Biomass Feedstock Removal and Transport Optimization

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Introduction

The research in conversion of agricultural biomass into ethanol has gained momentum due to high price of petroleum, the demand to reduce greenhouse gas emissions, and the recent US government policy on reducing foreign oil dependence. However, research in production and supply technologies should also be done in conjunction with ethanol conversion development. One challenge is in the collection, packaging, storage, and transport processes of the materials from the field to biomass refineries. This paper integrates the above processes into an optimized, multi-objective economic production model. We present a method that employs Shephard's activity analysis output model that is similar to the Data Envelopment Analysis (DEA). Activity analysis has been used to measure the efficiency and profitability of many agricultural and industrial production processes. The method that we propose to apply models dynamic production processes and intermediate production, among many other components of a production process. Shadow prices for undesirable outputs (pollutants) can also be calculated. Activity analysis is implemented in a linear program to calculate the optimum combination of inputs (costs) and outputs (revenues) of production processes, and can be dynamically linked to biophysical models to include environmental effects of production. We describe the components of our integrated modeling system below.

Optimization of Multiple Objecitives

A multi-objective optimization problem (MOOP) is generally understood to contain a number of objective functions that are to be minimized. Following Deb (Deb, 2001), the general form of a MOOP is:

$$\begin{array}{rlr} \text{Minimize/Maximize} & f_m(x), & m = 1,2,\ldots,M\ , \\ \text{subject to} & g_j(x) \geq 0, & j = 1,2,\ldots,J\ , \\ & h_k(x) = 0, & k = 1,2,\ldots,K\ , \\ & x_i^L \leq x_i \leq x_j^U & i = 1,2,\ldots,n\ . \end{array} \quad (1)$$

The MOOP consists of *M* objective functions, with *J* inequality constraints and *K* equality constraints. A solution *x* is a vector of *n* decision variables that are constrained by lower x_i^L and upper x_i^U boundaries.

