INCORPORATING RISK INTO A DYNAMIC PROGRAMMING APPLICATION: FLEXCROPPING

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Use of stochastic dynamic programming (DP) by agricultural economists has become increasingly common in recent years following the pioneering applications by Burt in the 1960s and early 1970s (e.g., Burt and Allison, Burt and Johnson, Burt). Recent applications include identification of optimal strategies for pest control (Zacharias, Liebman and Noel; Zacharias and Grube), rangeland management (Karp and Pope), and irrigation scheduling (McGuckin et al.).

Despite the fact that risk is pervasive in most agricultural applications of DP due to the stochasticity of biological response and market uncertainty, most applications have not explicitly considered the potential role of risk aversion. Two exceptions are an early study by Burt and Johnson and a recent study by Karp and Pope. These two studies incorporated risk aversion at two distinctly different levels. Karp and Pope substitute expected utility as the payoff for different annual decision-state combinations in order to illustrate the influence of risk aversion on a single optimal DP strategy. The decision rule relating state levels to prescribed decisions is responsive to risk aversion in this approach. Burt and Johnson, on the other hand, use the Markowitz E-V criterion to identify a combination of DP strategies which is E-V efficient with respect to long-run annual income variation. The former approach is appropriate for identifying a single optimal strategy for managing short-run or intraseasonal risk. The latter provides a risk-efficient diversified set of strategies for managing variation in annual returns over the long-run.

The current study addresses the problem of incorporating risk aversion into the algorithm for identifying an undiversified optimal DP strategy as in Karp and Pope. The primary methodological innovation of this study is the substitution of Katoaka's safety-first maximand into the DP objective function to incorporate risk considerations. Katoaka's criterion helps overcome risk preference elicitation difficulties which could limit the use of Karp and Pope's EU alternative in practical farm management applications.

We apply DP in this study to identify an optimal, risk-sensitive flexible cropping strategy, in much the same way as was done earlier by Burt and Allison for the risk neutral case. Studies by Burt and colleagues (1963, 1967, 1977) show that flexible cropping, using soil

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moisture available at planting time as the decision rule to fallow or crop, results in higher net returns to the operator. Reducing fallow also provides an important environmental dividend as fallow is a major contributor to soil erosion and saline seep in many western states (Brown et al.; Burt and Stauber).

In this paper, stochastic dynamic programming is used to determine flexcrop strategies which maximize long-run, risk-and-time-discounted net returns. The profitability and riskiness of flexible cropping are compared to those for fixed rotations. In the analysis, yield as a function of soil moisture is determined using data obtained from the Erosion Productivity Impact Calculator (EPIC)--a large biophysical process simulation model (Williams; Williams, Renard and Dyke). Risk is present in a flexcrop decision based only on soil moisture at planting time because a multitude of uncontrolled variables, including precipitation during the crop year, will influence the grower's final yield at harvest time. Hence, producer risk preferences are incorporated directly into the selection of the optimal strategy.

In the section which follows we initially present the DP optimization methodology for the flexcrop analysis. Second, we describe the data and procedures for obtaining crop yield and soil moisture relationships. Third, the procedure for incorporating risk preferences is described. Fourth, we present results of an application of the model to a southeastern Washington state farming region. The impact of both risk aversion and output price expectations on flexcrop strategies is presented. The paper closes with a brief summary and conclusions.

The Dynamic Programming (DP) Methodology

The decision to crop or summerfallow is an example of a multistage decision process. An optimal decision path for this problem can be obtained using dynamic programming (Dreyfus). The time at which a decision is to be made (i.e., the stage) is planting time in this application; the state variable is the level of soil moisture at planting time; and the control variable is the decision to crop or fallow.

A key ingredient in this stochastic dynamic programming problem is the initial soil moisture transition matrix P. The transition matrix gives the probabilities of attaining a particular soil moisture level next year, given (1) the current soil moisture level and (2) the current value of the control variable--crop or fallow. The probability is greater that the soil moisture level attained next year is higher when a field is currently being fallowed than if the field is currently in crop. Thus, the expected return next year will be higher when a field is in fallow this year. However, the net return during the current year will be lower (indeed negative) if the field is in fallow and not in crop. The DP methodology takes this fact into account, as well as the need to discount future returns.

