AgRisk 1.0 Technical Reference *

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Abstract

AgRisk is a Windows 95/98/NT program designed to assist corn, soybean, wheat, and sorghum farmers to manage harvest-time revenue risk. AgRisk derives the distribution of a farm's harvest-time gross revenue under alternative planting-time risk management strategies. Strategies may include any combination of multiple peril crop insurance, crop revenue coverage insurance, group risk plan insurance, income protection insurance, revenue assurance, price option contracts, futures contracts, forward price contracts, and minimum price contracts. The centerpiece of the AgRisk program is a numerical stochastic simulation model of farm, county, and national harvest yields and prices. This monograph explains the statistical methods used to build the AgRisk simulation model and the numerical simulation techniques used by AgRisk to derive the distribution of a farm's gross revenue under alternative risk management strategies.

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1 Introduction

AgRisk is a Windows 95/98/NT program designed to assist corn, soybean, wheat, and sorghum farmers to manage harvest-time revenue risk. AgRisk derives the probability distribution of a farm's harvest-time gross revenue under alternative planting-time risk management strategies. Strategies may include any combination of multiple peril crop insurance, crop revenue coverage insurance, group risk plan insurance, income protection insurance, revenue assurance, price option contracts, futures contracts, forward price contracts, and minimum price contracts. AgRisk permits the user to compare how the farm gross revenue distribution will vary across different risk management strategies, allowing the user to make better informed risk management decisions. For example, a user could examine how purchasing a put option in combination with multiple peril crop insurance compares to buying crop revenue coverage insurance alone.

The centerpiece of the AgRisk program is a numerical, discrete-state stochastic simulation model of harvest-time prices and yields. Associated with each possible state are unique harvest-time farm and county yields and local and Chicago Board of Trade (CBOT) delivery prices for crops grown on the farm. These yields and prices fully determine the net settlement values of all insurance and pricing contracts recognized by AgRisk, and thus also determine the farm's gross revenue under any risk management strategy based on those contracts. AgRisk computes the expectation and variance of gross farm income under an admissible risk management strategy by integrating over the discrete state probabilities. AgRisk also generates graphs of the probability distribution of prices, yields, and gross farm revenue using kernel smoothing techniques.

The AgRisk simulation model is calibrated to reflect individual farm characteristics and current market conditions using data provided by the user. User-provided data include the farm's yield history, the acreage planted to different crops, and planting-time CBOT futures prices and option premia for crops grown on the farm. AgRisk also draws from its own data base of historical county, state, and national yields and historical local versus CBOT price bases to construct the farm-level model. To derive the distribution of a farm's gross revenue under any given risk management strategy, AgRisk further requires the user to supply the number and types of contracts employed in the strategy and related contract information such as premiums paid, any strike, futures, and forward prices associated with the pricing contracts, and any price, yield, and revenue guarantees associated with the insurance contracts.

Several practical problems had to be overcome in order to build the AgRisk simulation model. First, many farms have incomplete yield records, making it difficult to build a reliable model of farm-level yields solely from user-supplied data. Second, a farm's gross revenue is generally a nonlinear function of numerous random variables, most of which exhibit significant correlation. These nonlinearities and correlations must be captured by the simulation model if it is to generate reliable predictions about the distribution of a farm's revenue under alternative risk management strategies. Third, AgRisk must compute a farm's gross revenue distribution quickly, accurately, and consistently, if it is to be practicable. This can be difficult, given the large number of random variables involved in the computations, particularly when multiple crops are grown on the farm and various risk management strategies are examined.

The AgRisk simulation model is designed to address all of these practical problems. First, AgRisk employs historical county yield data to improve predictions of farm-level yields. Improved predictions are possible because long time series of reliable county yield data are available and farm yields tend to be highly correlated with county yields due to the systemic nature of weather effects. Second, AgRisk employs nonparametric, empirical distribution methods to model the joint distribution of many of the key yield and price random variables. This approach allows observed correlations among variables to be replicated in model simulations without imposing unnecessary additional structure on the model. This approach also reduces the dimensionality of the numerical integrations that must be performed by AgRisk, reducing the number of computations required to accurately and consistently estimate the gross farm revenue distribution under alternative risk management strategies.

The remainder of this monograph discusses the methods used to build the AgRisk simulation model and the techniques used to predict the distribution of a farm's gross revenue under different risk management strategies. Section two of the monograph explains how AgRisk would construct a simple simulation model to assess the implications of hedging on the futures market for a single-crop farm under ideal conditions of complete, stationary data. Section three explains how the AgRisk simulation model addresses violations of the ideal conditions, including missing farm-level yield data and nonstationarity in both aggregate price and yield data. A complete description of the AgRisk model of the underlying stochastic variables is presented in Section four. A detailed description of the risk management contracts recognized by AgRisk is presented in Section five. The structure of the Fortran implementation of the AgRisk simulation model, including the subroutine structure, is outlined in Section six. And in Section seven, unresolved issues and pending improvements in the AgRisk program are discussed. An appendix provides a detailed description of the data used to build the AgRisk model.