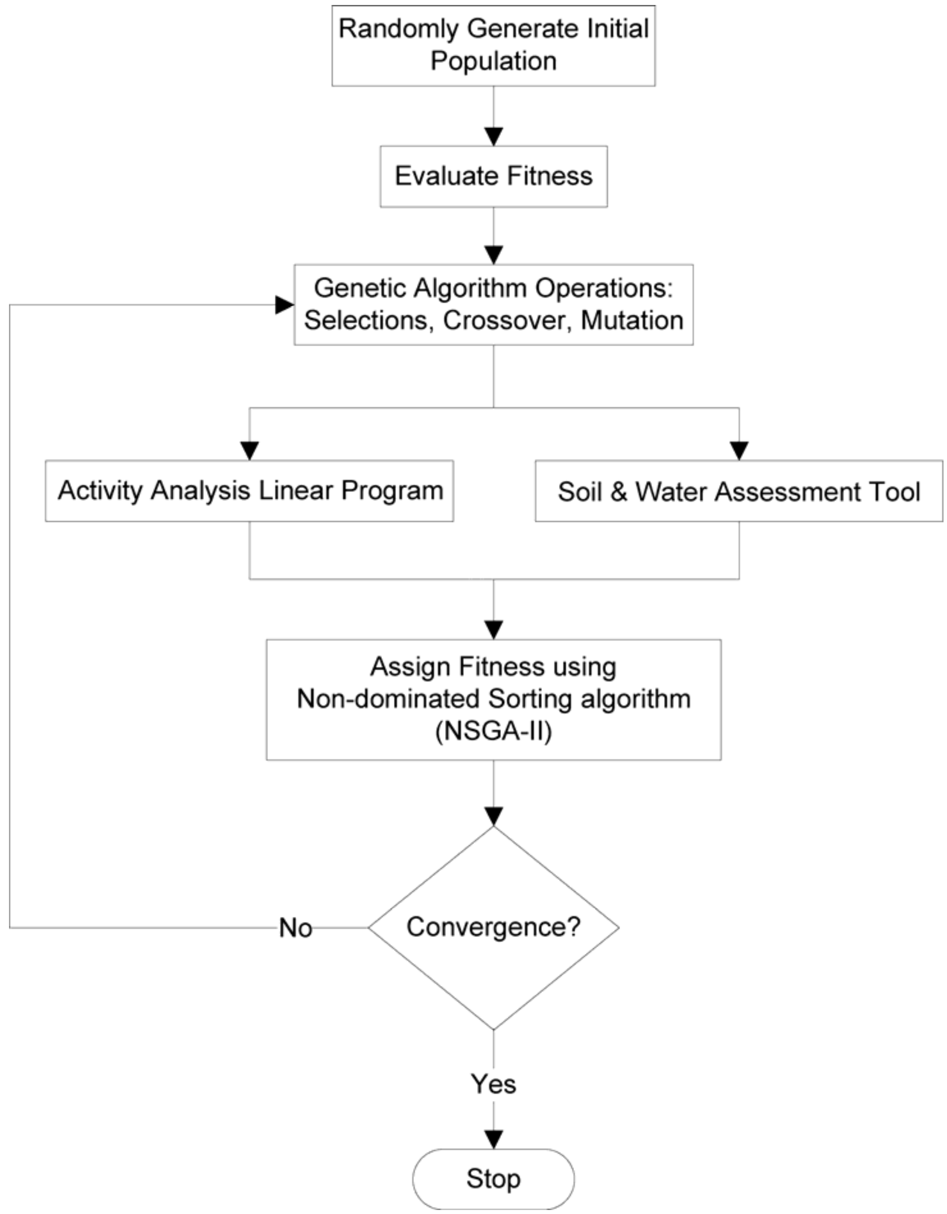

Figure 1. A hybrid genetic algorithm linking an economic model and a physical model (SWAT).

A simple genetic algorithm (GA) is an iterative algorithm based on retention of the best or "fittest" members of a population of answers until a stopping condition is satisfied (Goldberg, 1989). In an optimization application, the GA consists of an initial randomly generated population that is evaluated for fitness using an objective function, a test for convergence, and application of the GA operations of selection, crossover and mutation. These elements are followed iteratively until an optimum has been obtained (Figure 1). The non-dominated sorting algorithm (NSGA-II, Deb, 2002) is used to optimize over several objectives. This algorithm retains the non-dominated individuals from each generation, resulting in a estimate of the trade-offs among multiple objectives. The algorithm shown if Figure 1 uses and economic model to simulate producer behavior and a physical model to simulate the effect of producer behavior on the environment (Whittaker, el al., 2009). A novel feature of this algorithm is the dynamic linkage among models. Information is exchanged between models at each generation during the search for an optimal set. Almost all current integrated modeling systems optimize linked models in sequence, i.e., information only flows in one direction between the component models.

Economic Model – Activity Analysis

Each objective in the multi-objective genetic algorithm is specified by a model, or combination of models. In this study, profit maximization is assumed to be the objective of producers, and is optimized using activity analysis. In an activity analysis representation of a technology observed for a group of firms, there are $k=1,\ldots,K$ decision making units (DMUs). Each DMU uses $x=(x_1,\ldots,x_M)\in\Re_+^M$ inputs to produce $u=(u_1,\ldots,u_N)\in\Re_+^N$ outputs. The observed inputs $x^k=(x_1^k,\ldots,x_M^k)$ and the observed outputs $u^k=(u_1^k,\ldots,u_N^k)$ are used together with the intensity variables $z^k\geq 0,\ k=1,\ldots,K$, to form the reference technologies. Here we do not constrain the DMU profit, i.e., profit may positive or negative. We relax the assumption of constant returns to scale, and allow variable returns to scale by constraining the intensity variables to sum up to one. Our basic model is then

$$T=\left\{(x,u):\begin{array}{lr} u_n\leq\sum_{k=1}^{K} z^k u_n^k, & n=1,\ldots,N,\\ x_m\geq\sum_{k=1}^{K} z^k x_m^k, & m=1,\ldots M,\\ \sum_{k=1}^{K} z_k=1, & z_k\geq 0\end{array}\right\}. \tag{2}$$

Denote input prices by $p^k\in\Re_+^M$ and output prices by $r^k\in\Re_+^N$. Then the profit of DMU k can be computed as the solution to the following linear program:

$$\begin{aligned} \pi(r^k,p^k)=\max \sum_{n=1}^{N} r_n^k u_n-\sum_{m=1}^{M} p_m^k x_m & \\ s.t.\quad \sum_{k=1}^{K} z^k u_n^k\geq u_n, &\qquad n=1,\ldots N,\\ \sum_{k=1}^{K} z^k x_m^k\leq x_m, &\qquad m=1,\ldots M,\\ \sum_{k=1}^{K} z_k=1, & \\ z_k\geq 0, &\qquad k=1,\ldots,K\ . \end{aligned} \tag{3}$$

Additional constraints can be added to model optimization of transport from farm to a production facility.

