by an optimization method, GAMS/Minos (Brooke et. al., 1988) is widely used for reasons of ease and consistency. An alternative approach is to use an iterative fixed point algorithm (Scarf and Shoven, 1984) to solve for the set of prices that satisfies the set of nonlinear production and expenditure functions and identities. A problem with calibrating a model against a single data set and elasticity estimates, is that the resulting parameters have no measure of statistical robustness. The model results are consequently estimates of single realizations, rather than statistics. The realizations may be very close to an accepted statistic such as a maximum likelihood estimator, but the model maker has no formal method of testing this.

Despite the success of calibration in CGE models (A. Mansur and J. Walley, 1984) the approach has not been used to introduce a more general technology into optimizing models of agricultural production. One difficulty of integrating CGE calibration approaches into programming models is the calibration of production function parameters which are consistent with regional or farm level resource constraints and their associated shadow values. The applications of CGE models to agricultural sectors are almost all aggregated, and thus not bound by a vector of inequality constraints that may or may not be binding.

One exception to this is a regional water policy model (Berck, Robinson and Goldman, 1991). The authors note that "the specification of the technology for the agricultural sectors involves inequality constraints, so it is not possible to write out the factor demand equations explicitly. Instead, the explicit programming problem is written out for maximizing proprietor income for the agricultural sectors and solved as a subproblem."

The calibration approach shown in this paper overcomes the inequality constraint problem by using a two stage approach to first calculate the unique value of the duals on the binding resource constraints in the base year, and then in the second stage, use these dual values to solve explicitly for the parameters in the constrained factor demands.

## Calibrating an Agricultural Production Equilibrium

The ability to identify the regional constraints that restrict production in the base year, and calculate their shadow value is central to integrating programming and CGE methods. Since we are aiming for a numerical marginal shadow value at a point in the base year solution, an appropriately constrained LP model is used. By specifying perturbed calibration constraints, the dual values on the binding constraints are decoupled from the calibration constraints (Howitt 1991). This LP model specification enables the constraint duals to be derived as if the cost/production technology underlying the base year solution was nonlinear. For those production resources that can be modelled as having a perfectly elastic supply, such as regional fertilizers, the resource constraints are suitably perturbed.

Once the resource duals are derived, they are added to the monetary price of the input in the second stage. The effective input price is the monetary cost plus the regional opportunity cost derived in stage one. Under profit maximization this sum is the full resource cost facing the producer. A good example is where irrigation water is supplied to farmers from government subsidized, or long established regional facilities. The quantity of these surface supplies is restricted, often below the derived demand at the low prevailing cash price. The restricted water supplies thus have an opportunity cost equal to the difference between the cash cost and the VMP. In some Western districts, the opportunity cost of some Federal projects is two or more times the cash price. Ignoring the fixed but allocatable, and sometimes subsidized nature of farm resources would lead to a distinct underestimation of the marginal productivity.

Since the whole value of the modelling approach is its ability to represent disaggregated regions, the calibration method must solve readily for large dimensions. Thus the calibrating equations should be linearized if possible. In this model the supply side is driven by Cobb Douglas production functions for k inputs, the function has the familiar form of:

$$y_i = A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \ldots x_{i_k}^{\alpha_{ik}} \tag{1}$$

There are k+1 unknown parameters to be calibrated from observations on $y_i$ the crop specific regional output, and $x_{ik}$, the observed input allocations. In addition to the physical production data, the modeler has data on output prices $P_i$, cash input costs $w_k$, and regional input opportunity costs $\lambda_k$. The k+1 production parameters can be solved uniquely from the k input allocation conditions and the total output conditions. The factor demand conditions can be linearized as follows:

The constrained profit maximization facing the regional producer is:

$$\text{(2)}\quad \text{Max } L = \sum_i (P_i A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \dots x_{i_k}^{\alpha_{ik}} - w_1 x_{i1} - w_2 x_{i2} \dots - w_k x_{ik}) + \lambda_k (b_k - \sum_i x_{ik})$$

the first order conditions for input $x_k$ on crop i (a further regional subscript has been omitted for simplicity) is:

$$\text{(3)}\quad \frac{\partial L}{\partial x_{ik}} = P_i \alpha_{ik} A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \dots x_{i_k}^{\alpha_{ik-1}} - w_k - \lambda_k \overset{\text{set}}{=} 0$$

$$\text{(4)}\quad w_k + \lambda_k = P_i \alpha_{ik} A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \dots x_{i_k}^{\alpha_{ik-1}}$$

Under the constrained optimum, the cost share for input $x_{ik}$ is:

$$\text{(5)}\quad \frac{P_i y_i}{(W_k + \lambda_k) x_{ik}} \quad \text{substituting in equations (4) and (1)}$$

$$\text{(6)}\quad \frac{P_i y_i}{(W_k + \lambda_k) x_{ik}} = \frac{P_i A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \dots x_{i_k}^{\alpha_{ik}}}{\left(P_i \alpha_{ik} A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \dots x_{i_k}^{\alpha_{ik-1}}\right) x_{ik}}$$

cancelling the $P_i$, multiplying the expression in the parentheses in the denominator by $x_{ik}^{-1} x_{ik}$, and substituting in (1) we get:

$$\text{(7)}\quad \frac{P_i y_i}{(W_k + \lambda_k) x_{ik}} = \frac{y_i}{(\alpha_{ik} y_i x_{ik}^{-1}) x_{ik}} = \frac{1}{\alpha_{ik}}$$

Since all the parameters on the left hand side of (7) are known from the basic data set and the stage one optimization, equation (7) can be solved for a linear deterministic calibration of the Cobb Douglas factor elasticity coefficients $\alpha_{ik}$.

The remaining scale parameter $A_i$ for each crop and region can be solved using equation (1) and the $\alpha_{ik}$ parameters from (7).

$$\text{(8)}\quad A_i = \frac{y_i}{x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \dots x_{i_k}^{\alpha_{ik}}}$$

Using the parameters from (7) and (8), the Cobb Douglas optimization model can be formulated as:

$$\text{(9)} \qquad \underset{x_{ik}}{\text{Max}}\, \pi = \sum_{i=1}^{n} P_i \left( A_i x_{i_1}^{\alpha_{i1}} x_{i_2}^{\alpha_{i2}} \ldots x_{i_k}^{\alpha_{ik}} \right) - \sum_{i=1}^{n} \sum_{k=1}^{k} w_k x_{ik}$$

$$\text{subject to } \sum_{i} x_{ik} \leq b_k \text{ for all } k.$$

The above model solves readily on personal computers and calibrates to the base year data in all aspects. Output and input quantities are close to identical, and importantly, the binding resource constraints and associated dual values are also virtually identical to the base year data. However, when exogenous price or resource constraint parameters are changed, the model responds with the expected changes in output and input mix with changed dual values.

Reader familiar with most CGE or econometric specifications will note that the factor elasticity parameters are not constrained to sum to one in the calibration procedure. In fact, the only production activities for which the above parameters sum to one, are those that set the opportunity cost for the fixed, but allocatable resources. For these activities $\lambda_k$ is the difference between the total revenue and the cash factor costs, and thus the sum of the cost share exhausts the total revenue. For all other production activities the value marginal product is equal to the input price plus the opportunity cost (equation (4)) which is a necessary condition for optimal distribution of allocatable inputs across multiproducts. Since the intent of the model is to explain production and input use, the model is calibrated to the first order conditions rather than the arbitrary restriction of constant returns to scale. Total output is completely exhausted in the activity that sets the shadow value for the resource yielding constant returns to scale. To have an equal VMP for the input, the other more profitable production activities have to have an output level that is in the decreasing returns to scale region. Imposition of the constant returns to scale constraint will prevent the model from calibrating the use of allocatable inputs across multiproducts. Single products or elastic factor demands are needed for this condition to be satisfied.

