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Modeling Trend and Higher Moment Properties of U.S. Corn Yields

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The random nature of crop yields warrants careful attention by agricultural economists. Many economic decisions rest on the particular probability model used, including both aggregate policy prescriptions as well as micro-level risk management strategies. Concerns at the aggregate level include the apparent increase in the variability of production in major food and feed crops (Hazell) and its subsequent implications for buffer stock management and orientation of research effort. At the micro level there is evident interest in decision aids that use simulation models such as ARMS (King).

The most significant feature of the behavior of crop yields in this century has been their persistent increases. This feature has been most pronounced in corn, particularly with the introduction of hybrid varieties in the 1940s and 1950s. The upward trend, while persistent, has not necessarily been linear in time. This paper is concerned with the problem of modeling this trend. Ultimately what is desired is a model of crop yield behavior that can be used in simulation modeling of the effects of alternate decision strategies. In order to achieve this goal attention must first be given to the modeling of mean yields and how these have changed over time. Once this is done, the issues involved in modeling higher moment properties of yields can be addressed.

The topic of crop yield probability models is not new. Previous studies include those by Lin, Hildreth and Terfertiller and by Lutrell and Gilbert that address the serial correlation properties of crop yields. A pioneering study by Day focused on the importance of skewness in yield distributions, while Gallagher recently examined the capacity concept in yields. A number of researchers have directly addressed the question of modeling trends in yields, including Swanson and Nyankori (1979, 1981); Kogan; and McClelland and Vroomen. In addition a number of studies have attempted to identify specific factors affecting yields including fertilizer, weather, and acreage effects, treating trend as a residual effect (Thompson; Butell and Naive; Lin and Davenport; Merz and Pardey; Teigen; and Vroomen and Hanthorn).

Without exception these papers used one of two methods to model trend in yields. A few use a simple moving average approach (typically a centered 9 year moving average), while the majority use a deterministic function of time, generally linear or quadratic. There are a number of drawbacks to these approaches and a need for alternatives. Recently stochastic trend models have been developed that avoid a number of the problems inherent in using other methods. These models can be thought of as fitting local linear approximations to trend. A low dimensional set of hyperparameters that can be estimated using maximum likelihood methods control the balance between local and global linearity. The linear trend model is a nested special case.

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While fairly simple and parsimonious, such models are able to capture a wide range of behavior.

The paper proceeds as follows. First, a number of general aspects of trend decomposition and the behavior of the specific model used here are discussed. The specific model is then applied to the problem of estimating mean aggregate U.S. corn yields over the period 1929-86. Next are some comments on the interpretation of the trend component, followed by an examination of higher moment properties of corn yields.

Aspects of Trend Decompositions

The decomposition of observed time series into unobserved components representing trend, cycles, seasonalities and irregulars has a long history (Nerlove, Grether, and Carvalho). This paper focusses on the trend component, ignoring the issues of seasonality and cycles. Specifically examined is the case in which a time series y_t of yields is observed over n periods. It is assumed that $y_t = s_t + e_t$, with s_t being a trend component and e_t being a white noise process. A common method for obtaining an estimate of s_t is to employ a linear smoother based on a weighted moving average of the y_t series, i.e., an estimator that takes the form $S = WY$, where S and Y are (nx1) vectors and W is an (nxn) matrix of weights that are independent of Y.

A number of properties have been suggested as being desirable in trend estimators, including the imposition of population moment conditions on the sample. Typically two assumptions are made concerning S and E: (1) that $E[e_t] = 0$ and (2) $E[s_t e_t] = 0$. Imposing (1) on the estimator of W implies that $(Y-WY)'i = 0$, where $i = (1...1)'$. To hold for any Y it must be the case that $W'i = i$. Condition (2) implies that $(WY)'(Y-WY) = 0$, which, in turn, implies that $W'W = W$. Given (1) this imposes that the correlation between s_t and e_t is zero. This is the orthogonality condition discussed by Judge, et al. (pp. 259-62), and Maddala (pp. 338-40); it is equivalent to the joint condition that $W' = W$ and $W^2 = W$ (symmetry and idempotency). While the symmetry condition has no obvious heuristic rationale, the idempotency condition can be interpreted as ensuring that an estimated trend component will not "contain" an irregular component.

It is arguable that a more important feature in a trend estimator is flexibility in the shapes that can be fit. Typically, however, the decomposition into trend and irregular components carries with it the implication that the trend component represents long run behavior due to forces that exhibit persistence. One way to view the problem of trend estimation, therefore, is as a balancing act between smoothness and flexibility.

The elements of the ith row of W are the set of weights used to average Y to obtain the trend component for the ith observation. In general a trend estimator will be flexible if the greatest weight used to determine the ith trend component is put on the ith observation of Y and the weights decline as abs(i-j) increases. Smoothness, on the other hand, is ensured if each row of W is similar to those nearby.

Finally, the word trend connotes that the current direction of movement in the series can be used to extrapolate future movent in the same direction.

The linear trend model represents the most simple example of such behavior and has become the norm in empirical trend decomposition. The slope parameter can be interpreted as the expected rate of change of the series and the implied forecast function is linear with respect to the forecast horizon.

