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Since the potential for residue use in animal feed may be even more promising, these results are directly useful for the feed industry. They also indicate the profitability of investing in residue harvesting equipment.

From a methodological point of view, the paper contrasts the results of three OR approaches. Because of the stochastic nature of the problem both Monte Carlo simulation and chance-constrained programming are found to be computationally viable, even though they differ in the way they incorporate risk information.

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INTRODUCTION

Corn crop residues have the potential to provide energy through use as combustible fuel or as animal feed. They contain basically three materials: hemicellulose, cellulose, and lignin. The technology for converting cellulosic material into sugars is fairly simple and has been used in the production of the chemical feedstock furfural. Lignin cannot be converted to sugars and serves as a bonding agent which protects the cellulose portions of corn residue from chemical breakdown. The reduction of the residue requires mechanical pretreatment or pretreatment with acid to remove cellulosic material which is then susceptible to biological reduction. The resulting sugar solution can be fermented and distilled as in other processes. It is estimated that one tonne of dry residue may produce up to 50 gallons of alcohol (Turhollow, et al., p.13)[1]. Conversion of the cellulose into sugar and then into ethanol (a type of alcohol fuel) may be accomplished through acid or enzymatic processes (Moeller, p. 3).[2] Treatment of residues with alkaline hydrogen peroxide allows the cellulose to be more easily digested by ruminants (Kerley, et al., p. 820)[3]. Interest in the use of corn residues, considered a valueless byproduct of grain production, has been stimulated by the search for alternative fuel sources, in the first case, and by concern over competition for food between humans and animals, in the second.

At present, corn residues are not used extensively for either fuel or feed. Compared to the starch in corn grain, the cellulose in residue is relatively more difficult to break down, thereby presenting a challenge to the development of a viable conversion process on a commercial scale. Perfection of the chemistry and logistics of the conversion process is a necessary but not sufficient condition for commercial feasibility, however. The determinants and characteristics of the supply of the residue feedstock may be equally important. The purpose of this analysis is to evaluate the production of residue at the farm level when it is harvested for delivery to a large scale conversion plant. This effort was undertaken as part of a case study of the commercial feasibility of a 25 million gallon ethanol plant site in the Corn Belt (which represents about 0.5 percent of the 1990 ethanol demand for meeting a 5 percent ethanol-gasoline blend). While the technology for large scale treatment of residue for animal feed use has yet to be developed, ultimately many of the same considerations and constraints associated with the fuel process will be relevant in determining the feasibility of widespread substitution of corn residue for grain as an energy source in animal rations. Because the nature of the production of residue is invariant with respect to its end use as fuel or feed, the analysis presented here will have relevance for the future consideration of feed use of residue as well as for the present focus on fuel use.

The context for the analysis is provided by specifying a particular case study site. The specifications for the 25 million gallon ethanol plant were provided by the Solar Energy Research Institute. The acid process plant requires approximately 400,000 MT of dry weight (zero percent moisture) stover and/or cob material annually. However, in the absence of appropriate drying facilities on farms, it is assumed that the residue is delivered to the plant at moisture levels exceeding 14 percent. Site selection was made to correspond to favorable feedstock supply conditions in the Corn Belt; the city of Champaign-Urbana in central Illinois was chosen. The density of corn production in the surrounding area is as high as anywhere in Illinois (Antonopoulos, p. 28)[4] and probably as high as any location in the U.S. Corn and soybeans are the most important crops. Moreover, the importance of residue as a ground cover is less a factor here than elsewhere because the land is virtually flat and the soils wet, reducing the threat of wind and water erosion on relatively bare ground.

This paper presents a model of corn residue production at the farm level at the site described. The analysis assumes the production of corn grain is the producer's main objective. Consequently, corn residue harvest is viewed as subordinate to grain harvest, an assumption that is appropriate under a wide range of assumptions about the relative prices of grain versus residue. Accordingly, residue collection techniques are chosen for their consistency with grain harvest activities, and the farmer's behavior is modeled as if he or she evaluates the marginal gains and costs to an additional production activity--residue harvest.

The implication of this approach is that the range of possible residue harvest techniques is dictated by their compatibility with and constraints imposed by conventional machinery and cultivation practices. Thus, only three residue harvest systems are considered: (1) stover (plant parts other than grain) harvest following grain harvest performed by the farm operator, (2) stover harvest by a custom-hire operator, and (3) cob only collection simultaneous with grain harvest. In all three cases, grain is harvested by combines, and residue is harvested by modified combines or additional farm machinery. While other methods of grain harvest, for example by corn picker, might facilitate collection, these are not considered. Similarly, equipment used to harvest stover is assumed to be designed for forage harvest and available commercially, although large-scale residue harvesting might ultimately induce the development of specialized equipment. The conditions examined in this study represent those that would initially be encountered in the next five years of an ethanol plant operator. Thus, our perspective is that of a short term estimation of the supply of corn stover.

Three basic formulations of the production model, corresponding to each of the residue collection alternatives, are used in the analysis of residue supply response. Grain and stover yields as well as the time available for field operations vary with weather over the growing and harvest seasons from one year to the next. This essential stochastic nature of agricultural production and hence residue supply, will be explicitly represented.

The resulting stochastic linear program is solved using three different approaches. From a methodological point of view, the viability of Monte Carlo Simulation as a solution procedure for the problem under consideration is highlighted. Comparative results from chance-constrained programming and deterministic LP are also discussed.

The paper will be organized into four main sections, which will present, respectively: (i) the production model and its underlying economics, (ii) the mathematical formulation as a stochastic linear program, (iii) the solutions approaches and their corresponding results, and, (iv) general conclusions about both the usefulness of the results and the methodology used.

THE PRODUCTION MODEL

In this section, the elements of the linear programming model of a farm, representative of those found in the case study site of central Illinois, are presented. The farm has 500 acres, employs two full time operators and engages in two kinds of activities: the production of soybeans, corn and corn residues; and the selling of soybeans, corn and corn residues. The farm is assumed to employ conventional tillage practices with fall and/or spring plowing performed to incorporate any remaining residue into the soil. Because of the relative inefficiency of the residue (actually forage) machinery, which can recover only about a quarter of available residues (Richey),[5] sufficient cover residue would be left after collection activities to mitigate erosion and fertility concerns, even if reduced tillage practices were employed. Rotational requirements of soybeans and corn are met through the specification of a maximum of 250 acres for each crop. The farm is assumed initially to own a machinery complement which includes a combine for grain harvest and a tractor.

Three mutually exclusive alternatives for corn residue collection are considered. These include operator baling of corn stover (which requires the purchase of a baler), baling by custom hire operator, and cob collection by the farm operators coincident with grain harvest (which requires combine modification and the purchase of a trailing wagon). Baling cannot start until after grain harvest is complete, while cob collection occurs simultaneously with grain harvest. The amount of time available for these activities is limited to the fall harvest period which runs from September 15 to December 15.

To reflect the time constraint, the harvest season is divided into six two-week periods. The amount of time actually available for field work in each period is expressed in numbers of field days. A field day is defined as the number of hours (up to a maximum of 12) in which field work may be performed. Field work cannot occur during rain or snow or when the fields are subsequently too wet to allow heavy machinery to operate. Within a given two week period, then, a maximum of 14 field days (about 170 hours) are available for field work. However, in practice, the number of field days available for each period declines as the season progresses. With increasing precipitation and falling temperatures, fields tend to become wet. Harvest machinery has more difficulty moving, and moreover, the wet soil is more easily compacted by heavy equipment. This compaction is undesirable as it destroys the tilth of the soil. After the first snowfall, essentially no field work may be performed. Thus, not only the amount of time available but also its scheduling are of the essence. Historical data on the number of field days in each period for the state of Illinois were used as the basis for the application. Observations for the past ten years were available only until the middle of November. The data for the last two periods was approximated from the first four periods (see experimental design section).

