INCOME PROTECTION

Technical Report

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This report presents the principles of the income protection (IP) insurance policy as well as the procedures used to estimate the corresponding premia. An overview of the income protection concept is presented first. A general description of the rating procedure is presented followed by a technical discussion of the data and the statistical equations used in the premia estimations. Fortran code used in the rating process is provided in three appendices.

The Income Protection Policy

The income protection policy (IP) insures producers against low income events due to either low yields and/or low prices. In contrast to the traditional multiple peril insurance, however, the income protection policy will not provide indemnities if yields are low but prices are sufficiently high so that revenues exceeds the payment trigger levels. Conversely, the income protection policy will pay indemnities at higher yield levels in years when prices are low enough to reduce revenues to levels below payment trigger levels. Figure 1 graphically contrasts the situations in which the income protection policy would pay out to the current yield insurance payouts. In both cases, the assumed APH yield is 100 units with an expected prices of $2 per unit of output. Both the yield and IP payment triggers are assumed to be 75% of the mean values.

Figure 1
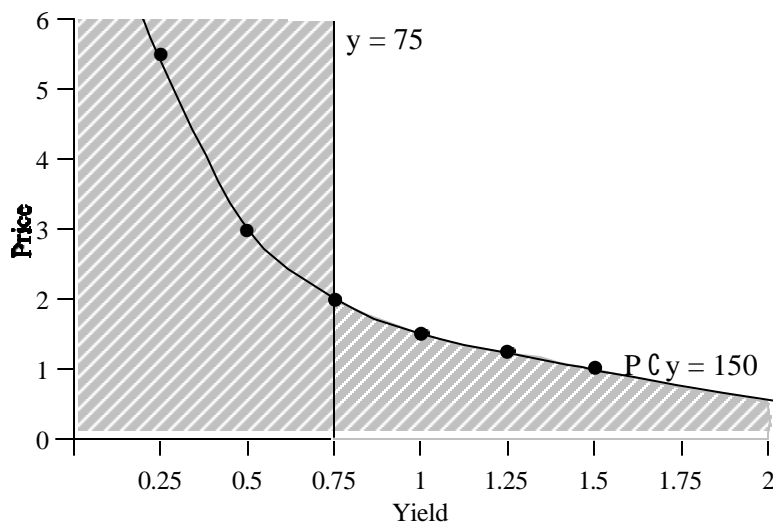
The current multiple peril yield insurance incurs indemnities whenever yields fall below 75%, regardless of the price received for the quantity actually produced. If prices are high enough to offset the yield loss, the revenues received from the crop may exceed $150 (75% of the expected gross return) with the producer receiving additional indemnities further increasing income. These events are graphically demonstrated by the area above and to the right of the curve, $PY = 150$, and to the left of the line, $Y = 75$.

If producers are concerned with low revenue events rather than low yield events, the producer would be more concerned with events below the curve, $PY = 150$. Thus a producer who would elect IP coverage would be forgoing payments associated with events to the left of the line, $Y = 75$, but below the curve $PY = 150$.

The payout distribution and hence the actuarily neutral premia associated with each policy will differ and will depend upon the joint probability density function of price and yield. The remainder of this report will describe the procedures used to estimate the joint distribution of prices and yields as well as the procedures used to estimate the actuarily neutral premia.

Basic Procedures

The procedures used to rate this product are somewhat involved. Figure 2 is a flow chart which graphically portrays the steps involved in the process. In this section we present an overview of the process described in the flow chart. In the following section a more detailed mathematical description is presented. The order of the presentation follows the steps of the flow chart in both discussions.

Steps 1 and 3. The prospective buyer is required to provide from four to ten years of yield history data on the farm's total acres grown in the county (units are not allowed in the IP pilot). If the producer does not have four years of data the appropriate t-yields are assigned. The producer is also required to provide the years associated with each reported yield. The producer's yields are used to calculate the normal APH yields and the revenue trigger levels.

Step 2. The model uses four additional sets of data in the rate-making process: (1) national or regional yield data [from National Agricultural Statistics Service (NASS)], (2) futures price data, (3) county yield data [NASS], and (4) panel or cross-sectional time series data on producer yields.

Steps 4 and 5. The national or regional yield series is used to estimate the yield trend. The estimated yield trend is then imposed on each county series of that crop. Figures 3, 4, and 5 graphically present the national yields and estimated trend for corn, spring wheat, and southeastern cotton, respectively. A discussion of the technical aspects of the estimation is presented later.

For each county we use a long yield history to more accurately estimate the frequency and severity of regional events, which cannot be adequately captured in 4–10 years of level data. The estimated national trend is imposed upon the county yield series. Figures 6–12 graphically portray representative county yields as well as the estimated trend for each of the counties reported. The rating procedure adjusts for differing productivity between counties by estimating separate intercepts for each county. Figure 13 contrasts the county yields in Benton County, Indiana to those of Adair County, Iowa. It is apparent that the county yields of Benton County are higher than those in Adair County. The estimated differences in the mean yields, after accounting for trend, is about 13 bushels per acre.

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In each county examined, the yield variability increases with expected county yields. To account for this heteroskedasticity, the county yields are converted to proportions. This is accomplished by dividing the actual county yield by the predicted county yield. Figures 14–20 graphically present the resulting proportions as a percent of the predicted yield. It is apparent that these geographically dispersed counties have experienced different regional events. When estimating premia, the long-term history of proportional deviations is used to estimate the likelihood of regional events.

Steps 6 and 7. APH farm level data from the Federal Crop Insurance Corporation (FCIC) is used to estimate the additional producer level yield variability beyond that contained in the long-term county yield series. It is assumed that the relative farm level variability around the county yields has remained unchanged across time. Data was extracted from FCIC's APH files for all farms reporting 8 (for corn and wheat) or 6 (for cotton) or more years of APH yields for each county. Each farm's yields were used to estimate that farm's average yields as a proportion of the county's expected yield. (This process is discussed more fully later in the report.) Farm level proportional errors are then regressed on the county proportional errors. This process decomposes total farm level proportional variability into two parts: events affecting the entire county and the remaining farm level variability. This residual farm level variability is recombined with the longer term county variability when premia are estimated.

The individual farms' data (from step 1) is also converted to proportional yields and a mean proportion computed. This mean proportion is the farm's yield as a proportion of the expected county yield. Hence, if a farm's yield were 120%, or 1.2 times the actual county yield for 4 years, the farm's expected proportion would be 1.2, or 120%. As will be noted in following examples, the resulting expected yield of the farm will usually not be the same as the farm's APH yield, which was used to

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determine the revenue payment trigger levels. The rating process adjusts rates to account for this possible divergence.

Step 8. Historical futures price data are used to estimate the variability in prices. Corn prices are based on the December corn contract on the Chicago Board of Trade (CBOT). Wheat uses the September CBOT contract, while cotton uses the December contract on the New York Cotton exchange. The process for corn is as follows: (1) At the time of sign-up, the February average of the December futures price is multiplied by the APH yield and used to determine the indemnity trigger levels. In the fall, the November average of the December futures prices is multiplied by the producer's yield to determine the revenue to count. (Cotton uses the average price from last two weeks of January and the first two weeks of February. Wheat uses the average of February futures prices.)

Thirty-five years of historical futures market data are used to estimate the probability distribution of price changes from February to November for the December futures price. Historical prices were calculated and inflated to 1995 purchasing power units. An examination of the data indicated that the presence of price stabilization loan rates significantly reduced the variability of potential price movements in years when prices were close to the loan rates. To account for the effect of loan prices upon price variability, the historical deviations were scaled up for those years. The scaled price deviations are then regressed upon county yield deviations to account for the correlation between price and the county's yield. The process decomposes the variation in prices into two parts, that associated with county yield variability and a residual variation.

Steps 9–13. The above steps estimate various parameters which are used to estimate actuarily neutral premia. However, the estimates of the parameters are themselves random variables. The

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precision with which these variables can be estimated varies with the length of the corresponding data sets as well as the structure of the statistic itself. (It is well known that the variance of an estimated sample mean decreases with increases in sample size.) When estimated statistics are used to estimate premia, an additional source of uncertainty enters the rate making process. Bootstrapping is a robust nonparametric statistical procedure that substitutes computer power for often intractable mathematical analysis. Premia are adjusted to account for the degree of parameter uncertainty inherent in the data set. Hence, other things equal, a farm with four years of APH yields will pay a slightly higher premia than will a farmer with 8 years of APH data due to the increased uncertainty with respect to the farm's mean yield levels.

Bootstrapping is essentially a Monte Carlo process which first regenerates a number of samples using the assumed statistical process and then reestimates the statistical parameters of interest. The distribution of the reestimated statistics is used to approximate the distribution of the original parameter estimates. After the original statistics are estimated in steps 4–8, a sample representing the entire process is regenerated in steps 9–13. The statistics of interest are reestimated in steps 4–8. The process is repeated until 200 sets of reestimated parameters are obtained.

Steps 14–21. Upon completion of the 200th reestimation, the model estimates the premia by completing 10,000 simulations of yield, price, and revenues using the parameters and variability from steps 4–13. After 10,000 simulations, actuarily neutral premia are calculated as the average payout over the simulations. Loads and subsidies are added to obtain the final premia for quote.

The above discussion summarizes the premia estimation process. The following section presents a more detailed mathematical description of the rating procedures. Numerical examples are also presented, which demonstrate certain key concepts in the rating process.

A Mathematical Description

National Yield Trend (Step 4). Due to heteroskedasticity, the national yield trend parameter is estimated using three stage least squares as follows.