It is a standard result the orthogonality property is satiafied by any trend component derived from a simple regression model (i.e., any model for which $s_t = X_t\beta$, with $W = X(X'X)^{-1}X'$). In particular, a model of trend as a polynomial in time will satisfy these properties. Polynomials in time, however, suffer from several drawbacks. First, fit can be quite poor unless enough terms included. Second, it is difficult to relate model parameters to intuitions concerning the underlying economic forces affecting yields, particularly when enough parameters are included to provide good fit. Finally, nonlinear polynomial models often imply forecast functions that are explosive, even for short forecast horizons.

A second type of trend model often encountered is the moving average model. Simple moving average models take the trend component to equal the simple average over some specified number of periods. Centered moving averages are the most satisfactory for estimating a historical trend component but even these suffer from three problems. First, it is unclear how the initial and end periods should be handled (often they are dropped). Second, there is no generally acceptable method to determine the number of terms to be included in the average. Third, there is no clear method for generating forecasts. In addition, it can be shown that these is no general method for handling end points that results in an orthogonal weighting matrix.

The centered moving average approach, while having a number of troublesome ad hoc features, has an intuitive appeal stemming from its flexibility in fitting time series. Many time series arguably have the property that the greatest amount of information about s_t is contained in those observations closest to time t. A moving average model implicitly accounts for this property by placing weight only on the closest observations. With moving average models the balance between flexibility and smoothness is determined by the number of terms included in the average.

Harvey and others have discussed a class of trend models that are derived from explicit assumptions concerning the behavior of S. The general form of these models can be described by the state transition equations

$$s_t = s_{t-1} + b_{t-1} + u_t$$
$$b_t = b_{t-1} + v_t.$$

Combining this with the measurement or observation equation

$$y_t = s_t + e_t,$$

and assuming that e_t, u_t and v_t are mutually independent gaussian white noise processes with standard deviations σ, σr_1, and σr_2 completely specifies the model. This model assumes that the trend term is a random walk with drift and that the drift parameter, b_t, itself follows a random walk. Special cases emerge by setting either one or both of r_1 or r_2 to zero. If both are zero then the simple linear trend model results. If r_2 is identically zero then the level of the trend is subject to random shocks but the growth rate remains constant. When $r_1=0$ the growth rate of trend is random but the trend component has no discrete jumps. For expositional convenience models 1 through 4 will be used to denote the cases $r_1=r_2=0$, $r_2=0$, $r_1=0$ and $r_1, r_2\neq 0$, respectively.

The fact that an explicit stochastic models is specified enables the estimation of the trend component to be based on statistical criteria. Akaike discusses a estimation strategy that, for given values of r_1 and r_2, results in an optimal (least squares) weighting matrix that balances the size of the observation errors (e_t) against the size of the measurement errors (u_t and v_t).[1] The approach can be thought of as an application of the Theil-Goldberger mixed estimation technique or as a Bayesian estimator with improper flat priors on initial conditions. The use of this least squares approach produces an identical smoothed estimator to that produced using state space estimation methods (Kalman filters and smoothers). The state space methods, though they are computationally far more convenient and efficient, do not allow one to recover the weighting matrix directly.

The r_1 and r_2 terms are treated as hyperparameters, while the σ term is a nuisance parameter and can be concentrated out of the likelihood. Likelihood values associated with the given values of r_1 and r_2 can then be computed and the maximum likelihood values found. Harvey contains further details on the Kalman filter and the estimation of the hyperparameters. The choice of r_1 and r_2 determines the relative balance between smoothness and flexibility. Increasing either of these parameters will result in a trend estimator that is less smooth and follows the realized series more closely.

These stochastic trend models, except the limiting linear trend case ($r_1=r_2=0$), fail to satisfy the orthogonality condition. In particular, though the symmetry condition is satisfied, the idempotency condition is not.[2] They do, however, satisfy the property that $W'i=i$, thus imposing the condition that the sample mean of the errors is zero.

Finally, forecast functions are directly available from these models. For forecasts based on data up through period n forecasts can be generated using:

$$\hat{y}_{n+k} = \hat{s}_{n+k} = s_n + b_n k.$$

This forecast function, being linear, avoids the explosive properties of forecasts based on higher order polynomials.

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1 The approach used here differs slightly from Akaike's approach in its handling of initial conditions.

2 The idempotency property ensures that repeated application of W to a time series will result in the same trend estimator as a single application. For the stochastic trend models examined here, however, repeated application results in a trend estimator that becomes increasing smooth and linear in time. In the limit repeated applications of W to Y (i.e., $\lim_{k\to\infty} W^k$) produces the linear trend model.

U.S. Corn Yields

The need for a flexible model of trend in U.S. aggregate corn yields is immediately apparent upon examination of the plot of yields over time, shown in Figure 1 (the data are given in Table 1). There has been a clear, persistent increase in the level of yields over the period. This rate of increase, however, has not been constant. In particular the immediate post-WWII period, which saw the widespread adoption of hybrid corn varieties, exhibits substantial rapid increases in yields. It is also noteworthy that the variability of yields has increased substantially, particularly since 1970. The significance of this feature will be commented on later.

Figure 1 also displays the optimal estimated trend components for models 1, 2 and 4 (model 3 is not shown as its estimated trend component and that of model 4 are essentially the same, differing by at most about one fourth of a bushel). Model 2 differs from model 4 in that it is less smooth, tending to follow the data more closely.

