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Background

Agricultural economists are becoming increasingly concerned with the implications of various dynamic attributes which characterize agricultural production problems. In the dynamic setting within which farmers allocate their scarce resources, relatively little attention has been given to variability of field time as a source of risk. Field time may be defined as the amount of time over a given period during which conditions are satisfactory for completing field operations, such as tillage, planting and harvesting. The purpose of this paper is to discuss the incorporation of field time risk into a discrete stochastic sequential programming (DSSP) model of a midwestern corn and soybean farm. The model is designed to investigate the significance of field time risk for optimal resource allocation on such farms. Stated more succinctly, the question to be answered is "Does field time risk matter?"

A few examples appear in the literature of the treatment of field time as a stochastic variable in farm models. Boisvert and Jensen used chance constrained programming for a farm planning problem in which field time was stochastic. Danok, McCarl and White used a combination of mathematical programming and stochastic dominance to analyze optimal machinery selection. They used cumulative probability distributions of field time in a mixed integer programming model to find optimal machinery complements with field days set at levels associated with various probabilities. The authors point out that their analysis assumes perfect correlation of field time levels across all time periods -- an issue critical to the analysis of field time as a source of risk. Pfeiffer and Peterson also used cumulative probability distributions of field time in an analysis of machinery selection. They found least cost machine sets for farms of given size and given probabilities of "timely performance of field operations."

The models used in Apland, McCarl and Baker and in Kaiser required the definition of discrete states of nature to represent field time variability in stochastic programming models. Apland, McCarl and Baker used a discrete stochastic programming model to analyze the variability of crop residue supply. Optimal crop residue harvest levels were derived under conditions of stochastic field time during harvest. Kaiser's model was used to analyze the risk impacts on commodity programs and was structured similarly to the model used by Apland, McCarl and Baker. In this paper, the stochastic programming approach to capturing field time risk is extended for a wider range of farm production problems.

The Use of Field Days in Flow Resource Constraints

For purposes of model building, it is useful to categorize inputs as stock or flow resources. The use and availability of stock resources may be accurately measured as physical quantities (for example, pounds of fertilizer or gallons of diesel fuel). Flow resources are those which are best measured as flows of services over time. For a farm firm, labor and machinery must often be treated as flow resources because the timing of field operations has important effects on the technical and economic efficiency of the firm. To capture these effects, whole farm models are often constructed with many intra-year time periods for which production activities and flow resource constraints are defined. The importance of disaggregating time in the definition of production activities and resource constraints was recognized by

Heady and Candler, who suggested a criteriON for selecting the appropriate definition of time periods [p. 208]. Much later, the importance of disaggregating time constraints in order to adequately represent crop mix decisions was demonstrated by Baker and McCarl.

The use of field time in a linear programming model of farm production may be illustrated by considering a flow resource constraint in a particular period. Suppose that the following describes a tractor time constraint in a particular period, for example, the first week in May:

$$\sum_{j \in J} a_j X_{ij} \leq b_i$$

Subscript i identifies the time period and J is the set of all production activities in period i. Coefficient a_j is the per acre tractor time requirement for production activity j. X_{ij} is production activity j, in period i, measured in acres and b_i is the amount of tractor time available in period i. The lefthand side of the constraint is total use of tractor time by production activities in period i. The righthand side, hours available, may be measured as follows:

$$b_i = \text{Hours/Day x Number of Tractors x Number of Field Days}$$

Many sources of risk may be identified for this constraint. Parameter a_j may vary as operating conditions change. In the righthand side of the constraint, the number of tractors (or, more generally, the number of machines) could vary as a result of breakdowns.[1] However, because of the pervasive impact of weather, field days would appear to be the major source of risk in such

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[1] In a long run context, number of machines is a decision variable -- an investment activity. Similarly, hours per day could be interpreted as a short run decision variable, suggesting the need for a work/leisure consideration.

constraints. While the model to be presented here will accommodate variability in any or all of the components discussed, variability of field days will be the source analyzed.

A Simple Example of a Whole Farm Linear Programming Model

The underlying structure of the linear programming models used in this study is a familiar one to many agricultural production economists. It is similar to that of the Purdue farm planning model (Model B) [McCarl, et al.], REPFARM [McCarl], and others [Debertin, et al.; and Schurle and Forster]. Before discussing the empirical models used here, a simple whole farm linear program (LP) will be presented to illustrate the underlying model structure. Table 1 shows the LP tableau for the example. Although the model is simplified and in some ways incomplete, it will serve well for discussion purposes. Activities in the model include net revenue, tillage, and corn and soybean production. The net revenue activities represent total revenue minus total variable cost for each of three price and yield states of nature.[2] Production activities and flow resource constraints are defined for eight time periods. Plowing may occur in the fall (periods 5 through 8) or in the spring (periods 1 through 4). Disking takes place in each of the spring periods. The production activities for corn and soybeans include planting and harvest operations. A production activity is included for each combination of planting and harvest period.