2 Empirical Distributions

One of AgRisk's innovative features is its use of nonparametric, empirical distributions to model prices and yields.[1] Empirical distributions offer a way to capture in the model the essential correlations that exist among price and yields, without having to impose unnecessary additional structure or having to perform complicated estimation procedures. Empirical distributions also greatly simplify the numerical integrations that must be performed to derive the farm's gross revenue distribution.

To understand how AgRisk employs empirical distributions, imagine a farmer who has never actively managed his harvest-time revenue risk, but who is now considering hedging his expected production in the futures market. Assume that the farmer lives in an idealized world in which, over the past twenty years: 1) the market has not undergone significant structural change, 2) yields have shown no noticeable trends, and 3) the farmer has complete farm-level yield records.

Without active risk management, the farmer's unhedged gross revenue per acre $\tilde{r}_u$ is simply the product of the local harvest price $\tilde{p}$ and the farm yield $\tilde{y}$:

$$\tilde{r}_u = \tilde{p} \cdot \tilde{y}. \tag{1}$$

If the farmer hedges q bushels per acre of his crop by selling futures contracts, his hedged gross revenue per acre $\tilde{r}_h$ will further depend on the change $\tilde{d}$ in

[1]Most of the better known farm-level revenue simulators, such as ARMS and Agsim, use parametric distributions fitted econometrically (King, Taylor). Empirical distributions are quite common in management science applications, but are rarely used by applied economists (Law and Kelton).

the delivery point futures price between planting time and harvest time:[2]

$$\tilde{r}_h = \tilde{p} \cdot \tilde{y} - q \cdot \tilde{d}. \tag{2}$$

In order to make an informed decision about whether to hedge, the farmer must better understand how the distributions of $\tilde{r}_u$ and $\tilde{r}_h$ differ.

How would one build a stochastic model of prices and yields to predict the effects of selling futures contracts on the farmer's gross revenue? A conventional approach familiar to most applied economists would be to pose a formal parametric model of the joint distribution of the driving random variables and to estimate the parameters using standard econometric techniques from available historical data. More specifically, one might posit a particular parametric functional form for the joint likelihood of $\tilde{y}$, $\tilde{p}$, and $\tilde{d}$

$$\Pr(\tilde{y} = y, \tilde{p} = p, \tilde{d} = d) = g(y, p, d; \alpha) \tag{3}$$

and estimate the unknown parameter α using standard econometric techniques, say, maximum likelihood estimation. The parameter vector α would have to contain at least nine parameters, the minimum number needed to capture independently the conditional means, variances, and covariances of the three random variables.

Having estimated a joint distribution for the random variables of interest, one would set out to compare the farm's gross revenue distribution, with and without the hedge. For example, to compute the mean and variance of the gross revenue distribution with the hedge, the analyst would have to evaluate the triple integrals:

$$E\tilde{r}_h = \int\int\int [p \cdot y - q \cdot d] g(y, p, d; \alpha)\ dy\ dp\ dd.$$

$$V\tilde{r}_h = \int\int\int [p \cdot y - q \cdot d - E\tilde{r}_h]^2 g(y, p, d; \alpha)\ dy\ dp\ dd.$$

Two difficult problems arise with the parametric modeling method just described, rendering it impracticable for use in AgRisk. First, the modeler must specify a distributional form that can accurately capture correlations among prices and yields. Correlations among prices and yields are important because they have a significant impact on the distribution of farm gross revenue, which is what AgRisk is designed to describe. For example, farm

[2] We assume brokerage and margin fees are negligible for now.

gross revenue will be less variable if prices and yields are negatively correlated and will be more variable if yields on different crops grown on the farm are positively correlated, than if all prices and yields are independent. The minimum number of parameters required to capture correlations among prices and yields grows with the square of the number of variables in the model. And in the working version of AgRisk, which involves as many as four crops and two levels of prices and yield per crop, the number of parameters that would have to be estimated independently would be exceedingly large.

A second problem associated with the parametric modeling approach involves the difficulty of evaluating the integrals to compute the mean and variance of the derived revenue distribution. An analytic approach will almost certainly be impracticable, given the high dimensionality of the integration and the complexity of the probability distributions. Monte Carlo and Gaussian quadrature methods offer numerical alternatives to the analytic methods, but not good ones. Monte Carlo methods are computationally imprecise and inconsistent. Gaussian quadrature rules suffer from the curse of dimensionality, which implies that the number of computations grows exponentially with the dimension of the integration, making it impracticable to include more than one or two crops simultaneously. And both Monte Carlo and Gaussian quadrature methods are generally difficult to implement for correlated multivariate distributions, except under special assumptions, such as joint normality.