Figure 2 illustrates this model with a technology consisting of 3 observations (a,b and c) of production where one input is used to produce a single output. The technology *T* is bounded by the line including a, b, and c, and includes the area under the boundary. The maximum profit is obtained by production at the facet where the price line is tangent to the boundary of the technology. There are three different input prices shown in Figure 2, p_1, p_2, p_3, while the output price remains constant.

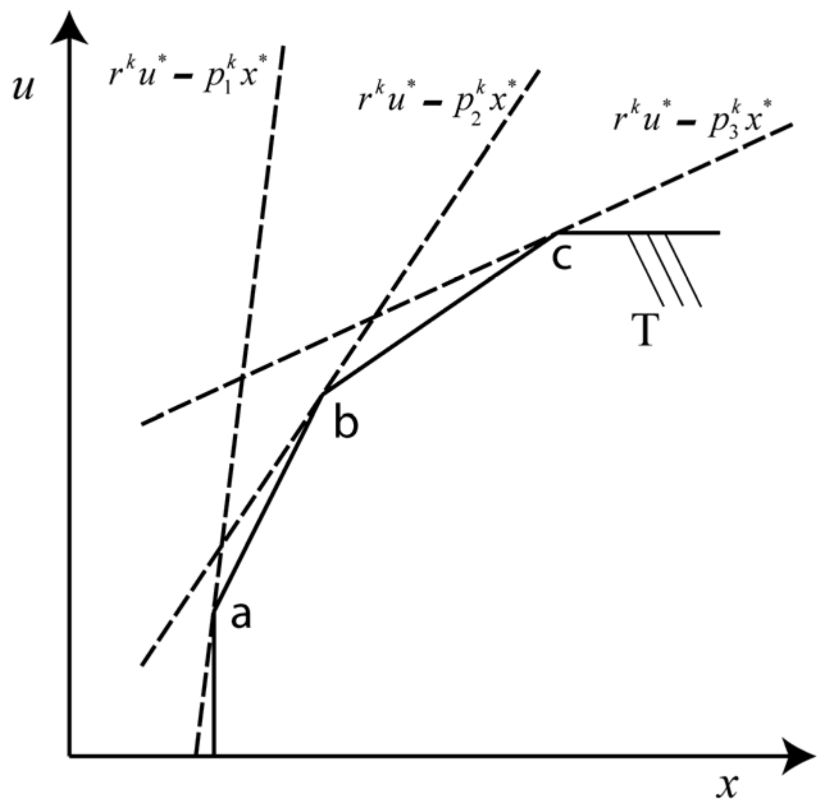

Figure 2. Profit maximization using Activity Analysis for technology T, facing three different input prices.

Physical Model

We use the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) to simulate stream flow and associated movement of nitrogen, phosphorus, and sediment (among other variables) in the agricultural production of biofuel feedstock. SWAT is a geographically distributed model that simulates stream flow, plant growth and fate and transport of chemicals and sediment. In the genetic algorithm used for optimization, the profit maximizing amounts of inputs to production are calculated using activity analysis, and fed into SWAT to simulate the environmental effects of profit maximizing production.