The objective function is expected net revenue, which is to be maximized. Objective function coefficients on the net revenue activities are the probabilities of the associated price/yield state. The net revenue constraints

[2] Readers who are familiar with risk programming will recognize that price and yield risk as captured here could easily be captured in a MOTAD or EV framework.

Table 1: LP Tableau for a Simple Farm Production Model

	Net Revenue[a]			Fall Plowing[b]				Spring Plowing[b]				Spring Disking[b]				Corn Plant/Harvest[c]						Soybean Plant/Harvest[c]						
	1	2	3	5	6	7	8	1	2	3	4	1	2	3	4	2/6	2/7	3/6	3/7	4/6	4/7	2/5	2/6	3/5	3/6	4/5	4/6	RHS
Max E(Net Revenue)	+	+	+																									
Net Revenue 1	1															-	-	-	-	-	-	-	-	-	-	-	-	≤ 0
Net Revenue 2		1														-	-	-	-	-	-	-	-	-	-	-	-	≤ 0
Net Revenue 3			1													-	-	-	-	-	-	-	-	-	-	-	-	≤ 0
Land																1	1	1	1	1	1	1	1	1	1	1	1	≤ +
Labor 1								+				+																≤ +
Labor 2									+				+			+	+					+	+					≤ +
Labor 3										+				+				+	+					+	+			≤ +
Labor 4											+				+					+	+					+	+	≤ +
Labor 5				+																		+		+		+		≤ +
Labor 6					+											+		+		+			+		+		+	≤ +
Labor 7						+											+		+		+							≤ +
Labor 8							+																					≤ +
Corn/Soy Rotation																-1	-1	-1	-1	-1	-1	1	1	1	1	1	1	≤ 0
Soy/Corn Rotation																1	1	1	1	1	1	-1	-1	-1	-1	-1	-1	≤ 0
Disk/Plant 2												-1	-1			1	1					1	1					≤ 0
Disk/Plant 3												-1	-1	-1		1	1	1	1			1	1	1	1			≤ 0
Disk/Plant 4												-1	-1	-1	-1	1	1	1	1	1	1	1	1	1	1	1	1	≤ 0
Harvest/Plow 5				1																		-1		-1		-1		≤ 0
Harvest/Plow 6				1	1											-1		-1		-1		-1	-1	-1	-1	-1	-1	≤ 0
Harvest/Plow 7				1	1	1										-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	≤ 0
Plow/Disk 1				-1	-1	-1	-1	-1				1																≤ 0
Plow/Disk 2				-1	-1	-1	-1	-1	-1			1	1															≤ 0
Plow/Disk 3				-1	-1	-1	-1	-1	-1	-1		1	1	1														≤ 0
Plow/Disk 4				-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1													≤ 0
Non-Negativity																												

[a] The numbers above each net revenue activity indicate the price/yield state of nature.
[b] The numbers above each tillage activity indicate the time period in which the operation takes place.
[c] The two numbers above each crop plant/harvest activity indicate the periods in which planting and harvest take place, respectively.

define the corresponding net revenue activities. The net revenue constraint coefficients on the production activities are minus the corresponding per acre net revenues. Across the net revenue rows for a particular activity, the coefficients reflect the prevailing price/yield state. Across the production activities in a particular row, the unit net revenues reflect the effects of planting and harvest dates on yields and variable costs. The land constraint limits the sum of the production activities to no more than the total acreage available.

The eight labor constraints, one for each period in this example, will illustrate the structure of flow resource constraints in general. The coefficients on the tillage and production activities are the per acre labor requirements and are placed in the constraint for the period in which the corresponding operation takes place. The righthand sides are hours of labor available in each period -- a function of field days.

The production activities shown here are assumed to be for corn and soybeans in a two year rotation. The rotation constraints require that acreage of rotated corn not exceed soybean acreage, and visa versa. The inclusion of continuous corn and continuous soybeans would involve adding additional sets of production activities without the rotation constraints. The unit net revenues for continuous soybeans and corn would reflect the lower yields and/or higher variable costs of the continuous crops relative to the rotated crops. Harvest labor and machine time requirements may also be reduced because of lower yields.

The last three sets of constraints preserve the essential sequencing of field operations. The disk/plant constraints insure that for each period in which both disking and planting may take place, the cumulative acreage disked through that period must be greater than or equal to the cumulative acreage planted.[3] The last two sets of constraints insure the proper sequencing of the harvest and fall plowing operations, and plowing and disking operations, respectively. Note that the primary tillage operation, plowing, may take place in the fall or spring prior to disking and planting. This "wrap around" feature of the model allows the inter-year relationship implied by the cycle of field operations to be captured endogenously without having (explicitly) a multi-year model. Because of this structure, linear programs of this type may be thought of as intermediate run equilibrium models. They are not long run in that some resources are fixed (in this case labor and land) and they are not short run because they are designed to provide an optimal solution to the crop planning problem which may be repeated year after year.