The maximum likelihood estimator of (r_1,r_2) for U.S. corn yield was calculated using a grid search of the values defined by $r_1=0(0.01)0.6$ and $r_2=0(0.0025)0.1$ (thus 61x41=2501 points). Likelihood contours as functions of r_1 and r_2 are displayed in Figure 2. The maximum likelihood estimator is the point $(r_1,r_2)=(0.11,0.035)$ associated with a loglikelihood of -166.81. Models 1, 2 and 3 are special cases associated, respectively, with the origin, the x-axis, and the y-axis. The maximum likelihood values for models 2 and 3 occur at the points (0.36,0) and (0,0.038), with associated loglikelihood values of -167.90 and -166.82. The loglikelihood value at the origin (model 1) is -177.40.

To gain intuition on the nature of these trend component estimators Figures 3-6 display the weighting functions for the optimal values of (r_1,r_2) for each model. In each figure the weighting functions for s_t, $t=1$, 4, 7, 10, 20, and 29 are displayed. For the linear trend model these weighting functions are linear, which forces global linearity on the trend component. The other models all display weighting functions that peak on the current observation (except at the end points of the sample). The higher the peaks, the more s_t is determined by current and nearby observations of y_t. In terms of Figure 2, the height of the peaks increases as (r_1,r_2) moves out from the origin.

The weighting functions for model 2 clearly have higher peaks than do those for models 3 and 4. This feature accounts for the differences evident in Figure 1. It is interesting to note that the weighting functions for models 3 and 4 do display some differences (figures 5 and 6). In particular, model 3 has weighting functions with more rounded peaks than model 4. In spite of this and other slight differences the two models yield very similar results.

As noted previously, these models share the feature that forecast functions are linear in time $(\hat{s}_{n+k}=s_n+b_nk)$. Estimated values of b_{1986} are 1.72, 1.62, 2.14 and 2.15 for models 1 through 4, respectively. The maximum likelihood estimates of the whole s_t and b_t series are provided in Table 1. The estimates of the growth rate range from about 0.6 bu./acre/year in the

1930s to a high of nearly 2.4 bu./acre/year in the mid-1960s, with a leveling off of about 2 bu./acre/year in the 1970s and 1980s. The two models with constant growth rates are unable to capture this feature of yields and instead produce a growth rate that averages the extremes.

Of the four models examined, model 1 clearly provides a poor estimate of the trend component. Not only is the likelihood associated with this model far lower than for the other models, but simple inspection of Figure 1 indicates that the linear trend is not able to capture significant features in the data. As models 3 and 4 provide essentially equivalent results it suffices to confine attention to a comparison of models 2 and 4. Model 3 cannot be rejected on loglikelihood grounds, differing from the maximum by just over 1. If model selection was determined by application of an information criterion model 3 would be selected, while the choice between model 2 and 4 would be in favor of 4 using the Akaike criterion and model 2 using the Schwarz criterion. Such ambiguous criteria aside, it is the behavior of the estimated trend for model 2 that argues against its use. Its sensitivity to individual observations produces several cases in which the trend component exhibits humps or dips that subsequently dissipate. This feature is particularly evident in the drought years of 1973 and 1983. In contrast models 3 and 4 produce trend components with very smooth behavior that are not sensitive to a single extreme value.

Interpreting the Trend Component

In order for trend estimation to be an economically interesting exercise it is necessary that some interpretation be given to the trend component. There are at least three factors accounting for the sustained growth in yields: technological change, capital accumulation, and long run changes in relative prices. At any given time the mean level of yields can be thought to represent the combined effects of accumulated technological innovation and accumulated investment in crop production related capital, including managerial capital. In addition, for a variety of reasons, the marginal value products of agricultural inputs, particularly fertilizers and pesticides, have fallen relative to output prices. This has led to increased use and a consequent increase in yields. Together these forces can be thought of as producing the current technology. A reasonable goal in estimating a trend component is to capture time series behavior of the state of technology.

An intuitively reasonable proposition about the state of technology is that there is some lumpiness in the rate at which it changes. It is likely, therefore, that there will be some periods of rapid change in mean yields and others of slower change. Models for which both the level and the rate of change of mean yields can vary, such as models 3 and 4, would therefore be desirable.

There is another aspect to crop yields that is important to account for if an estimated trend component is to be associated with the state of technology. For some crops there can be annual carryovers in crop growing conditions. In dryland wheat production, for example, drought periods can be persistent due to their impact on soil moisture. This would imply that a decomposition such as has been suggested would need to be altered if the irregular component is to be interpreted as arising from short run weather conditions and other short run natural causes. While it is possible to complicate the basic framework thus far developed to account for such a possibility, in the case of corn yields this does not seem to be necessary. In effect, with aggregate corn yields, the impacts on yields of natural causes can be modeled as a serially independent random variable.

It is also arguable that longer run climate effects, such as the greenhouse effect, cannot be distinguished from what are more properly considered to be technology changes. In fact the situation is complicated by the response of investment in technology to long run climatic changes. Any estimated trend component based on a univariate yield series will be subject to such a caveat. It may be useful to think of the trend component as reflecting the state of technology given currently available resources. For the purposes considered here, however, this caveat is not troublesome.

<u>Higher Moment Properties of Corn Yields</u>

From a purely statistical perspective, the trend component can be thought of as representing the mean yield, conditioned on time. From this perspective it makes sense to use the trend component to normalize the yields in order to create a series with a common mean that can be used to investigate the higher moment properties of yields. The analysis up to this point has assumed that the differences between yields and trend are gaussian white noise with variance σ^2. It is unlikely that this assumption is satisfied however. It is clear from Figure 1, for example, that the variance of yields has increased with time. There are also numerous suggestions in the literature that crop yield distributions are not symmetric but are skewed.