Empirical, nonparametric distribution methods offer a practical alternative for modeling the joint distribution of prices and yields that avoid most of the difficulties encountered with the parametric methods described above. An empirical distribution is simply the available historical data treated as if it were a joint uniform discrete distribution. The empirical distribution is constructed by identifying each contemporaneous realization of prices and yields with one of the possible states of the model distribution and assigning it a probability of $1/T$, where T is the number of years for which observations are available.

The most important practical feature of the nonparametric approach is that the empirical distribution exactly captures the variation and co-variation historically observed among prices and yields. This is true, of course, because the empirical distribution and the historical data are one and the same. Because no parametric form is imposed on the empirical distribution, no restrictions, implicit or explicit, are imposed on the moments of the joint distribution in order to obtain a parsimonious, estimable model. Moreover, no estimation need to take place at all, offering a savings of time and effort to the modeler.

Another important practical feature of the nonparametric empirical model is that the distributions are discrete, making them particularly easy to integrate. With a discrete distribution, computing the mean and variance of gross revenue under alternative risk management scenarios involves only simple weighted sums. For example, let y_t, p_t, and d_t, denote, respectively, the yield, local price, and harvest-planting futures price differential observed in year t. Then the expectation and variance of gross revenue implied by the empirical distribution model, assuming a full hedge, may be computed as

$$E\tilde{r}_h = \frac{1}{T}\sum_{t=1}^{T} p_t \cdot y_t - q \cdot d_t \tag{4}$$

$$V\tilde{r}_h = \frac{1}{T}\sum_{t=1}^{T} [p_t \cdot y_t - q \cdot d_t - E\tilde{r}_h]^2. \tag{5}$$

These computations can be easily carried out on a spreadsheet program.

3 Violations of Ideal Conditions

Nonparametric, empirical distributions offer many advantages over parametric distributions in simulation analysis, but are applicable only if certain assumptions are satisfied. The key condition that must be met is that the data be serially independent and generated from a stationary stochastic process. This condition, when satisfied, assures that the historical observations form a random sample and that the sample means and variances of functions of the variables, such as the mean and variance of revenue under alternative risk management strategies, are asymptotically efficient estimators of their true values.

The ideal conditions, however, are violated by agricultural prices and yields. In particular, three salient features of agricultural price and yield data series undermine the use of empirical distributions directly in AgRisk. First, it is rare that individual farmers have long and reliable yield records, making it impossible to model the farm-level yield directly with observed historical data. Second, what yield data are available typically exhibit a noticeable secular trend. And third, the structure of agricultural markets has been shifting over time due to the decline in government price support intervention in these markets.

Although agricultural commodity markets do not satisfy the ideal conditions for the direct use of empirical distributions in simulation analysis, it is nonetheless possible to construct reasonable stochastic models of the underlying price and yield distributions that preserve many of the desirable practical properties of pure empirical distributions. We now describe how AgRisk handles the violations of ideal conditions, beginning with the paucity of farm-level data, and then turning to issues of yield trends and nonstationary price generating processes.

3.1 Missing Farm Data

Farmers generally do not maintain accurate yield records or, if they do, typically do not have them readily accessible for inputting the data into AgRisk. AgRisk addresses this problem by using historical county yield data to improve predictions of farm-level yields. Improved predictions are possible because long time series of reliable county yield data are generally available and farm yields tend to be highly correlated with county yields due to the systemic nature of weather effects.

AgRisk assumes that the farm yield $\tilde{y}_f$ and the county yield $\tilde{y}_c$ are related as:

$$\tilde{y}_f = \tilde{y}_c \cdot \tilde{\epsilon} \tag{6}$$

where $\tilde{\epsilon}$ is an idiosyncratic farm-level yield shock that is independent of the county yield and uncorrelated with local and national prices.

The distribution model of $\tilde{\epsilon}$, the ratio of the farm yield to the county yield, is constructed using the nonparametric methods discussed in Section 2. Specifically, suppose farm-level yield data are available for, say, n, of the T years for which county yield data are available. The distribution of the yield shock is then posited to be the uniform, discrete n-point distribution whose values $\epsilon_1, \epsilon_2, \ldots, \epsilon_n$ are the n observed ratios the farm- and county-level yields for the years in which both yields were observed.

Given the n possible values for the idiosyncratic farm-level yield shock $\tilde{\epsilon}$ and the assumption that it is independent of the county yield, we construct an uniform, discrete distribution for the farm-level yield by considering all nT equiprobable combinations of the county-level yield and the idiosyncratic farm-level yield shock. More specifically, the farm-level yield is assumed to take on the values $\tilde{y}_{fti} = \tilde{y}_{ct} \cdot \epsilon_i$, for $t = 1, 2, \ldots, T$ and $i = 1, 2, \ldots, n$, each with probability $(nT)^{-1}$. Although the idiosyncratic farm-level yield shock is assumed independent of prices and aggregate yields, the individual farm-level yield exhibits the same covariance with prices as the county-level yield by construction.