The Empirical Model With Deterministic Field Days

What will be referred to as the deterministic model in the remainder of this paper is a more elaborate version of the example LP. This model treats field days deterministically, but does allow for price and yield variability as in the example. Activity sets include net revenue, fall and spring disking and plowing (with a moldboard plow system), planting, cultivation, and harvest for corn and soybeans. Corn and soybeans may be grown as continuous crops or in rotation. The activities and labor and machinery constraints are defined over 14 time periods. The dates of the periods and the calender of field operations are given in Table 2.

The objective function of the model is expected net revenue which is maximized. Constraints include those to define net revenue for each price and yield state of nature. There is a constraint on total crop acreage. Flow

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[3] If disking and planting did not occur in the same period, sequencing constraints would not be necessary. Only a constraint requiring the total planted acreage to be tilled would be needed.

Table 2: Calender of Field Operations.

				------ Corn ------			--- Soybeans ----	
---- Period ----	Disk 1[a]	Plow	Disk 2[b]	Plant	Cult	Harvest	Plant	Harvest
Spring/Summer:								
1 06-Apr 25-Apr	X	X						
2 26-Apr 02-May	X	X	X	X				
3 03-May 09-May	X	X	X	X			X	
4 10-May 16-May	X	X	X	X	X		X	
5 17-May 23-May	X	X	X	X	X		X	
6 24-May 30-May			X	X	X		X	
7 31-May 06-Jun			X		X		X	
8 07-Jun 26-Jun					X			
Fall:								
1 15-Sep 24-Sep		X						X
2 25-Sep 08-Oct		X						X
3 09-Oct 22-Oct	X	X				X		X
4 23-Oct 05-Nov	X	X				X		
5 06-Nov 19-Nov	X	X				X		
6 20-Nov 03-Dec	X	X						

[a] After corn only.

[b] Concurrent with planting.

resource constraints are defined for labor in the 14 periods, and for planter, harvester and tractor time in periods during which the machines may be used. Other constraint sets include those for harvest/tillage sequencing, tillage operation sequencing, and tillage/plant sequencing, and constraints to properly link planting, cultivation and harvest activities. Rotation constraints require that rotated corn acreage not exceed rotated soybean acreage, and visa versa.

The same activity and constraint sets used in the deterministic LP model are used in the stochastic programming formulation with modifications to allow for the incorporation of field time risk. The DSSP model builds on the "wrap around" structure of the deterministic model implied by the operation sequencing and crop rotation constraints. The specific structure of the stochastic programming model is presented in the next section.

The Empirical Model With Stochastic Field Days

The activities and constraints in the DSSP model are the same as those in the deterministic model with certain groups of activities and constraints duplicated for several discrete field time states of nature. In moving from the multi-period, deterministic LP to the stochastic programming model with sequential stages in the decision process, the idea of defining the 14 production periods as decision stages is appealing. However, because of the profound effect of the number of decision stages on the overall model size, such an approach would be impractical [Rae].[4] Instead, a more modest three

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[4] The effect of the number of decision stages on the size of the programming matrix is much less severe than Rae's discussion of the general stochastic programming model would suggest. This is because not all production activities occur in all production periods. Even so, the number of stages must be limited.

decision stages were used. Figure 1 illustrates the decision stages and states of nature. For purposes of clarity, the decision tree in Figure 1 shows three states of nature in each stage -- the empirical model included four states in each of the first two stages and eight in stage three. Complete knowledge of the past and present is the assumed information structure [Rae]. Complete knowledge of the past and present implies here that when spring and summer production activities are selected, the stage one field time state of nature is known. However, only probabilistic information is available about future (stage two and stage three) states.[5] Stage one covers spring and summer production periods during which spring tillage, planting and cultivation take place. Stage two covers fall production periods and harvest and fall tillage activities. The calender of operations is the same as that for the deterministic model (see Table 2). During stages one and two, variability in field days per period is the source of risk. In stage three, grain yield and price states are realized and crop sales decisions are made.

Spring and summer flow resource constraints appear in the DSSP model for each stage one state with the righthand side values reflecting the prevailing field day state of nature. Because an information structure of complete knowledge of the past and present is assumed, spring tillage, planting and cultivation activity sets are replicated for each stage one state. Constraints sets other than those for flow resources, such as land, rotation and sequencing constraints, must also be replicated for each state. Fall activities and constraints are similarly replicated for each joint spring and fall field day state of nature. Corn and soybean sales are incorporated in net revenue constraints defined for each joint stage one field day, stage two