### Stochastic Calibration

If there is additional information available in the form of aggregate econometric estimates of some of the parameters, the calibration system now has some degrees of freedom and an error minimizing approach to calibration must be taken. In the Cobb Douglas case, priors on the aggregate factor elasticities can be imposed with varying weights. The calibration procedure then solves an error minimizing optimization to yield regional coefficients that are a weighted combination of the priors and base year data. The process is an informal Bayesian calibration. An example of a simpler regional national model calibrated on this basis can be found in Howitt (1991). For the empirical model described in the next section, the dimensions of the model and the lack of econometric priors on factor elasticities led to the deterministic calibration method being used.

### Calibrating Government Programs

The empirical model described in this paper is a twelve region national model of the U.S. cropping sector, and as such, the model has to calibrate the different levels of regional acreage enrollment in the Federal price support programs.

The fundamental driving motive behind enrollment in the programs is assumed to be profit maximization. Since the programs offer a higher expected price and reduced risk, the only explanation for the partial enrollment of acreage in the program that is observed in most regions, is that the farmers have, or act as if they have, a cost of being enrolled in the program which increases with increasing acreage enrolled. The direct component of this hedonic cost of program enrollment is the opportunity cost of land required in the set aside provision. Another cost on better yielding land, is the difference between the fixed program yield and the actual yield. In some areas, maintaining the base acreage allotment may involve costs. In addition, enrolling in programs may involve other intangible costs.

If the model is to respond to changes in support price policy parameters, it has to be possible for crop land and other resources to move in and out of the program enrollment. It follows that specifying different production technologies for program and nonprogram crop production is unrealistic and would prevent the resource transfer. The model is specified to have the same factor elasticities for program and nonprogram production, but the scale parameters are different with the different levels of scale. The calibration procedure sets the program elasticities equal to the nonprogram crops, and then uses equation (8) to calibrate a scale parameter for each program crop.

With the calibration on program crops, the marginal products, and particularly the value marginal products for each input, will differ between program and nonprogram crops. With the higher prices, program crops will be higher. A hedonic program cost coefficient is calculated for each input and region. In the objective function the deficiency payment is added for program crops, while the hedonic cost function increases with program crop enrollment, and calibrates the program crop inputs.

The resulting model calibrates precisely to the base year resource use, but has the desirable policy characteristics of the same factor elasticities in program and nonprogram crop production, and the ability to endogenize program enrollment. Increasingly realistic constraint structures on the program crop acreage can be added later.

## A Twelve Region Model of U.S. Crop Production

The Cobb Douglas calibration approach described in the previous sections was used on a twelve region, five input model of U.S. crop production. The twelve regions were based on the ten production regions used in USARM (Konyar and McCormick, 1990) and USMP (House, 1987). The western region was subdivided into California and the Northern Pacific regions. Likewise the Mountain region was subdivided into Mountain1 and Mountain2 (Figure 1). Since the aim of the model is to analyze the impact of government programs and input policies on regional production and input use, five inputs were specified. Land, Water, Capital, Nitrogen, and Pesticides. The crops specified were Barley, Corn, Cotton, Hay, Oats, Rice, Sorghum, Soybeans and Wheat. In any region the crops can be produced by dryland or irrigated agriculture, depending on the regional climate and water availability. Seven of the nine crops are also produced partly under the government commodity program, and partly for the free market.

The different combinations of production under dryland and irrigation, or program and nonprogram require the interaction of different sets and subsets. In any given region there are thirty potential separate production activities which have different combinations of the five inputs used in production. Most regions have between twenty and twenty five activities in the base year.

The linkage across the cropping activities within a region comes from the jointly used allocatable inputs of land and water. The interregional linkages are between commodities whose production supplies a common demand for the commodity, whether it is produced by irrigated or dryland agriculture, or in or out of the government price support programs.