3.2 Secular Yield Trends

Agricultural yields exhibit secular trends. This implies that current yields are not generated by the same process as historically observed yields, precluding directly applying the nonparametric distribution methods discussed in Section 2 to model yields. In this subsection, we discuss how AgRisk detrended national- and county-level yield distributions; the farm-level yield distribution is constructed the methods discussed in the preceding subsection.

In order to detrend national- and county-level yields, AgRisk posits a formal, structural model motivated by the following stylized facts: first, yields have been increasing over time, but at a declining rate; second, deviations of yields around trend are serially uncorrelated; and third, yields have exhibited a constant coefficient of variation. To capture these stylized facts, Agrisk assumes that the logs of the national- and county-level yields over time are described by a second order polynomials in time t with additive serially independent and identically distributed errors:

$$\log y_{ct} = \gamma_{c0} + \gamma_{c1} t + \gamma_{c2} t^2 + \psi_{ct} \tag{7}$$

$$\log y_{nt} = \gamma_{n0} + \gamma_{n1} t + \gamma_{n2} t^2 + \psi_{nt}. \tag{8}$$

Here, y_{nt} and y_{ct} are the national- and county-level yields observed in year t.

AgRisk performs ordinary least squares to fit the yield equations, then computes trend factors which measure the proportional growth in trend yields between year t and the current marketing year T:

$$k_{ct} = \exp[\gamma_{c1}(T - t) + \gamma_{c2}(T - t)^2] \tag{9}$$

$$k_{nt} = \exp[\gamma_{n1}(T - t) + \gamma_{n2}(T - t)^2]. \tag{10}$$

AgRisk uses these trend factors to convert the historical yields y_t to detrended, year T equivalent yields as follows:

$$\tilde{y}_{ct} = k_{ct} \cdot y_{ct} \tag{11}$$

$$\tilde{y}_{nt} = k_{nt} \cdot y_{nt}. \tag{12}$$

AgRisk replaces the historical yields in the empirical distribution with the detrended yields. More precisely, AgRisk assumes that the national- and county-level yields possess a joint uniform discrete distribution with possible realizations $(\tilde{y}_{ct}, \tilde{y}_{nt})$, $t = 1, 2, \ldots, T$, each occurring with probability $1/T$.

Purging historical yields of their secular trends in this manner allows us to retain the simple, numerically tractable structure of the nonparametric empirical distribution. The joint national- and county-level yield distribution constructed in this manner is uniform, and captures the essential co-variation among prices and trend-adjusted, base-year equivalent yields, which is precisely what is needed to accurately describe the distribution of revenue under current marketing year conditions.

3.3 Price Distribution

Specification of the price distribution is a particularly challenging problem. Most US crop markets have experienced profound structural changes over the last thirty years. In particular, there has been a substantive decline of direct government price support intervention. Historical prices, therefore, have exhibited less responsiveness to yield variations than one would expect under current conditions. This precludes directly applying the nonparametric distribution methods discussed in Section 2 to model prices.

In order to explain price behavior, AgRisk posits the following relationship between the harvest-time national price $\tilde{p}_n$, the planting-time futures price for delivery at harvest f, and the harvest-time national yield $\tilde{y}_n$:[3]

$$\log(\tilde{p}_n/f) = \alpha - \beta \log(\tilde{y}_n) + \tilde{\eta}. \tag{13}$$

The parameter $\beta > 0$ measures the sensitivity of the national harvest price to variations in the national yield. More specifically, a one percent increase in the national yield induces a β percent decrease in the national harvest price. The random variable $\tilde{\eta}$ captures variations in the national price that are uncorrelated with variations in national yield. We assume that $\tilde{\eta}$ is independent of the national yield and normally distributed with mean 0 and standard deviation σ.

In order to completely describe the national price distribution, we must specify the distribution of the national yield and the values of α, β, and σ.

[3]National harvest and futures prices refer to Chicago Board of Trade harvest spot and planting-time futures prices, respectively.

Specification of the price sensitivity β is a particularly difficult. One might consider estimating the sensitivity by regressing the log of the ratio of the national price to the futures price against the log national yield using historical yield data adjusted for trends. This approach, however, is inadequate for most US crops, due to the structural changes these markets have experienced over the last thirty years. Estimates of the price sensitivity derived from a long time series of historical data would likely produce values severely biased downward in absolute value. Our current practice in building AgRisk is to perform the simple regression to fit β, but to do so only with data between 1987 and 1997, a period of relative stability with market conditions similar to the present.

