ECONOMIC AND CLIMATIC FACTORS IN 'ACREAGE ABANDONMENT' OVER MARGINAL CROPLAND

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Abstract. Crop yield projections made at planting time or during the growing season often ignore the fact that an unknown percentage of planted acreage is not harvested. As a solution, we present a model for 'acreage abandonment , based upon both economic and weather variables. Weather is shown to be a much more important determinant of the decision not to harvest than is the expected price. The explained variance in abandonment of spring wheat acreage by future delivery price is approximately 16%, but rises to over 60% when weather variables are added. In a similarly designed model for winter wheat in the southern plains, the price contribution is less than 5%.

The spring wheat model was tested on two extensive sets of withheld data: three-year successive deletions through the entire (1932–1975) data set, and a ten year block at the beginning of the modelling period that included substantial weather and price perturbations induced by the dust bowl, depression, and attendant market gyrations. Predictive capability was retained in both tests.

'Current' weather appears to weigh more heavily in the abandonment decision than does 'future' price.

1. Introduction

In response to a temporary oversupply, the U.S. Department of Agriculture (USDA) initiated the payment-in-kind (PIK) program for the 1982–83 crop year. The primary goal was a reduction in future supply resulting from a voluntary set-aside, with the secondary effect being an increase in prices.

In assessing production potential, USDA crop yield estimates at the beginning of the crop year are based upon the number of acres planted. In any year, a certain percentage of that land is not harvested, particularly in climatically marginal regions where stress-tolerant crops (such as wheat or sorghum) are grown in anticipation of the likelihood of bad weather. Figure 1 details the time series of wheat acreage not harvested for a region of the northern U.S. Great Plains with relatively harsh growing season climate.

National production projections based upon PIK would logically be founded on the assumption that an anticipated rise in prices should be associated with a low percentage of the non-harvest of planted land (hereafter referred to as 'acreage abandonment'). The purpose of this paper is to address the associated problem: what are the relative roles of weather and market conditions in determining the amount of land that is not harvested?

There is certainly considerable confusion in the public sector concerning this problem. For example, in recent years, the American Agriculture Movement, based in relatively arid eastern Colorado, has staged media oriented 'plowdowns', claiming that market conditions were so bad that it was more economical to abandon winter wheat crops rather than

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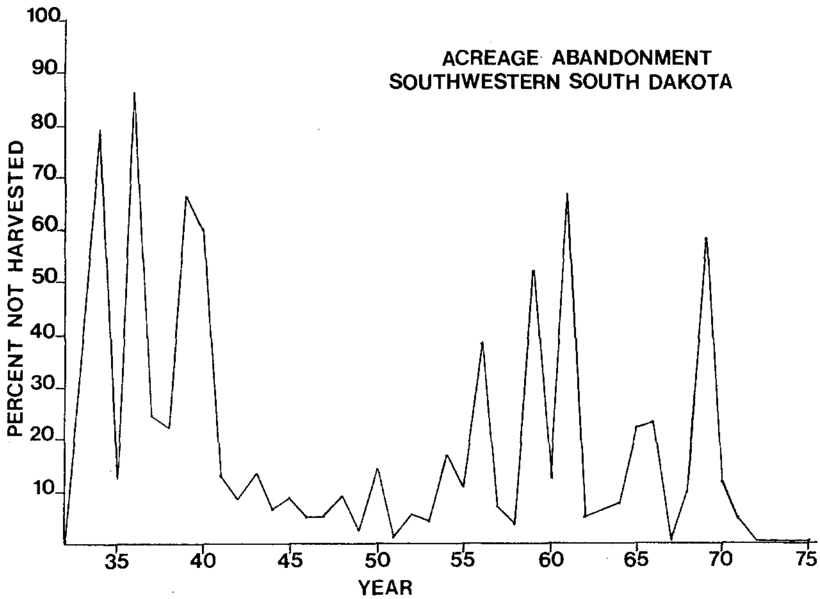

Fig. 1. Time series of abandonment, as percent planted acreage, for Southwestern South Dakota, a region with relatively high abandonment.

bringing them to harvest. However, our results indicate it is much more likely that the abandonment was based on weather considerations.

2. Previous Work

With the exception of Michaels (1983), a search of the recent literature revealed no refereed publications germane to this subject. We found this surprising, particularly in light of the economic importance of the subject. At the same time, we note that we are preparing another manuscript based primarily upon econometrics (as opposed to the purely statistical methodology here) to address the problem.

In Michaels (1983), the study was confined to the winter wheat regions of Nebraska, Colorado, Kansas, Oklahoma, and Texas (Figure 2). Principal component analysis was used to isolate the major spatial modes of abandonment. As in this study, the most important oscillations were shown in the drier regions – the western portions and high plains. In that work, interannual changes in abandonment over those areas was related, with multiple regression, to weather and price factors. The overall statistical model, including constants, price terms, and weather variables, explained 77% of the variance in abandonment. 36.5% of the variation not due either to non-climatic or spatial factors was explained by the weather signal.