The dynamic programming problem can be reduced to a single recursive equation which needs to be solved for period n, where n is the number of years left in the planning horizon. For the general case, where returns from soil moisture cropping choice combinations are stochastic and producers are risk averse, risk-adjusted net returns can be substituted in the DP algorithm (Karp and Pope). Of course, under risk neutrality, use of expected returns is appropriate (Zacharias, Liebman and Noel). Mathematically, the standard problem is to choose a value of the control variable k (crop or fallow) which maximizes:

$$f_n(i) = \max_k \left[R^k(i) + \beta \sum_{j=1}^{m} P^k(i,j) f_{n-1}(j)\right], \tag{1}$$

where $f_n(i)$ is the discounted value of future risk-adjusted net returns, given soil moisture level i at the beginning of an n-stage process; $f_{n-1}(j)$ is the discounted value of future adjusted net returns over the remaining n-1 years of an n-year process, given soil moisture j and that the optimal path is followed; $R^k(i)$ is the current risk-adjusted net return for decision k, given soil moisture level i and that there are m soil moisture levels; $P^k(i,j)$ is the probability of moving from the current soil moisture level i to soil moisture level j in the next period, given that the current decision is k (crop or fallow); and $\beta = 1/(1+r)$, where r is the real rate of discount.

Karp and Pope incorporate risk in (1) by converting dollar payoffs to expected utility assuming an arbitrary constant absolute risk aversion utility function. In a later section, we propose an operationally more tractable risk adjustment based on Katoaka's safety-first criterion.

The dynamic programming problem is recursive, and the solution algorithm begins at the end of the multi-stage process. Further, it is assumed that soil moisture level in a given year has no influence on the level of soil moisture two years in the future; today's soil moisture only affects soil moisture next year. This is the standard Markovian assumption, which was validated statistically in this application by regressing current soil moisture on soil moisture lagged two years. No significant influence was detected at the 5 percent level (Young 1986).

The recursive relationship described above converges to a constant strategy if the time horizon is chosen sufficiently long (n is large) and returns to cropping or fallowing within states are constant in every time period--that is, the objective function is stationary. The optimal policy can be found by the algorithm employed by Burt and Allison, and initially described by Howard as the policy-iteration approach. The method is to carry out the iterations of the recursive relationship (1) until a number of repetitions of the same policy occur. This policy is checked to determine if it is optimal. If it is not optimal, additional iterations are performed until a new strategy is found. The new strategy is then checked for optimality and the process is repeated until a constant solution is found.

The procedure for finding the long-run average annual net return and the variance of long-run annual returns is to find the solution vector (Π) to the equation $\Pi Q = \Pi$, where Π is the vector of long-term probabilities for achieving each of the soil moisture levels (Kemeny and Snell). In accordance with the Double Expectations Theorem (Bickel and Docksum, p. 6), the long-run expected net return is then found simply by pre-multiplying R (the vector of expected monetary returns for each soil moisture level under the optimal risk-sensitive strategy) by Π. As usual, one would anticipate the expected net returns to decline for strategies which are found to be optimal for more risk averse growers. The variance of the long-run annual returns under the optimal strategy is (Burt and Johnson):

$$\text{Variance of return} = \sum_{i=1}^{m} \Pi_i \, (R_i - \overline{R})^2 + \sum_{i=1}^{m} \Pi_i \, S_i^2 \,, \qquad (2)$$

where Π_i is the long-run probability of attaining soil moisture level i in a given year, S_i^2 is the variance of returns <u>within</u> soil moisture level i, R_i is the expected return for the i^{th} soil moisture level given the strategy, and $\overline{R}$ is the overall expected return for the strategy. The variance decomposition in (2) can be directly derived from the familiar partitioning of total sum of squares in analysis of variance between treatment and error sum of squares. The first term in (2) measures variation in predicted returns at planting time when a grower follows the DP flexcrop strategy at each soil moisture level. The second term measures the within-year components of a strategy's variance. S_i measures the risk which still confronts the grower each spring when the flexcrop decision is made. In this study, one would expect risk averse growers to select strategies which reduce this component of variance.