The advantage of breaking the estimation procedure into two stages is that linear filtering methods can be applied to the estimation of trend. These methods provide optimal (least squares) estimates of the trend component for given (r_1,r_2), given additive, homoskedastic errors. In principle a weighted least squares approach, along with a model of the trend in variance, could be used to obtain a more efficient trend estimator. Furthermore, the optimal (r_1,r_2) could be calculated simultaneously with the parameters of a non-gaussian parametric distribution. These refinements would make the analysis considerably more complicated and computationally more difficult.

Given the evident trend in variance it is both sensible and convenient to normalize yields by dividing them by the estimated trend component. When multiplied by 100 this provides a measure of the percentage deviation from trend. This normalized series is shown in Figure 7. The important question at this point is whether this series represents random draws from a single marginal distribution or whether there is evidence that the distributional properties of the normalized series have undergone change over the sample period. To test this the sample was divided in half and a Smirnov test was calculated (Conover). The hypothesis that the two subsamples are drawn from a common probability distribution cannot be rejected at the 0.2 significance level (the value of the test statistic is 0.201, with subsamples of 29 observations each).

While it is questionable how powerful this test is, the result certainly does not favor the hypothesis that radical changes in the distribution of the normalized series have occurred. This is an important result, as it suggests that the apparent variability in yields does not imply that yields are riskier if reasonable criteria of riskiness are applied. Instead it suggests that yields have changed by a scale factor alone and that normalized higher moments such as the coefficient of variation and the standard skewness and kurtosis measures have remained constant.

This view runs counter to what seems to have become a stylized fact, particularly as expressed by Hazell, who claims that yields are becoming more risky. Hazell (1988), however, examined a far shorter sample that did not include the 1930s and 1940s, periods when yields experienced a significant amount of volatility. The 1950 and 1960s were periods of unusually favorable weather in the corn belt, which experienced no drought conditions between 1958 and 1972. A comparison of this earlier period with the period since 1973 therefore makes it appear that yields are becoming relatively, as well as absolutely, more variable. Inclusion of the 1929-1949 period, however, leads to the conclusion that relative variability has not changed.

It is also of interest to determine whether yields exhibit "bunchiness", which can be defined by the presence of serial correlation in the normalized series. Evidence of serial correlation was not found, using either the Box-Ljung test or a nonparametric runs test (there were 25 runs, with 31 values above 1 and 27 below 1, implying a p-value of 0.88). This is consistent with the results of Luttrell and Gilbert, who estimated trend using 9-year centered moving averages.

The evidence presented provides support for the contention that the normalized yields can be treated as random draws from a common distribution. The empirical distribution function, plotted in Figure 8, can therefore be used to examine the properties of that distribution. The median of the series is slightly greater than 1, while its mean is 1. The probabilities that the crop falls short of trend by 5%, 10% and 20% are .21, .12 and .05. These estimates are somewhat different from the .25 and .08 5% and 10% values estimated by Lutrell and Gilbert for 5 corn growing states over the period 1932-1970. Whether this difference is due to the difference in the sample or in detrending method is not clear. Estimates that a crop is 5%, 10% and 20% above trend are .34, .10 and .02.

Summary

Having a flexible methodology for estimating the state of technology represents a significant step in the modeling of the stochastic nature of crop yields. Prior trend estimates have used either polynomial trend models or ad hoc moving average specifications. The stochastic trend models examined here exhibit the flexibility of moving average models, while being embedded in an explicit stochastic model. This enables the relative balance between smoothness and flexibility (global versus local linearity) to be determined by statistical criteria.

An estimate of the trend component is needed to normalize yields in order to examine their higher moment properties. While it would be optimal to estimate all distributional properties simultaneously, such an approach is often impractical. The approach taken here provides a practical way to break the estimation process into more manageable pieces. In the case of corn yields evidence has been provided supporting the hypothesis that ratios of yield to trend are random draws from a common marginal distribution. While such a hypothesis may not be valid for other crops or levels of aggregation, when it is valid the properties of this common distribution can be easily examined using the empirical CDF or parametric representations. This provides a complete stochastic model of yield behavior for use in simulation models and strategic planning.

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Table 1. Data and Model 4 Estimates