There was no significant loss of fidelity in a test consisting of sequential withholding of three year blocks of data throughout the entire model period (1932–1975). Depending upon model, only between 3% and 5% of the interannual variation was explained by price,

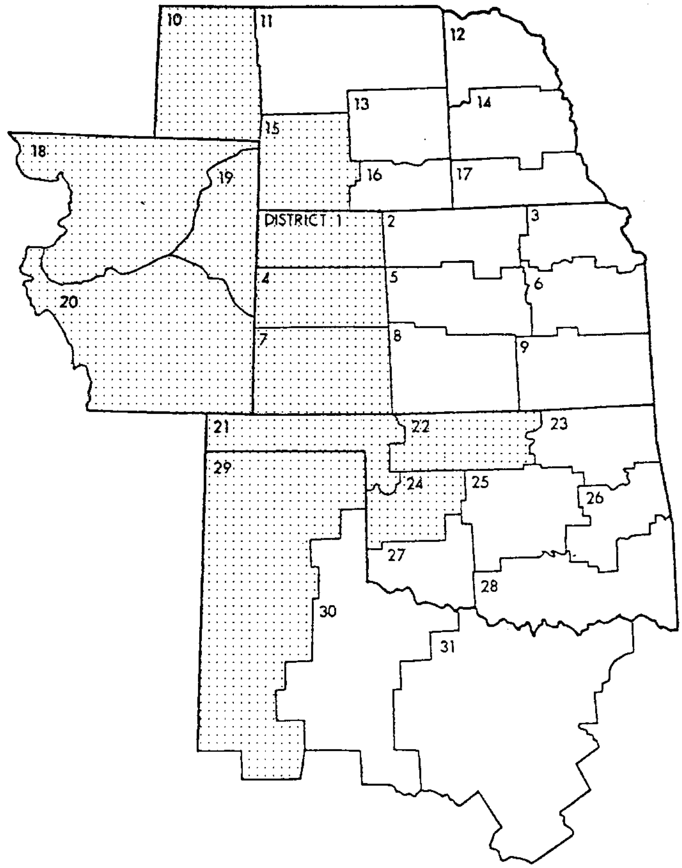

Fig. 2. U.S. winter wheat area. Analyses of acreage abandonment over the shaded areas indicated that the weather signal was much stronger than the price signal (Michaels, 1983).

when the weather data was withheld from the regression.

3. Current Work

This paper extends that initial analysis to the spring wheat regions of North and South Dakota, and Minnesota (Figure 3). We also examine the major weather factors that are associated with *yield* (rather than abandonment) changes, and attempt to relate the two sets of predictors.

As in our earlier work, the spatial subunit we use is the USDA Crop Reporting District (CRD), which has been shown to be an appropriate measure of disaggregation in other climate/crop models (see Starr and Kostrow, 1978; Feyerherm and Paulsen, 1981; Phinney *et al.*, 1979; and Michaels, 1979, among many others).

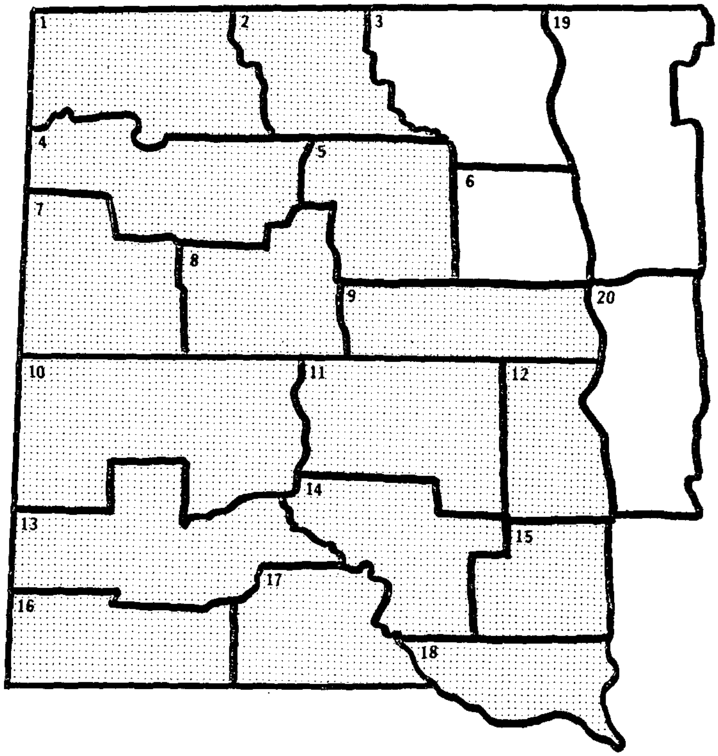

Fig. 3. U.S. spring wheat area. Preliminary analyses, detailed in this paper, confined study to the shaded areas. CRD's 1–9 are in North Dakota, 10–18 in South Dakota, and 19–20 in Minnesota.

3.1 Preliminary Hypothesis and Descriptive Statistics

We tender a simple preliminary hypothesis concerning abandonment and climate: The areas with the lowest yields under average climate will be those that will be subject most to abandonment.

Abandonment was expressed as ((planted acreage–harvested acreage)/(planted acreage) to account for size differences between CRD's. Means and standard deviations for the study period (1932–1975) are shown in Figures 4 and 5. As was the case for our earlier winter wheat study, both are highest in the western portions that have lowest average yields. Lowest means and standard deviations are in the fertile and productive Red River Valley regions to the northeast.

To explore the hypothesis, we then undertook a study of 'base level' yields, or those that would accrue under mean climate for each CRD. These are also those that would occur in the absence of 'modern' technological input.