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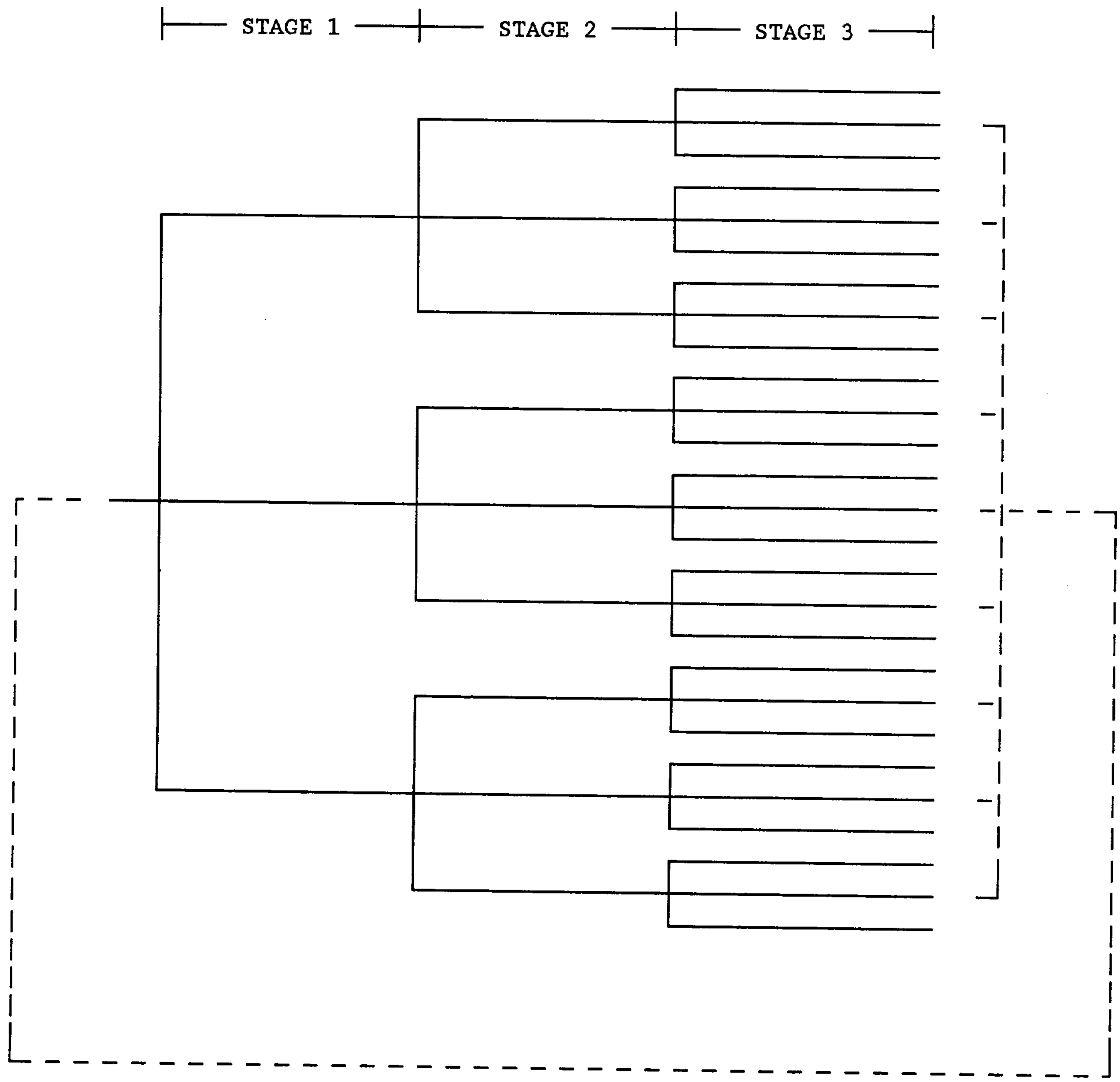
[5] Complete knowledge of the past and present was selected rather than complete knowledge of the past so as to understate rather than over state the impact of field time risk.

Figure 1: Tree Diagram of the Stochastic Field Time Model



States of Nature:

Field Time	Field Time	Grain Prices Yields

Decision Vectors:

Spring Tillage Planting Cultivation	Harvest Fall Tillage	Sales

field day and stage three price/yield state.

The stochastic field time model borrows the "wrap around" structure of the deterministic model which is implied by the sequencing and rotation constraints. But because the levels of fall tillage activities vary by state, it is necessary to establish which quantity of fall-tilled acreage will be made available in the spring. To facilitate this inter-year relationship, the expected value of fall-tilled acreage for each crop was carried over into spring. This was accomplished by setting the sequencing constraint coefficients on fall tillage activities equal to minus the probability of the corresponding joint stage one and stage two states of nature. The implied assumption is that cropping decisions are following an average year or, stated differently, that the implicit demand for fall tilled acreage is that for an average year.[6] A similar approach was taken for the rotation constraints.