<u>Yield and Soil Moisture Relationships</u>

The model is applied to the Lacrosse region of western Whitman county in eastern Washington. Farmers in this 12 to 15 inch annual rainfall region generally employ a fixed two-year, winter wheat-fallow

(W-F) rotation. However, a few growers plant continuous spring barley (SB), except when soil moisture at planting time is extremely low, in which case they fallow. Hence, spring barley is considered for flexcropping and is compared to a winter wheat-fallow rotation.

Expected yield is estimated as a function of soil moisture at spring planting time. Since adequate empirical data on spring barley yields and soil moisture did not exist for the study region, synthetic yield and soil moisture data were obtained using the EPIC simulation model (Williams; Williams, Renard and Dyke). Unfortunately, EPIC is not a panacea for those seeking production function relationships when data are lacking. Considerable effort is required to calibrate EPIC to new regions. For the Lacrosse region, this was done by adjusting EPIC input data and parameters to achieve a correspondence between a 1971-85 spring barley yield series for a farm in the region and an EPIC simulation of continuous spring barley for the same period (Young 1986, Dorman). Actual daily rainfall and the farmer's management practices over the 15-year period were utilized in the simulation.

Yield as a function of soil moisture was estimated by nonlinear least squares using the Mitscherlich-Spillman functional form:

$$Y = \alpha + \beta(1-\gamma^{SM}), \tag{3}$$

where Y is spring barley yield in lbs/ac, SM is soil moisture in inches at planting time, and α, β and γ are parameters. Based on 100 years output from the EPIC model for the Lacrosse region, the following relationship was estimated:

$$\underset{(-0.21)}{Y = -88.0} + \underset{(7.50)}{3{,}137.0}\ (1 - \underset{(4.54)}{0.636}^{SM}), \quad R^2 = 0.473, \tag{4}$$

where the asymptotic t-statistics are provided in parentheses. The standard error of the estimate is 538.0, the mean of the dependent variable (barley yield) is 1,767 lbs, the mean and standard deviation of available soil moisture are 2.15 or 0.90 inches, respectively.

The standard error of the estimate times expected output price is used as an estimate of S_i in equation (2) for those soil moisture levels where the optimal strategy indicates cropping. This approach considers only yield or production risk since nonstochastic output price and production costs are assumed. This is consistent with the usual purpose of flexcropping as a means of managing the moisture-dependent yield risk of spring cropping. S_i equals zero for fallowing because the costs of fallowing are assumed known with certainty.

Simulated yields reasonably approximated those for the study site used for calibration (Dorman), but they were below the average yields for the entire Lacrosse region. To ensure that the continuous spring barley yields used in the DP model exactly reflect published average yields for the region, the response function (4) was adjusted vertically upwards by 154 lbs--that is, α was set equal to 66.0.

For the purposes of the DP model, soil moisture was divided into ten discrete intervals. The intervals and their mid-points are provided in Table 1. The soil moisture transition matrix (P) for Lacrosse was obtained by first conducting a 300-year EPIC simulation of a SB-SB-fallow rotation. Then, spring (April 1) soil moisture in the year following fallow was regressed on spring soil moisture of the preceding fallow year. Similarly, spring soil moisture in the year following a crop year was regressed on spring soil moisture of the preceding crop year. A double-logarithmic functional form was used for both regressions. This implies that the error term is multiplicative and that soil moisture has a log-normal distribution. The regression results are as follows:

$$\begin{aligned} &\text{Fallow:} && \ln SM_t = \underset{(19.76)}{1.02} + \underset{(5.22)}{0.33} \ln SM_{t-1}, \\ &&& R^2 = 0.301,\ SEE = 0.227 \text{ and } n = 100. \\ &\text{Crop:} && \ln SM_t = \underset{(12.99)}{0.87} + \underset{(2.04)}{0.16} \ln SM_{t-1}, \\ &&& R^2 = 0.021,\ SEE = 0.452 \text{ and } n = 200. \end{aligned} \tag{5}$$

In the regressions, SEE is the standard error of the estimate, n is the number of observations and the t-statistics are provided in parentheses. As expected, the intercept and slope for the crop equation are lower than for the fallow equation.