The model for an individual CRD yield estimate was

$$\begin{aligned} \widehat{Y_{\text{yield}}} &= Y_c + Y_t + Y_b; \\ Y_{\text{yield}} &= \widehat{Y_{\text{yield}}} + e_i \end{aligned} \tag{1}$$

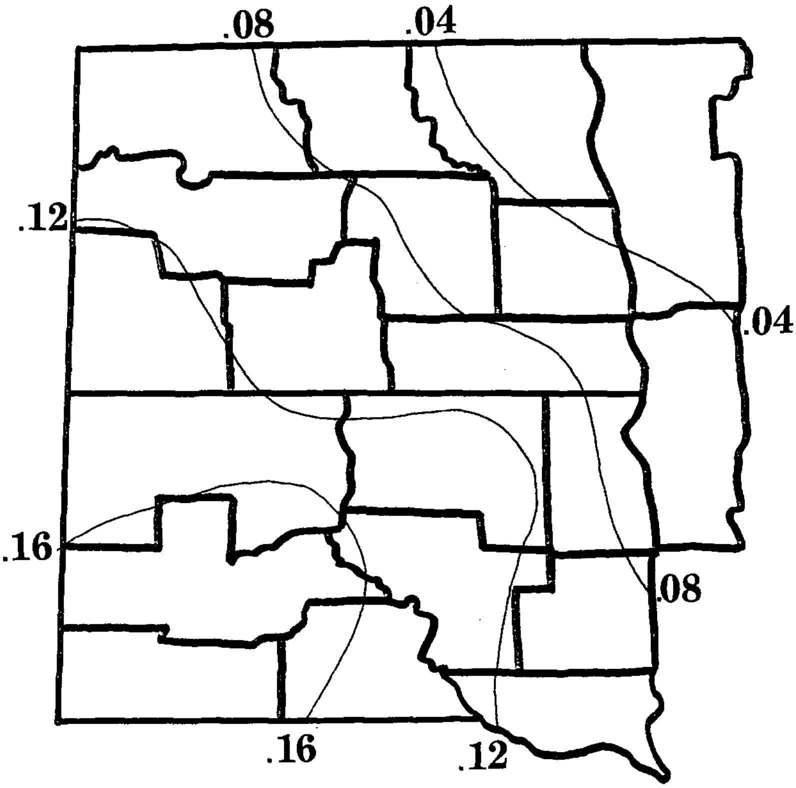

Fig. 4. Mean percent of acreage abandonment (1932–75) over the spring wheat area.

where $\widehat{Y_{yield}}$ is the yield estimate, in (metric tons/planted hectare) x 10, regressed upon the variables on the right side of the equation. Y_c, Y_t, and Y_b are climatic, trend, and base terms respectively. Their formulation is detailed in Michaels (1982, 1983). Y_{yield} is the observed value, which is the sum of $\widehat{Y_{yield}}$ and e_i, the unexplained residual. The residuals are assumed to be normally distributed with a mean of zero, a constant variance, and a serial correlation of zero.

The climatic data consist of monthly mean temperature and total precipitation for May through August, as well as a March–April 'preseasonal' aggregate. Data were pooled and expressed as departures from the grand mean over all of the CRD's; thus the expected value of the climate terms, expressed as departures from the mean, is zero. Departures from the mean were also expressed as squares; thus, when the climate is at the mean value, the value of this term is also zero. Note that the mean value of the square is not zero; this somewhat biases the base level terms, but analyses indicate the effect is small.

The trend term is the best fitting slope to the yield series for each CRD beginning in 1950. Thus it is an increase term over time that adds to the overall model specification. It was calculated objectively by the least square regression, fitting a multiplier to a dummy variable whose value in each CRD is zero prior to 1951, and increases by one for each year thereafter.

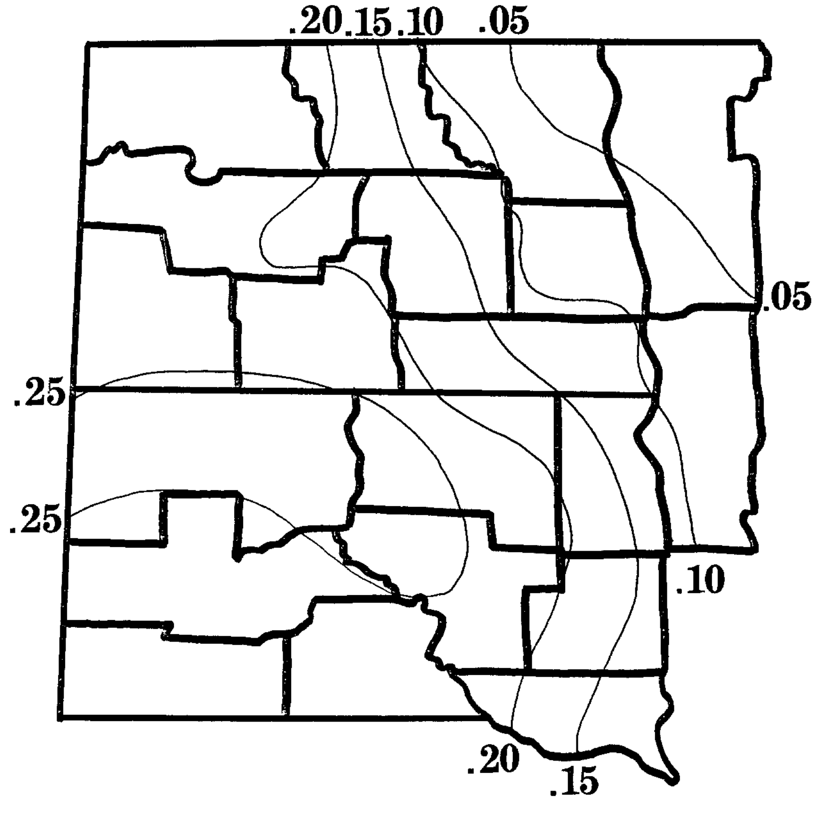

Fig. 5. Standard deviation of acreage abandonment (1932–75) over the spring wheat area.