Regress:

$$N_t = \hat{b}_1^N + \hat{b}_2^N t + \hat{u}_t^N \tag{1}$$

where N_t is the national yield in year t, $\hat{b}_1^N \ and \ \hat{b}_2^N$ are estimated national parameters, and $\hat{u}_t^N$ is the estimated residual. There are T years of national yield data.

Regress:

$$*\hat{u}_t^N* = \hat{a}_1^N + \hat{a}_2^N t + \hat{v}_t^N \tag{2}$$

where $*\hat{u}_t^N*$ is the absolute value of the original residuals.

Predict:

$$\hat{au}_t = \hat{a}_1^N + \hat{a}_2^N t \tag{3}$$

where $\hat{au}_t$ is the predicted absolute value of the original residual.

Construct the transformed variables:

$$\tilde{N}_t = N_t / \hat{au}_t$$

$$\tilde{1}_t \ ' \ 1/a\hat{u}_t \tag{4}$$

$$\tilde{t}_t \ ' \ t/a\hat{u}_t$$

Regress:

$$\tilde{N}_t \ ' \ \hat{b}_1^N \tilde{1}_t \ \% \ \hat{b}_2^N \tilde{t}_t \ \% \ \tilde{e}_t^N \tag{5}$$

where $\hat{b}_2^N$ is the estimated trend after accounting for heteroskedasticity.

For the later bootstrap sample regeneration, construct

$$\hat{N}_t \ ' \ \hat{b}_1^N \ \% \ \hat{b}_2^N t \tag{6}$$

The County Model (Step 5)

Let $C_s = 1, ..., S$, be the county yield series over S years. Again, three-stage least squares is used to estimate the desired parameters.

Compute:

$$cds \ ' \ C_s \ ! \ \hat{b}_2^N s \tag{7}$$

where CDs is the difference between the observed county yield and $\hat{b}_2^N s$ for year s.

Estimate the intercept term as

$$\hat{a}_1^C \ ' \ \frac{1}{S} \ \overset{S}{\underset{s'1}{:}} \ cds \tag{8}$$

Construct:

$$\hat{C}_s \ ' \ \hat{a}_1^C \ \% \ \hat{b}_2^N s \tag{9}$$

$$c\tilde{d}s \ ' \ cds/\hat{C}_s \tag{10}$$

$$\tilde{1}_s \ ' \ 1/\hat{C}_s$$

Estimate:

$$c\tilde{d}s \quad ' \quad \hat{a}_1^c \; \tilde{1}_s \; \% \; \tilde{e}_s^c \tag{11}$$

using least squares, where $\hat{a}_1^C$ is the estimated intercept after accounting for heteroskedasticity and $\tilde{e}_s^C$ is the estimated proportional county error. To facilitate later estimates, construct:

$$\hat{C}_s \quad ' \quad \hat{a}_1^C \; \% \; \hat{b}_2^N s \tag{12}$$

and

$$\tilde{C}_s \quad ' \quad C_s / \hat{C}_s. \tag{13}$$

The Panel Data (Step 6)

The panel data consists of historic APH yields as recorded in the FCIC's data base. Let y_q^f be the reported APH yield for farm $f = 1, ..., F$ in year q. Let Q^f be the number of observations reported by farm f. In the data base, Q^f is far less than the number of observations available on the county data but there are usually many farm level observations (F of them for each year in the data series).

The rate making process uses information contained in the county data series to adjust for the representativeness of the years for which the producer reports yields. This process is demonstrated with a numerical example. Figure 21 presents the last 10 years of Benton County, Indiana corn yields. An examination of Figures 8 and 16 indicate that the years 1988 and 1991 were two of the three lowest county yield events (as a percent of the expected trended yield) in the past 50 years. A farmer whose APH yield series contains the years 1988 and 1991 would have seen the farm's APH average yield drop substantially. Given the information within the county yield series and assuming the farm is a

member of the county pool, the farm's simple APH average yield is biased downward as an estimate of the farm's true expected yield.

The rate making process adjusts the premia to account for the potential bias. The following discussion presents the procedures used to account for the information contained in the county series concerning the representativeness of the farm's yield series. The process is completed for each farm in the panel data and later for the individual purchasing insurance. To proceed, compute:

$$\underline{\tilde{C}}^f \ ' \ 1/Q_f \ ' \ \sum_q \tilde{C}_q^f \tag{14}$$

for each farm where $\tilde{C}_q^f$ is the county yield proportion (from (13)) for year q as reported by farm f, and Q^f is, again, the number of observations reported by farm f. $\underline{\tilde{C}}^f$ is the average of the $\tilde{C}$ values for the years reported by producer f.

Construct:

$$\tilde{y}_q^f \ ' \ y_q^f / (\hat{C}_q \ \underline{\tilde{C}}^f) \tag{15}$$

and

$$\underline{\tilde{y}}_f \ ' \ (1/Q_f) \ ' \ \sum_q \tilde{y}_q^f \tag{16}$$

where, again, y_q^f is the yield for farm f in year q and $\hat{C}_q$ is the predicted county yield for year q. The expression $\tilde{y}_q^f$ is a transformed yield proportion that has been normalized for the representativeness of the county yields in the years reported by the producer. The value $\underline{\tilde{y}}_f$ is the average farm yield proportion as a proportion of the expected county yield.

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To demonstrate the above process, consider the values in Table 1. The table contains county data from Benton County Indiana as well as data from a hypothetical farm. The farms' yields, y_f, are 120%, or 1.2 times the county yields in each year. The table demonstrates the effect of the years reported on the farms' estimated APH yield as well as the $\tilde{\underline{y}}_f$ values (from (16)), which is termed the proportional APH. In the table the notation used is CHAT = $\hat{C}_q$, CTILD = $\tilde{C}_q^f$, CTILDHAT = $\tilde{\underline{C}}^f$, and Yf = y_q^f. If only the last four years are used, the estimated yield APH of the farm is 167.3, while $\tilde{\underline{C}}^f \approx 0.99098$. The latter number indicates that the county yields for the years 1992–1995 are approximately centered on the trend line. The resulting APH yield is not likely to be very biased as a prediction of the farm's yield (if trend is accounted for). Note that the proportional APH or $\tilde{\underline{y}}_f \approx 1.2$, as would be expected given that farm yields were, by construct, 1.2 times the county yield.

When eight years of data are used to calculate the APH, the result is considerably different. In this case, the abnormally low yields from 1988 and 1991 result in a APH yield of 149.0—more than eighteen bushels below the result when four years are used. Similarly, $\tilde{\underline{C}}^f$ now equals 0.90487, indicating that county yields for 1988–1995 are centered about 10% below the trend line. The resulting APH yields is now biased downward even after adjusting for trend. The proportional APH, or $\tilde{\underline{y}}_f$ again equals 1.2 as should be the case given the construct of the example farm yield series.

The implications of the above example are potentially serious. By construct, the actual expected yield and the yield distribution is the same in both cases at 120% of the expected county yield. Yet with the current APH rules, the two cases would result in different revenue trigger levels which correspond to different percentages of the producer's expected revenue, conditional upon information contained in the county data. The IP rates are adjusted to account for the different revenue percentages actually being insured. The estimation process continues as follows.

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Construct:

$$\tilde{u}_q^f \doteq \tilde{y}_q^f \,!\, \underline{\tilde{y}}_f \tag{17}$$

and regress

$$\tilde{u}_q^f \doteq \hat{b}_1^f \,\%\, \hat{b}_{2|}^f \bigl(\tilde{C}_q^f \,!\, \underline{\tilde{C}}^f \bigr) \,\%\, \tilde{e}_q^f. \tag{18}$$

The above process decomposes the farm level proportional variation into two components: (1) that explained by the county proportional variation and (2) the remaining uncorrelated variability. To facilitate the bootstrapping exercise, construct

$$\hat{u}_q^f \doteq \hat{b}_1^f \,\%\, \hat{b}_{2|}^f \bigl(\tilde{C}_q^f \,!\, \underline{\tilde{C}}^f \bigr). \tag{19}$$

The Individual Farm's Data (Step 7)

A similar process is completed for the insured's yield history. Let Z_i be the farm's yield in year I with I total observations. As before, construct:

$$\underline{\tilde{C}} \doteq \frac{1}{I} \,\dot{}\, \sum_i \tilde{C}_i \tag{20}$$

$$\tilde{Z}_i \doteq Z_i /_{\bigl(} \hat{C}_i \underline{\tilde{C}}_{\bigr)} \tag{21}$$

$$\underline{\tilde{Z}} \doteq \frac{1}{I} \,\dot{}\, \sum_i \tilde{Z}_i \tag{22}$$

and

$$\hat{u}_i \doteq \hat{b}_1^f \,\%\, \hat{b}_{2|}^f \bigl(\tilde{C}_i \,!\, \underline{\tilde{C}}_{\bigr)} \qquad \text{(for bootstrapping only)} \tag{23}$$

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The Price Model (Step 8)

Let pd_u, $u = 1, ..., U$, be U scaled price deviations. To estimate the relationship between price deviations and yield deviations, regress:

$$pd_u \ ' \ \hat{b}_1^P \ \% \ \hat{b}_2^P (C_u \ ! \ \hat{C}_u) \ \% \ \hat{e}_u^P \tag{24}$$

where $\hat{b}_1^P$ and $\hat{b}_2^P$ are estimated parameters, C_u is the county yield in year u, $\hat{C}_u$ is the predicted county yield in year u, and $\hat{e}_u^P$ is the estimated deviation remaining after accounting for the county yield deviations. To facilitate the bootstrapping, construct:

$$\hat{pd}_u \ ' \ \hat{b}_1^P \ \% \ \hat{b}_2^P (C_u \ ! \ \hat{C}_u) \tag{25}$$

Bootstrapping New "Samples"

Bootstrapped samples are regenerated as follows.[1]

National Yields. For the original T years and for $j = 1, 2, ..., 200$

<   Draw $\tilde{e}_{t,j}^N$ (from (5)) with replacement.