YEAR	YIELD	S	B	YEAR	YIELD	S	B
1929	25.7	20.86	0.59	1958	52.8	52.88	2.18
1930	20.5	21.39	0.59	1959	53.1	55.18	2.24
1931	24.1	21.94	0.60	1960	54.7	57.58	2.28
1932	26.5	22.47	0.62	1961	62.4	60.05	2.31
1933	22.6	22.96	0.65	1962	64.7	62.52	2.32
1934	15.7	23.50	0.70	1963	67.9	64.97	2.32
1935	24.0	24.17	0.74	1964	62.9	67.39	2.30
1936	16.2	24.89	0.79	1965	74.1	69.84	2.28
1937	28.1	25.76	0.83	1966	73.1	72.22	2.24
1938	27.7	26.64	0.86	1967	80.1	74.55	2.19
1939	29.2	27.54	0.89	1968	79.5	76.76	2.14
1940	28.4	28.45	0.92	1969	85.9	78.89	2.09
1941	31.1	29.39	0.94	1970	72.4	80.89	2.05
1942	35.1	30.34	0.96	1971	88.1	82.94	2.01
1943	32.2	31.25	0.99	1972	97.0	84.90	1.98
1944	32.8	32.17	1.03	1973	91.3	86.68	1.96
1945	32.7	33.13	1.08	1974	71.9	88.38	1.98
1946	36.7	34.14	1.13	1975	86.4	90.30	1.99
1947	28.4	35.16	1.19	1976	88.0	92.28	2.01
1948	42.5	36.33	1.25	1977	90.8	94.34	2.03
1949	38.2	37.49	1.33	1978	101.0	96.45	2.03
1950	38.2	38.72	1.41	1979	109.5	98.51	2.04
1951	36.9	40.03	1.50	1980	91.0	100.44	2.05
1952	41.8	41.47	1.60	1981	108.9	102.51	2.06
1953	40.7	43.01	1.71	1982	113.2	104.50	2.08
1954	39.4	44.68	1.81	1983	81.0	106.41	2.12
1955	42.0	46.53	1.92	1984	106.7	108.67	2.14
1956	47.4	48.53	2.02	1985	118.0	110.97	2.15
1957	48.3	50.65	2.10	1986	119.3	113.20	2.15

Source: USDA.