Because corn has a longer growing season than soybeans, shifts from soybeans to corn tend to imply increased need for field time. Or, shifts from corn to soybeans will tend to ease field time restrictions. To allow for crop mix adjustments to be made as field time availability may suggest, the crop rotation constraints were structured so as to limit the acreage of rotated corn in each state to no more than the expected value of rotated soybean acreage over all states and visa versa.

The Empirical Data

Per acre variable costs, field rates and average per acre yields were taken from Kaiser and from Apland et al. In both the deterministic model and the stochastic model, yields for the price/yield states were defined based on actual farm records for eight years: 1975 through 1983. Price states were

[6] Again, this approach will understate the impacts of field time risk.

defined by applying the 1975 through 1983 deviations from a price trend line to published farm planning prices [Center for Farm Financial Management]. Four field time states of nature were defined for decision stages one and two. The righthand sides of the labor and machinery constraints were calculated using the field days observations shown in Table 3 as states.[7]

For the deterministic model, field days were set to the four year mean values. The actual observations were used as field days states of nature in the stochastic model. By defining states in this way, the correlations between field days in each period of a particular stage are implicitly captured. The observations were treated as a random sample so the probability of each was 1/4. Fall field time states were assumed to be independent of spring/summer states so the probabilities of each joint stage one and stage two states was set to 1/(4x4) or 0.0625. Independence was also assumed between field time and price/yield states, so the implied probability of each joint event was 1/(4x4x8) or 0.0078125.[8] The deterministic model had 132 rows and 130 columns -- the stochastic model had 1305 rows and 1501 columns.

In the next section, solutions to the deterministic and stochastic models are compared. Because machine capacity is a central issue in establishing the significance of field time risk, sensitivity analyses with respect to farm size were performed.

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[7] These data are derived from daily observations taken at the Agricultural Experiment Station in Lamberton, Minnesota.

[8] The DSSP model does not require the simplifying assumption of independence. However, sufficient data was not available to accurately account for all covariability. The approach used here does account for covariability of stochastic parameters within a particular stage -- field time across periods, and prices and yields across crops.

Table 3: Field Days Data.[a]

----- Period -----			Days	Field Days by Observation 1980	1981	1982	1983	Mean	Pct of Total	Coef of Variation
1	06-Apr	25-Apr	20	5	8	0	0	3.25	16.3%	105.2%
2	26-Apr	02-May	7	7	3	6	1	4.25	60.7%	56.1%
3	03-May	09-May	7	7	3	3	1	3.50	50.0%	62.3%
4	10-May	16-May	7	3	5	0	6	3.50	50.0%	65.5%
5	17-May	23-May	7	4	5	1	4	3.50	50.0%	42.9%
6	24-May	30-May	7	3	5	2	5	3.75	53.6%	34.6%
7	31-May	06-Jun	7	0	4	4	3	2.75	39.3%	59.6%
8	07-Jun	26-Jun	20	13	10	8	9	10.00	50.0%	18.7%
Stage 1 Totals ----			82	42	43	24	29	34.50	42.1%	23.8%
1	15-Sep	24-Sep	10	6	9	5	4	6.00	60.0%	31.2%
2	25-Sep	08-Oct	14	11	6	4	10	7.75	55.4%	36.9%
3	09-Oct	22-Oct	14	9	5	4	5	5.75	41.1%	33.4%
4	23-Oct	05-Nov	14	11	14	11	13	12.25	87.5%	10.6%
5	06-Nov	19-Nov	14	12	13	4	7	9.00	64.3%	40.8%
6	20-Nov	03-Dec	14	10	0	0	0	2.50	17.9%	173.2%
Stage 2 Totals ----			80	59	47	28	39	43.25	54.1%	26.2%
Totals, Both Stages			162	101	90	52	68	77.75	48.0%	24.5%

[a] Unpublished field days data form the Southwestern Experiment Station, Lamberton Minnesota [Kaiser].

Results

Each model was solved with total crop production constrained to no more than 600 acres. Then maximum acreage was increased in increments of 100 acres until slack occurred in the land constraint(s). In the case of deterministic field time, crop production peaked at 1134 acres when constrained to no more than 1200. When field time was stochastic, slack occurred in the land constraint under two states of nature when maximum acreage was set at 1100--average acres planted over all field day states was 1077. Table 4 summarizes the optimal solutions to the deterministic and stochastic models for maximum acreages of 600 to 1200. For each of the models, the table shows the optimal objective function value (expected net revenue), the variance of net revenue and acres produced. In the case of the stochastic field time model, acres produced is the mean over stage one states of nature.[9] Figure 2 shows the optimal values of the objective functions, expected net revenues, as functions of acres produced and Figure 3 shows the variances of net revenue as functions of acres produced.

In the case of deterministic field time, net revenue increases steadily from 104.6 thousand at 600 acres to 181.6 thousand at 1134 acres. Variance of net revenue increases from 632.4 thousand to 2,085.7 thousand.[10] Expected net revenue in the stochastic case increases from 102.9 thousand with a variance of 625.6 thousand at 600 acres to 154.1 thousand with a variance of 2581.6 thousand at 1077 acres. Expected net revenue and variance of net revenue for the deterministic and stochastic models are quite similar at farm sizes of

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[9] Only when acreage was constrained to no more than 1100 did acres produced in any state of nature fall below the total available.