Having specified the value of the price sensitivity and the distribution of the marketing year national yield, one still must specify the value of α and σ. AgRisk specifies these two parameters by calibrating them to contemporaneous market information. In particular, under the assumption of market efficiency and arbitrage free pricing, the following two conditions are satisfied by the distribution of the harvest-time market price:

$$f = E\tilde{p}_n \tag{14}$$

$$\pi = E\max\{0, K - \tilde{p}_n\}. \tag{15}$$

Here, f is the current futures price and π is the current premium for the near at-the-money put option, both for delivery at harvest. Using the current values of f, π, and options strike price K input by the user, AgRisk employs Newton's method to solve the two nonlinear equations for the implied values of α and σ. Gauss-Hermite quadrature methods are used to compute the expectations numerically (Judd; Miranda and Fackler).

Having computed σ, we replace $\tilde{\eta}$ with a discrete random variable in order to preserve the discrete-event structure of the AgRisk simulation model. More specifically, we choose an order of discretization, m, and posit that $\tilde{\eta}$ assumes the m values $\sigma z_1, \sigma z_2, \ldots, \sigma z_m$ with probabilities $w_1, w_2, \ldots, w_n$, where the $\{z_j, w_j\}$ are the Gauss-Hermite quadrature nodes and weights for the standard normal distribution (Judd; Miranda and Fackler).

Given the m possible values for the demand shock $\tilde{\eta}$ and the assumption of independence, we construct an nonuniform, discrete distribution for the national price by considering all mT equiprobable combinations of the national yield and the demand shock. More specifically, the national price is assumed to take on the values

$$\log(\tilde{p}_{ntj}/f) = \alpha - \beta \log(\tilde{y}_{nt}) + \tilde{\eta}_j. \tag{16}$$

for $t = 1, 2, \ldots, T$ and $j = 1, 2, \ldots, m$. The probability of the tj^{th} event is w_j/T.

4 Stochastic Model Summary

We now summarize the structure of the AgRisk model. Again, we limit discussion to the modeling of a single crop. The model and methods described here are easily generalized to more than one crop.

The single-crop version of AgRisk comprises eight stochastic variables:

$$\begin{aligned}
\tilde{y}_f &= \text{farm yield} \\
\tilde{y}_c &= \text{county yield} \\
\tilde{y}_n &= \text{national yield} \\
\tilde{p}_f &= \text{farm harvest price} \\
\tilde{p}_n &= \text{national harvest price} \\
\tilde{\epsilon} &= \text{farm yield shock} \\
\tilde{\eta} &= \text{national demand shock} \\
\tilde{b} &= \text{basis ratio at harvest}
\end{aligned}$$

The net settlement values of all contracts recognized by AgRisk, and thus the farm's gross income under any admissible risk management strategy, depend solely on these random variables. The distribution of a farm's gross revenue under any strategy, therefore, can be computed by integrating over the distribution of these variables.

Of the eight random variables that comprise AgRisk, five variables, $\tilde{y}_c$, $\tilde{y}_n$, $\tilde{\epsilon}$, $\tilde{\eta}$, and $\tilde{b}$ are driving variables. The remaining three variables $\tilde{p}_n$, $\tilde{p}_f$, and $\tilde{y}_f$ are derived variables whose distributions are obtained from the distribution of the driving variables via the following structural relationships:

$$\log(\tilde{p}_n/f) = \alpha + \beta \log(\tilde{y}_n) + \tilde{\eta} \tag{17}$$

$$\tilde{p}_f = \tilde{p}_n \cdot \tilde{b} \tag{18}$$

$$\tilde{y}_f = \tilde{y}_c \cdot \tilde{\epsilon}. \tag{19}$$

To make the AgRisk stochastic simulation model operational, we must explicitly specify the distribution of the driving variables and the parameters α and β of the structural equations. We must also obtain the current value of the futures price f.

AgRisk posits stochastically independent, discrete distributions for $\tilde{\epsilon}$, $\tilde{\eta}$, and the vector $(\tilde{y}_c, \tilde{y}_n, \tilde{b})$. (AgRisk does not, however, assume that $\tilde{y}_c$, $\tilde{y}_n$, and $\tilde{b}$ are mutually independent). More specifically, AgRisk posits a uniform discrete distribution for $(\tilde{y}_c, \tilde{y}_n, \tilde{b})$ that can assume T different values, each with probability $1/T$; we index the possible realizations with t. AgRisk posits a uniform discrete distribution for $\tilde{\epsilon}$ that can assume n different values, each with probability $1/n$; we index the possible realizations with i. And AgRisk posits a nonuniform discrete distribution for $\tilde{\eta}$ that can assume m different values, with probabilities $\{w_1, w_2, \ldots, w_m\}$; we index the possible realizations with j.