The farm structure assumes that the equivalent, in hours, of two full time operators is available for the harvest season. Given the number of field days available each period, this labor may be used to harvest soybeans, corn grain, and/or corn residue. Further constraints are required since the combine and the baler can only operate so fast, thus establishing a ceiling on the amounts of grain and stover harvested each day. In the first period, only corn and soybeans compete for labor resources. In the next four periods, corn grain and corn stover compete for the same labor resources; this allows the farmer the flexibility to harvest stover immediately following corn grain or to allow for some time in between. During the last period only corn stover can be harvested, and so it is the only activity that requires labor at that time.

The optimal timing of harvest will depend on the returns and costs of production as well as on the availability of field days. Variable production costs per acre include seed, fertilizer, chemicals, fuel, machinery repairs, depreciation, hauling, and, for corn grain, drying costs. Soybean harvest precedes that of corn grain and is accomplished in the first period. Corn grain harvest may occur at any time in the first five periods. Its cost per acre decreases as the season progresses because the corn grain dries in the field, thereby lowering drying costs. Selling prices correspond to $2.35 per bushel for corn grain and $5.65 per bushel for soybeans (see Table 1). Data, for the 1982-84 growing seasons, which were used in the feasibility study of the ethanol plant (Offutt)[6], were developed from Illinois farm records maintained by the University of Illinois (Hinton)[7].

Production costs of the three residue collection alternatives are presented in Table 2. These costs are broken down into initial investment and variable costs per acre. For the own baling alternative, harvest costs include fuel and equipment maintenance and repair. For custom baling, harvest cost is the per acre charge for hiring an outside operator. Since cob collection occurs simultaneously with grain harvest, no additional harvest costs are incurred (although cob collection slows grain harvest). Storage costs were developed by figuring the space required to store the bales of residue and calculating the revenue foregone because that land could then not be used for growing crops. No storage costs are allocated to cob collection because cobs will not require much storage space compared to bales (which cannot be stacked on top of one another). Transportation charges of $0.145 per MT per mile, assuming a round trip of 40 miles between farm and plant, are included, as developed for the study by USDA's Office of Transportation.

The amount of corn residue available for harvest depends on corn grain yields per acre. Under good conditions, about a pound of residue is produced per pound of corn grain, as determined by a harvest index of plant composition (Aldrich and Leng, p. 11).[8] In the model, the average moisture content at harvest for corn grain is 14.5 percent, each bushel weighing approximately 55 pounds. Given corn grain yield, then, residue (stalks and leaves, or stover) production per acre is figured and adjusted upwards to allow for a higher moisture content at collection after the residue has laid in the fields. Cob yield on a weight basis is approximately one-tenth of grain yield. Then, final yield per acre for stover is found by adjusting these production figures for the inefficiency of the collection equipment, assumed to gather only a quarter of the available residues (Richey).[5] In contrast, all cobs are assumed to be caught when a modified combine blows the cobs back into a trailing wagon.

THE MATHEMATICAL MODEL

The mathematical model of production described in the previous section is now given in detail:

$$Max\ R = -\sum_{j=1}^{5} c_j x_j - c_b x_b - \sum_{i=2}^{6}\sum_{j=1}^{5} h_{ij} y_{ij} + \sum_{n=1}^{3} s_n z_n - k_t \tag{1}$$

$$ST: \quad \sum_{j=1}^{5} x_j + x_b \leq M \quad \textit{Total Land} \tag{2}$$

$$\sum_{j=1}^{5} x_j \leq M1 \quad \textit{Max Corn} \tag{3}$$

$$x_b \leq M2 \quad \textit{Max Beans} \tag{4}$$

$$-\sum_{j=1}^{5} d_j x_j + z_1 \leq 0 \tag{5}$$

$$-d_b x_b + z_2 \leq 0 \quad \textit{Max Sell} \tag{6}$$

$$-\sum_{i=1}^{6}\sum_{j=1}^{5} y_{ij} + z_3 \leq 0 \tag{7}$$

$$\sum_{i=j+1}^{6} y_{ij} - e_j x_j \leq 0 \quad j=1,\ldots,5 \tag{8}$$

Residue Harvesting Schedule

$$a_1 x_1 + a_b x_b \leq L_1 \tag{9}$$

$$a_v x_v + \sum_{j=1}^{v-1} a_{vj} y_{vj} \leq L_v \quad v=2,3,4,5 \tag{10}$$

Labor Supply

$$\sum_{j=1}^{5} a_{6j} y_{6j} \quad \leq \quad L_6 \tag{11}$$

$$\sum_{j=1}^{i-1} t_{ij} y_{ij} \quad \leq \quad B_i \quad \begin{matrix} i=2,\ldots,6 \\ \textit{Baler Time} \end{matrix} \tag{12}$$

$$f_j x_j \quad \leq \quad N_j \quad \begin{matrix} j=1,\ldots,5 \\ \textit{Combine} \end{matrix} \tag{13}$$

$$\begin{matrix} x_j \;\geq\; 0 \quad j=1,\ldots,5 \;;\; x_b \geq 0 \;;\; z_n \;\geq\; 0 \quad n=1,2,3 \\ y_{ij} \;\geq\; 0 \quad i=1,\ldots,6 \;;\; j=1,\ldots 5 \end{matrix} \tag{14}$$

Where:

Decision variables:

x_j : acres of corn grain harvested during period j (j=1,...5).

x_b : acres of soybeans planted and harvested.

y_{ij} : Metric Tons of residue harvested in period i (i=1,...,6) from corn harvested in period j (j=1,...,5), with i>j for all i and j.

z_n : metric tons of corn (n=1), soybeans (n=2), and corn residue (n=3) sold.

Parameters:

c_j : corn production costs per acre; j=1,...,5.

c_b : soybean production cost per acre.

s_n : unit selling price for corn (n=1), soybeans (n=2) and residue (n=3).

k_l : fixed costs of residue harvesting equipment, l=1 for own baling, l=2 for custom baling, and l=3 for cob collection.

d_j : grain yield (MT) per acre harvested in period j, (j=1,...,5 for corn and j=6 for soybeans).

e_j : residue yield (in MT) in any period per acre of corn harvested in period j (j=1,...,5).

h_{ij} : variable unit cost of harvesting stover.

a_i : labor requirement per acre for corn (i=1,...,5) and soybeans (i=6).

a_{ij} : labor requirement per metric ton of residue harvested in period i (i=2,...,6) of corn harvested in period j (j=1,...,5).

t_{ij} : baler time requirement per metric ton of residue harvested in period i (i=2,...6) of corn harvested in period j (j=1,...5).

f_i : combine time requirement per acre of corn harvested in period i (i=1,...,5).

M, M_1, M_2: land resources (total, max corn, max soybeans).

L_v : number of field days (expressed in hours) available for harvesting during period v (v=1,...,6).

B_i : number of field days available (expressed in hours) for baling during period i (i=2,...,6).

N_j : combine time (expressed in hours) available during period j (j=1,...,5) for corn harvesting.

R : total net return for the farm operation.

Notes:

(i) Like k_l, the parameters h_{ij}, e_j, t_{ij}, and a_{ij} will depend on residue harvesting alternative.

(ii) Operator, baler, and combine times are resticted separately in the model, producing 16 constaints, but they are all defined simultaneously over the six periods of stochastic suitable field work days (all six periods for labor, periods 1-5 for combine, and periods 2-6 for baler).