<   Construct $N_{t,j} \ ' \ \hat{N}_t \ \% \ \hat{au}_t (\tilde{e}_{t,j}^N)$. $\qquad\qquad\qquad$ (26)

        where $\hat{N}_t$ is obtained from (6) and $\hat{au}_t$ is from (3).

County Yields. For the original S years and $j = 1, 2, ..., 200$

<   Draw $\tilde{e}_{s,j}^C$ (from (11)) with replacement.

<   Construct $C_{s,j} \ ' \ \hat{C}_s \ \% \ \hat{C}_s \tilde{e}_{s,j}^C \ ' \ \hat{C}_s(1 \ \% \ \tilde{e}_{s,j}^C)$ $\qquad$ (27)

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[1] Space prevents a complete discussion of the bootstrapping literature. The interested reader is referred to the articles in the reference list.

where $\hat{C}_s$ is from (9).

<u>Panel Data</u>. For each of the F farms and Q_f observations per farm

<   Draw $\tilde{e}^f_{q,j}$ from (18) with replacement.

<   Construct $y^f_{q,j} \; ' \; \{\underline{\tilde{y}^f} \; \% \; \hat{u}^f_q \; \% \; \tilde{e}^f_{q,j}\} \{ \hat{C}_q \; \underline{\tilde{C}^f}\}$

$$(14).$$

where $\tilde{y}^f$ is from (16), $\hat{u}^f_q$ is from (19), $\hat{C}_q$ is from (9), and $\underline{\tilde{C}^f}$ is from

<u>Individual Data</u> For the I observations,

<   Draw $\tilde{e}_{i,j}$ from (18) with replacement.

<   Construct $Z_{i,j} \; ' \; \{\underline{\tilde{Z}} \; \% \; \hat{u}_i \; \% \; \tilde{e}_{i,j}\} \{ \hat{C}_i \underline{\tilde{C}}\}$ (29)

where $\underline{\tilde{Z}}$ is from (22), $\hat{u}_i$ is from (23), $\hat{C}_i$ is from (9), and $\underline{\tilde{C}}$ is from (20).

<u>Price Data</u>. For the U observations,

<   Draw $\hat{e}^P_{u,j}$ from (24) with replacement.

<   Construct $pd_{u,j} \; ' \; p\hat{d}_u \; \% \; \hat{e}^P_{u,j}$ (30)

As can be seen by an examination of (1)–(30), the regenerated bootstrapped samples are

constructed by reversing the original estimation transformations with resampled errors. For each of the RHS j system samples the parameters $\hat{b}^N_j$, $\hat{a}^C_{1,j}$, $\hat{b}^C_j$, $\hat{b}^f_j$, $\underline{\tilde{Z}}_j$, and $\hat{b}^P_j$ are reestimated using the

variables from the original regressions. The reestimated parameter estimates are used to approximate

the uncertainty in the original parameter estimates.

Before proceeding to a discussion of the revenue simulation it should be noted that the code

distributed to vendors does not actually complete all the estimations described above. To reduce

execution time the resulting parameter estimates and residuals were written to data files. In addition, the

large and varying (by county) number of observations in $\tilde{e}_q^f$ (from (18)) were mapped into an inverse cumulative density function (CDF) from which the errors used in the simulations are actually drawn. The process involved in doing so is included in the code presented in Appendix C.

Simulating the Distribution of Revenue

Actuarily neutral premia are estimated using the above parameter estimates and estimated residuals. Ten thousand possible revenue realizations were generated and used to estimate the expected payouts and the resulting premia. The possible revenue levels are generated as follows. The assumed year is S. The variable names correspond to the variable names in the attached code.

The Bootstrap Number

<   Randomly draw j from the integers 1, ..., 200 with replacement.

County Yield

<   Draw $\tilde{e}_S^C$ from (11) with replacement.

<   Construct $\text{ychats} = \hat{a}_1^C \% \hat{b}_2^N S$ (31)

$$\text{ychatsj} = \hat{a}_{1,j}^C \% \hat{b}_{2,j}^N S \qquad (32)$$

$$\text{ycts} = \text{yctsj} \; ' \; (1 \% \tilde{e}_j^C) \qquad (33)$$

$$\text{ycs} = \text{ychats} \; (\; \text{ycts} \qquad (34)$$

$$\text{ycsj} = \text{ychatsj} \; (\; \text{yctsj} \qquad (35)$$

In the above, as well as the following expressions, the variable names ending with j represent the estimated or forecast levels of the associated variable if the jth bootstrapped parameter estimate had been used in lieu of the original parameter estimates.

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<u>Individual Yield</u>

<   Draw $\tilde{e}_S^f$ from (18) (actually from the inverse CDF function described above).

<   Construct   us $= \hat{b}_{2,}^f\, \text{ycts} \,!\, 1, \,\%\, \tilde{e}_S^f$ (36)

                       usj $= \hat{b}_{2,j,}^f\, \text{yctsj} \,!\, 1, \,\%\, \tilde{e}_S^f$ (37)

$$\tilde{Z}_S = \text{yits} \,{}^{\backprime}\, \underline{\tilde{Z}} \,\%\, \text{us} \tag{38}$$

$$\tilde{Z}_{S,j} = \text{yitsj} \,{}^{\backprime}\, \underline{\tilde{Z}}_j \,\%\, \text{usj} \tag{39}$$

$$Z_S = \text{yitsj} \,(\, \text{ychatsj} \tag{40}$$

<u>Price Model</u>

<   Draw e_u^P from (24)

<   Construct   dpns $= \hat{b}_{2,}^P\, \text{ycs} \,!\, \text{ychats}, \,\%\, e_u^P$ (41)

                     dpnsj $= \hat{b}_{2,j,}^P\, \text{ycsj} \,!\, \text{ychatsj}, \,\%\, e_u^P$ (42)

$$\text{pns} = \text{fp} + \text{dpns} \tag{43}$$

$$\text{pnsj} = \text{fp} + \text{dpnsj} \tag{44}$$

where fp is the spring average price.

<u>Revenue</u>

<   Construct   revs $= \text{pns} \,(\, Z_S$ (45)

$$\text{revsj} = \text{pnsj} \,(\, Z_{S,j} \tag{46}$$

$$\text{rev} = \text{revs} + (\text{revs} \,!\, \text{revsj}) \tag{47}$$

where rev is the simulated revenues. Expression (47) can be explained by recognizing what the

bootstrap process actually does. The bootstrap is essentially a Monte Carlo study which uses the

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originally estimated parameters as the actual parameters. With these known parameters a new sample

is generated and new parameters estimated. During the simulation process, alternative values are

generated that differ only in the bootstrapped parameter estimates, which vary from the original

parameter estimates. However, in the bootstrapped sample the original parameter estimates were

actually the true values of the parameters from which the samples were generated. Hence, in the Monte

Carlo exercise, a value generated with the original estimates, revs is the "true" value, while the estimate,

revsj, is the "forecast" value using the jth possible set of parameter estimates. In the Monte Carlo

study, the "forecast error" is the "actual" value less the "forecast" value, or

$$\text{"forecast error"} = revs\ !\ revsj. \tag{48}$$

In reality, the original forecast revs is merely a "forecast value," which itself has an associated

forecast error. Since we cannot obtain a description of the true forecast error structure, the "forecast

error" from the Monte Carlo exercise is used, i.e.,

$$rev = revs + \text{"forecast error"} \tag{49}$$

or

$$rev = revs + (revs\ !\ revsj) \tag{50}$$

For a more detailed (and perhaps clearer) discussion of these concepts, the reader is referred to the

paper by Prescott and Stengos.

The above process is repeated to generate 10,000 possible revenue realizations. Actuarily

neutral premia are computed as the average payout for a given revenue trigger.