Because of the zero-reference to both the climatic and trend terms, given average climate in years prior to 1951,

$$Y_{\text{yield}} = 0 + 0 + Y_b + 0 = y_b. \tag{2}$$

The spatial distribution of Y_b values is shown in Figure 6. Lowest values, of less than 0.5 metric ton/planted hectare (mt/p-ha) are in the southwestern portion of the region, while highest ones, of approximately 1.0 mt/p-ha are confined to the eastern CRD's.

We tested the hypothesis that areas with lowest yields under average climate (lowest Y_b values) would be those most subject to abandonment with a simple second order regression model. The relationship was highly significant ($F_{2,\ 17,\ .001} = 10.66$; calculated F=61.59).

3.2. Spatial Patterns of Abandonment

The 1932–1975 time series of abandonment was then examined with a principal component analysis (PCA). Kendall (1975) describes the methodology. A considerable number of meteorological and climatological researchers use this technique to handle highly intercorrelated data sets; see Walsh *et al.* (1982) for a recent review.

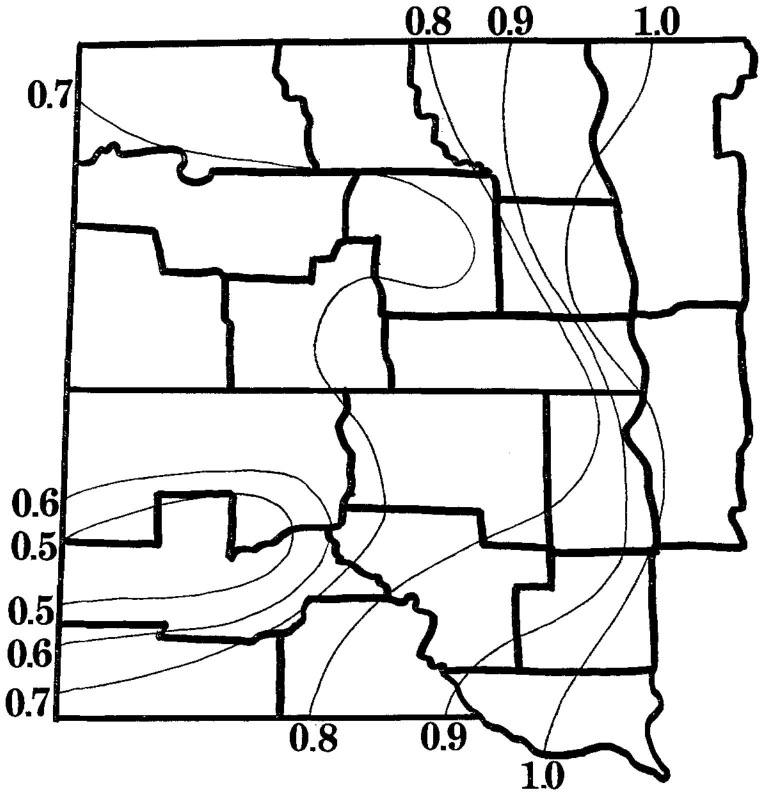

Fig. 6. Base yield values (Y_b) over the spring wheat area (1932–75).

In this case, PCA forms statistically uncorrelated linear combinations of the CRD abandonment figures of the form,

$$\mathrm{PC}_1 = \sum_{i=1}^{20} \alpha_i\,(\mathrm{ABAN}_i) \tag{3}$$

where the multipliers (α_i) weight the individual district abandonment values, which are themselves normalized. The entire operation is performed on the correlation matrix. Each successive linear combination explains less of the correlation structure of the data, after allowing for previous ones.

Richman (1981) has suggested that an alternative oblique (non-orthogonal) solution may be more appropriate for meteorological data. However, the popular Monte-Carlo based significance test of Preisendorfer *et al.* (1981) and Overland and Preisendorfer (1982) was designed for the orthogonal solution. In using that significance test we therefore may have sacrificed some utility, but at the same time have increased confidence in our results.

We determined significant components by applying a linear interpolation to the Overland and Preisendorfer (1982) table, using $n = 44$ (number of years), $p = 20$ (number of cells), and j = 1, 2, etc. . . (order of component). Only the first one, explaining 69.9% of the spatial variation in abandonment from year to year, met the significance criterion at the 0.05 level. The table does not give any other level.

North *et al.* (1982) show that order ambiguities may occur in principal components when their eigenvalues are similar. Fortunately, our first component absorbs so much of the variance that this discrimination problem does not occur between it and the second (eigenvalues of 13.99 and 2.24, respectively). The third component may be indistinguishable in order because of its relatively similar eigenvalue of 1.45, but both it and the second don't meet the Monte Carlo significance test, as described above.

The spatial distribution of the α_i for the first principal component is shown in Figure 7. Areas with the largest absolute magnitude – the southeastern and southwestern portions of the study region – explain the greatest proportion of variation within the pattern. The sign of each is different, indicating that the principal mode of departure from mean abandonment is represented by an out-of-phase oscillation between these two regions. The signs themselves are ambiguous (i.e. could be interchanged), and do not indicate that either area is likely to be above or below normal in a given year.