Equation (1) gives the net revenue for the farm operation; Equations (2) - (4) restrict land supply and enforce rotational requirements; constraints (5) - (7) are used to bound farm selling activities to maximum production. The triangular set of constraints (8), restrict, for any period j, the harvesting of the corresponding residue to all future periods; in addition, constraints (9) - (11) in particular allow corn and all stover harvested in period i of corn harvested in previous periods to compete for labor. This gives the farmer a schedule of residue harvest dependent on corn harvest and weather conditions. Finally, constraints (12) and (13) describe machinery time availability (which is weather dependent): baler for stover, and combine for corn.

MODEL SOLUTIONS

It is worth noting at this point that a reliable estimate of the supply of stover at the farm level is very important because it will serve as the basis for an aggregate estimate within a fixed radius of the ethanol plan. But the model described in the last two sections is essentially a stochastic linear program since both corn yield (and thus stover yield) and the number of field days available per period are not know with certainty. Therefore, both a deterministic set of solutions and the results of a stochastic approach are provided. This will give the decision maker some choice, and underscore some methodological differences between the solution approaches.

Initially the analysis incorporates the assumption that the farm operator knows at the start of the season how many field days will be available in each of the succeeding two week periods. In practice, this information will become known only as the harvest season progresses. If a farmer does not forecast field days correctly, he or she may allocate work effort differently than depicted here (e.g., harvest corn grain as soon as possible rather than allowing it to dry in fields). Thus, the deterministic and Monte Carlo analyses are "ex-ante" representations of an uncertain decision environment. In practice, producers must devise a strategy based on their perception of the likelihood of outcomes and their subjective valuation of the alternative outcomes. The chance-constraints approach actively incorporates such perceptions before the optimization is performed.

Deterministic Solutions

From empirical distributions of corn yield and field day availability over the period 1975-1984 sample means are used to obtain LP solutions for all stover harvesting alternatives. The relevant results are given in Table 3. It is noted that the total return figures are based on a $30.00 selling price per wet ton of corn stover, but the ranges for which the same production levels are optimal are also given. These ranges indicate that below the lower bound no stover should be collected, as it becomes non profitable, and beyond the upper bound more corn grain should be substituted for soybeans to increase stover production.

In addition to these average solutions, some relevant scenarios are considered based on observed extreme values in the data. The scenarios indicate that the supply of stover may range from 160 MT to 245 MT for the own and custom baling alternatives, and from 50 MT to 90 MT for cob collection.

Stochastic Simulation

The deterministic LP solutions certainly contain enough information to estimate an aggregate amount of stover around the proposed plant, but they do not include any information about the variability in some of the model's coefficients. Therefore, it is proposed here to generate a distribution of solutions through an appropriately constructed simulation. This will allow the decision maker more choice based on his/her own preferences.

It is important to recall that the approach taken here is from the point of view of the ethanol plant whose management wants to estimate input supply which depends of farmers' behavior when faced with risky prospects. In other words, one can think of the plant management's utility function as dependent on farmers' behavior.

In this part the farm problem is treated as a linear program with stochastic coefficients (corn yield, stover yield, and field day supply).

As discussed previously, an "ex-ante" analysis amounts to assuming that the realization of the random variables in the model occurs before decision making. This approach corresponds to solving "the distribution problem" in stochastic programming (Dempster,[9] Kall and Prekopa[10]). That is, the optimal values of the objective function (R^*) and that the decision vector (x_j^*, $j=1,...,5$; x_b^*; y_{ij}^*, $i=1,...6$, $j=1,..,5$; z_n^*, $n=1,2,3$) become random variables and their probability distribution functions are sought to be able to make probabilistic statements about the solution. However, analytically this is a very hard problem. To illustrate the difficulties involved, in a very small problem with 5 variables and 3 constraints, assuming all the coefficients are random, a 23-dimensional joint pdf needs to be derived. Several approximation procedures exist (Wets[11], Boisvert[12]). The approach taken here is a Monte Carlo simulation for generating the desired distributions. This approach seems to fit the problem very nicely for two main reasons: 1) the farm problem formulated is small (24 variables and 27 constraints); 2) only seven distributions need to be sampled from; this allows designing an experiment with a large enough sample size. It is noted, however, that this approach may not be efficient for large scale problems. But for production problems at the farm level where activities are aggregated enough (i.e., no separate variables for plowing, tilling, chemicals application, harvesting, etc.) this approach is very attractive.

(i) Design of the Simulation Experiment

A Monte Carlo experiment was designed as illustrated in Figure 1, where SEED1 and SEED2 are two different initial seeds used to generate two independent streams of random numbers. The first seed is used to generate a corn yield d_j ($j=1,...,5$) from a normal distribution with mean $\overline{d_j}$ and variance $\sigma^2_{d_j}$, and stover yield $e_j = \beta_l * d_j$ (where β_l is a yield adjustment factor for residue harvesting alternative l). The simulation is performed the same way for each residue harvesting alternative with the appropriate data changes.

For each run k, the second seed is used to generate a set of six field day observations from six normal distribution with means $\overline{L_v}$ and variances $\sigma^2_{L_v}$, $v=1,...,6$. The distributions of the six field day periods are identical except for the last two periods for which the standard deviation was decreased by one day to account for more variability closer to the winter time (Hinton[13]). Baler and combine time is based on a twelve-hour availability and is computed from L_v (since labor time and equipment time overlap) as follows: $B_i = \frac{1}{2} * L_v$ ($i=v=2,...,6$) and $N_j = \frac{1}{2} * L_v$ ($j=v=1,...,5$). Note that this design allows the field day availability at harvest time to be independent of corn yield on the ground. It also allows the specification of more variability in the field day supply through the sampling distributions of field day availibility.

The major issues of the design were the determination of the number of replications (i.e., sample size N and the accuracy of the simulation output). The sample size was determined using the following approach. Based on some initial experimentation with the model (which is also confirmed by 5 out of 8 scenarios in table 12) it was concluded that the LP solutions may not be normally distributed. Therefore, Chebyshev's theorem (Shannon)[14] was used to determine a lower bound on the sample size. Chebyshev's theorem (Mood et al.)[15] states that if X is a random variable with finite mean μ and variance σ^2, then for any value k > 0,

$$P\{|X - \mu| \geq k\} \leq \frac{\sigma_x^2}{k^2} \quad \textit{or equivalently,} \quad P\{|X - \mu| < k\} \geq 1 - \frac{\sigma_x^2}{k^2} \qquad (15)$$

We want to guarantee that the mean output, x_m is within one-half standard deviation (i.e. within $\frac{1}{2}\sigma_x$) of the true mean with a probability of at least 0.95. Therefore, setting $k=\frac{1}{2}\sigma_x$, and noting that the random variable in question is now x_m, we can write Chebyshev's theorem as

$$P\left\{|x_m - \mu| < \frac{1}{2}\sigma_x\right\} \geq 1 - \frac{\sigma_{x_m}^2}{\left(\frac{1}{2}\sigma_x\right)} = 0.95. \qquad (16)$$

Using the equality on the right hand side of (16), and noting that

$$\sigma_{x_m}^2 = \frac{\sigma_x^2}{N},$$

we have that 4/N=0.05, or N=80. Had we assumed normality of output and no autocorrelation, the same requirement on the mean output expressed as a test of hypothesis and a significance level of 5 percent, together with a desired power of the test of at least 90 percent, would have resulted in a sample size of at least 45 (which can be determined from a power curve for a two-sided t-test with $\alpha = .05$, $\beta = .1$, and $|d| = 1/2$; see for example Hines and Montgomery, p. 604[16]). Finally, the actual sample size used was N = Max {45,80}=80.