The estimated premia are loaded by .88. If the producer elects to purchase insurance at a level less than 65% of the APH revenue level, the subsidy is set at 60% of the 50% revenue premium. At election levels of 65% or higher, the subsidy is set at 75% of the 50% revenue premia.
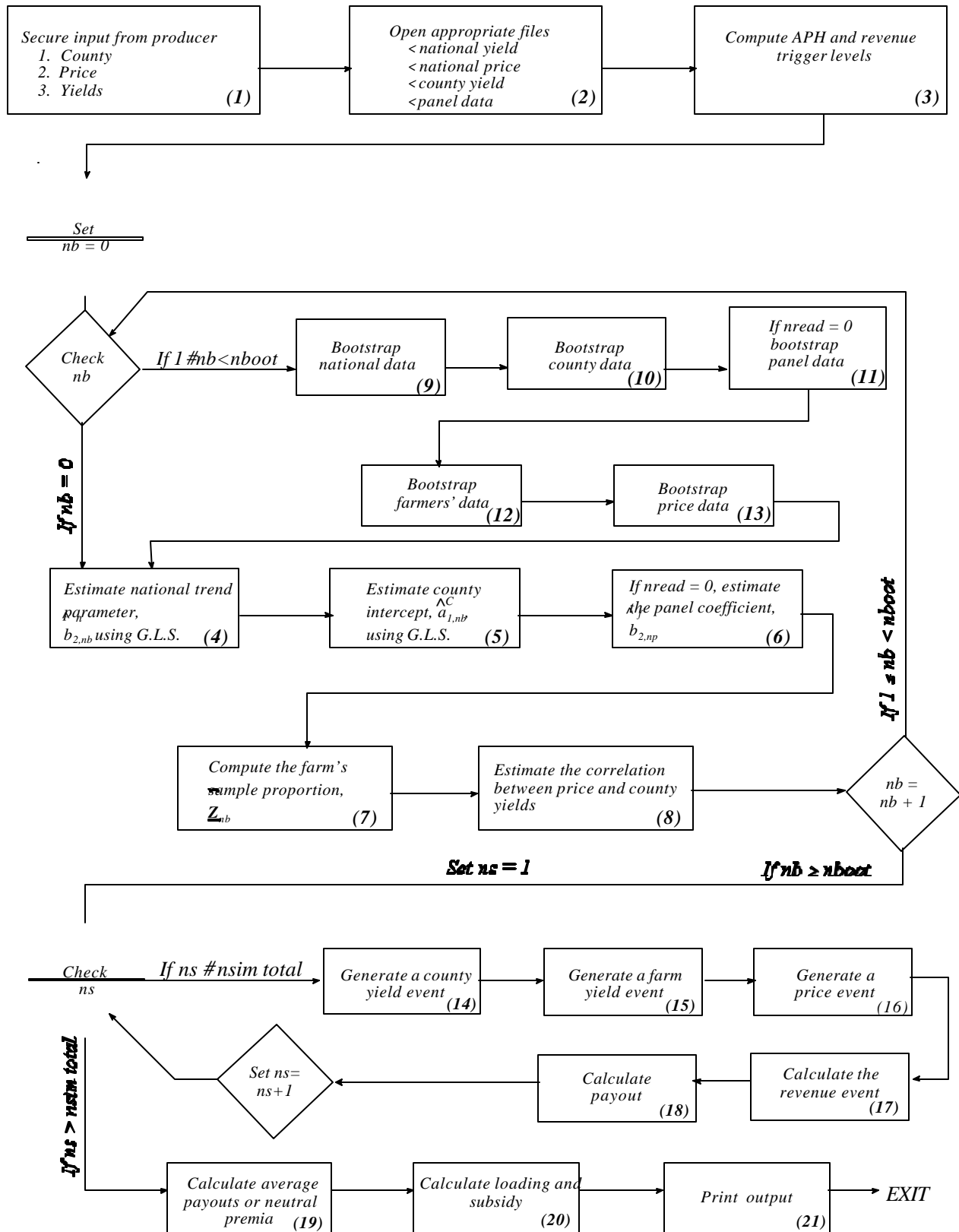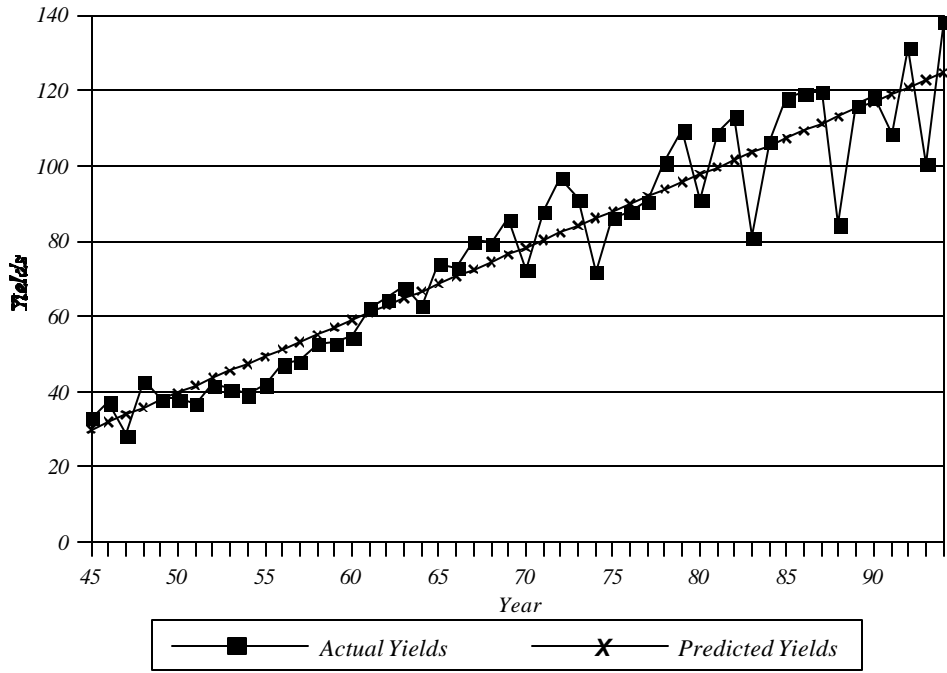
FIGURE 2

FIGURE 2

| Secure input from producer
1. County
2. Price
3. Yields *(1)* | → | Open appropriate files
< national yield
< national price
< county yield
< panel data *(2)* | → | Compute APH and revenue trigger levels *(3)* |

Set $nb = 0$

Check nb — If $1 \leq nb < nboot$ →

Bootstrap national data *(9)* → Bootstrap county data *(10)* → If nread = 0 bootstrap panel data *(11)*

If $nb = 0$

Bootstrap farmers' data *(12)* → Bootstrap price data *(13)*

Estimate national trend parameter, $b_{2,nb}$ using G.L.S. *(4)* → Estimate county intercept, $\hat{a}^{C}_{1,nb}$, using G.L.S. *(5)* → If nread = 0, estimate the panel coefficient, $b_{2,np}$ *(6)*

If $1 \leq nb < nboot$

Compute the farm's sample proportion, $\underline{Z}_{nb}$ *(7)* → Estimate the correlation between price and county yields *(8)* → $nb = nb + 1$

Set $ns = 1$ If $nb \geq nboot$

Check ns — If $ns \leq nsim\ total$ → Generate a county yield event *(14)* → Generate a farm yield event *(15)* → Generate a price event *(16)*

If $ns > nsim\ total$

Set $ns = ns+1$ ← Calculate payout *(18)* ← Calculate the revenue event *(17)*

Calculate average payouts or neutral premia *(19)* → Calculate loading and subsidy *(20)* → Print output *(21)* → EXIT

FIGURE 3

National Corn Yields

FIGURE 4

National Wheat Yields

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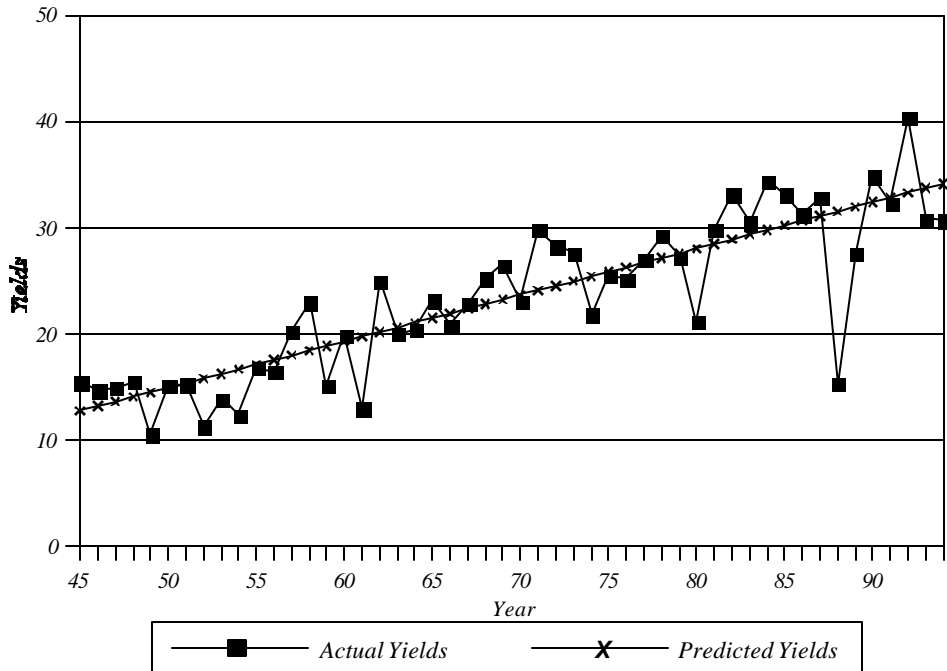
FIGURE 5
Southeastern Cotton Yields
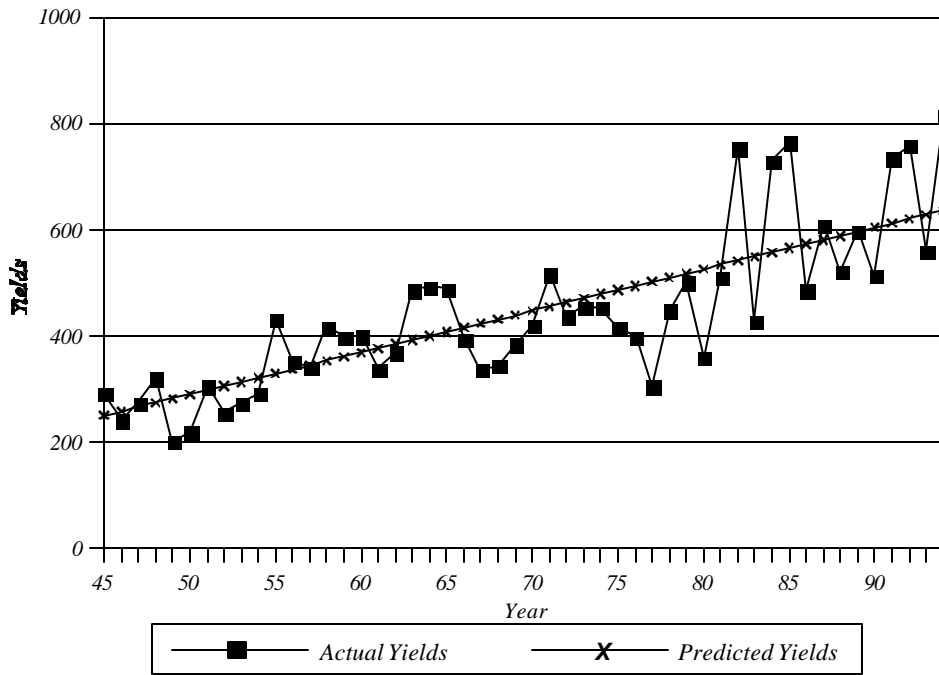
FIGURE 6: CORN YIELDS
Champaign County, Illinois