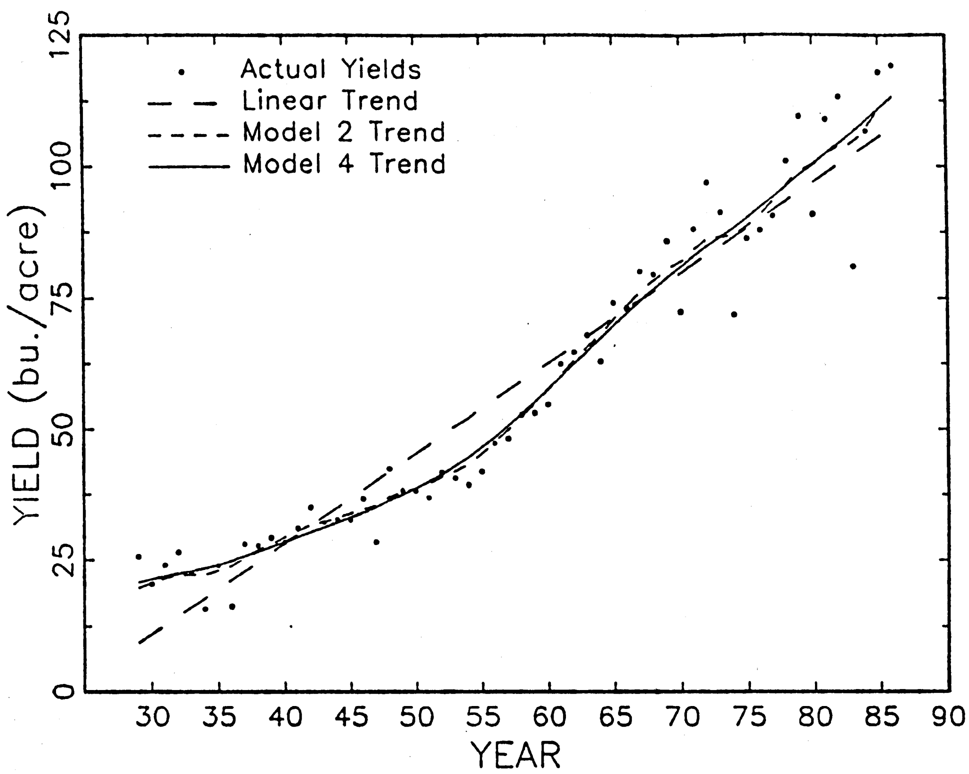

Figure 1. U.S. Corn Yields with Trend Estimates: 1929–86

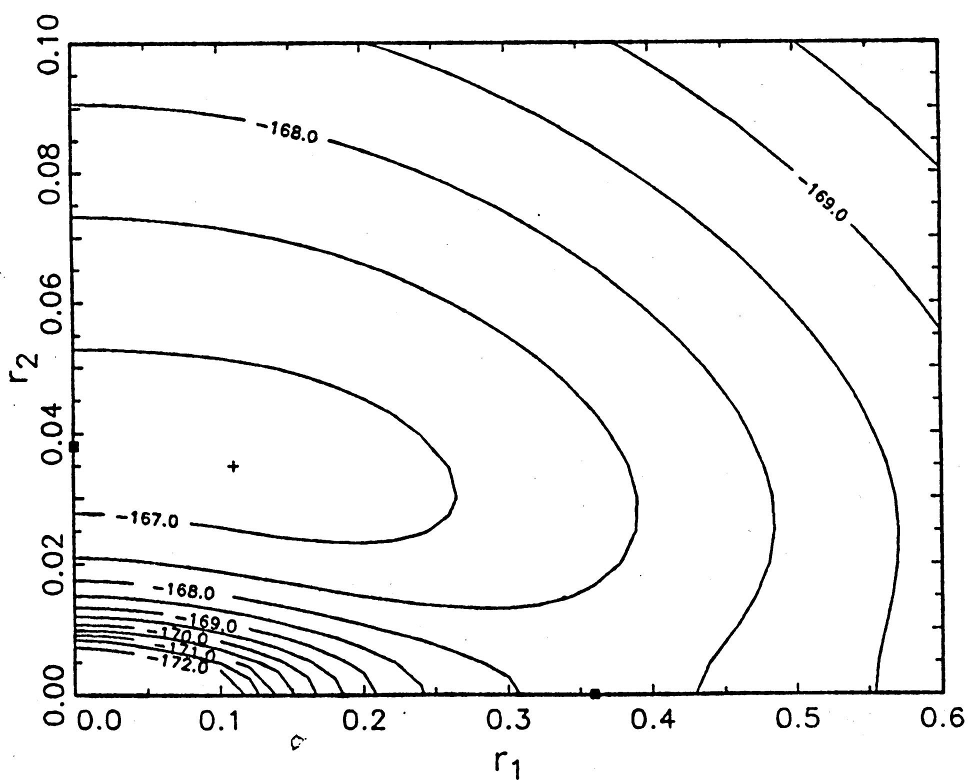

Figure 2. Loglikelihood Contours for U.S. Corn Yields

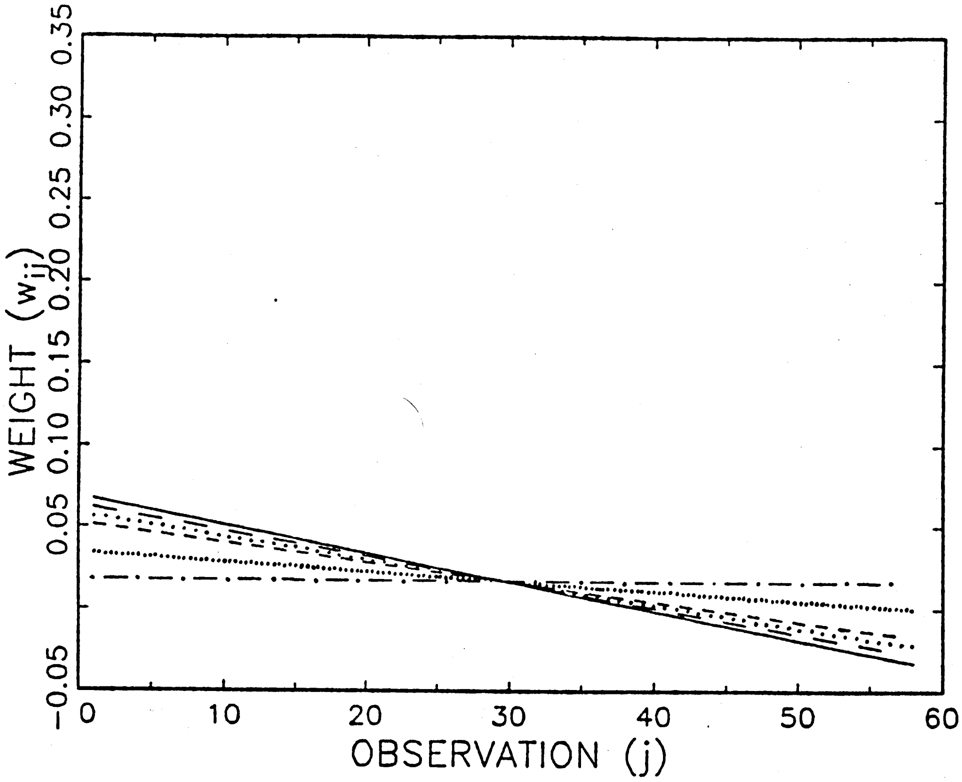

Figure 3. Weighting Functions for Model 1 (i=1 4 7 10 20 29)

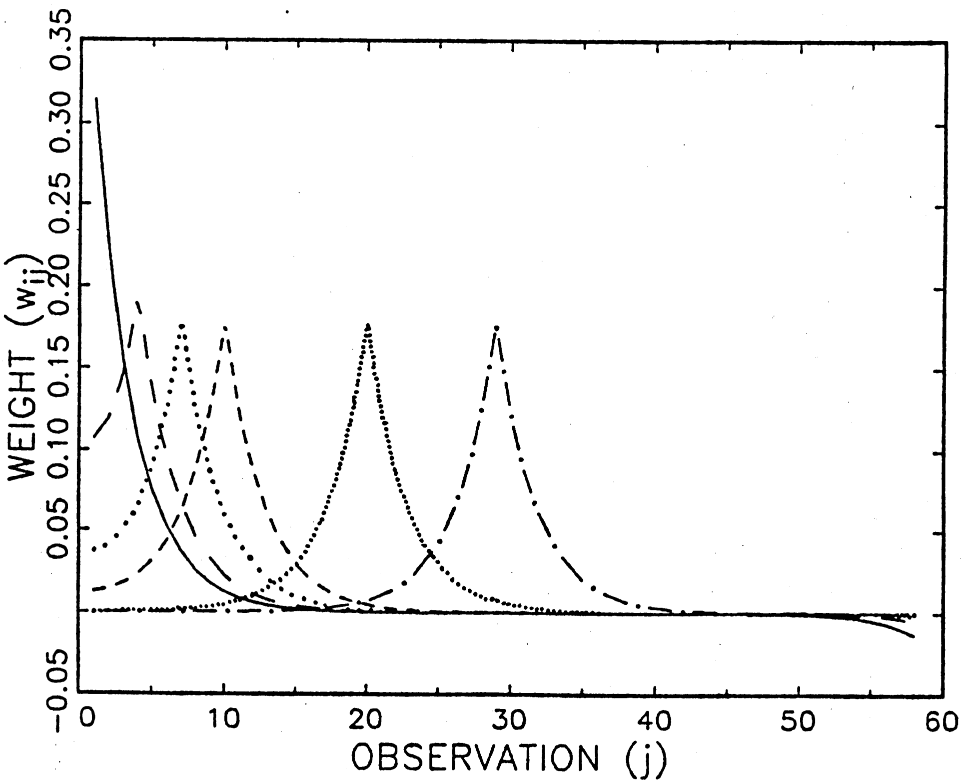

Figure 4. Weighting Functions for Model 2 (i=1 4 7 10 20 29)