The accuracy of the simulation output is achieved by using an appropriate variance reduction technique (Rubinstein[17]) to end up with output estimates whose variances are as small as possible. Because the ultimate goal here is to compare the four alternative baling systems: own, custom, cob collection, and no baling, the "correlated sampling" technique is used (see for example Rubinstein, p. 203)[17]. The method is simple but effective because the random error is reduced by making all four alternatives go through the same history and be compared under the same conditions. This is achieved by using the same random streams for all alternatives. The same approach is also used within each alternative, between the two distribution scenarios under which the simulation is run.

(ii) **Results of the Simulation**

The simulations were run under two sets of distributions for field days:

(i) Empirical distribution from past weather data, $N_v(10.6, 4.45)$ for $v=1,...,4$ and $N_v(10.6, 5.45)$ for $v=5,6$.

(ii) Theoretical distribution in the range 0 to 14 days, N(7.0,5.43).

The corn yield distribution sampled from is estimated from time series data to be normal : N(2.83, 0.35) MT/acre. We note that in all cases where the normality assumption was used, it was justified by a significant goodness of fit test.

The results from the 8 simulations (4 alternatives and 2 field day distributions) are given in Tables 4 to 11.

Analyses of variance were conducted to determine statistical differences between the corn residue production alternatives, and the effect of field day distributions. The variables tested for were tonnage of stover and total net return. It was found that differences between all three stover production alternatives were significant at the 1 percent level, irrespective of the distribution of field days. In addition, it was found that no significant differences existed between distributions, except for "own baling" which was significant only at and below 5 percent. Interestingly, the deterministic solutions of Table 3 are very close to the mean simulation output under the empirical distribution of field days. One of the advantages of having conducted the simulation is to be able to construct confidence intervals on the production at the farm level and determine a distribution of aggregate supply at the ethanol plant level.

From the farmer's point of view the following information conveyed by the simulation LP approach is quite interesting:

(1) On average, corn will yield .72 MT of stover per acre with the own baling and custom baling alternatives, while it will only yield .30 MT per acre with the cob collection alternative.

(2) The custom baling alternative, on average, yields higher net return for the maximum average stover production,

(3) Corn production should be privileged even at the expense of soybeans,

(4) As indicated by the distribution of corn acreage and stover tonnage harvested (see tables 4 to 11), over the six period production planning horizon, the farmer should harvest corn as late as possible and immediately use all the remaining time to harvest all the stover; early periods harvest has a high opportunity cost and should be avoided.

In addition, the solution provides a real harvesting schedule which is summarized in table 13. This table gives harvesting schedules under average conditions; confidence intervals for these schedules can be easily constructed for use by either the farmers or the ethanol plant management. From this table we draw the following conclusions:

(1) Instead of a one-time, all-in-one period job, a flexible schedule is provided to the farmer between october 1st and december 15.

(2) Irrespective of the stover harvesting alternative, more than 95 % of all corn and stover should be harvested no earlier october 30th which conforms very well with observed practices. Moreover, most corn should be harvested during the last two weeks of november, and most stover should be harvested during the first two weeks of december.

(3) Under the theoretical distributions scenario, relatively less harvesting should be done during the last period (about 63% for corn and 71% for stover), compared to the empirical distributions scenario (88% for corn and 93% for stover). This is a very intuitive conclusion since we expect more weather

variability to have an important impact on the harvesting schedule.

A Chance-Constrained Approach

In this section the effects of relaxing the assumption of an "ex-ante" or "passive" approach behind the simulation model of the previous section are discussed. It is assumed now that the decision maker must act before the outcomes of the stochastic coefficients become known. In other words, he/she optimizes first, then the realization of the random variables occurs. This corresponds to the "active (or here-and-now)" approach in stochastic programming (Dempster[8], Kall and Prekopa[10]). Risk levels are built into the decisions before nature's outcomes. To achieve this, a chance-constrained programming approach (Charnes and Cooper[18] and Charnes[19]) is used. However, because corn and stover yields appear in the constraints, the resulting deterministic program would include quadratic constraints. Instead of reverting to linearization, we avoid this complication by directly replacing corn and stover yields by their sample means. To see why this approximation directly results in a deterministic equivalent which is a linear program, we first note that stochastic field days appear in the original model's right hand side as independent; second, only terms including a model variable will add a quadratic expression coming from the variance component, as illustrated by the following example, assuming a sinle general constraint for simplicity: Let $d = b - a^t x$, where $b \in R^1$, a and $x \in R^n$, then, if both -b- and -a- are stochastic, $E(d) = E(b) - x^t E(a)$ and $V(d) = V(b) + x^t V(a) x$, where E is the expectation operator and V is the variance-covariance opeartor. The quadratic term will drop from the variance expression if -a- is deterministic (for more details on various aspects of chance-constrained programming, see also Vajda[20], Wagner[21], Boisvert[12], and Kim et al.[22]).

The transformation of the original problem is accomplished by first defining chance-constraints in the original mathematical model (1)-(14), resulting in the stochastic problem (17), and then using distributional properties of field days with some algebraic manipulations to derive the linear deterministic equivalent (18). This treatment is undertaken under the assumption that field day constraints are independent. Jointly distributed RHS's require a different approach also involving a nonlinear procedure (see for example Wagner[21]).

The derivation of the deterministic equivalent constraints in (18) can be easily seen from the case of only one constraint, say when v=1, as follows. We assume the decision maker is willing to make a probabilistic statement about the frequency with which the constraint needs to be satisfied; namely, that the probability of the constraint being satisfied is greater than or equal to a prespecified value α.

$$P(a_1 x_1 + a_b x_b \leq L_1) \geq \alpha_1$$

If the constraint is standardized by subtracting the expected value of field days and dividing by the standard deviation of filed days, it becomes:

$$P\left\{\left[\frac{a_1 x_1 + a_b x_b - \overline{L_1}}{\sigma_{L_1}}\right] \leq \left[\frac{L_1 - \overline{L_1}}{\sigma_{L_1}}\right]\right\} \geq \alpha_1$$

If we let Z denote the standardized random variable $\{(L_1 - \overline{L_1})/\sigma_{L_1}\}$, which represents the number of standard errors that L_1 is away from its mean, then for a given value of $\alpha = \alpha_1$, $Z = Z_{\alpha_1}$ is determined from the probability distribution of L_1 using a standard normal table. We note that a conservative estimate for Z_{α_1} could have also been generated from Chebyshev's inequality if the distribution of field days were not available. After this transformation, the constraint becomes:

$$P\left[\frac{a_1 x_1 + a_b x_b - \overline{L_1}}{\sigma_{L_1}} \leq Z_{\alpha_1}\right] \geq \alpha_1$$

which, after a simple manipulation, yields:

$$-Z_{\alpha_1} = Z_{1-\alpha_1} \geq \frac{a_1 x_1 + a_b x_b}{\sigma_{L_1}}$$

from which we get the two equivalent forms:

$$a_1x_1 + a_bx_b \leq \overline{L_1} + Z_{1-\alpha_1} \cdot \sigma_{L_1}$$
$$a_1x_1 + a_bx_b \leq \overline{L_1} - Z_{\alpha_1} \cdot \sigma_{L_1}$$

Applying the above procedure, the original problem is rewritten as:

$$\begin{array}{rll} MAX: & R & \\ ST: & (2) - (4) & \\ & (5) \ \textit{with } d_j \textit{ replaced by } \overline{d}_j) & (5)' \\ & (6) - (7) & \\ & (8) \ \textit{with } e_j \textit{ replaced by } \overline{e}_j) & (8)' \\ & P(a_1x_1 + a_bx_b \leq L_1) \ \geq \ \alpha_1 & (9)' \\ & P(a_vx_v + \sum_{j=1}^{v-1} a_{vj}y_{vj} \leq L_v) \ \geq \alpha_v, \quad v=2,3,4,5 & (10)' \\ & P(\sum_{j=1}^{5} a_{6j}y_{6j} \leq L_6) \ \geq \ \alpha_6 & (11)' \\ & (12) - (14) & \end{array} \qquad (17)$$

where $\overline{d}_j$ and $\overline{e}_j$ are the mean corn and stover yields. The final step produces the deterministic equivalent:

$$\begin{array}{rll} MAX: & R & \\ ST: & (2) - (4) & \\ & (5)' - (8)' & \\ & a_1x_1 + a_6x_6 & \leq \overline{L_1} + Z_{1-\alpha_1} \cdot \sigma_1 \\ & a_vx_v + \sum_{j=1}^{v-1} a_{vj}y_{vj} & \leq \overline{L_v} + Z_{1-\alpha_v} \cdot \sigma_v \ ; v=2,3,4,5 \\ & \sum_{j=1}^{5} a_{6j}y_{6j} & \leq \overline{L_6} + Z_{1-\alpha_6} \cdot \sigma_6 \\ & (12) - (14) & \end{array} \qquad (18)$$

where $\overline{L}_v$ and $\sigma^2_{L_v}$ are the mean and variance of field days in period v=1,...6.