21
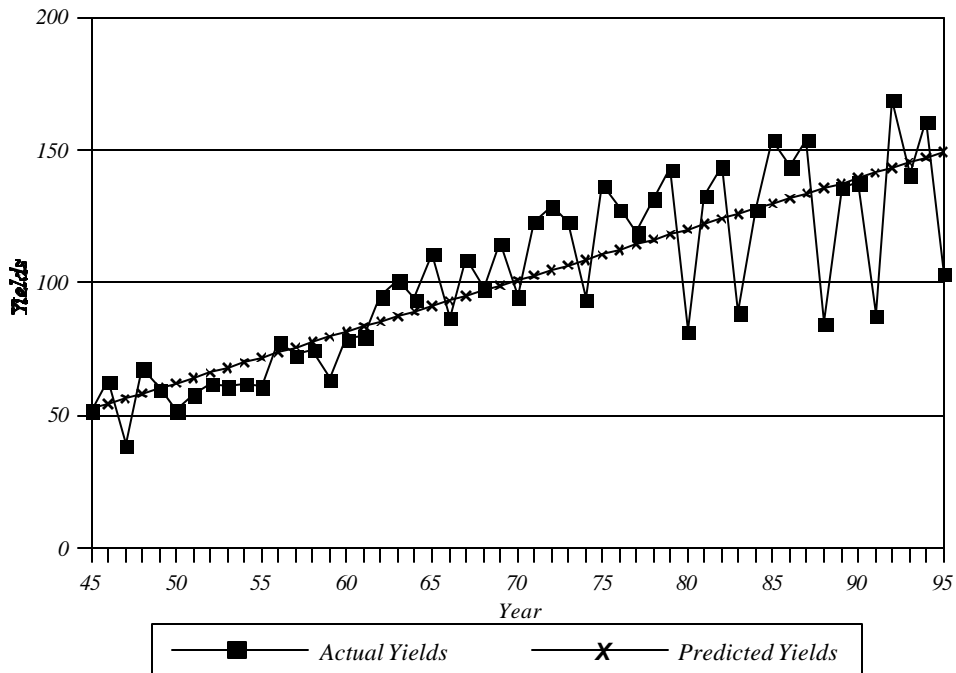
FIGURE 7: CORN YIELDS

Adair County, Iowa

Actual Yields   Predicted Yields
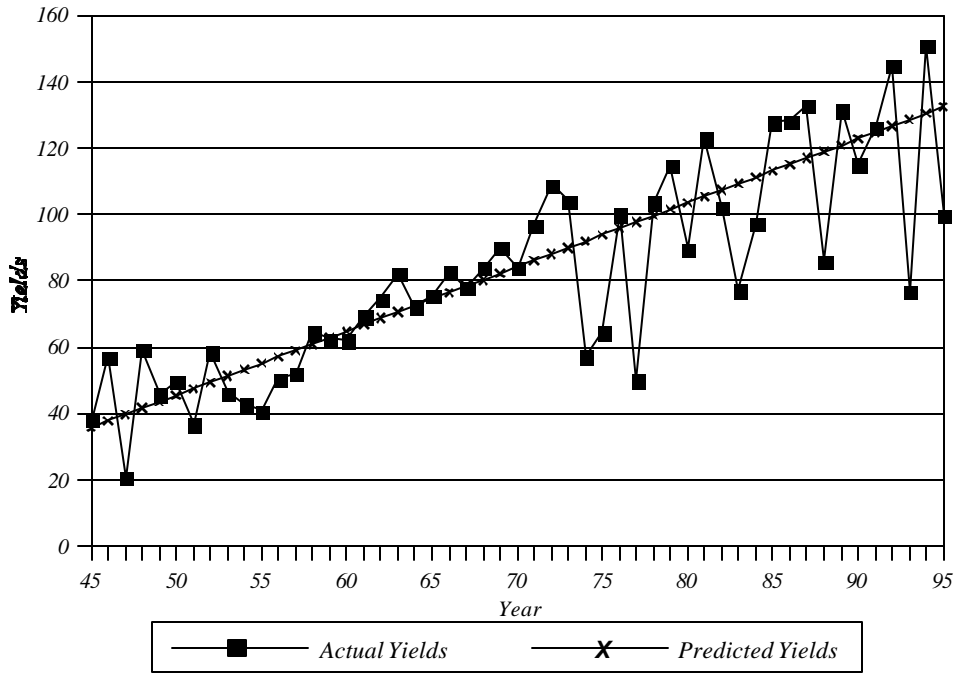
FIGURE 8: CORN YIELDS

Benton County, Indiana

Actual Yields   Predicted Yields

22
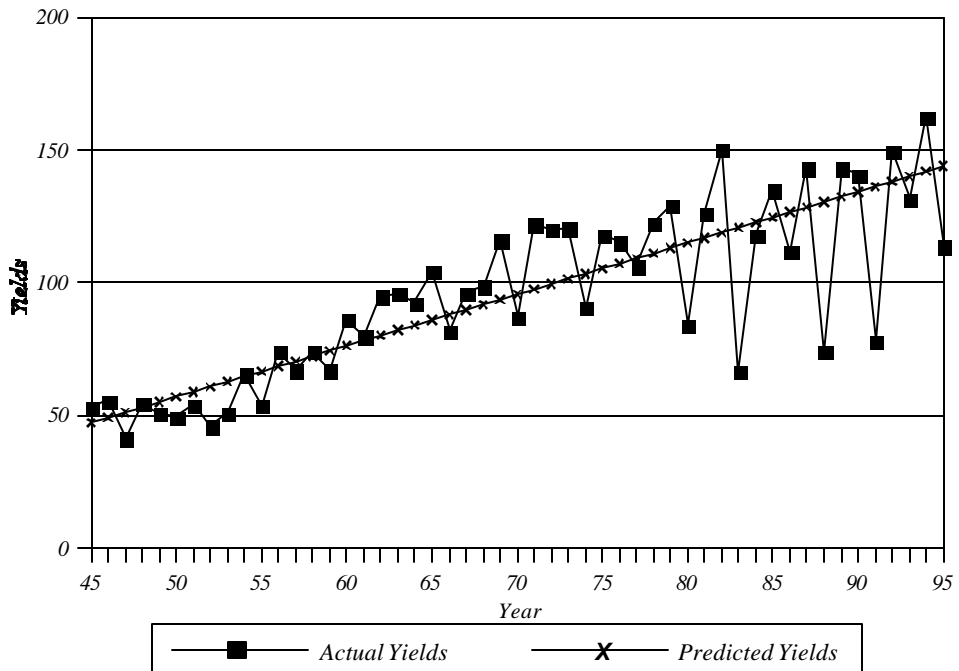
FIGURE 9: WHEAT YIELDS
Kittson County, Minnesota

Year

■ *Actual Yields* ✕ *Predicted Yields*
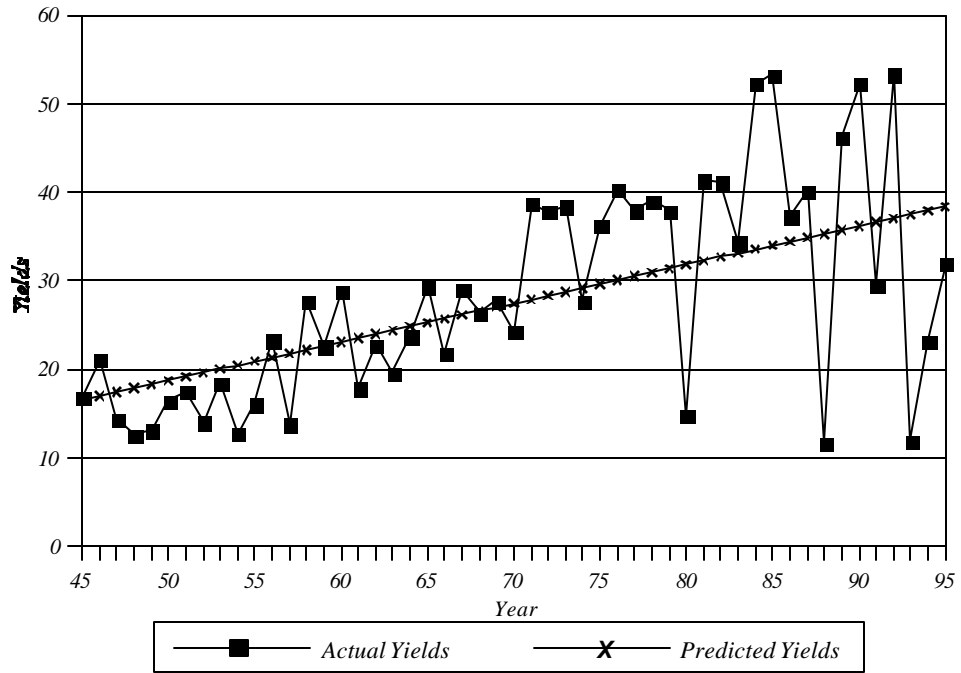
FIGURE 10: WHEAT YIELDS
Grand Forks County, North Dakota