[10] Recall that the objective function is expected net revenue. Thus, the variance of net revenue is an attribute of the solution but does not affect the optimal solution.

Table 4: Summary of Optimal Solutions by Acreage.

	Maximum Crop Acreage						
	600	700	800	900	1000	1100	1200
Deterministic Model:							
Expected Net Revenue	104.6	120.6	136.6	151.9	166.8	179.7	181.6
Variance of Net Revenue	632.4	850.7	1100.9	1375.6	1676.1	1983.4	2085.7
Acres Produced	600	700	800	900	1000	1100	1134
Stochastic Model:							
Expected Net Revenue	102.9	119.1	133.6	142.0	149.5	154.1	
Variance of Net Revenue	625.6	847.0	1086.9	1447.1	2057.2	2581.6	
Mean Acres Produced[a]	600	700	800	900	1000	1077	

[a] Mean of acres produced over all states of nature.

Table 5: Marginal Value of Land.

		Maximum Crop Acreage						
		600	700	800	900	1000	1100	1200
Deterministic Model		160.33	160.33	157.97	150.6	146.94	91.2	0.0
Stochastic Model:	State 1	41.5	41.1	26.5	27.5	27.5	19.7	
	State 2	43.0	38.3	25.1	22.5	18.4	17.9	
	State 3	41.5	41.1	16.4	10.5	2.3	0.0	
	State 4	36.3	41.1	22.8	17.2	15.1	0.0	
	Sum Over All States	162.3	161.6	90.8	77.7	63.4	37.6	

Figure 2: Expected Net Revenue as a Function of Acreage

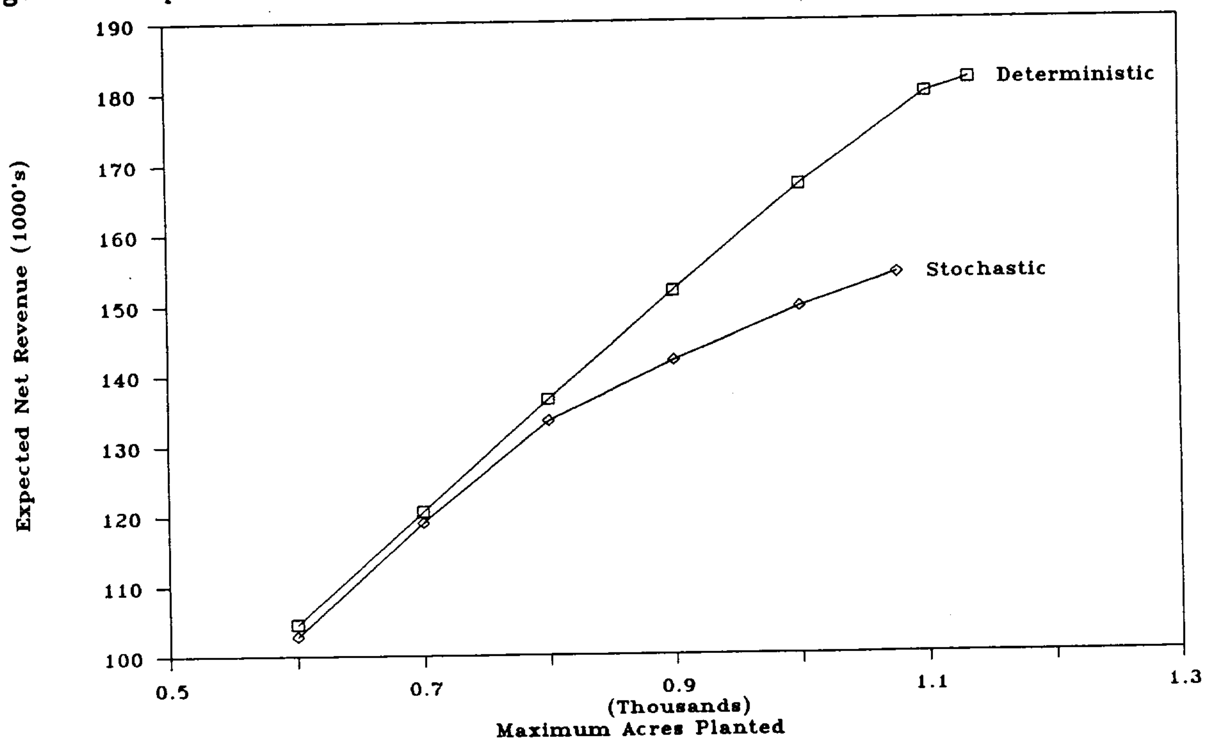
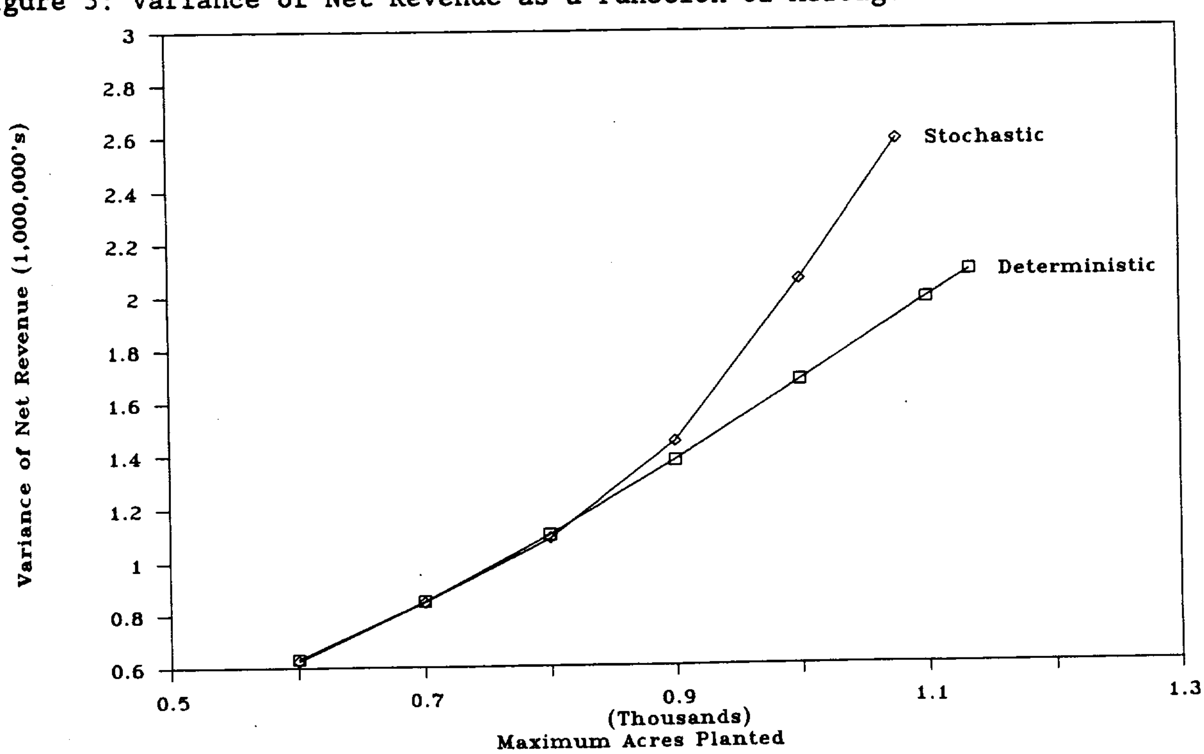