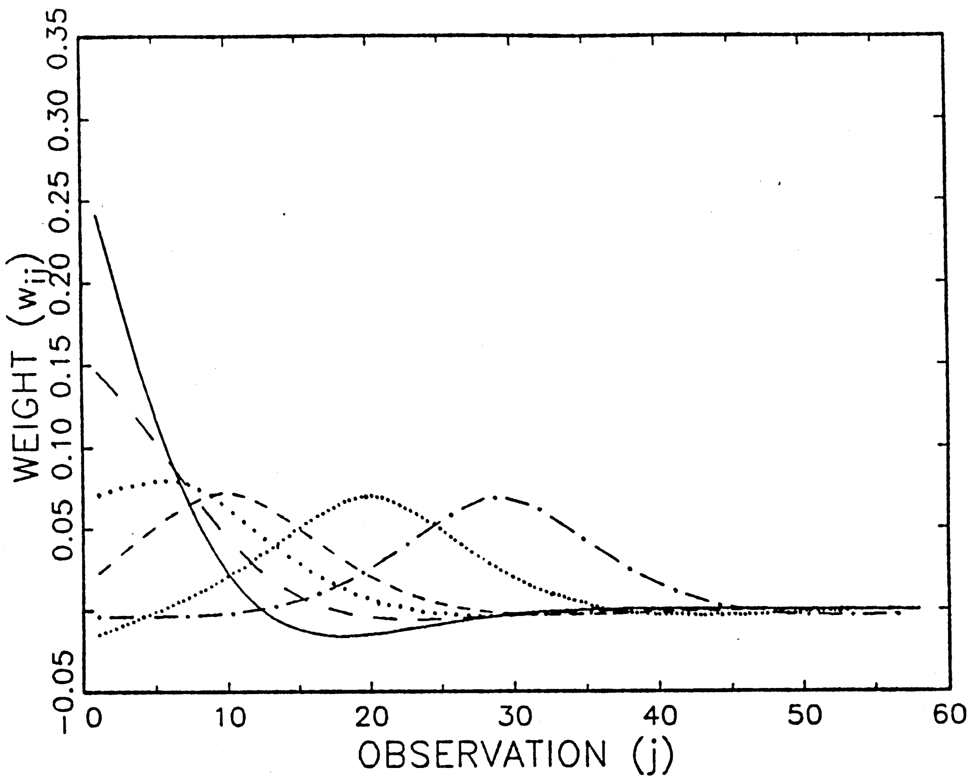

Figure 5. Weighting Functions for Model 3 (i=1 4 7 10 20 29)

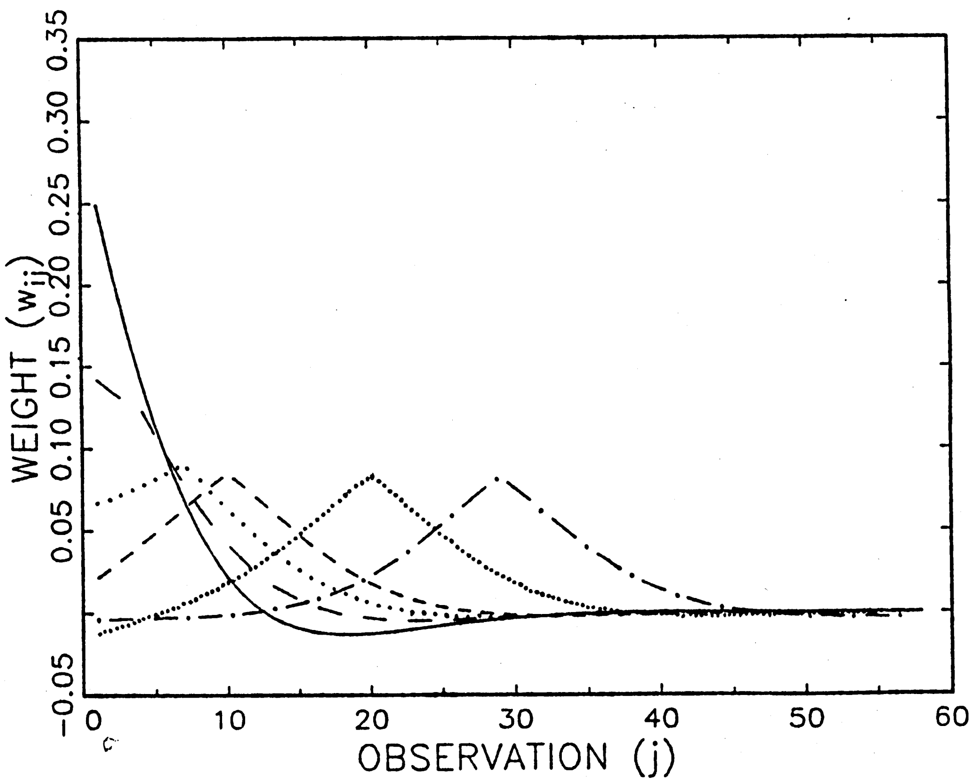

Figure 6. Weighting Functions for Model 4 (i=1 4 7 10 20 29)