AgRisk is thus a discrete-event stochastic simulation model with $N = T \cdot n \cdot m$ distinct possible states, each of which can be identified by the index (tij). The $(tij)^{th}$ event corresponds to the t^{th} realization of $(\tilde{y}_c, \tilde{y}_n, \tilde{b})$, the i^{th} realization of $\tilde{\epsilon}$, and the j^{th} realization of $\tilde{\eta}$. Due to the independence assumption, the probability of the $(tij)^{th}$ event is $w_j/(T \cdot n)$.

Agrisk models the joint distribution $\tilde{y}_c$, $\tilde{y}_n$, and $\tilde{b}$ using the empirical distribution and detrending methods discussed in Section 2.[4] Agrisk constructs the independent distributions of $\tilde{\epsilon}$ and $\tilde{\eta}$ using the methods outlined in Sections 3.2 and 3.3, respectively.

5 AgRisk Contracts

AgRisk recognizes ten distinct classes of risk management contracts. Below, we explain how AgRisk computes the settlement value of the contracts at harvest. The settlement values depend on contract specifications, such as premiums paid, quantities covered, and trigger prices, yields, and revenues. Specifications vary across contracts and are supplied by the user. The settlement values also depend on harvest time market prices and yields that are unknown at harvest, and which are modeled using the stochastic modeling methods described in the preceding sections. In this section, the random

[4]The price basis is computed as $\tilde{b}_t = p_{ft}/p_{nt}$ where p_{ft} and p_{nt} are the local and national level harvest prices observed in year t.

variables are given more descriptive, full length, which are identical to those used in the Fortran 90 code:

$$\begin{array}{lcl} \text{pcbot} &=& \tilde{p}_n &=& \text{CBOT spot price at harvest (\$/bu)} \\ \text{ploc} &=& \tilde{p}_l &=& \text{local spot price at harvest (\$/bu)} \\ \text{yfarm} &=& \tilde{y}_f &=& \text{farm yield (bu/a)} \\ \text{ycnty} &=& \tilde{y}_c &=& \text{county yield (bu/a)} \end{array}$$

5.1 Put Option

When buying or selling a put option, the user must specify:

pstrike	=	strike price ($/bu)
quant	=	contract size (bu)
brokfee	=	brokerage fee ($/5000 bu)
margreq	=	margin requirement (%)
margint	=	margin interest (%)
premium	=	premium rate ($/bu)
buysell	=	1 if buy, -1 if sell.

The net settlement value of the put option at harvest is

$$\text{value} = \text{buysell} * \text{quant} * \text{optval} - \text{margcost} - \text{brokcost}$$

where

$$\text{optval} = \max(0, \text{pstrike} - \text{pcbot}) - \text{premium}$$

$$\text{margcost} = \begin{cases} \text{margreq} * \text{quant} * \text{pstrike} * \text{margint}, & \text{if sell} \\ 0, & \text{if buy} \end{cases}$$

$$\text{brokcost} = \begin{cases} \text{brokfee} * \text{quant}/5000, & \text{if pstrike>pcbot} \\ 0.5 * \text{brokfee} * \text{quant}/5000, & \text{otherwise} \end{cases}$$

are the per-bushel value of the option before marketing costs, total margin costs, and total brokerage costs, respectively.

5.2 Call Option

When buying or selling a call option, the user must specify:

pstrike	=	strike price ($/bu)
quant	=	contract size (bu)
brokfee	=	brokerage fee ($/5000 bu)
margreq	=	margin requirement (%)
margint	=	margin interest (%)
premium	=	premium rate ($/bu)
buysell	=	1 if buy, -1 if sell.

The net settlement value of the call option at harvest is

$$\text{value} = \text{buysell} * \text{quant} * \text{optval} - \text{margcost} - \text{brokcost}$$

where

$$\text{optval} = \max(0, \text{pcbot} - \text{pstrike}) - \text{premium}$$

$$\text{margcost} = \begin{cases} \text{margreq} * \text{quant} * \text{pstrike} * \text{margint}, & \text{if sell} \\ 0, & \text{if buy} \end{cases}$$

$$\text{brokcost} = \begin{cases} \text{brokfee} * \text{quant}/5000, & \text{if pstrike<pcbot} \\ 0.5 * \text{brokfee} * \text{quant}/5000, & \text{otherwise} \end{cases}$$

are the per-bushel value of the option before marketing costs, total margin costs, and total brokerage costs, respectively.

5.3 Futures Contract

When buying or selling a futures contract, the user must specify:

pfuture	=	futures price ($/bu)
quant	=	contract size (bu)
brokfee	=	brokerage fee ($/5000 bu)
margreq	=	margin requirement (%)
margint	=	margin interest (%)
buysell	=	1 if buy, -1 if sell.