Water Quality Index

In this study, we calculate the effect of agricultural production on water quality using the outputs from SWAT. An index gives a single number that represents the water quality of at the outlet of the simulated basin, and is calculated as the weighted sum of the metrics of water quality. These metrics include total suspended solids, levels of nitrogen and levels of phophorus, among others. By applying a variation of the Malmquist (1953) index, the weights are endogenous to the calculation. That is, they are derived from the observed data rather expert opinion , or some other method. We assume there are N characteristics of water quality x, and $k = 1,\ldots,K$ measurements (observations) of water characteristics at $t = 1,\ldots,T$ time periods. Our data is represented

$$x_k^t, \quad k = 1,\ldots,K, \quad t = 1,\ldots,T, \quad x_k^t \in \Re_+^N \quad . \tag{4}$$

In this study we define the reference technology (or benchmark) using all $K \times T$ observations, i.e., it is defined as

$$\begin{aligned} \Big\{ x = (x_1,\ldots,x_N) : & \sum_{k=1}^{K}\sum_{t=1}^{T} z_k^t x_{kn}^t = x_n \qquad n = 1,\ldots,N, \\ & \sum_{k=1}^{K}\sum_{t=1}^{T} z_k^t = 1 \\ & z_k^t \geq 0,\ t = 1,\ldots,T,\ k = 1,\ldots,K \Big\} \end{aligned} \tag{5}$$

where $z_k^t \geq 0$, are intensity variables. The intensity variables from the convex combinations of all the data points. The lower boundary of this set is the best practice benchmark isoquant II in Figure 1. For each observation $(k^{'},t)$ we compute

$$\begin{aligned} & [\theta_{k't}]^{-1} = \min \theta \\ s.t. \quad & \sum_{k=1}^{K}\sum_{t=1}^{T} z_k^t x_{kn}^t \leq \theta x_{k'n}^t \qquad n = 1,\ldots,N \quad , \\ & \sum_{k=1}^{K}\sum_{t=1}^{T} z_k^t = 1 \\ & z_k^t \geq 0,\ t = 1,\ldots,T,\ k = 1,\ldots,K \ . \end{aligned} \tag{6}$$

Suppose we compare (k',t) with $(k',t+1)$, then the water quality index (WQI) is

$$WQI_{k'} = \frac{\theta_{k',t+1}}{\theta_{k',t}} \quad . \tag{7}$$

In this application, we compare all measurements through all time periods, so $\theta_{k',t}$ is set equal to 1. If WQI = 1, water quality is equal to the best practice. WQI values greater than 1 indicate a poorer water quality. To implement the calculation, we use a linear program to solve (6) for each observation, then calculate (7), the water quality index.

For this study, we assume that the water characteristics are undesirable, and should be minimized. The two dimensional case is illustrated in Figure 1, where we wish to compare vector x^0 of length 0C with vector x^1 of length 0B. The benchmark that we use for comparison is the best practice benchmark II, where we are indifferent as to choice among points that lie on the benchmark. Each distance AB and DC, known as Shephard's input distance function, is the distance that each vector can be proportionally reduced to reach the benchmark (II). The ratio of the input distance functions, i.e. $\frac{OB/OA}{OC/OD}$ is the Malmquist consumer/input quantity index, and we conclude for this example that x^1 has better water quality than x^0.

Integrated Modeling System

Figure 4 shows the data flow of the complete integrated modeling system. The system is implemented in the statistical programming language R and FORTRAN. Given the large computational requirements of the modeling system, we set it up to run on a Beowulf cluster. The algorithm is parallelized by running the evaluation step of the GA for an individual on a node in the cluster.

The results from the use of this integrated modeling system may be used to assess the efficiency and economic viability of alternative technologies employed in agricultural biomass removal and transport for ethanol production. The system requires substantial knowledge to set up and run. We propose that the output of the modeling system distributed to stakeholders will be a database containing the set of trade-offs among objectives. Any stakeholder can find the optimum solution that fits their preferences by querying the database. Stakeholder choices will be informed by a state of the art modeling system, without a requirement to understand or run the modeling system.