It is clear that α reflects decision makers' risk attitudes, because it is a measure of their willingness to accept that the constraint no be satisfied some of the time. The lower α is, the higher the frequency that the constraint may not be satisfied, and the higher the expected return. Intuitively, a decision maker who is risk averse (conservative in some sense) will require that α be close to one and accept a very small net return (as $\alpha \rightarrow 1$, $R \rightarrow 0$ and as $\alpha \rightarrow 0$, $R \rightarrow$ increases). The Term $[Z_{1-\alpha}.\sigma]$ can be interpreted as a risk premium which discounts average field day availibility. Risk is incorporated into the model through the specification of the reliability level α, which can be chosen from one of three ranges:

(1) $\alpha \in (0,0.5)$ for "optimists" who plan on field day availibility being more than its expected value (this can be interpreted as a risk seeking attitude),

(2) $\alpha = 0.5$ for practitioners who plan on field day availibility being exactly equal to its expected value (this can be interpreted as a risk neutral attitude),

(3) $\alpha \in (0.5,1.0)$ for "pessimists" who plan on field day availibility being less than its expected value (this can be interpreted as a risk averse attitude).

Figure 2 summarizes the trade-offs faced by decision makers, between net return and the frequency of not meeting field day.

Tables 14 and 15 provide a summary of solutions resulting from a parametrization of α, the confidence or reliability level. These tables correspond to the "own baling" alternative. Tables for the other alternatives are similar and convey the same conclusions, therefore they are omitted here.

The following observations can be made about the chance-constrained results:

1) As the reliability level on field day availability is tightened ($\alpha \rightarrow 1$ in table 14), both total net return and corn and stover production fall substantially. As α ranges from .92 to .6, corn and stover productions reach their maximum but net return keeps increasing due to savings from delayed harvesting. For $\alpha <= .57$, no extra savings are observed since time resources are sufficient to confine all harvesting to the last period (table 15). Decision makers who are risk averse will maintain the same level of production at a somewhat declining net return as the reliability level α ranges from .6 to .92.

For $\alpha >= .95$, substantianl reductions in both net return and production occur.

2) In comparison to the simulation approach, the average net return and corn and stover production (see table 4) are attained in the chance-constrained approach for α between .82 and .85. However, the two approaches differ substantially in the "optimal scheduling harvest". While the average simulation solution calls for leaving most harvesting (89% for corn and 93% for stover) to the last period, the chance-constrained approach (with $.82 <= \alpha <= .85$) calls for a much more conservative schedule with harvesting about 55% of all corn and stover before the last period (relevant lines appear in bold in both tables 14 and 15). An intuitive explanation for this difference comes from the way the two approaches incorporate risk information. While chance-constrained solutions are obtained by actively including a form of risk attitude (linked to the underlying variability in the data) into the optimization process, simulation results only reflect the variability in the system, and risk information may be used ex-post after the entire distribution of outcomes is generated. Keeping in mind the assumptions we used in our chance-constrained model (independence of the six field day periods and use of a certainty equivalent for corn and stover yields to avoid nonlinear constraints), we observe that the average net return from the simulation, which could be interpreted as a risk-neutral solution, corresponds to a chance-constrained solution with a reliability level in the risk-averse range, thus explaining the more conservative harvesting schedule called for. Figure 2 also shows what reliability level is implied by the average LP solution (AVE LP), the maximum simulation solution (MAX SIM), the minimum simulation solution (MIN SIM), and the average simulation solution (AVE SIM).

Finally, we note that from the point of view of the ethanol plant, if the average simulation solution is used as a guide to planning input procurement, than by assuming that each individual producer can supply 178 MT of stover, a wide range of farmers' risk attitudes would be covered ($\alpha <= .95$), except for those who require a reliability level to be more than .95.

Remark

Throughout this study the sampling distributions used were implicitly truncated to avoid negative yields and field day values outside the range [0-14].

CONCLUSION

The basic unit of analysis used in estimating the corn residue supply is the individual, representative farm. The production practices and economic structure of the farm are represented mathematically using stochastic linear programming to assess the feasibility and profitability of residue collection. Three alternative collection systems were considered: baling of stover (stalks and leaves) by the farmer; baling of stover by a custom-hire operator; and simultaneous cob collection and grain harvest performed by the farm operator. The linear programming approach allows recognition of important resource and environment constraints on corn residue collection. In particular, the model can be used to determine the sensitivity of grain and residue collection to the availability of days suitable for field work at harvest time. Weather conditions cause variations in field availability as well as in grain and residue yields, from one year to the next. The variability affects the feedstock supply and creates uncertainties for individual farmers and the manager of a large-scale ethanol plant.

This paper presented the results of a case study in which the supply of corn residue was estimated based on the specifications of a 25 million gallon ethanol plant. Since the potential for residue use in animal feed is even more promising, these results are directly useful for the feed industry. In addition, farmers can now measure the potential revenue from investment in residue harvesting equipment.

From a methodological point of view the paper contrasted the use of three OR approaches. Because of the stochastic nature of the problem it was found that Monte Carlo simulation and Chance-Constrained Programming were both robust and viable methods. However, because of the way they incorporate risk attitudes, we suggest that these two methods be used in a complementary fashion. For the farmer who is the bearer of the production risk, chance constraints allow an active incorporation of preferences into production decisions. For the industry, however, simulation gives the possibility of considering the full range of scenarios before the final plant capacity is chosen.

The characteristics of the aggregate supply schedule faced by an ethanol plant manager are thus derived from the conditions that underlie individual producer's decisions. Sources of shift in supply are identical and classified according to whether they may be predicted by the plant manager or not. Unpredictable variation in supply, due to the vagaries of weather and disease, is the hallmark of agricultural markets and therefore the source of uncertainty to the ethanol plant manager. With the methodology developed here, the magnitude and the likelihood of random supply shifts may be estimated. Such uncertainty is an integral part of the environment faced by the producer and is reflected in the analysis of producer behavior. Ignoring the possibility of random shifts in input supply underestimates the risks associated with ethanol production using an agricultural feedstock.

Based on the analysis of the representative farm, market supply characteristics can be derived. The ethanol plant's annual feedstock requirement is constant. A 25-million-gal plant uses 410,000 MT (at 0% moisture) (Offutt)[6] of stover annually. However, the likelihood of year-to-year variability in field day availability and in grain and residue yield has important implications for the operation of the ethanol plant. When residue availability on farms falls bellow that expected under normal conditions, the ethanol plant must increase its residue collection radius, which increases both the cost and the number of farm suppliers. Coordinating delivery of the supply from these varying numbers of farmers represents a considerable logistical challenge. More important, however, is the problem of assuring supply from farmers whose residue will be required only occasionally. This has influence on some strategic decisions at the ethanol-plant level, like the decision to invest in residue harvesting equipment and contracting services to farmers.