Result (5) was used to find the probability p(i,j) of attaining soil moisture interval j given that soil moisture in the previous year was in interval i. This probability p(i,j) will depend upon whether the field was fallowed or cropped the previous year and is found as the area under a log-normal distribution function between the (logarithmic) end-points for interval j (Aitchison and Brown, p. 8). The resulting soil moisture transition matrix is provided in Table 1.

The annual costs of summerfallowing and of planting spring barley, excluding returns to land, labor and management, were \$31.27 and \$109.86 per acre, respectively.

Including Producer Risk Preferences

In the DP decision algorithm, the decision maker is assumed to maximize, at each time period and for each soil moisture level, the present value stream associated with cropping (k=1) versus fallow (k=0). This binary choice is represented in equation (1). In the case of zero risk and/or risk neutrality, it is appropriate to substitute expected values for all current year returns in $R^k(i)$ and $f_{n-1}(j)$. However, in the case where the forecasted returns for soil moisture level i and decision k are risky, and the decision maker is risk averse, Katoaka's safety-first criterion suggests substituting the lower bound of the $(1-\alpha)$ percent one-tailed confidence interval for all random current year returns. Net returns will exceed or equal this lower bound $(1-\alpha)$ percent of the time.

Formally Katoaka's objective function under risk can be expressed as

$$\text{Maximize } L \quad \text{subject to } \Pr(R < L) \leq \alpha,$$

where L is the lower bound and R is random returns. It contrasts with Roy's safety-first criterion which proposes minimizing the probability of falling below a specified minimum ("disaster") level, and Telser's criterion which maximizes expected profit subject to the probability of returns falling below a specified level not exceeding α. Katoaka's criterion requires eliciting only one risk preference parameter, the assured confidence level $(1-\alpha)$, whereas Telser's method requires eliciting two preference parameters, the decision maker's personal disaster level and disaster exposure tolerance (α). Unlike Roy's and Telser's criteria, Katoaka's criterion transforms every risky option into a risk-adjusted equivalent L, which is measured in dollars. This is convenient from an operational perspective when incorporating risk-adjusted results into the DP equation (1). It also facilitates communication of results to users. These advantages have motivated previous use of Katoaka's risky choice criterion in both extension (Musser, Ohannesian and Benson) and research (Moscardo and de Janvry) applications.

From a numerical perspective, Katoaka's criterion and the simple expectation-variance expected utility (EU) model used by Karp and Pope (and in most non-DP applications of EU theory) are very similar. Both subtract from expected returns (ER) a "risk premium", which is a function of standard deviation (σ), to obtain a (risk-adjusted) certainty equivalent. For the former, $L = ER - Z_{(1-\alpha)}\sigma$, where $Z_{(1-\alpha)}$ is the desired confidence-level statistic from the appropriate probability distribution; for the latter, $C = ER-(\lambda/2)\sigma^2$, where λ is Pratt's absolute risk aversion coefficient (Freund).

While the Katoaka and the simple EU model are algebraically similar, as both are simple functions of the mean and standard deviation of outcomes, the greater theoretical generality of EU maximization has favored its use in most applications. EU maximization can be derived from the von Neumann-Morgenstern "axioms of preference" hypothesized as reasonable tenets of individual behavior (Anderson, Dillon and Hardaker). However, Pyle and Turnovsky show that there is a close relationship between Katoaka's criterion and the expectation-variance EU model. They show one can always identify a unique assumed confidence level $(1-\alpha)$ for maximizing L which yields the same solution as a given two-moment EU model. Of course, the reverse correspondence is not unique because any linear monotonic transformation of a utility function yields equivalent rankings. Consequently, there are an infinite number of utility functions which can generate the same solution as a unique Katoaka objective function.

Unfortunately, the popularity of EU maximization based on its theoretical appeal has not been matched by equal progress in eliciting empirical risk aversion coefficients. Many researchers, like Karp and Pope (p. 442), simply select an arbitrary value for the risk aversion coefficient, which may or may not represent the range of risk preferences of their study group. Others (e.g., Harris and Nehring) conveniently "borrow" risk preference elicitations from producers in one region of the country to characterize a different set of producers in another region.

The reluctance of researchers to elicit situationally-specific risk preferences for EU applications probably relates to the time consuming and difficult nature of the task. EU risk aversion coefficients are theoretical constructs which cannot be provided directly by decision makers, but must be derived from elicited utility functions. Past attempts to directly elicit utility functions has lead to serious concerns about their stability and accuracy (Binswanger; Whittaker and Winter; Young 1979).