The commodity demand functions linear and quantity dependent, making total revenue a quadratic function of the total national production. The aggregate elasticities of production are taken from the USARM (Konyar and McCormick, 1990) data base. Calibration of the demand slope and intercept coefficients uses a well known method of weighting the base year regional prices by output levels to get a weighted national price. The commodity demand function is then derived as:

$$\beta_i = \frac{P_i \eta_i}{Q_i} \tag{10}$$

where $\beta_i$ is the commodity demand slope, and P = weighted aggregate price, $\eta$ = elasticity of demand in the base year, Q = aggregate quantity produced in the base year. The demand intercept $\delta_i$ is now derived as:

$$\delta_i = P_i - (B_i Q_i) \tag{11}$$

Since the base year data includes the regional commodity prices, they should be explicitly modelled in the objective function since they may explain some of the differences in regional crop production. Regional price differences arise primarily from differences in transportation and marketing costs, with commodity quality differences also playing a role. We assume that this regional comparative advantage is not changed per unit of output by small changes in the national commodity price. The regional deviations in commodity price from the weighted national average are calculated as positive and negative regional market cost adjustments. These regional marketing costs are also included in the objective function. This specification enables regionally differentiated prices to be changed by aggregate supply conditions.

Due to the joint effect of the demand and allocatable input linkages, every crop production activity is interdependent. In the same manner, the Cobb Douglas production specification introduces a somewhat restricted interdependence between inputs. Thus there exists a formal, but possibly tenuous linkage between regional crop specific input use. An example could be that changes in water use on irrigated corn in the Northern Plains region could change the nitrogen levels applied to Soybeans in the South East region.

### Model Performance

A listing of the two stage model calibration program is given in the appendix. When policy runs are made with the model, only the second Cobb Douglas stage is used and the calibrated production function and demand parameters are held constant.

In short the calibrating model performs exactly as it theoretically should. The input and output calibration was very precise. Of the two hundred and thirty-eight production activities in the model, only two calibrated with an error of above one percent from the base year input quantities. The deviations in the two activities were due to their having very low input levels relative to other crops in the region. When this occurs, the perturbed calibration constraints in the first stage cause a slight shift in resources from the least profitable crops, due to their small acreage. This combination can only occur in crops that have both a very low production level and the lowest profit potential in the region. In the base run of this model, the crops were irrigated oats in Northern Pacific and Southern Plains regions.

The constraint side of the model also calibrated precisely. The fixed resources that are binding in the base year LP model are also binding in the Cobb Douglas model. More interestingly, the dual values on these binding resources are within a few cents of those in the base year. This result shows that the nonlinear calibration procedure was successfully decoupled from the resource constraints, but yields the same value marginal product.

The data set used for the model is from Konyar and McCormick (1990), and is not included in the appendix for brevity. The data set can be obtained from the author. The program listed in the appendix is written so that it will calibrate a constrained Cobb Douglas model from any consistent data set that is required to formulate an LP. In short, any LP model data set can be automatically and exactly calibrated as a Cobb Douglas model by this GAMS Minos program. The data needed for the base year is:

| | |
|---|---|
| X(I,G,J) | Total input quantities by crop and region |
| C(I,G,J) | Per unit costs for inputs |
| YB (I,G) | Regional crop yields |
| V(I,G) | Regional crop prices |
| ELAS(D) | Commodity demand elasticities |

The resource right hand side constraint values are generated for the sets of inputs that are designated as fixed or purchased inputs. Additional policy constraints on input use or output prices can be added if they can be empirically specified.

The model with two hundred and thirty-eight Cobb Douglas activities, endogenous prices, and five inputs per production function, ran readily on a 386 based microcomputer using GAMS/Minos software. On a twenty megahertz system, the calibration of both stages took sixty eight minutes. Policy runs using the calibrated parameters would be substantially faster.

## Summary

Given that the cost of computing has fallen to less than one hundredth of its cost in 1981, it is very strange that optimization model methodology has been essentially unchanged over this same period. The modelling approach advocated in this paper makes use of the newfound computing power and nonlinear software advances to generate more general self calibrating models of agricultural production and resources use. The more flexible Cobb Douglas specification can interact directly with more aggregated econometric and CGE models. In this role, the calibrated model can be looked on as a rational disaggregation of the agricultural production sector of the more general models. The aggregate supply and demand elasticities can be used in the model calibration to ensure that the sectoral results of the calibrated regional model are consistent with the aggregate model.