The likely variability in residue yields and in the time available for its collection introduces an element of risk to the farmer and the ethanol plant manager. Two aspects of this potential year-to-year instability in feedstock supply are particularly relevant: the first is the way the presence of risk affects the farmer's willingness to collect residue, and the second is the means by which the plant can cope with this uncertainty. If farmers are averse to risk, they will require a higher return than under certainty and will be reluctant to invest in residue collection equipment. For farmers whose residue supplies will only be needed occasionally, the element of risk is compounded. The nature of risk and risk attitudes can be expected to vary between farmers and locations. Locational decisions regarding the ethanol plant should consider survey information on farmers' attitudes toward these issues, because this behavioral information is not explicitly captured in the empirical methodology described here.

For the ethanol plant, feedstock supply risk implies the need for flexible input procurement procedures to insure uninterrupted operation. The plant could rely solely on contracts with individual farmers, or on operating its own fleet of custom balers, or a combination of the two, with varying levels of risk borne by both sides.

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Table 1. Crop Harvest Variable Costs and Selling Prices

	Variable Costs (exc. labor) ($/ac)*	Selling Price ($/MT)
Period 1 Corn	73.70	93.15
Period 2 Corn	70.70	93.15
Period 3 Corn	67.70	93.15
Period 4 Corn	64.70	93.15
Period 5 Corn	60.70	93.15
Soybeans	29.50	207.60

* (1 acre = 0.405 hectare, a metric tonne (MT) = 2204 pounds)

Table 2. Corn Stover Harvesting Costs

	Own Baling ($)	Custom Baling ($)	Cob Collection ($)
nitial Investment	$18,000	0	7,000
Variable Costs ($/MT)*	22.84	13.74	0
Includes:			
Harvesting	17.10	8.00	
Storage	0.24	0.24	
Transportation	5.50(a)	5.50(a)	5.50**(a)**
Residue Yield (MT/ac)			
High	1.0	1.0	0.38
Low	0.65	0.65	0.25

* (1 metric tonne (MT) = 2204 pounds).
(a) Assuming a 40 mile round trip at a cost of $0.145/MT/mile.

Table 3. Average Linear Programming Solutions

	Own Baling	Custom Baling	Cob Collection	No Baling
Stover Harvested (MT)	178	178	71	--
Total Net Return ($)	115,244	116,859	102,073	113,973
Stover Price Range ($)	23-93	14-84	0-176	--

Table 4. OWN BALING WITH EDFD (OE) #

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN($)	**114646.0885**	**11379.8835**	**53530.2400**	**137898.0000**
TCORN (AC)	250.0000	.0000	250.0000	250.0000
BEANS (AC)	245.7860	21.4596	58.9300	250.0000
TSTOVER(MT)	**178.6176**	**24.3078**	**123.5000**	**250.0000**
STOVER2 "	.0000	.0000	.0000	.0000
STOVER3 "	.4566	4.6111	.0000	46.5700
STOVER4 "	5.4035	21.4187	.0000	129.8200
STOVER5 "	6.1008	22.3050	.0000	127.4900
STOVER6 "	166.6568	40.7705	.0000	250.0000
CORN1 (AC)	.0000	.0000	.0000	.0000
CORN2 "	.6561	6.6261	.0000	66.9200
CORN3 "	7.8491	31.0733	.0000	183.0800
CORN4 "	19.5077	40.7331	.0000	200.4600
CORN5 "	221.9869	58.5902	.0000	250.0000

Table 5. OWN BALING WITH TDFD (OT)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**101234.2018**	**26502.7998**	**15261.9000**	**137898.0000**
TCORN	238.5596	44.6177	.0000	250.0000
BEANS	202.6996	85.9779	.0000	250.0000
TSTOVER	**171.1441**	**39.1587**	**.0000**	**250.0000**
STOVER2	1.1969	9.3521	.0000	88.6800
STOVER3	6.8123	30.3592	.0000	187.5000
STOVER4	19.3911	52.4965	.0000	218.2500
STOVER5	21.2846	45.9626	.0000	196.7500
STOVER6	122.4593	73.4478	.0000	250.0000
CORN1	1.8540	12.0977	.0000	107.6200
CORN2	10.1094	42.0824	.0000	250.0000
CORN3	29.1153	69.8471	.0000	250.0000
CORN4	45.7567	61.4674	.0000	250.0000
CORN5	151.7242	97.2334	.0000	250.0000

\# **EDFD** = Empirical Distribution of Field Days
TDFD = Theoretical Distribution of Field Days

Table 6. CUSTOM BALING WITH EDFD (CE)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**116271.5115**	**11575.0320**	**54829.2600**	**140173.0000**
TCORN	250.0000	.0000	250.0000	250.0000
BEANS	245.7860	21.4596	58.9300	250.0000
TSTOVER	**178.6176**	**24.3078**	**123.5000**	**250.0000**
STOVER2	.0000	.0000	.0000	.0000
STOVER3	.4566	4.6111	.0000	46.5700
STOVER4	5.4035	21.4187	.0000	129.8200
STOVER5	6.1008	22.3050	.0000	127.4900
STOVER6	166.6568	40.7705	.0000	250.0000
CORN1	.0000	.0000	.0000	.0000
CORN2	.6561	6.6261	.0000	66.9200
CORN3	7.8491	31.0733	.0000	183.0800
CORN4	19.5077	40.7331	.0000	200.4600
CORN5	221.9869	58.5902	.0000	250.0000

Table 7. CUSTOM BALING WITH TDFD (CT)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**102791.6127**	**26718.9973**	**15261.9000**	**140173.0000**
TCORN	238.5596	44.6177	.0000	250.0000
BEANS	202.6996	85.9779	.0000	250.0000
TSTOVER	**171.1441**	**39.1587**	**.0000**	**250.0000**
STOVER2	1.1969	9.3521	.0000	88.6800
STOVER3	6.8123	30.3592	.0000	187.5000
STOVER4	19.3911	52.4965	.0000	218.2500
STOVER5	21.2846	45.9626	.0000	196.7500
STOVER6	122.4593	73.4478	.0000	250.0000
CORN1	1.8540	12.0977	.0000	107.6200
CORN2	10.1094	42.0824	.0000	250.0000
CORN3	29.1153	69.8471	.0000	250.0000
CORN4	45.7567	61.4674	.0000	250.0000
CORN5	151.7242	97.2334	.0000	250.0000

Table 8. COB COLLECTION WITH EDFD (CCE)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**115496.8529**	**11481.3627**	**54185.2600**	**138958.0000**
TCORN	250.0000	.0000	250.0000	250.0000
BEANS	245.7860	21.4596	58.9300	250.0000
TSTOVER	**71.3897**	**9.5895**	**49.5000**	**95.0000**
STOVER2	.0000	.0000	.0000	.0000
STOVER3	.2168	2.1892	.0000	22.1100
STOVER4	2.3422	8.7688	.0000	52.9400
STOVER5	2.7734	9.4826	.0000	51.8800
STOVER6	66.0574	16.6152	.0000	95.0000
CORN1	.0000	.0000	.0000	.0000
CORN2	.7798	7.8756	.0000	79.5400
CORN3	8.4762	31.8002	.0000	185.1200
CORN4	21.1082	41.5325	.0000	203.4600
CORN5	219.6360	60.0791	.0000	250.0000