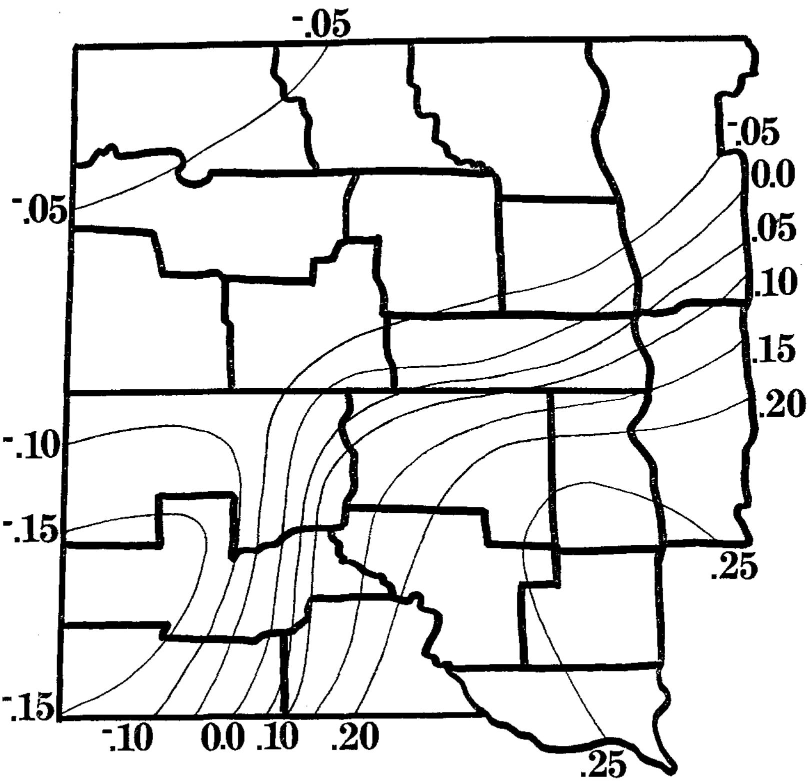

Fig. 7. Spatial pattern of CRD multipliers for the first principal component of abandonment over the spring wheat area (1932–75).

When the value of the first component is positive, abandonment tends to be above normal in the regions of positive weighting and below normal in the negative areas.

Inspection of the time series of mathematical values ('amplitudes') of this component (Figure 8) indicates that in most of the years it is near zero. In only 12 of 42 years was it greater than ± 0.40 (1957 and 1958 were deleted from the analysis because of missing planted acreage data in Minnesota). Thus there are relatively few degrees of freedom within the component, and therefore in the entire abandonment system. Subsequent regression models that relate weather, price, and abandonment will also have inflated estimates of the number of degrees of freedom. This necessitates testing on independent data, rather than reliance on regression summary statistics.

Based on these preliminary analyses, we limited subsequent regression models of price, weather, and abandonment to regions with low base level yields and mean annual abandonment of more than 5% of planted land. The four northeastern CRD's were therefore deleted.

3.3. Weather and Price Models of Abandonment

We then developed a series of multiple regression models to determine the relative roles of

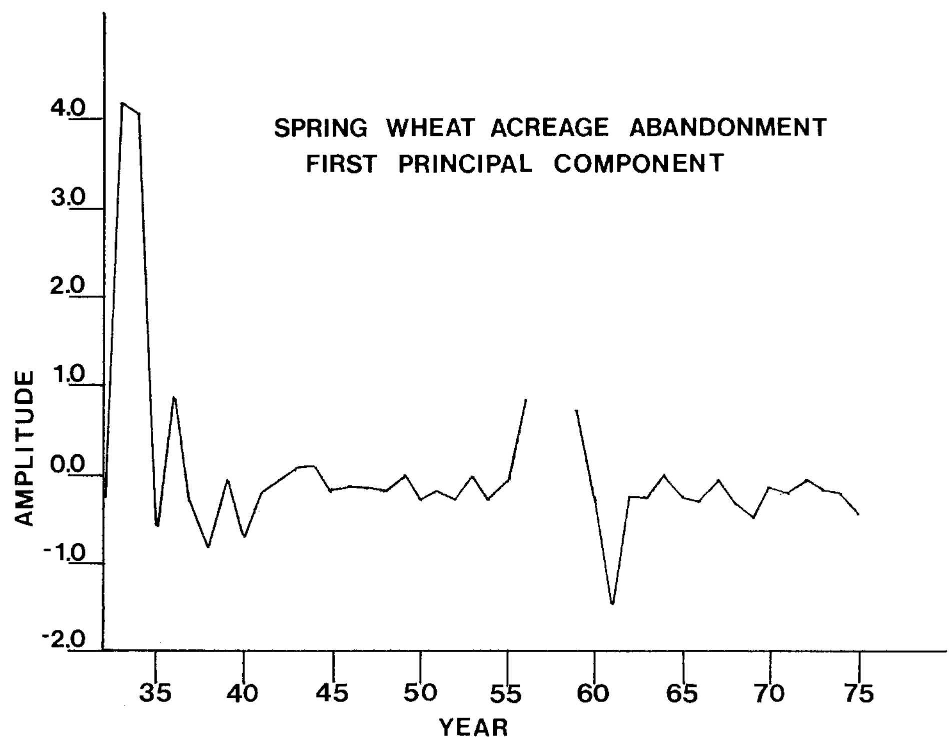

Fig. 8. Time series of the amplitude of the first principal component of abandonment over the spring wheat area (1932–75). 1957–8 were omitted because of missing data over Minnesota.

price and weather in the abandonment process. The overall model was again based upon 1932–1975 data, and was of the form:

$$Y_{\widehat{\text{aban}}} = Y_b + Y_c + Y_{\text{price}} \qquad (4)$$
$$Y_{\text{aban}} = Y_{\widehat{\text{aban}}} + e_i.$$

Y_{aban} is the predicted abandonment, expressed as a percent of CRD plantings. It is fit by regression on the variables on the right side of the first equation. Y_{aban} is the observed abandonment, which is equal to the predicted value plus the residual, e_i.