Even if improvements in procedures for eliciting utility functions could resolve all concerns about their accuracy and stability, it is likely that purely logistic problems would preclude their use in many practical farm management decisions. Extension agents are unlikely to have the time or training to elicit updated utility functions for each grower desiring a cropping recommendation.

The Katoaka model, on the other hand, permits characterizing risk preferences by a single "desired confidence level" $(1-\alpha)$ which can be provided by the grower himself. This made it possible, in the current study, to achieve the research funder's goal of collecting all input information, including individual risk preferences, with a brief interactive program on microcomputer diskette. Consequently, we selected the Katoaka model for its strong operational advantage despite a possible sacrifice in theoretical generality.

To implement the Katoaka risk adjustment in the DP algorithm, it is necessary to substitute forecast confidence interval lower bounds for the expected spring barley yields in equations (3) and (4). In accordance with the assumed normality of the individual yield forecasts from equation (4), the lower bound (L) of the (1-α) percent, one-tailed confidence interval of each current year return from growing spring barley is calculated as:

$$L = ER - P[Z_{(1-\alpha)} S_F] , \tag{6}$$

where ER is expected returns at the prevailing soil moisture level, which is calculated as expected price (P) times expected yield minus annual production costs. S_F is the appropriate yield forecast standard error, as discussed below. $Z_{(1-\alpha)}$ is the standard normal variate which encloses 100(α) percent of the probability in the lower tail. Z is used as a convenient proxy for the t-statistic in this user-oriented analysis to avoid adjusting the risk aversion coefficients for differences in degrees of freedom over different response functions. Given the large sample size (N = 100) for the Lacrosse region application reported here, the normal distribution closely approximates the t-distribution.

As noted above, risk is induced in the dynamic decision sequence by the remaining variability in spring barley yield even when measured soil moisture at spring planting time is known. A conceptually appropriate measure for the current problem is the variance of a single year's barley yield forecasted from response function (4) for soil moisture level i. These forecast variances are used to represent crop yield variances in (6). It is appropriate to use forecast variance as opposed to simple regression variances because they encompass the total risk confronted by a decision maker basing a decision on yield (and thus return) forecasts at each soil moisture level. The forecast variances are appropriately adjusted for the type of estimation used and for the distance of the soil moisture level used in the forecast from the mean of soil moisture data used to estimate the equation.

The expression for the standard error of an OLS regression forecast is well known (e.g., Johnston, p. 154.).[1] We derive the corresponding approximation for the NLS estimate of the nonlinear equation (3) below.[2] Consider $y = f(X, \theta) + \varepsilon$ and

$$\hat{y} = f(\hat{x}, \hat{\theta}), \tag{7}$$

where y and $\hat{y}$ are actual and predicted dependent variable vectors, respectively, X and $\hat{x}$ are the matrix of actual values used for the estimation and the vector of new values (for the forecast) of the explanatory variable, respectively, θ and $\hat{\theta}$ are true and estimated parameter vectors, respectively, f is the functional operator for the (potentially) nonlinear function, and ε is the well-behaved additive error term.

A first-order Taylor series approximation of nonlinear (7) about θ is:

$$f(\hat{x}, \hat{\theta}) \simeq f(\hat{x}, \theta) + (\partial f/\partial \theta)'_{\substack{\theta=\hat{\theta} \\ x=\hat{x}}} (\hat{\theta} - \theta). \tag{8}$$

Recognizing that $f(\hat{x}, \theta)$ is deterministic, and substituting the consistent estimator $\hat{\theta}$ for the unknown θ, we obtain the following consistent variance of (8):

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[1] The OLS standard error of the forecast is calculated as follows:

$$\sigma_F = \sigma[1 + c' \ (X'X)^{-1} \ c],$$

where σ is the standard error of the estimate, c is the vector of explanatory variables used in the forecast, and X is the matrix of data on the explanatory variables used to estimate the original equation.