The net settlement value of the futures contract at harvest is

$$\text{value} = \text{buysell} * \text{quant} * (\text{pcbot} - \text{pfuture}) - \text{margcost} - \text{brokcost}$$

where

$$\text{margcost} = \text{margreq} * \text{quant} * \text{pfuture} * \text{margint}$$

$$\text{brokcost} = \text{brokfee} * \text{quant}/5000$$

are the total margin and brokerage costs, respectively.

5.4 Forward Price Contract

When entering into a forward price contract, the user must specify:

$$\begin{array}{lcl} \text{pforward} & = & \text{forward price (\$/bu)} \\ \text{quant} & = & \text{contract size (bu).} \end{array}$$

The net settlement value of the forward price contract at harvest is

$$\text{value} = \text{quant} * (\text{pforward} - \text{ploc}).$$

5.5 Minimum Price Contract

When entering into a minimum price contract, the user must specify:

$$\begin{array}{lcl} \text{pmin} & = & \text{minimum price (\$/bu)} \\ \text{quant} & = & \text{contract size (bu).} \end{array}$$

The net settlement value of the minimum price contract at harvest is

$$\text{value} = \text{quant} * (\max(\text{pmin}, \text{ploc}) - \text{ploc}).$$

5.6 Multiple Peril Crop Insurance Contract

When buying a multiple peril crop insurance contract, the user must specify:

$$\begin{array}{lcl} \text{pfcic} & = & \text{FCIC expected price (\$/bu)} \\ \text{acres} & = & \text{acres insured (a)} \\ \text{yaph} & = & \text{APH yield (bu/a)} \\ \text{yelect} & = & \text{yield election (\%)} \\ \text{pelect} & = & \text{price election (\%)} \\ \text{premium} & = & \text{premium rate (\$/a)} \end{array}$$

The net settlement value of a multiple peril crop insurance contract at harvest is

$$\text{value} = \text{acres} * (\max(0, \text{ycrit} - \text{yfarm}) * \text{pcrit} - \text{premium}).$$

where

$$\text{pcrit} = \text{pfcic} * \text{pelect}$$

$$\text{ycrit} = \text{yaph} * \text{yelect}$$

are the critical price ($/bu) and critical yield (bu/a), respectively.

5.7 Crop Revenue Coverage Insurance Contract

When buying a crop revenue coverage insurance contract, the user must specify:

pbase	=	base price ($/bu)
acres	=	acres insured (a)
yaph	=	APH yield (bu/a)
cover	=	coverage level (%)
crclim	=	price rise limit ($/bu)
premium	=	premium rate ($/a)

The net settlement value of a crop revenue coverage insurance contract at harvest is

$$\text{value} = \text{acres} * (\max(0, \text{revguar} - \text{cropval}) - \text{premium})$$

where

$$\text{pcrc} = \min(0.95 * \text{pcbot}, \text{pbase} + \text{crclim})$$

$$\text{revguar} = \text{cover} * \text{yaph} * \max(\text{pbase}, \text{pcrc})$$

$$\text{cropval} = \text{yfarm} * \text{pcrc}$$

are the CRC harvest price ($/bu), the CRC revenue guarantee ($/a), and the CRC crop value ($/a), respectively.

5.8 Income Protection Insurance and Revenue Assurance Contract

When buying either an income protection insurance or revenue assurance contract, the user must specify:

pproj	=	projected price ($/bu)
acres	=	acres insured (a)
yaph	=	APH yield (bu/a)
cover	=	coverage level (%)
premium	=	premium rate ($/a)

The net settlement value of an income protection insurance or revenue assurance contract at harvest is

$$\text{value} = \text{acres} * (\max(0, \text{revguar} - \text{cropval}) - \text{premium})$$

where

$$\text{cropval} = \text{yfarm} * \text{pcbot}$$

$$\text{revguar} = \text{cover} * \text{yaph} * \text{pproj}$$

are the crop value ($/a) and the revenue guarantee ($/a), respectively.

5.9 Group Risk Plan Contract

When buying group risk plan insurance, the user must specify:

pfcic	=	FCIC expected county price ($/bu)
acres	=	acres insured (a)
yexp	=	expect county yield (bu/a)
cover	=	coverage level (%)
premium	=	premium rate ($/a).

The net settlement value of group risk plan insurance contract at harvest is

$$\text{value} = \text{acres} * (\max(0, \text{ycrit} - \text{ycnty}) * \text{pfcic} - \text{premium})$$

where

$$\text{ycrit} = \text{cover} * \text{yexp}$$

is the critical yield (bu/a).