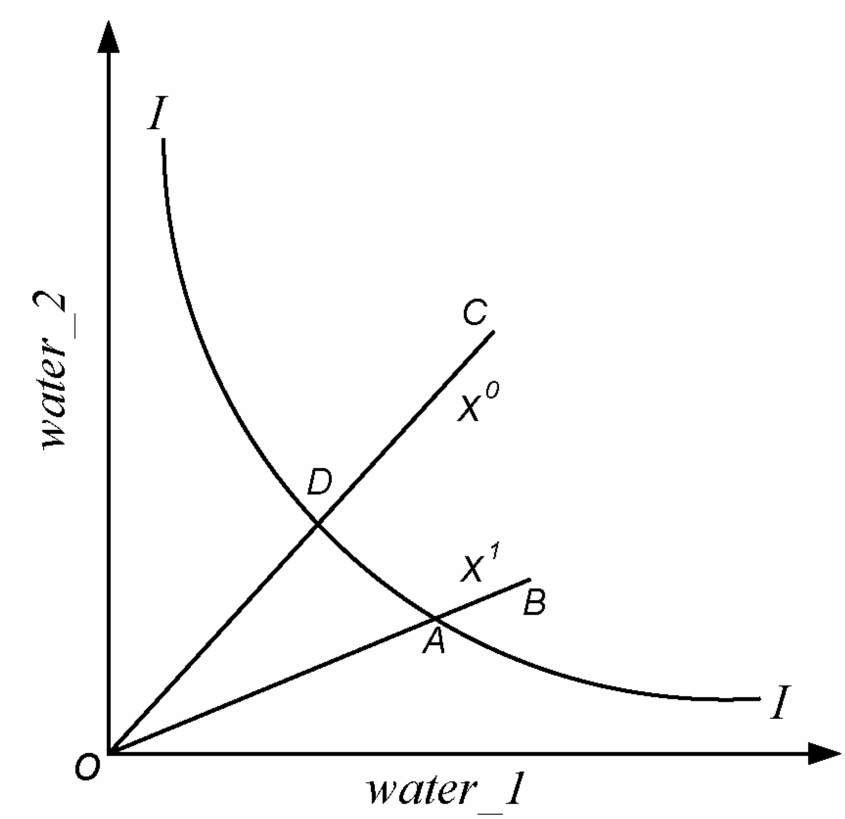

Figure 3. Construction of the Malmquist index with two constituents of water quality.

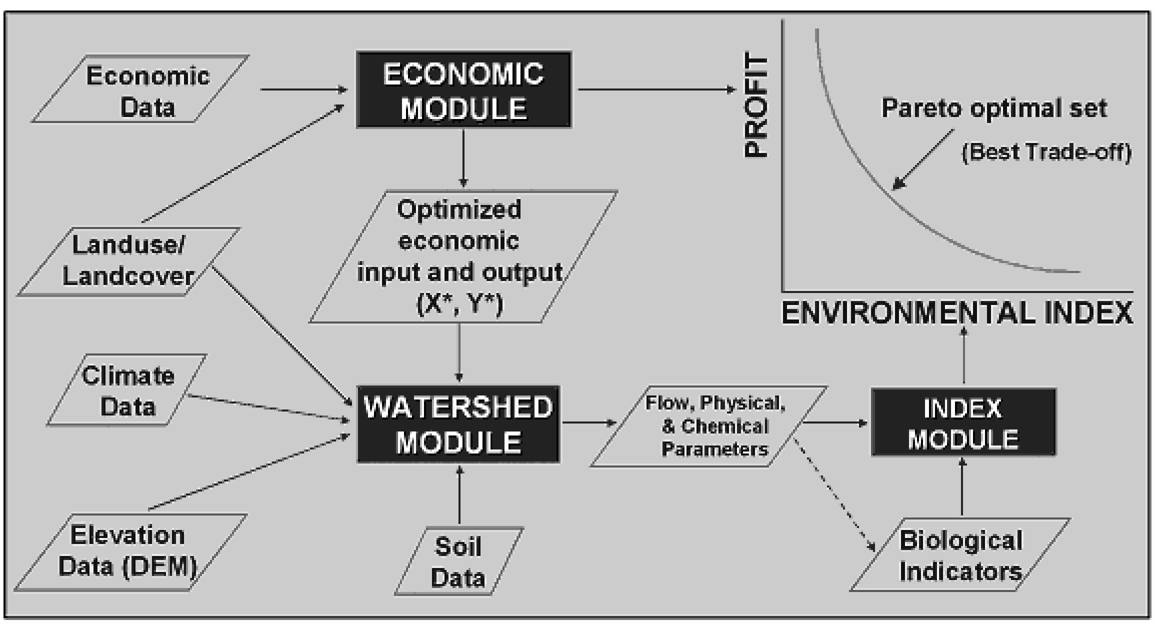

Figure 4. Information flow for integrated modeling system for multi-objective simulation of agricultural bio-fuel feed stock production.

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