[2] The assistance of Ron Mittelhammer is gratefully acknowledged for this derivation.

$$s^2[(\partial f/\partial\theta)'_{\substack{\theta=\hat{\theta}\\ x=\hat{x}}} \; ((\partial f/\partial\theta)'_{\substack{\theta=\hat{\theta}\\ X=x_{sample}}} \; (\partial f/\partial\theta))^{-1}_{\substack{\theta=\hat{\theta}\\ X=x_{sample}}} \; (\partial f/\partial\theta)_{\substack{\theta=\hat{\theta}\\ x=\hat{x}}} + 1], \qquad (9)$$

where s^2 is the estimated variance of ε. The general expression (9) includes the familiar linear forecast variance as a special case. When f is linear in θ, $\partial f/\partial\theta$ equals X, so (9) reduces to:

$$s^2[\hat{x}'(X'X)^{-1}\hat{x} + 1]. \qquad (10)$$

Because the Katoaka criterion bases choices on comparisons of forecast confidence interval lower bounds, it is necessary to elicit the decision maker's desired confidence level $(1-\alpha)$ on these bounds. Obviously, a grower who requires a 90 percent assurance that stochastic yields and returns exceed the level utilized in the model when planting spring barley at a particular moisture level is more risk averse than one requiring only a 50 percent (risk neutral) assurance level. We successfully elicited these assurance levels using a sequence of questions in an interactive microcomputer program asking whether the grower would be willing to base the decision to plant or fallow on a soil moisture based (risk-adjusted) forecast of crop yield if

...the actual yield will exceed the forecasted yield ONE-HALF the time, and fall below it ONE-HALF the time?

...the actual yield will exceed the forecasted yield TWO-THIRDS of the time, and fall below it ONE-THIRD of the time?

...and similar questions with increasing assurance levels.

The first question in the sequence receiving an affirmative answer was taken to represent the respondents required assurance level. For example, the preferences of a respondent requiring a 75 percent probability that actual yields exceed forecasted yields were modeled by substituting the 75 percent one-tailed confidence interval lower bound as the utilized "forecast" of spring crop yield (and returns) at each soil moisture level.

Results of Flexcrop Application

The previously described dynamic programming algorithm was used to determine the impact of risk aversion on the critical level of available soil moisture (ASM) for flexcropping spring barley in southeastern Washington. The decision rule is to fallow if measured soil moisture at planting time is below the critical level and to plant otherwise. Since the discount rate did not affect the analysis over a realistic range of variation, only the price and level of risk aversion are varied in Table 2; a real discount rate of 5.4 percent is used. Two levels of risk aversion are considered--risk neutral (Z=0) and moderate risk aversion (Z=0.674 for 75 percent assurance level). The results are presented in Table 2.

At 1987 target prices for both wheat and barley, \$4.38/bu and \$108/ton, respectively, a risk neutral grower can expect a net annual return of \$16.19/acre by planting spring barley whenever available soil moisture exceeds 2.0 inches on April 1; winter wheat-fallow provides an average annual return of \$16.84/acre, somewhat more than flexcropping SB. However, under the current Farm Bill, the ratio of the target to market price of barley is lower than that for wheat. Thus, government programs are biased toward the planting of wheat as opposed to barley, thereby making the wheat-fallow rotation more attractive than it would otherwise be. The Lacrosse producer who grows barley every year at target prices would average only \$13.80, about \$2.40 per acre less than under a flexcrop program and \$3 per acre less than under the continuous wheat-fallow rotation (Table 2). This illustrates the capacity of flexible cropping to increase returns over a fixed program such as continuous spring barley. As expected, and as indicated in Table 2, higher barley prices lead to less conservative flexcrop strategies in the sense of less summerfallow.

Notice that the flexcrop grower will fallow 18 percent of the time, versus 50 percent for the W-F rotation. From a social soil conservation perspective, the flexcrop system pays large dividends. Due to the reduction in fallow and the switch from fall- to spring-planted crops, soil loss can be reduced by five-fold or more. Furthermore, since the flexcrop system is relatively profitable from a private standpoint, public costs to motivate its adoption should be modest.