One area of extension of this approach is to a less restrictive production function specification. The choice of a CES form is the natural next choice, given its extensive use in CGE models. Currently, work on using a nested CES specification is progressing.

One problem with this calibration method is that since it is guaranteed to accurately calibrate almost any data set that is consistent with profit maximization, alternative criteria are needed to measure model validity. In the past, the obligatory linearized production specification enabled models to be judged on their calibration precision over several parameters (Hazell and Norton, 1986). With the self calibrating nonlinear models proposed in this paper, the emphasis is placed, correctly we believe, on the ability of the base year data set and constraints to represent future behavioral response. Ideally, optimization models should be calibrated on a weighted average of base year realizations, or a time series of calibrations. The value of the model should then be assessed against the common statistical criterion of the mean squared error of out of sample predictions of behavioral response.

Hopefully this viewpoint could start to integrate the diverse methodologies of econometric and optimization production modelling in Agricultural Economics.

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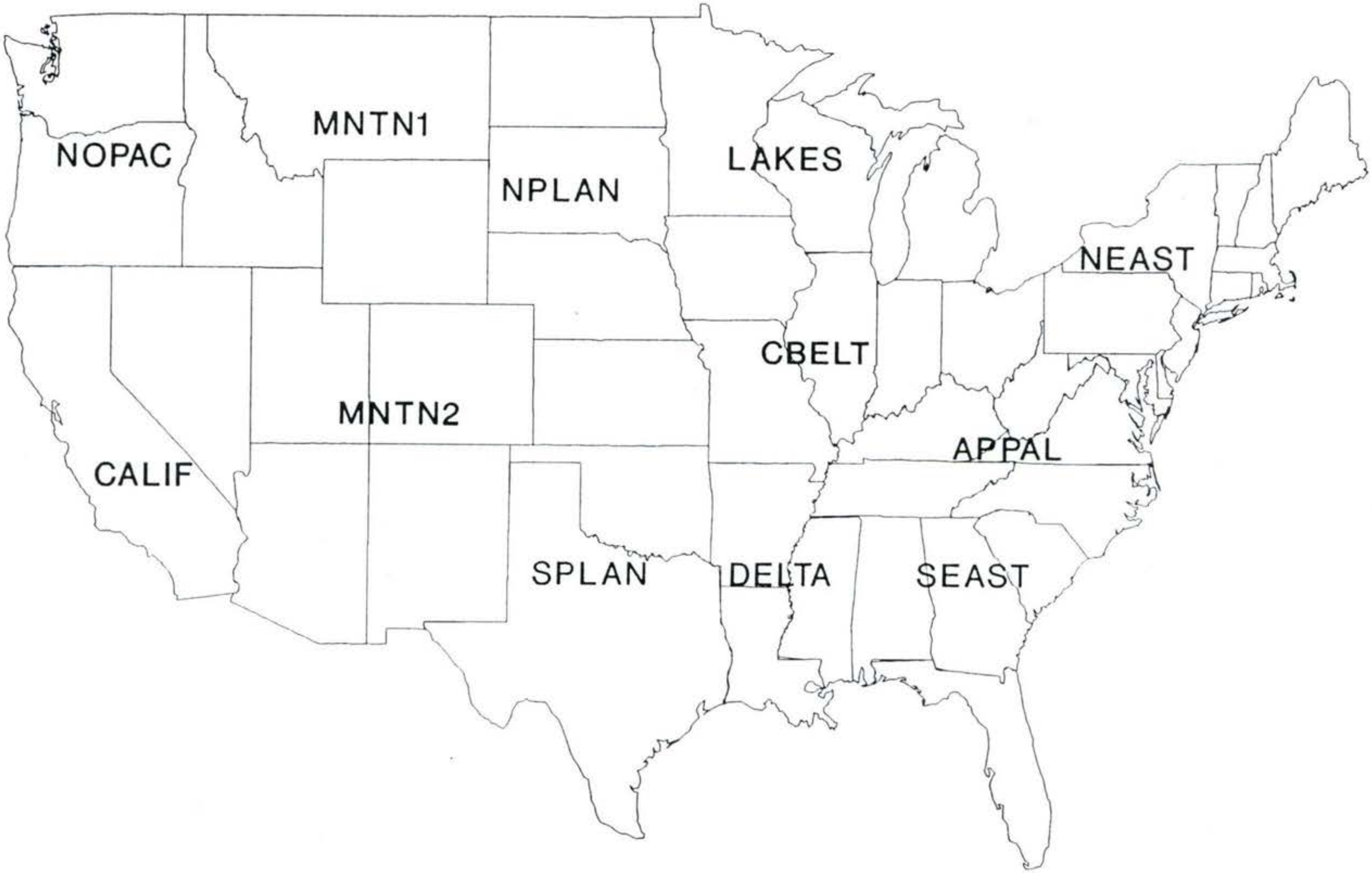
FIGURE 1