Figure 3: Variance of Net Revenue as a Function of Acreage

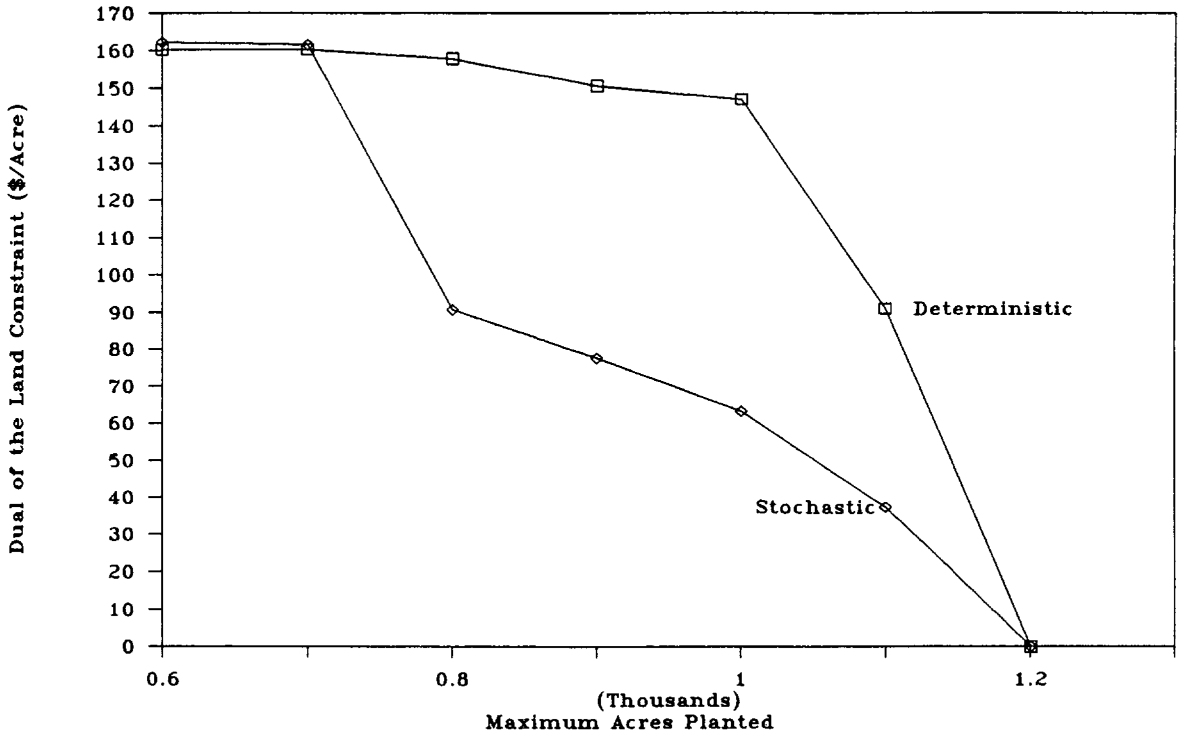


600, 700 and 800 acres. Above 800 acres, as acreage is increases, expected net revenue increases relatively slowly in the stochastic model while variance increases relatively quickly. The differences in expected net revenue and variance between the deterministic and stochastic models is attributable to differences in the timing of production activities.

As acreage is increased in the stochastic model, field operations become more scattered across production periods as dictated by the availability of field time. The timing of planting and harvest operations influence yields and grain moisture levels and thus per acre net revenues. The variability in the timing of these activities may be attributed directly to changes in the distribution of available field time over planting and harvest periods. Also, variability in the scheduling of tillage activities influences the timing of planting and harvest due to the essential sequencing of operations. For the 700 acre farm, the average planting date for the deterministic model was May 4th -- in the stochastic model the average was May 6th. For the deterministic model, planting took place in three of the six week-long planting periods. Four of the periods were used in the stochastic model. The differences in the solutions to the two models were slightly more pronounced as the farm size was increased. At 1100 acres, the average planting date was May 9th and May 12th for the deterministic and stochastic cases, respectively. Four of the six planting periods were used with field time fixed, while all six planting periods were used under various field time states in the stochastic model.

A notable difference in the two sets of solutions has to do with the marginal value of land. The optimal values of the land constraint dual variables are reported in Table 5 and are shown graphically in Figure 4. Recall that in the stochastic model, a land constraint is imposed on production under each of the four stage one states of nature. Table 5 also

Figure 4: The Dual Value of Land as a Function of Acreage



gives the sum of the land constraint duals for the stochastic model. This sum may be interpreted as the overall marginal value of land and is therefore comparable to the dual of the land constraint in the deterministic model. In both the deterministic and stochastic models, the marginal value of land begins at just over $160 at 600 acres and remains so at 700 acres. The marginal value of land remains fairly constant in the deterministic case up to 1000 acres, when the dual falls to $147. But when acreage is increased to 1100 and 1200, the marginal value of land falls to $91 and $0, respectively. In contrast, the marginal value of land falls steadily in the stochastic model from $262 at 600 acres to $0 at 1200 acres. The difference in the marginal value functions for land is illustrated clearly in Figure 4 which shown the dual values as functions of acres.[11] These results imply that when field time variability is ignored, optimal land use for a given labor and machine endowment tends to be rather constant. In this example, at rents between about $150 and $75 per acre, optimal land use would be between 1000 and 1100 acres. However when field time variability is considered, optimal land use appears to be much more responsive to price.

Summary and Conclusions

Many modeling issues pertaining to field time risk remain. One involves the appropriate definition of field time states of nature. Annual observations on field days were used as states in this analysis. This approach is appealing in its simplicity and allows the covariability of field days across periods in a particular stage to be captured. However, it may be

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[11] The relationship between the marginal value of land and acres available in linear programming models is, of course, a step function. Figure 4 simply characterizes the relationship using representative points on the underlying step functions.

useful to base the definition of states on estimates of field day probability distributions, also. Direct observations of field time are often kept on experiment station farms. However, stochastic simulation might be effectively used to develop field days estimates which are current, location-specific and adaptable to a variety of crop production technologies.

The results here suggest that field time variability has important implications for the economic decisions of farm managers, because of its influence on both average income and income variability. The results are of particular concern when analyses focus on the fixed resource decisions of farm firms, such as machinery and land investment, and labor use. The significance of timeliness in crop production operations is central to the findings here and is central to the choice of optimal crop mixes. As such, it may be important to consider field time risk in many studies which focus on selection of an optimal product combination. While the discrete stochastic programming model developed for this study is large and complex relative to its deterministic counterpart, the use of the "wrap-around" structure found in many annual, whole-farm planning models makes the inclusion of field time risk relatively manageable. Further research could examine the categories of problems for which modeling of field time risk is critical. Also, models such as the one developed in this study could be used to evaluate alternative ways of accounting for field time risk which are computationally simpler.

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