Year

■ *Actual Yields* ✕ *Predicted Yields*

23
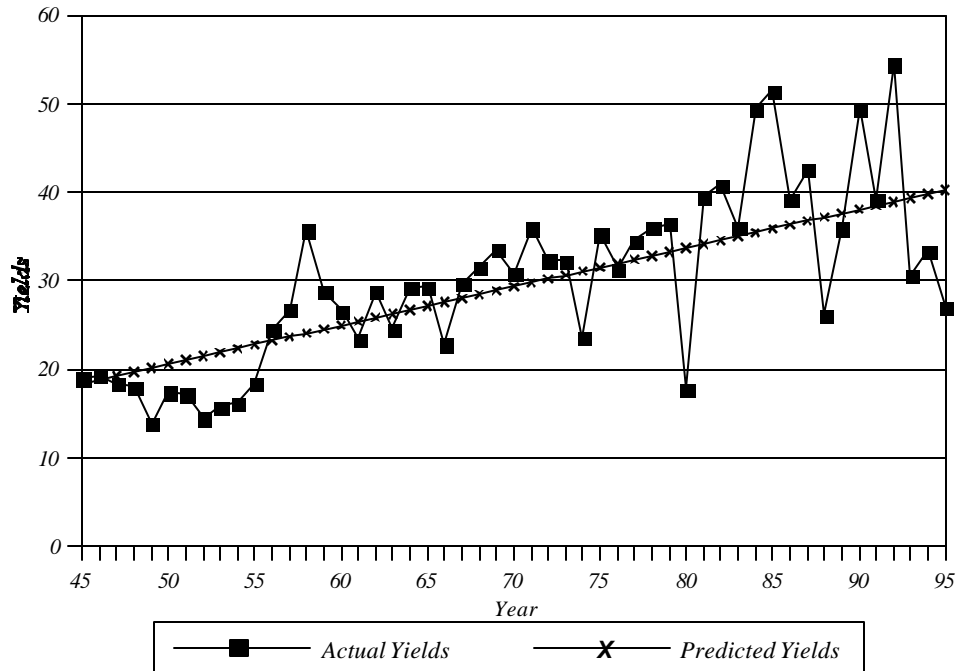
FIGURE 11: COTTON YIELDS

Alabama
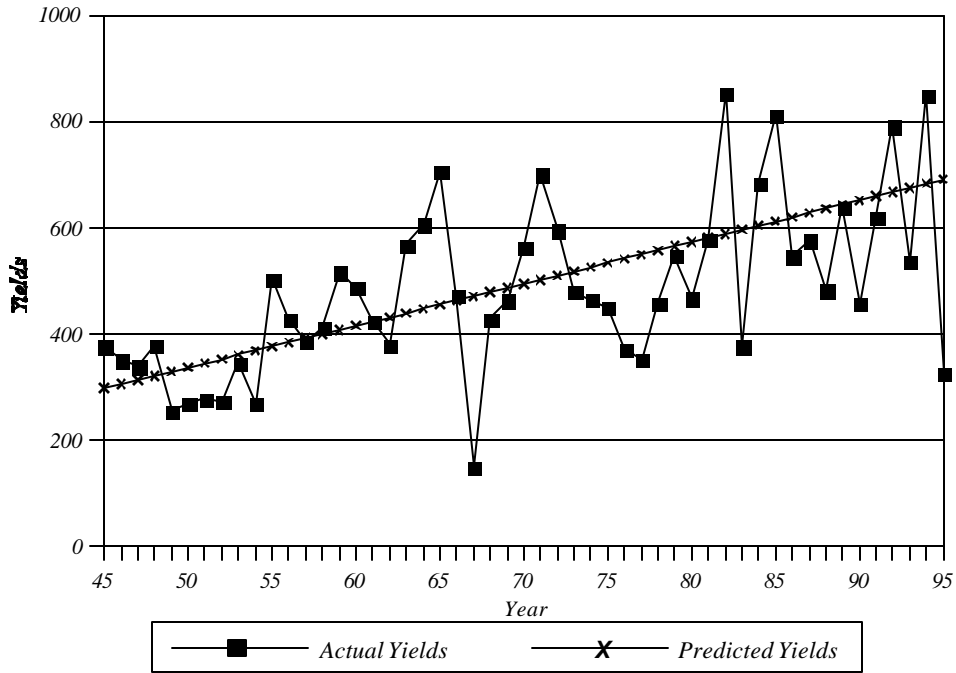
FIGURE 12: COTTON YIELDS

Georgia

24
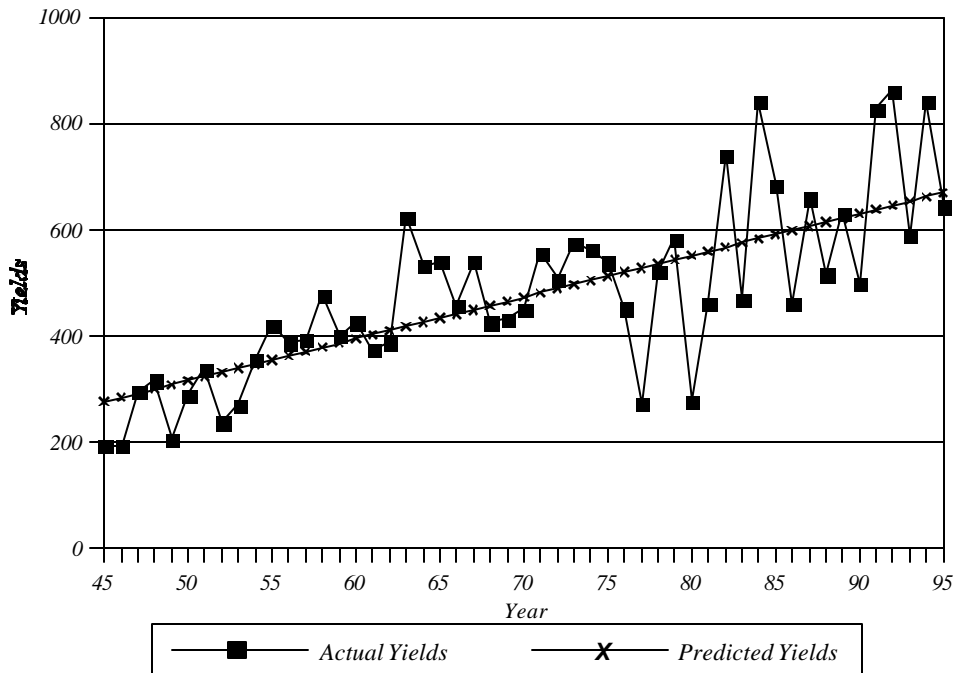
FIGURE 13: CORN YIELDS
Adair County, Iowa and Benton County, Indiana

Legend:
- Adair Co., Actual Yields
- Adair Co., Predicted Yields
- Benton Co., Actual Yields
- Benton Co., Predicted Yields
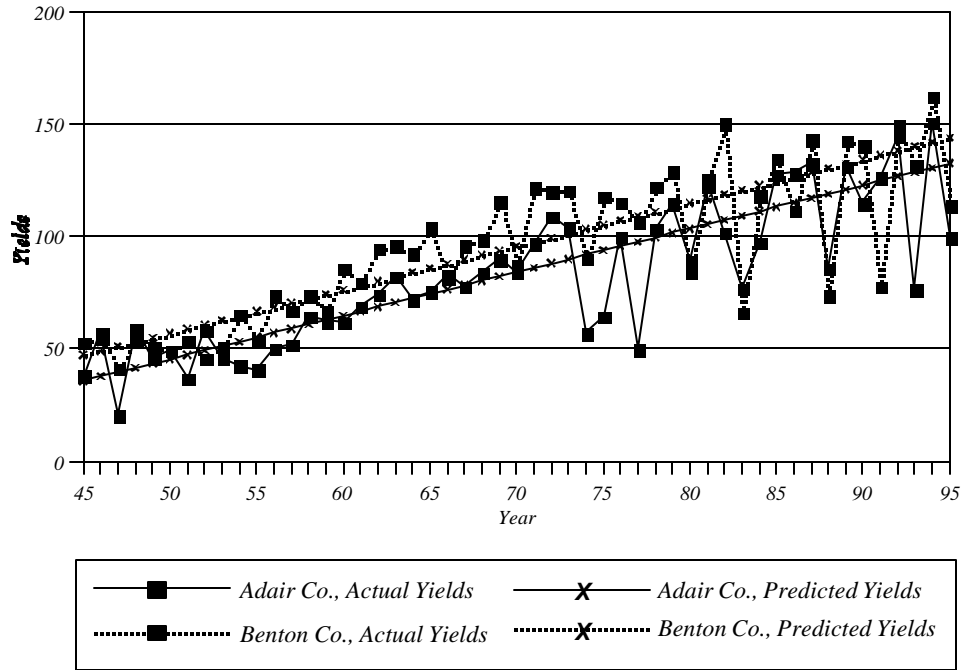
FIGURE 14: PROPORTIONAL CORN YIELDS
Champaign County, Illinois