Table 9. COB COLLECTION WITH TDFD (CCT)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**101896.3136**	**26722.6987**	**15261.9000**	**138958.0000**
TCORN	237.9475	45.5656	.0000	250.0000
BEANS	202.6996	85.9779	.0000	250.0000
TSTOVER	**68.2126**	**15.7610**	**.0000**	**95.0000**
STOVER2	.5102	3.8626	.0000	35.4900
STOVER3	2.8745	12.1280	.0000	75.0000
STOVER4	7.9307	21.0641	.0000	87.2500
STOVER5	8.9894	18.4641	.0000	78.7500
STOVER6	47.9079	29.0412	.0000	95.0000
CORN1	1.9523	12.6096	.0000	107.8600
CORN2	10.7567	42.2232	.0000	250.0000
CORN3	30.1522	70.1282	.0000	250.0000
CORN4	47.5396	60.7909	.0000	250.0000
CORN5	147.5468	96.0726	.0000	250.0000

Table 10. NO BALING WITH EDFD (NBE)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**110826.4297**	**14804.8072**	**38630.8000**	**136108.0000**
TCORN	250.0000	.0000	250.0000	250.0000
BEANS	236.8054	46.8982	.0000	250.0000
CORN1	.0000	.0000	.0000	.0000
CORN2	.0000	.0000	.0000	.0000
CORN3	.0000	.0000	.0000	.0000
CORN4	16.6424	47.8724	.0000	250.0000
CORN5	233.3576	47.8724	.0000	250.0000

Table 11. NO BALING WITH TDFD (NBT)

NAME	MEAN	STD. DEV.	MINIMUM	MAXIMUM
TRETURN	**100401.0674**	**23997.0166**	**37303.1900**	**136108.0000**
TCORN	250.0000	.0000	250.0000	250.0000
BEANS	196.3779	89.0490	.0000	250.0000
CORN1	.0000	.0000	.0000	.0000
CORN2	1.6009	14.8507	.0000	148.8200
CORN3	9.7430	35.5334	.0000	214.6100
CORN4	46.5586	76.6445	.0000	250.0000
CORN5	192.0974	89.1424	.0000	250.0000

Table 12. Coefficients of Variation* from the Simulation Output								
Variable	OE	OT	CE	CT	CCE	CCT	NBE	NBT
TRETURN	9.9	26.2*	10.0	26.0*	9.9	26.2*	13.4*	23.9*
TCORN	--	18.7	--	18.7	--	19.1	--	--
BEANS	8.7	42.4	8.7	42.4	8.7	42.4	19.8	45.3*
TSTOVER	13.6	22.9*	13.6	22.9*	13.4	23.1*		
STOVER2	--	781.4	--	781.4	--	757.1		
STOVER3	1010.0	445.7	1010.0	445.7	1010.0	422.0		
STOVER4	364.4	270.7	396.4	270.7	374.4	265.6		
STOVER5	365.6	215.9	365.6	215.9	341.9	205.4		
STOVER6	24.5*	60.0*	24.5*	60.0*	25.1*	60.6*		
CORN1	--	652.5	--	652.5	--	646.0	--	--
CORN2	1010.0	416.3	1010.0	416.3	1010.0	392.5	--	927.6
CORN3	395.9	239.9	396.0	239.9	375.2	232.6	--	364.7
CARN4	208.8	134.3*	208.8	143.3*	196.8	127.9*	287.7	164.6*
CORN5	26.4	64.1*	26.4	64.1*	27.4	65.1*	20.5	46.4*

0=own baling, C=custom baling, CC=cob collection, NB=no stover collection, E=empirical distribution, T=theoretical distribution.

* Normality hypothesis rejected at 95% confidence level.

Table 13. Harvesting Schedules Resulting from the Stochastic LP								
	Own & Custom Baling				Cob Collection			
	ED	TD				TD	ED	
	C%	S%	C%	S%	C%	S%	C%	S%
Period 1	0.0	--	0.8	--	0.0	--	0.8	--
Period 2	0.3	0.0	4.2	0.7	0.4	0.0	4.5	0.8
Period 3	3.1	0.3	12.2	3.9	3.4	0.3	12.7	4.2
Period 4	7.8	3.0	19.2	11.3	8.4	3.3	20.0	11.6
Period 5	88.8	3.4	63.6	12.5	87.8	3.9	62.0	13.2
Period 6	--	93.6	--	71.6	--	92.5	--	70.2
Total	100%				100%			

* ED = empirical distribution; TD = theoretical distribution, C(S)% = % corn (stover) harvest during period.

Table 14. Chance-Constrained Solutions

ALPHA	NET RETURN ($)	CORN (AC)	BEANS (AC)	STOVER (MT)
.9999	00.000	00.00	00.00	00.00
.98	86250.640	115.59	250.00	82.07
.95	113112.800	249.56	250.00	177.18
.92	114010.600	250.00	250.00	177.50
.90	114232.600	250.00	250.00	177.50
.88	114487.700	250.00	250.00	177.50
.85	**114639.200**	**250.00**	**250.00**	**177.50**
.82	**114733.400**	**250.00**	**250.00**	**177.50**
.80	114783.500	250.00	250.00	177.50
.77	114854.000	250.00	250.00	177.50
.75	114898.500	250.00	250.00	177.50
.72	114962.300	250.00	250.00	177.50
.70	115003.200	250.00	250.00	177.50
.67	115062.600	250.00	250.00	177.50
.65	115101.200	250.00	250.00	177.50
.62	115157.900	250.00	250.00	177.50
.60	115195.000	250.00	250.00	177.50
.57	115243.900	250.00	250.00	
...				
0.0001	115243.900	250.00	250.00	177.50

Table 15. **Chance-Constrained Harvesting Schedules** (acres)										
ALPHA	STOVR2	STOVER3	STOVER4	STOVER5	STOVER6	CORN1	CORN2	CORN3	CORN4	CORN5
.9999	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
.98	12.38	32.01	30.29	7.39	.00	17.43	45.08	42.67	10.41	.00
.95	26.97	58.86	55.15	30.54	5.67	37.99	82.90	77.68	43.01	7.98
.92	.00	6.11	83.72	57.13	30.54	.00	8.60	117.91	80.47	43.02
.90	.00	.00	61.59	71.72	44.19	.00	.00	86.74	101.02	62.24
.88	.00	.00	24.87	90.69	61.94	.00	.00	35.03	127.73	87.23
.85	**.00**	**.00**	**3.07**	**101.95**	**72.47**	**.00**	**.00**	**4.33**	**143.60**	**102.07**
.82	**.00**	**.00**	**.00**	**90.61**	**86.89**	**.00**	**.00**	**.00**	**127.62**	**122.38**
.80	.00	.00	.00	81.72	95.78	.00	.00	.00	115.10	134.90
.77	.00	.00	.00	69.21	108.29	.00	.00	.00	97.48	152.52
.75	.00	.00	.00	61.31	116.19	.00	.00	.00	86.35	163.65
.72	.00	.00	.00	49.98	127.52	.00	.00	.00	70.40	179.60
.70	.00	.00	.00	42.72	134.78	.00	.00	.00	60.17	189.83
.67	.00	.00	.00	32.17	145.33	.00	.00	.00	45.31	204.69
.65	.00	.00	.00	25.32	152.18	.00	.00	.00	35.67	214.33
.62	.00	.00	.00	15.27	162.23	.00	.00	.00	21.51	228.49
.60	.00	.00	.00	8.68	168.82	.00	.00	.00	12.23	237.77
.57	.00	.00	.00	.00	177.50	.00	.00	.00	.00	250.00
...										
0.9999	.00	.00	.00	.00	.00	.00	.00	.00	.00	250.00