Y_b represents a CRD-specific base level for abandonment, and is calculated analogously to the base level yields described above. Note that there is no time-dependent trend (Y_t) term in these models, as it is not needed. Y_b attempts to account for spatial differences in mean abandonment that are not related to interannual weather or price fluctuations.

Y_c is an additive climate term used to relate variation in abandonment to variation in monthly mean temperature and total precipitation. The form is

$$Y_c = \sum_{i=1}^{n} \mathrm{A}_i' (\mathrm{Te})_i \, , + \sum_{i=1}^{n} \mathrm{A}_i'' (\mathrm{Te})_i^2 + \sum_{i=1}^{n} \mathrm{B}_i' (P_i) + \sum_{i=1}^{n} \mathrm{B}_i'' (P_i)^2 \qquad (5)$$

Te_i refers to monthly mean temperature for May through August, plus an additional 'preseasonal' aggregate of March and April combined. The P_i are similarly defined total monthly precipitation, transformed into $\log_{10}$. All of the terms were also expressed as squares, to allow for curvilinear responses of abandonment to the climatic input. n is the number of periods (in this case, five), and the A_i and B_i (and associated primes) are the least-squares regression coefficients.

Y_{price} is a weighted average of future delivery quotations, with the regression weights calculated simultaneously with those of the other Y_{aban} predictors. The raw data were November 1 future delivery prices on the Chicago Board of Trade, extracted from the Wall Street Journal (1932–1975) for May 1 (planting), July 1 (transition from vegetative to reproductive growth), and August 1 (grain filling). Each was also entered as a squared value, to again allow for curvilinear fits to the abandonment data. As the crop year progresses, individual operators must decide whether or not to undertake operations that require capital and labor inputs, such as weed and insect control, and possible fertilizer applications. The choice of input to these activities should be determined by the expected return.

Prices were indexed to the 1948 Gross National Product as a deflator. For example, 1932 GNP was approximately 0.66 times the 1948 value. It was therefore divided by 0.66. Similarly, 1972 prices were divided by 1.41. This deflator certainly does not encompass many of the factors associated with the wheat economy, and we only use it as a first approximation. The time series of the Consumer Price Index (CPI) might be more appropriate, but it again is not directly related to agriculture.

In earlier work (Michaels, 1983), we used an additional price variable to account for the change in price from one quotation to another, as well as squared changes. The former is a linear combination of other input data, and therefore does not change the resultant regression fit. While this is not the case for the squared departures, it only makes sense to use linear and squared terms together.

In all of the models and subsequent submodels, each of the predictor terms of Equation (5) was initially included in the regression. Models were then recomputed, with the least significant terms successively removed. This standard backwards elimination procedure (see Draper and Smith, 1966) was continued until all of the remaining variables had partial F-values of 3.00 or greater, a significance level of 0.06 with the sample size of 702. However, we caution, as *per* above, that the number of observations certainly substantially overestimates the true number of degrees of freedom in the abandonment data set.

3.4 Analyses of Variance

Table I summarizes explained variance for both the full (March–August) model, as well as for a series of submodels that ended successively earlier in the spring wheat year. Percent variations explained was calculated as (Raw data variance – residual variance)/(Total variance) x 100. The Table details improvement over base values, base and price, and base, price, and climate values, as more predictor variables are included.

The base models explain virutally none of the total temporal variation in abandonment, as Y_b terms are only spatial constants that substitute for an area-wide value. In the full-

TABLE I. Analyses of variance for the full (March–August) model, and for shorter season submodels.

Full model (March–August)	Residual Std. deviation	% Variance explained	% From previous step
Base	0.1989	0.7	0.7
Base + price	0.1839	16.0	15.3
Base + price + climate	0.1254	60.6	53.3
Reduced (March–April)			
Base	0.1989	0.7	0.7
Base + price	0.1989	0.7	0.0
Base + price + climate	0.1920	7.5	6.9
Reduced (March–May)			
Base	0.1989	0.7	0.7
Base + price	0.1910	8.5	7.7
Base + price + climate	0.1560	39.0	33.2
Reduced (March–June)			
Base	0.1989	0.7	0.7
Base + price	0.1910	8.5	7.7
Base + price + climate	0.1325	56.3	52.2
Reduced (March–July)			
Base	0.1989	0.7	0.7
Base + price	0.1860	13.2	12.5
Base + price + climate	0.1260	60.2	54.1

season version, the price terms result in an increase of explained variance of only 16% over the raw data. This is statistically significant at the 0.01 level. However, the overall full-season model, with base, price, and climate together, reveals that price is not primarily important. While it explains 60.3% of the raw data variance, the inclusion of price terms is not particularly important, as shown in the Table. 53.3% of the remaining variance, after allowing for base and price, is explained by the climate data. A statistical summary of the full model, including all variables, is in Table II.

3.5. Critical Periods in the Abandonment Process

Performance of various models that run through successively less of the crop year is shown in Table II, and graphically in Figure 9. While the price terms are statistically significant, they do not explain an appreciable portion of the variation in abandonment as the crop year progresses, when compared to the climatic data. Further, the increase in explained variance over time is not the same for the two terms. Explanation by the climatic data climbs rapidly early in the season, while the larger increases due to price tend to occur later in the year. If the abandonment variance were being explained by random numbers, the two sets of variables should have explained approximately the same amount at the beginning of the season and increased uniformly through the year.