NOPAC
MNTN1
NPLAN
LAKES
NEAST
CBELT
MNTN2
CALIF
APPAL
SPLAN
DELTA
SEAST

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 SOLVE CALIBRATE   USING LP MAXIMIZING LINPROF;

 DISPLAY   LX.L;

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*CALCULATING COBB DOUGLAS PARAMETERS
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    PARAMETERS
       OP(J,G)              RESOURCE OPPORTUNITY COST
       TO(I,G)              TOTAL BASE OUTPUT
       ALP(I,G,J)           C D ALPHAS
       CNS(I,G)             SCALE PARAMETER ;


     OP(J,G) = RESOURCE.M(J,G) ;
     TO(I,G) =  YB(I,G) * X(I,G,"LAND") ;

   ALP(O,G,J) $ X(O,G,"LAND") = ((C(O,G,J)+OP(J,G))*X(O,G,J))/(V(O,G)*TO(O,G));

   ALP(P,G,J) $ X(P,G,"LAND")= SUM(NP$MAP(NP,P) , ALP(NP,G,J) ) ;


   CNS(O,G) =  TO(O,G) / PROD(J$X(O,G,J),X(O,G,J)**ALP(O,G,J)) ;


   CNS(P,G) =  TO(P,G) / PROD(J$X(P,G,J),X(P,G,J)**ALP(P,G,J)) ;

    DISPLAY ALP, CNS,OP,TO;

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**                            DEMAND EQUATIONS                             *
**=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*=*
  PARAMETERS
            QD(D)     TOTAL QUANTITY OF ACTIVITY (ALL TECHNOLOGIES)
            INT(D)   INTERCEPT OF DEMAND EQUATION
            RMC(I,G)  REGIONAL MARKETING COST
            PBASE(D)  WEIGHTED BASE YEAR PRICE
            BETA(D)  SLOPE OF DEMAND EQUATION
            DEF(P,G)  DEFICIENCY PAYMENT
            WGT(I,G)   WEIGHTED OUTPUT ;

            DEF(P,G) =   V(P,G)-SUM(NP$MAP(NP,P), V(NP,G)) ;



  QD(D) =
     SUM(I, MAP2(D,I) * SUM(G, X(I,G,"LAND")* YB(I,G)));

     WGT(I,G)$(X(I,G,"LAND") NE 0)
           = (X(I,G,"LAND")*YB(I,G)) / (SUM(E, MAP2(E,I) * QD(E))) ;

  PBASE(D) = SUM((O,G), MAP4(D,O)*WGT(O,G)*V(O,G)) +
  SUM((P,G), MAP5(D,P)*WGT(P,G) * SUM(NP$MAP(NP,P),V(NP,G)))    ;

  BETA(D)$(ELAS(D) NE 0 AND QD(D) NE 0) =
       PBASE(D)/QD(D)/ELAS(D);