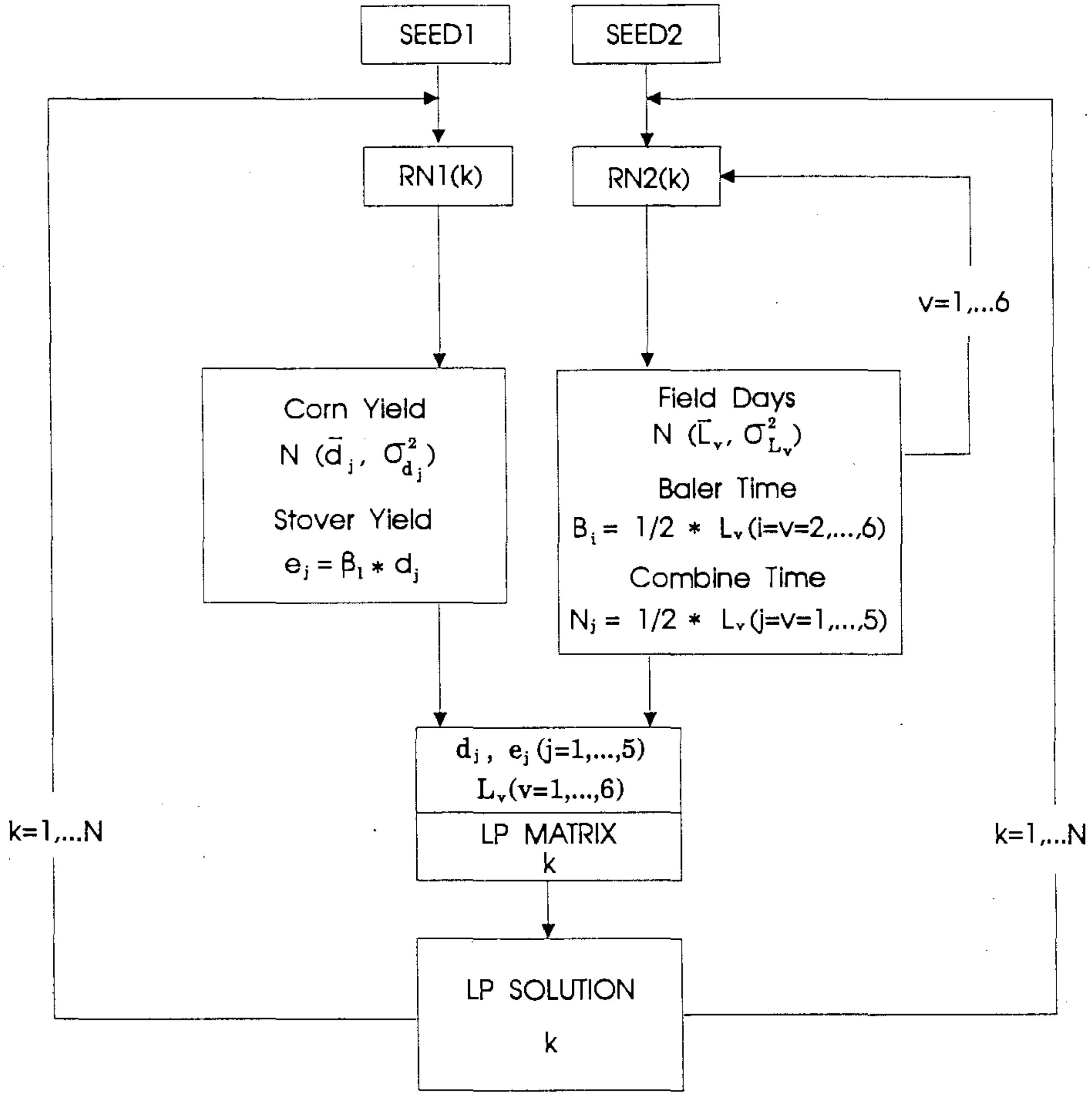

Figure 1. Flowchart of the Monte Carlo Simulation

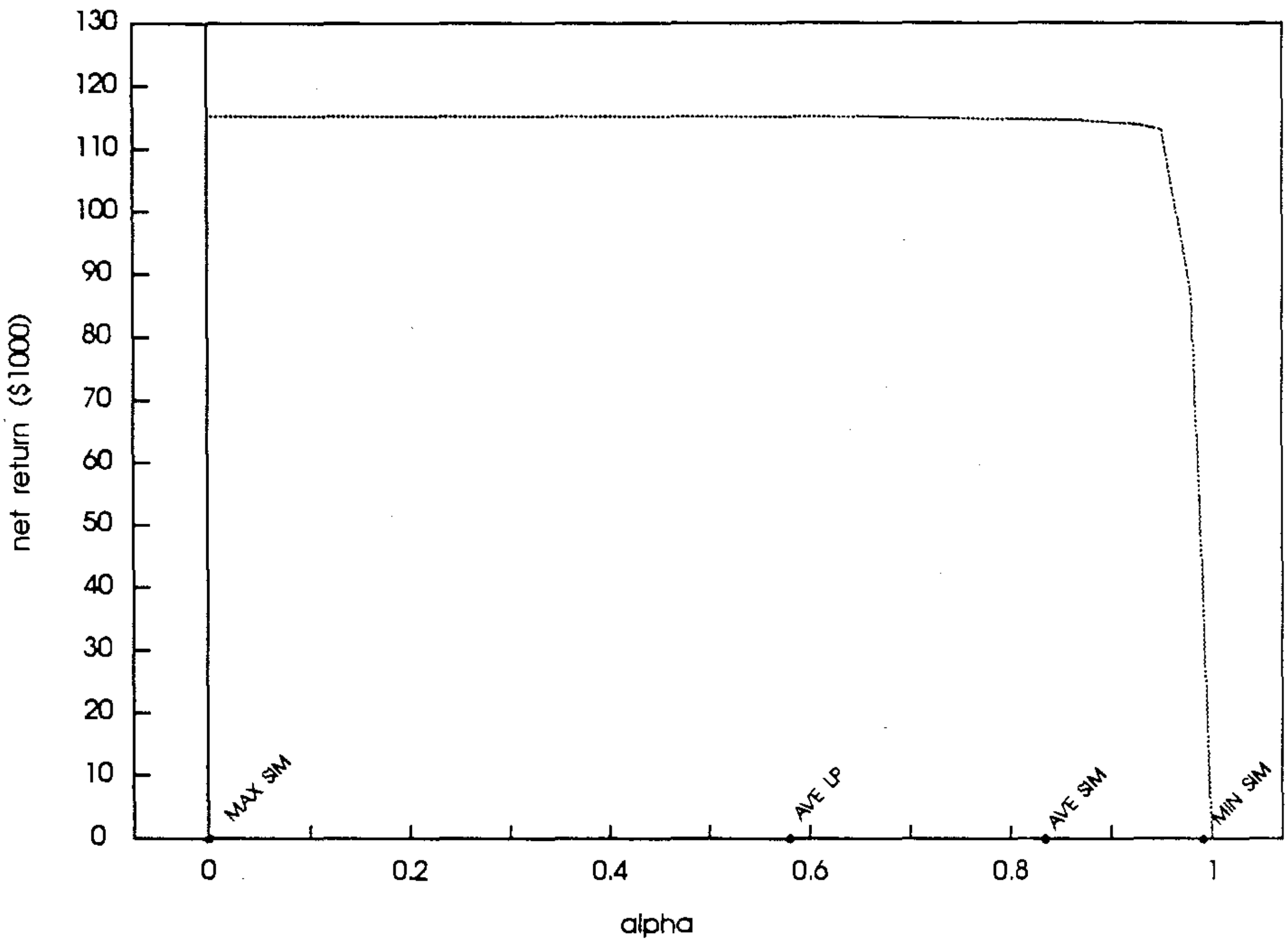

Figure 2. Chance Constrained Results
Own Baling Case

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