6 AgRisk Program Structure

The AgRisk program consists of a dynamically linked user interface and simulation engine. The user interface, which is written in Visual Basic, consists of a series of subroutines that manage all input and output to the screen. The simulation engine, which is written in Fortran 90, performs all model calibration and simulation computations. The flow of the AgRisk program is illustrated in the figure below, with interface routines indicated by (I) and engine routines indicated by (E). Brief synopses of the main routines follows.

```
START
  |
  v
GET_USER_FARM_MARKET_DATA (I)
GET_NASS_PRICE_YIELD_DATA (I)
BUILD_REVENUE_SIMULATION_MODEL (E)
GEN_PRICE_YIELD_DISTRIBUTION (E)
OUTPUT_PRICE_YIELD_DISTRIBUTION (I)
GET_USER_STRATEGY (I) <---------------
SIMULATE_REVENUE_MODEL (E)           |
GENERATE_REVENUE_DISTRIBUTION (E)    |
OUTPUT_REVENUE_DISTRIBUTION (I)      |
DONE? --------------no----------------
  |
 yes
  |
  v
EXIT
```

GET_USER_FARM_MARKET_DATA: Obtain acreages and historical farm yields, location, and market discount rate, futures price, options premia, options strike price, and buy-sell spread from user.

GET_NASS_PRICE_YIELD_DATA: Obtain regional and national yield data, historical price basis ratios and demand elasticities from yield database accompanying AgRisk.

BUILD_REVENUE_SIMULATION_MODEL: Using historical price and yield data, and current market data, build a stochastic simulation model of national-, county-, and farm-level yields, and of local and CBOT prices.

GEN_PRICE_YIELD_DISTRIBUTION: Takes simulated prices and yields and generates kernel-smoothed probability densities and cumulative distribution functions.

OUTPUT_PRICE_YIELD_DISTRIBUTION: Prints probability distribution of prices and yields.

GET_USER_STRATEGY: Obtains contract specifications for a risk management strategy from user.

SIMULATE_REVENUE_MODEL: Using revenue simulation model, simulates net revenues under the current risk management strategy.

GENERATE_REVENUE_DISTRIBUTION: Takes simulated net revenues and their probabilities and generates the kernel-smoothed probability density and cumulative distribution functions of revenue, together with the mean, standard deviation, and 5, 10, and 20% quantiles of the revenue distribution.

OUTPUT_REVENUE_DISTRIBUTION: Prints to screen the probability density and cumulative distribution functions of revenue, together with the mean, standard deviation, and 5, 10, and 20% quantiles of the revenue distribution.

7 Conclusion

AgRisk continues to be improved and extended in a collaborative project between The Ohio State University and the University of Illinois. Extensions planned in the near future include the introduction of additional crops, including cotton, rice, and barley. Also, wheat will be disaggregated into winter and spring wheat. AgRisk data bases, which currently run only through 1996 will be updated, hopefully to include 1998 yield and price data. The simple polynomial yield detrending scheme also will be replaced with more accurate, state-of-the-art time series methods. Finally, the AgRisk project will conduct "beta testing" sessions throughout the Midwest to obtain input from users regarding the optimal way to organize and present the user interface. The most recent version of AgRisk may always be downloaded from the AgRisk website, www-agecon.ag.ohio-state.edu/agrisk.

References

Judd, Kenneth L. *Numerical Methods in Economics*, MIT Press:Cambridge, MA, 1998.

Law, Averill M. and W. David Kelton,*Simulation Modeling and Analysis*, McGraw-Hill: New York, 1982.

Miranda, Mario J. and Paul D. Fackler,*Computational Economic Dynamics*, Manuscript, The Ohio State University, 1999.

Taylor, C. Robert, "A Flexible Method for Empirically Estimating Probability Functions." *Western Journal of Agricultural Economics*, 9(1984):61-76.

King, R.P., J.R. Black, F.J. Benson, and P.A. Pavkov "The Agricultural Risk Management Simulator Microcomputer Program." *Southern Journal of Agricultural Economics*, 20(1988):165-71.

Appendix: Data Sources

The AgRisk simulation model is constructed from empirical price and yield data, most of which is stored in the AgRisk program database and the rest of which is supplied by the AgRisk user. Specifically, to construct the farm-level yield-price simulation model, AgRisk requires annual data on the local harvest price, national harvest price, national planting-time futures price, national yield, county yield, and farm yield.

The present implementation of AgRisk comes with its own database of local harvest prices, national harvest price, national planting-time futures price, national yield, and county yields for the period 1972-96. The AgRisk database includes Chicago Board of Trade planting-time futures prices and harvest prices for corn, soybeans, wheat, and sorghum over the period. The AgRisk database also includes National Agricultural Statistical Service yields for all corn, soybean, and wheat producing counties in Kansas, Illinois, Indiana, Iowa, Minnesota, Missouri, Montana, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin over the period, as well as state and national yields for these states and crops.

The AgRisk user inputs his or her own farm yield data. If the farmer inputs less than three years of data, AgRisk rejects it, assumes that the farmer's yields are identical to the county yields, and prints a message to the user warning that the data substitution has taken place.