Winter wheat-fallow exhibits consistently less total annual income variability than flexcrop spring barley. At target prices and a risk neutral flexcrop strategy, the standard deviation of annual net returns per acre for the W-F rotation is 20 percent less than that for flexcrop spring barley (\$27.77 versus \$34.70). As noted by Burt and Johnson, an acre of wheat-fallow rotation is comprised of 1/2 acre wheat and 1/2 acre fallow and this diversification lends stability to annual returns compared to a flexcrop system where the entire acre is in crop or fallow depending upon soil moisture.[3]

A moderately risk averse flexcropper facing a \$108/ton barley price will employ a more conservative decision rule, planting spring barley

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[3]The wheat-fallow standard deviations are calculated as:

$$SD = [(1/2)^2 P^2 \, Var(Y_w)]^{1/2} = (1/2) P \, S_Y,$$

where P is the price of wheat per bushel, $Var(Y_w)$ is the variance of wheat yields per acre under a winter wheat-fallow rotation, and S_Y is the standard deviation of wheat yields. The fallow acre has zero variance, consistent with the assumption that production costs are known. The standard deviation of wheat yields in the study region is 12.68 bu/acre (Young 1986).

only when soil moisture exceeds 2.5 inches, compared to 2.0 inches for a risk neutral grower. This one-half inch increase in the soil moisture critical level reduces the producer's within-year risk (recall equation (2)) from 26.31 to 24.48, but at a sacrifice of expected returns of almost a dollar per acre (see Table 2). Seemingly paradoxically, the long-run annual (total) variation in income increases from 34.70 to 35.38 under the more risk averse strategy. This result is due to a reduction in the within-year random component but increase in the variation in annually predicted returns, represented by the first component of expression (2). Under the more conservative strategy, the grower frequently switches from spring cropping to fallowing, resulting in substantial swings in mean income which are predicted as of each April 1. The flexcrop decision maker in this study is concerned with the short-run risk he faces at planting time. These risk components are reflected by the random term in expression (2) and are, indeed, reduced by the more conservative strategy. These are the same short-run components addressed by the expected utility approach employed by Karp and Pope. In practice, growers under greater financial pressure are likely to be more concerned about year-to-year short-run risk. Those whose secure financial base permits a longer-run planning horizon are more likely to be concerned about variation in long-run annual returns. In practice, the relative concern about short-run versus long-run risk will vary by producer and business situation. An interesting implication of the results of this study is that pressures by lenders, landlords, or others for growers to manage risk on a short-run year-to-year basis can actually destabilize long-run annual returns.

Summary and Conclusions

Use of Katoaka's criterion provided an operationally tractable procedure for incorporating within-year risk aversion into a dynamic programming problem. The approach facilitates use of DP for generating risk-sensitive farm management extension recommendations because the risk preference parameter can be provided by growers themselves.

The Katoaka criterion was applied in a stochastic dynamic programming model used to identify optimal flexible cropping plans for spring barley in southeastern Washington. Increasing risk aversion was found to lead to more conservative flexcrop strategies. More risk averse growers required higher threshold soil moisture levels before planting spring barley but this conservatism came at the cost of reduced expected returns.

Optimal risk neutral flexcrop plans were shown to generate similar expected returns compared to the currently predominant, but erosive, winter wheat-fallow rotation. However, the flexcrop SB system displayed greater total annual income variability than winter wheat-fallow, which suggests that efforts to promote flexcropping for soil conservation may require supplemental financial incentives for some growers. Nonetheless, the potentially competitive expected returns and substantial soil savings of flexible spring cropping systems make them attractive as cost effective soil conservation alternatives.

Flexcropping is likely to take on additional appeal as the conservation compliance provision of the Food Security Act of 1985 is phased in over 1990-95. This provision will require farmers cultivating erodible land to meet soil conservation standards in order to qualify for government programs. In view of the extreme erosiveness of the summerfallow systems prevalent over much of the Great Plains and western states, flexcropping may provide one profitable option for meeting compliance standards without large-scale land retirement or expensive new farming practices.