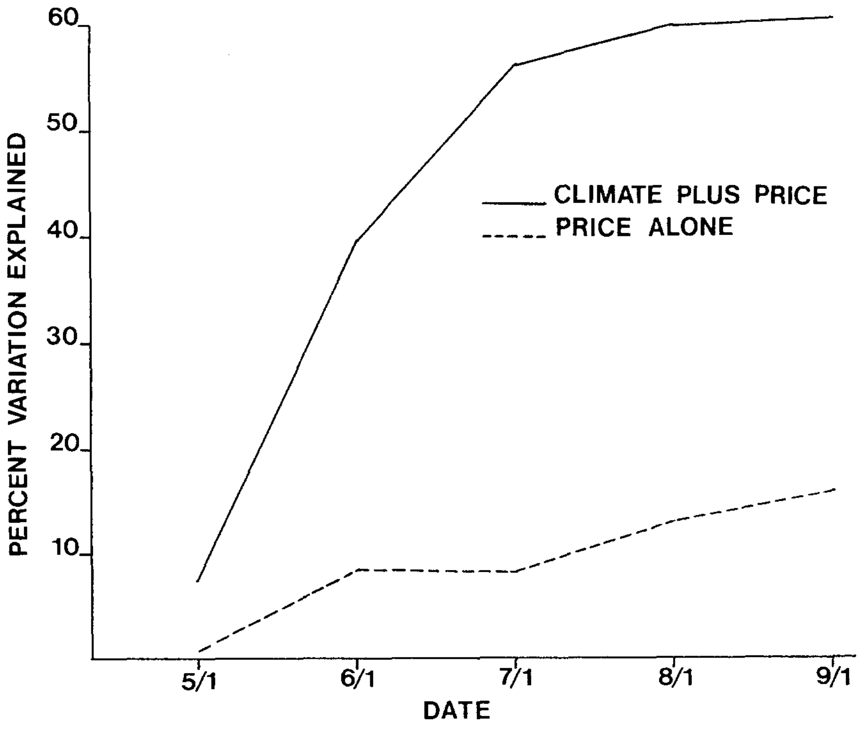

Fig. 9. Summary of the price and price + climate models as the crop year progresses.

TABLE II: Regression summary for the full (March–August) model.

Variable	Regression Coefficient	F-value	Significance
Base terms			
SE South Dakota	−0.362	131.25	0.000
ECent South Dakota	−0.298	97.93	0.000
SCent South Dakota	−0.268	76.16	0.000
Central South Dakota	−0.187	40.70	0.000
NE South Dakota	−0.178	38.95	0.000
NCent South Dakota	−0.161	32.03	0.000
SCent North Dakota	−0.115	17.18	0.000
SE North Dakota	−0.111	16.14	0.000
Central North Dakota	−0.111	15.91	0.000
SW South Dakota	−0.110	14.54	0.000
NCent North Dakota	−0.106	13.69	0.000
NW South Dakota	−0.102	13.48	0.000
WCent North Dakota	−0.094	11.42	0.001
NW North Dakota	−0.087	9.19	0.003
SW North Dakota	−0.082	8.86	0.003
Climate terms			
Temp May^2	0.0018	90.24	0.000
Temp June	0.0149	79.58	0.000
Temp July	0.0130	58.43	0.000
Temp June^2	0.0016	55.79	0.000
Precip May^2	0.2176	31.83	0.000
Precip March–April	−0.1115	21.85	0.000
Precip June^2	0.2314	11.71	0.001
Temp May	0.0048	8.96	0.003
Precip July^2	0.1158	6.74	0.010
Temp August	0.0037	3.82	0.051
Precip May	−0.0410	3.55	0.060
Price terms			
July 1 Quotation	0.3382	151.53	0.000
July 1 Quotation^2	−0.0943	75.20	0.000
August 1 Quotation^2	−0.0091	5.02	0.025
Summary statistics			
Standard deviation of estimates		0.1254	
Multiple correlation coefficient		0.8413	
Coefficient of determination (R^2)		0.7078	

Analysis of variance

Source	Sum of squares	Degrees of freedom[a]	Mean square
Regression	25.65	29	0.844
Residual	10.59	673	0.016
Total	36.24	702	
F ratio with 29 and 673 degrees of freedom:		56.22	
Significance level for overall regression:		0.0000	

[a] Analysis of the data indicates far fewer degrees of freedom than the total number of observations. The overall regression equation should only be considered reliable because of its predictive ability on withheld data (see text).

In fact, the climate terms add much more 'early warning' information than do those for price. While 92.9% of the total explained variance by price and climate (combined) is explained by July 1, only 53.0% of the ultimate explained variance by price (alone) occurs by that date. Weather data yields important information about abandonment as soon as June, while subsequent price data yields little after that date.

Data earlier in the crop year are also important. Price + climate by June 1, only a month after planting, gives more information than does a similar data set for winter wheat running further into the crop year (see Michaels, 1983).

The models for spring and winter wheat do not directly imply causation. However, they do indicate there is no reason to reject a hypothesis that weather (primarily in the early portion of the crop year) is a more important determinant than price (throughout the crop year) in the decision to abandon planted land. In Section 3.7 we use crop yield models to strengthen that hypothesis.

3.6. Abandonment Model Testing

As indicated by our preliminary analyses, there are far fewer degrees of freedom in the abandonment data set than are indicated by the sample size of 702 observations. This induces an overall upwards bias in the statistical significance of individual terms and the overall regression. Thus the model terms have an unexplained unreliability.

There is no documented statistical test to deal with this problem; rather, it is more appropriate to test models on withheld data and empirically determine whether fidelity is retained in the test mode.

This comprises an 'operational' test, or what one would subject unproven regression models to under field conditions. We chose two: First we withheld successive three-year blocks of data for the entire (1932–75) period without overlap, and attempted to predict abandonment, using the newly defined regression parameters, for the periods of missing data. Note that our abandonment model formulation does not use time-trend terms that might bias the tests towards fidelity.