25
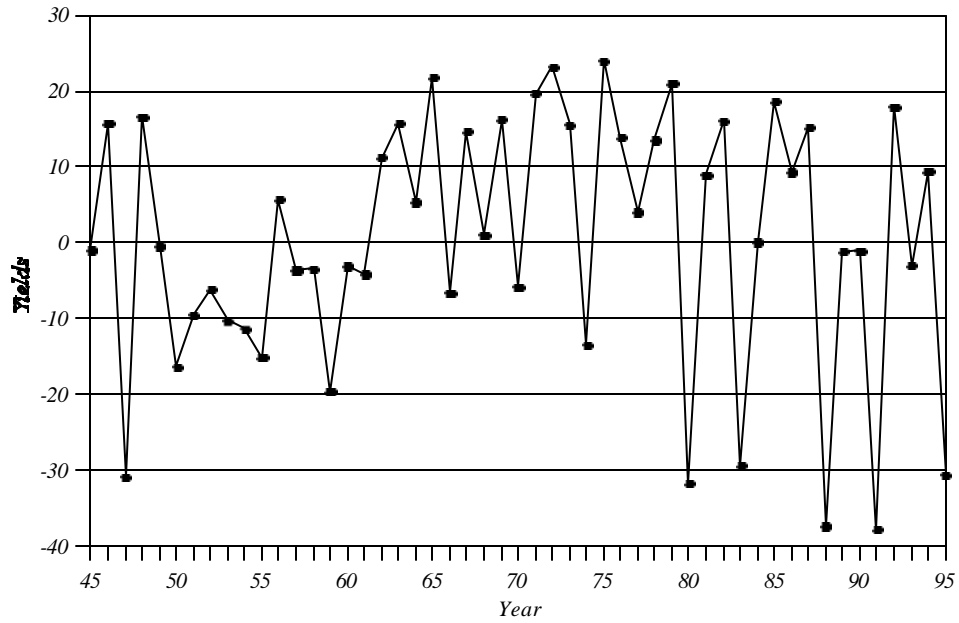
FIGURE 15: PROPORTIONAL CORN YIELDS
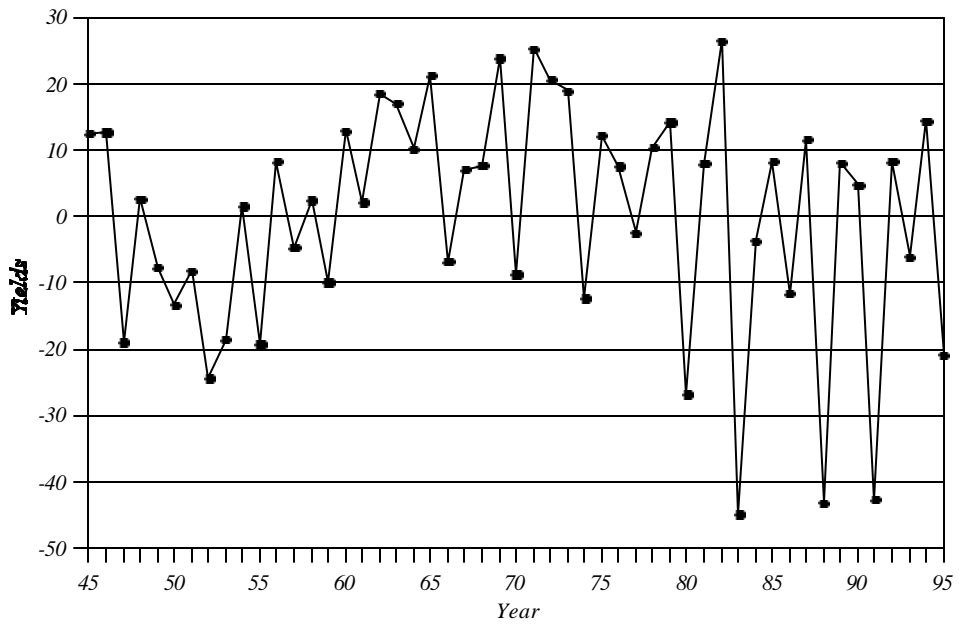### Adair County, Iowa
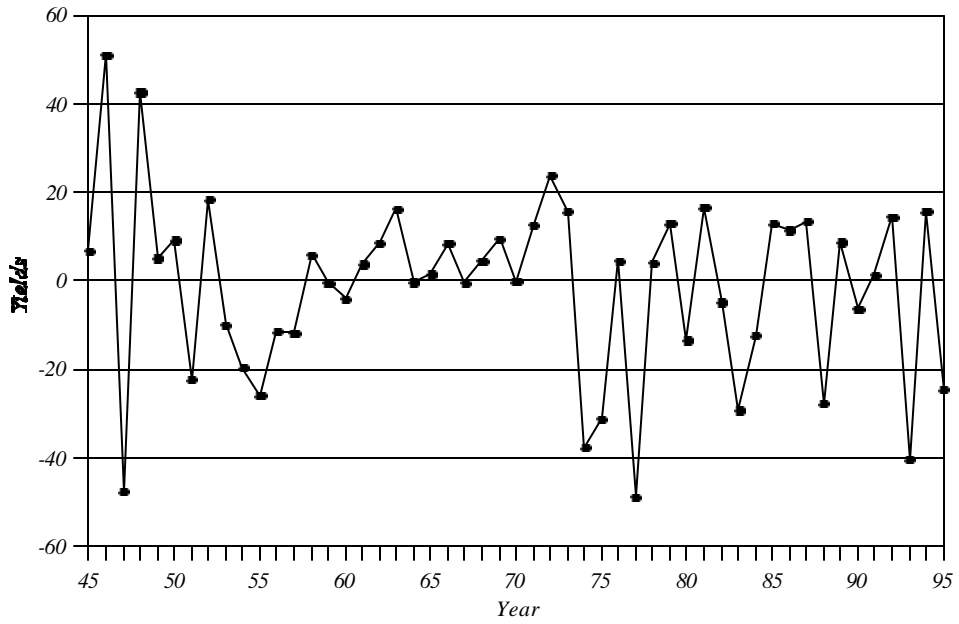
FIGURE 16: PROPORTIONAL CORN YIELDS
Benton County, Indiana

26

FIGURE 17: PROPORTIONAL WHEAT YIELDS
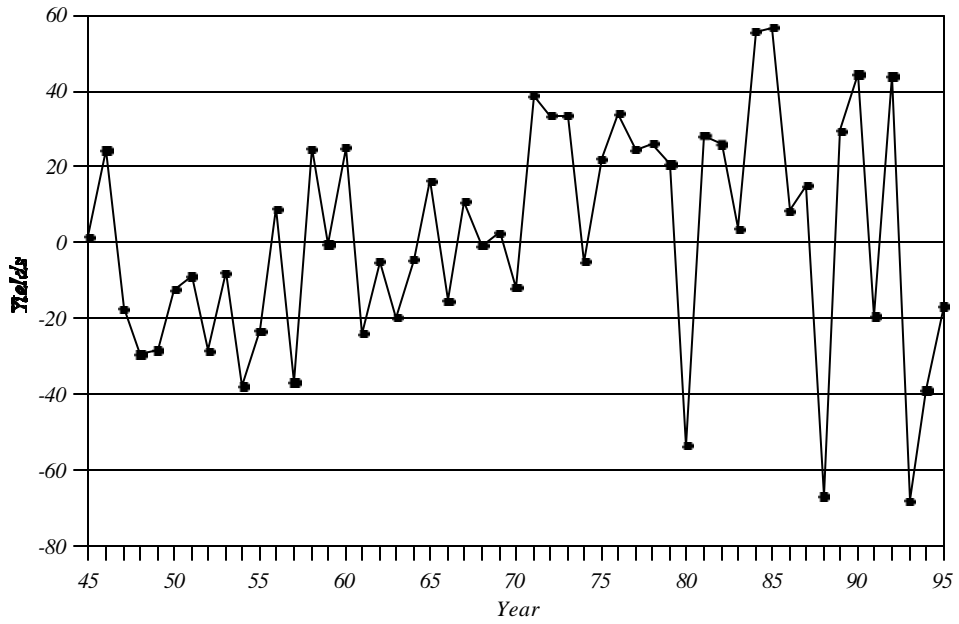### Kittson County, Minnesota