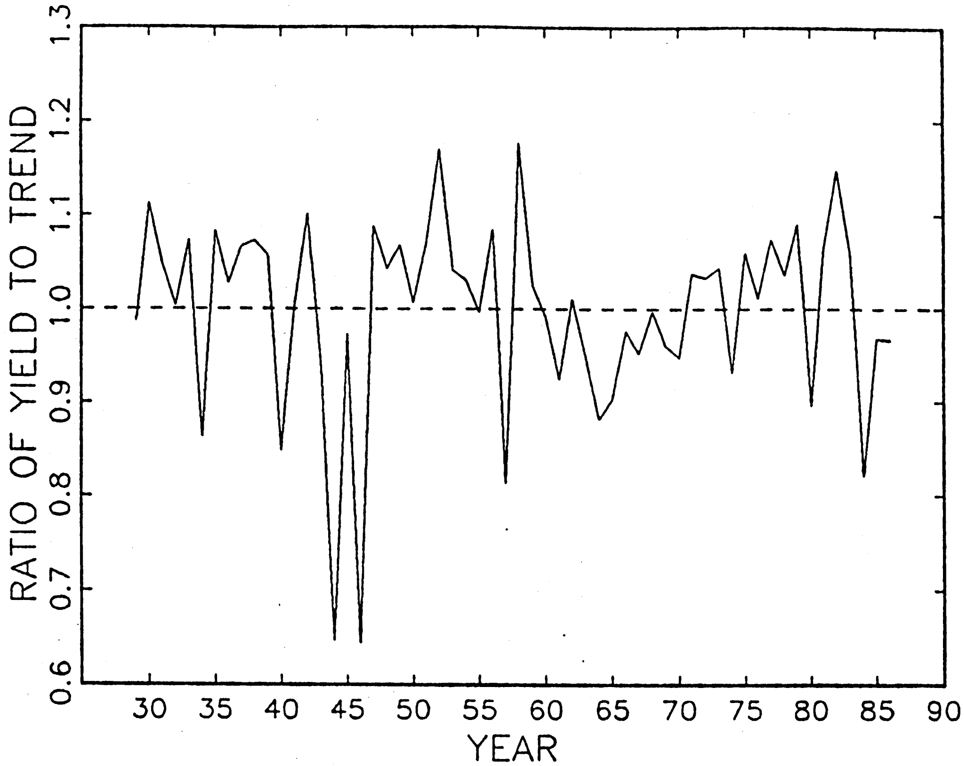

Figure 7. Normalized Corn Yields: 1929–86

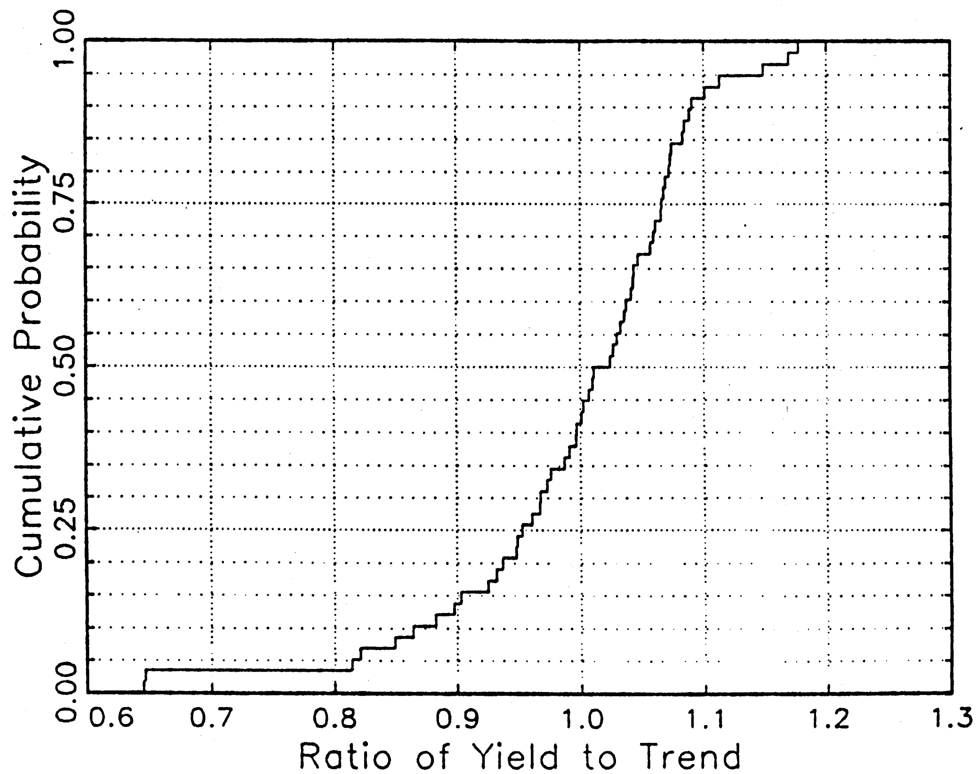

Figure 8. Empirical CDF for Normalized Yields