  INT(D) =  PBASE(D) - BETA(D) * QD(D) ;
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```
 RMC(O,G) $ X(O,G,"LAND")  = SUM(D,MAP4(D,O) * PBASE(D)) - V(O,G);
 RMC(P,G) $ X(P,G,"LAND")  = SUM(D, MAP5(D,P)* PBASE(D))
                           -SUM(NP$MAP(NP,P),V(NP,G));

     ALP(I,G,L) $ (X(I,G,L) EQ 0) = 0 ;
 DISPLAY  INT, BETA, QD, RMC,WGT, PBASE, DEF;

***************************************************************************
*  COBB DOUGLAS PRODUCTION PROBLEM
***************************************************************************


PARAMETER

         NUM(J)   RESOURCE COUNTER
         CHEK(J)  ANOTHER RESOURCE COUNTER
         PROG(I,G,J)  PROGRAM COST
         MP1(I,G,J)  PART OF MP
         MP2(I,G,J)  OTHER PART OF MP
         MP(I,G,J)   MARGINAL PRODUCT
         HED(I,G,J)  HEDONIC PROGRAM COST;

         NUM(J) = ORD(J);
         CHEK(J) = ORD(J) ;
         MP1(I,G,J)$((NUM(J) EQ CHEK(J)) AND (X(I,G,J) NE 0)) = ALP(I,G,J)
                *CNS(I,G) *1/(X(I,G,J)**ABS(ALP(I,G,J) - 1)) ;
         MP2(I,G,J)$X(I,G,J) = PROD(L$((CHEK(L) NE NUM(J))
                  AND (X(I,G,L) NE 0)),(X(I,G,L)**ALP(I,G,L))) ;
         MP(I,G,J)$X(I,G,J)  = MP1(I,G,J) * MP2(I,G,J) ;
         PROG(I,G,J)$X(I,G,J) = (V(I,G)*MP(I,G,J) -C(I,G,J)) - OP(J,G) ;
         HED(I,G,J)  = 0.0 ;
         HED(P,G,J)$X(P,G,J) = PROG(P,G,J)/(2* X(P,G,J)) ;


VARIABLES  XN(I,G,J) RESOURCE ALLOCATION
           Q(I,G)  PRODUCTION
           NSB     NET SOCIAL BENEFIT
           QM(D)   MARKET QUANTITY;

POSITIVE VARIABLE XN, Q, QM;

EQUATIONS
          PRO(I,G)        PRODUCTION FUNCTION
          INPUT(J,G)      FIXED INPUTS
          OBJ             OBJECTIVE FUNCTION
          MARKET(D)       MARKET AGGREGATION;

PRO(I,G)..
    Q(I,G) =E= CNS(I,G)*PROD(L$X(I,G,L),((XN(I,G,L)+.0001)**ALP(I,G,L)));

INPUT(J,G)..    SUM(I, XN(I,G,J) )  =L= R(J,G);

MARKET(D).. QM(D) =E= SUM(I, MAP2(D,I) * SUM(G, Q(I,G)));

OBJ.. NSB =E= SUM(D, INT(D) * QM(D) + 0.5 * BETA(D) * (QM(D)**2))
                - SUM((I,G,J),(XN(I,G,J)*C(I,G,J)))
                - SUM((P,G,J), HED(P,G,J)* SQR(XN(P,G,J)))
                + SUM((P,G), DEF(P,G) * Q(P,G) )
```

```
                - SUM((I,G), RMC(I,G) *Q(I,G)) ;
***********************************************************************
* INITIAL VALUES
    XN.L(I,G,J)  = X(I,G,J) ;

 MODEL PRODUCTION /INPUT,PRO,MARKET, OBJ/;

 SOLVE PRODUCTION USING NLP MAXIMIZING NSB;

 DISPLAY XN.L,ALP,CNS,HED,RESOURCE.M,INPUT.M;
***********************************************************************

  PARAMETER DIFF(I,G,J)   ALOOCATION DIFFERENCE;

  DIFF(I,G,J) $ X(I,G,J) = ((XN.L(I,G,J) - X(I,G,J))*100) /X(I,G,J) ;

  DISPLAY DIFF ;
```