FIGURE 18: PROPORTIONAL WHEAT YIELDS
Grand Forks County, N. Dakota

27
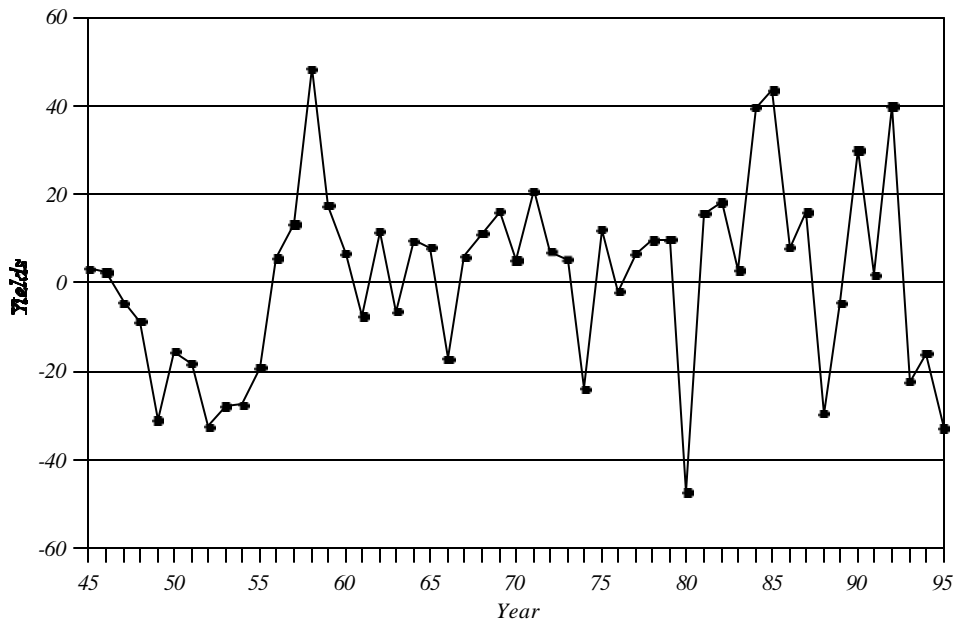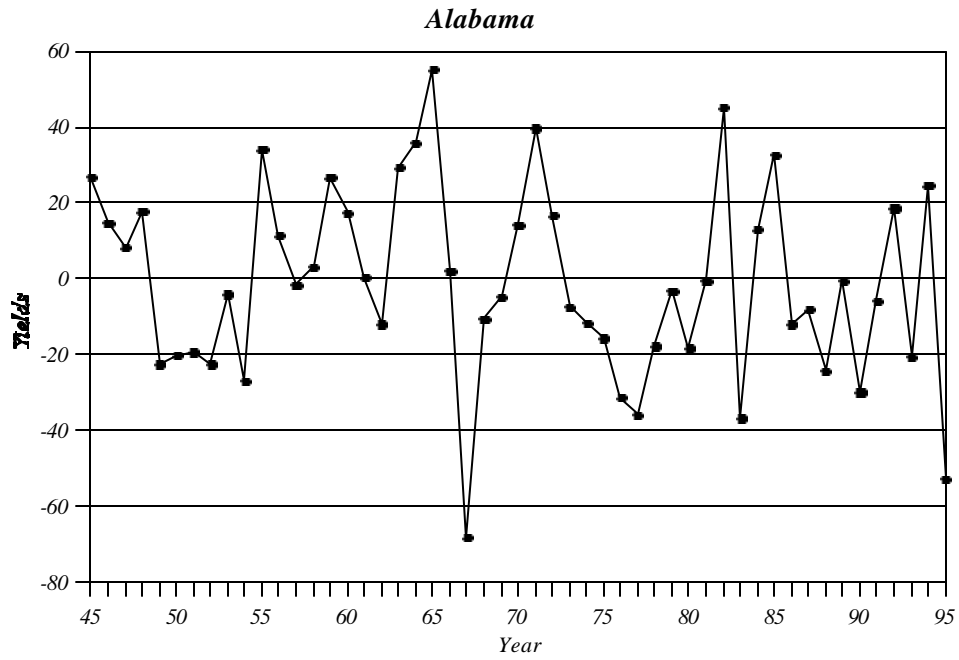
FIGURE 19: PROPORTIONAL COTTON YIELDS

Alabama

FIGURE 20: PROPORTIONAL COTTON YIELDS
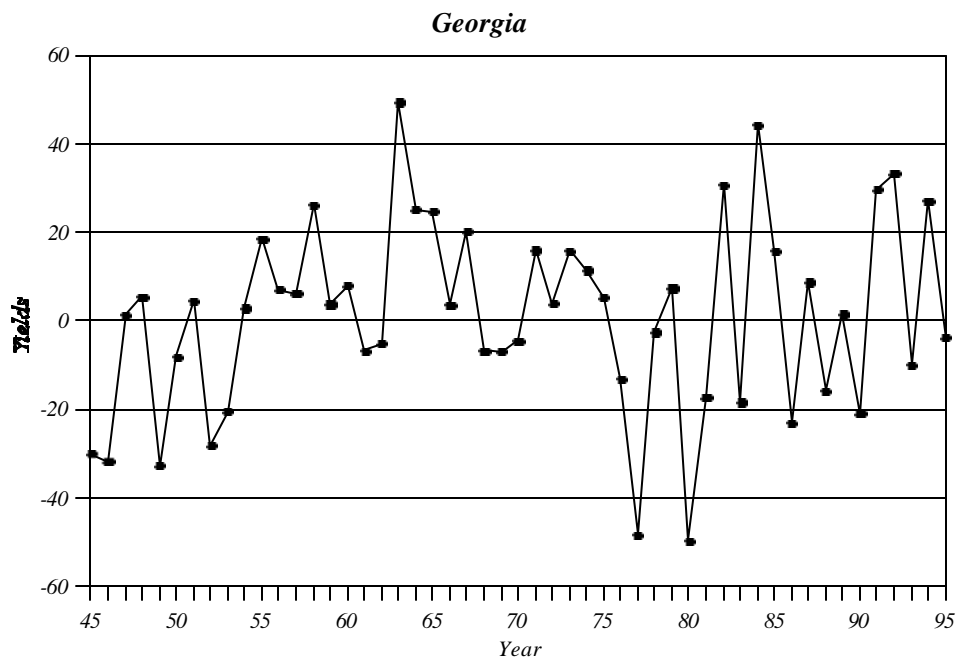
Georgia

28

FIGURE 21
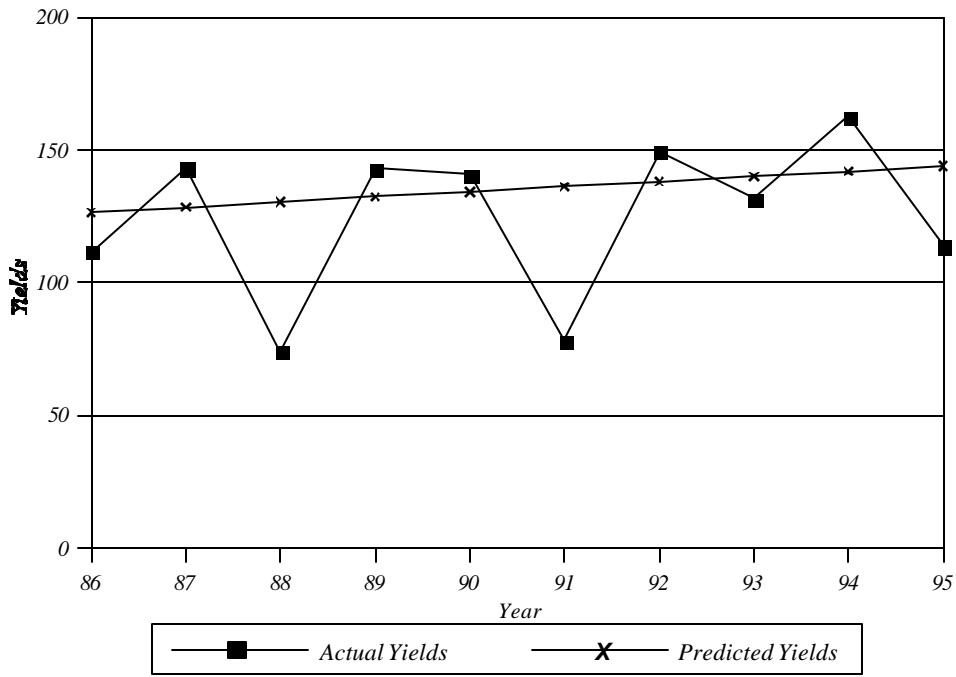
Benton County, Indiana

TABLE 1

Example APH Calculations and Premia Adjustment, Benton County, Indiana

Example with four years in the APH history

Years	C	CHAT	CTILD	Yf	$\dfrac{Yf}{CHAT \cdot CTILDHAT}$
1995	113.9	143.73	0.7925	136.7	0.9596
1994	162.5	141.80	1.1460	195.0	1.3877
1993	131.6	139.87	0.9409	157.9	1.1394
1992	149.6	137.93	1.0846	179.5	1.3133
CTILDHAT			0.99098		
YIELD APH				167.3	
PROPORTIONAL APH					1.2
ESTIMATED PREMIUM PER ACRE					$13.17

Example with eight years in the APH history

Years	C	CHAT	CTILD	Yf	$\dfrac{Yf}{CHAT \cdot CTILDHAT}$
1995	113.9	143.73	0.7925	136.7	1.0509
1994	162.5	141.80	1.1460	195.0	1.5198
1993	131.6	139.87	0.9409	157.9	1.2478
1992	149.6	137.93	1.0846	179.5	1.4383
1991	78.1	136.00	0.5743	93.7	0.7616
1990	140.6	134.07	1.0487	168.7	1.3908
1989	143.1	132.14	1.0830	171.7	1.4362
1988	74.1	130.20	0.5691	88.9	0.7547
CTILDHAT			0.90487		
YIELD APH				149.0	
PROPORTIONAL APH					1.2
ESTIMATED PREMIUM PER ACRE					$5.92

SELECTED READINGS ON BOOTSTRAPPING

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Jinook, J. and G.S. Maddala. "A Perspective on Application of Bootstrap Methods in Econometrics." In *Handbook of Statistics*, vol. 2, editors: Maddala, Rao, and Vinod. Amsterdam: North Holland, 1993, p. 573–610.

Prescott, D.M. and T. Stengos. "Bootstrapping Confidence Intervals: An Application to Forecasting the Supply of Pork." *American Journal of Agricultural Economics* 69(1987): 266–73.