The overall performance in the test years indicated fidelity, with 45.1% of the variation in abandonment explained by price and climate; this compares to 60.6% when all of the years were included in the overall fitting model.

Our second test was more stringent: we withheld, as a block, the first ten years (1932–1941) of model input. This is a deletion of approximately one-quarter of the data for the overall fitting regression. It also includes abandonment perturbations that should be associated with changing market conditions associated with both the dust bowl and the major economic depression of the period. The largest abandonment values also occur here, when over 90% of the planted acreage in some climatically marginal districts was not harvested.

Only 11% of the variation in abandonment was explained in this test. Given the difference in performance between the sequential three-year deletions and this test, it is reasonable to conclude that the usefulness of this regression model lies somewhere between future applications of three to ten years.

This is not unusual in regression models, and should be viewed favorably given the stringency of the ten year test. In that specification, we withheld data from what most experts would agree is the most unusual agroeconomic period of the twentieth century. At the same time, when three-year successive blocks of data were withheld, the performance was much better.

3.7. Analogy to Crop Yield Models

Ideally, our results should be similar to those that would be suggested by crop yield models for both winter and spring wheat. Starr and Kostrow (1978) noted that spring wheat yields in the Dakotas were reduced mainly by high temperatures, although their model did not allow for curvilinear responses to the climatic predictors. In a large-area model for winter wheat by Michaels (1982), the main determinants of yield were precipitation, rather than temperature.

For spring wheat, we developed yield models of the form of Equation (1); Y_c was expressed as in Equation (5). The monthly climatic data were aggregated the same way they were for abandonment. Five different periods were used for winter wheat: September–October ('preseason', planting, and germination), November–February (overwintering), March–April (vegetative phase), and the flowering, grain filling, and harvest months of May and June.

We hypothesize that there should be a correspondence between yield models, based upon planted acreage, and similar abandonment models. The significant climatic terms should be opposite in sign, as increased abandonment implies lower yields. In Tables IIIa and IIIb are comparative rankings of the most important predictors in both the abandonment and yield models, based upon partial F-values. Regression coefficients are also included. Where comparisons are appropriate, 11 of 12 yields regression coefficients for climatic data in the yield models are opposite in sign to those of the abandonment models.

Overall, the same factors that are important in the abandonment models are important in the yield models. In winter wheat, September through April precipitation dominates both abandonment and yield. The same applies to June and July temperatures in spring wheat. One significant lack of correspondence in the spring wheat abandonment and yield

TABLE IIIa: Comparison of the five most significant terms in the yield and abandonment models.

Winter wheat	Regression Coefficient	F-value	Significance
Yield model climate terms			
1. Precip Sept.–Oct.	3.185	135.64	0.000
2. Precip Nov.–Feb.	4.021	89.53	0.000
3. Precip Mar.–Apr.	3.249	69.76	0.000
4. Temp Sept.–Oct.^{2}	0.090	56.47	0.000
5. Precip Mar.–Apr.^{2}	–5.773	51.60	0.000
Abandonment model climate terms			
1. Precip Nov.–Feb.	–0.273	74.38	0.000
2. Precip Sept.–Oct.	–0.221	73.56	0.000
3. Precip Mar.–Apr.	–0.181	38.44	0.000
4. Temp Sept.–Oct.	0.024	17.87	0.000
5. Precip Mar.–Apr.^{2}	0.290	17.67	0.000

TABLE IIIb:

Spring wheat	Regression Coefficient	F-value	Significance
Yield model climate terms			
1. Temp July	–0.509	171.11	0.000
2. Temp June	–0.446	170.55	0.000
3. Precip Mar.–Apr.	4.340	72.77	0.000
4. Temp Mar.–Apr.	0.250	62.76	0.000
5. Temp July^2	0.0028	32.70	0.000
Abandonment model climate terms			
1. Temp May^2	0.0019	90.23	0.000
2. Temp June	0.015	79.08	0.000
3. Temp July	0.013	58.43	0.000
4. Temp June^2	0.0016	55.78	0.000
5. Precip May^2	0.217	31.83	0.000

models is in the strength of the (Temp May^2) term, which appears only in the abandonment model. When combined with its linear counterpart in the overall abandonment model (Table II), the functional form suggests relatively little signal until monthly temperatures are far above normal.

This result leads to speculation that some perception of future returns dictated by May temperatures does not show up in the yield models, but only in abandonment. Perhaps operators should disregard their perceptions of the crop through May, even if the climatic signal might appear negative. In a similar speculative vein (these are correlative, rather than causative models), winter wheat farmers should trust their perceptions concerning final yields during the September–April period.

This report does not attempt to define the *mechanics* of abandonment; rather we only show its climatic associates. We do not know at what times in the crop year the decisions are explicitly formulated. Further, we have not attempted to parameterize the effects of government price and/or acreage controls that clearly influence the decision. We are currently researching more complicated climate/econometric models that may be more causative.

4. Conclusions

We presented here an acreage abandonment model for spring wheat in the northern Great Plains. Reference was provided for an analogous version for winter wheat in the southern Plains. Our abandonment model presented here was robust under test conditions, as was the one for winter wheat (Michaels, 1983).

The abandonment models were based both upon price and weather considerations. Both were much more responsive to monthly temperature and total precipitation figures than they were to expected future delivery prices. The results lead one to tentatively entertain the hypothesis that, over the historical period of the models (1932–1975), farmers must have considered their perceptions of the crop return, based upon weather, were more of a signal than those resulting from the market. The implication is that markets react more slowly to expected supply than do farmers.

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