Table 1: Transition Probabilities Matrix for Lacrosse, WA: Probability of Moving to Available Soil Moisture (SM) Level in Column j Next Year, Given SM Level is i This Year, for Fallow/Crop Current States

April 1 SM This Year (Inches)	April 1 Soil Moisture Level Next Year									
Current State: FALLOW										
	1	2	3	4	5	6	7	8	9	10
< 1.0	0.000	0.044	0.288	0.376	0.203	0.067	0.017	0.003	0.001	0.001
1.0-1.5	0.000	0.001	0.038	0.178	0.291	0.249	0.143	0.063	0.035	0.012
1.5-2.0	0.000	0.000	0.012	0.090	0.218	0.264	0.204	0.118	0.094	0.037
2.0-2.5	0.000	0.000	0.004	0.046	0.152	0.236	0.229	0.162	0.170	0.078
2.5-3.0	0.000	0.000	0.002	0.025	0.103	0.198	0.229	0.189	0.254	0.130
3.0-3.5	0.000	0.000	0.001	0.014	0.071	0.160	0.214	0.202	0.338	0.189
3.5-4.0	0.000	0.000	0.000	0.008	0.049	0.127	0.194	0.204	0.416	0.250
4.0-4.5	0.000	0.000	0.000	0.005	0.034	0.101	0.172	0.199	0.488	0.311
4.5-5.0	0.000	0.000	0.000	0.003	0.024	0.079	0.148	0.189	0.558	0.370
> 5.0	0.000	0.000	0.000	0.002	0.015	0.056	0.119	0.170	0.182	0.457
Current State: CROP										
	1	2	3	4	5	6	7	8	9	10
< 1.0	0.047	0.170	0.225	0.194	0.138	0.089	0.055	0.033	0.050	0.030
1.0-1.5	0.023	0.112	0.185	0.190	0.156	0.113	0.077	0.051	0.093	0.060
1.5-2.0	0.017	0.093	0.168	0.184	0.159	0.121	0.086	0.058	0.114	0.075
2.0-2.5	0.013	0.081	0.154	0.178	0.160	0.126	0.092	0.064	0.132	0.089
2.5-3.0	0.011	0.072	0.144	0.172	0.160	0.129	0.096	0.068	0.148	0.101
3.0-3.5	0.010	0.065	0.135	0.167	0.159	0.131	0.099	0.072	0.162	0.111
3.5-4.0	0.008	0.059	0.128	0.162	0.158	0.132	0.102	0.075	0.175	0.122
4.0-4.5	0.007	0.054	0.121	0.158	0.156	0.134	0.105	0.078	0.187	0.131
4.5-5.0	0.007	0.050	0.115	0.153	0.155	0.134	0.107	0.080	0.058	0.139
> 5.0	0.006	0.046	0.108	0.148	0.153	0.135	0.109	0.083	0.061	0.152
Soil Moisture Mid-Point Levels	0.50	1.25	1.75	2.25	2.75	3.25	3.75	4.25	4.75	5.54

Table 2: Optimal Spring Barley Flexcrop Results for Lacrosse, WA Region for Alternative Levels of Risk Aversion and Barley Prices With a Comparison to a Fixed Winter Wheat-Fallow Rotation

Risk Aversion/ Barley Price ($/ton)[a]	ASM Critical Level (in)	Long-Run Expected Yield (lbs/ac)	Long-Run Expected Return ($/ac/yr)	Standard Deviation (S.D.) of Long-Run ($/ac/yr)	Long-Run Frequency of Fallow (%)
Continuous Spring Barley					
$78	n.a.	2,290	-20.55	27.60	0
108	n.a.	2,290	13.80	38.21	0
121	n.a.	2,290	28.69	42.81	0
Flexcropping Spring Barley					
Risk Neutral					
$78	3.0	2,690	-11.40	18.67 (16.39)	39
108	2.0	2,487	16.19	34.70 (26.31)	18
121	1.5	2,380	30.24	40.48 (31.39)	7
Moderate Risk Aversion					
$78	4.0	2,846	-12.53	17.37 (13.20)	60
108	2.5	2,594	15.22	35.38 (24.48)	29
121	2.5	2,594	27.19	43.00 (27.43)	29
Winter-Wheat Fallow[b]		bu/ac			
$4.38	n.a.	45.0	16.84	27.77	50

[a]Prices of $78/ton and $121/ton represent 10-year low and high barley prices in the region; $108/ton is the recent target price for barley.

[b]$4.38/bu reflects the target price for wheat in the region.

NOTE: Results are based on a real discount rate of 5.4 percent with no discount for long-run productivity inpacts of fallow. The random component S.D. appears in parentheses.

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