PN-ABL-536
77782

August, 1990

Measuring The Risk Effects of New Technologies for On-Farm Trials: A Case Study in North Cameroon

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Paper presented at the American Agricultural Economics Association Meetings, August 1990, Vancouver, B.C.

This research is supported by the U.S. Agency for International Development, Science and Technology Bureau, Technology of Soil Moisture Management Project under USDA PASA No. BST-4021-P-AG-1080-00 and by the OAU/STRC/SAFGRAD/CAMEROON Farming Systems Research Program.

ABSTRACT

In formulating objective functions for farm models in a risk context, historical income data have been weighted equally to represent both weather and cross-sectional sources of risk. To represent weather risk adequately, a long time series (rarely available in developing countries) would be needed. A method to measure yield risk associated with some new technologies introduced in Cameroon in 1986-89, based on the concept of stochastic production and the method of moments, is demonstrated. Data used for the study are a long time series for weather and a short cross-sectional/time series for yield-weather-technology relationships.

Key Words

Yield risk, stochastic production, technology assessment, method of moments.

Measurement of The Risk Effects of New Technologies For On-Farm Trials in Dryland Agriculture

Introduction

New technologies are aimed at reducing the risk in dryland agriculture. However, new varieties and production methods are developed and tested at experiment stations under controlled conditions. It is well-known that the effects of such technologies under farm conditions can be quite different than when crops are grown under controlled conditions. New varieties developed by plant breeders may increase mean yields and reduce variability of yields due to weather but may also increase yield variability at the farm level compared to traditional technologies if new varieties do not respond well to farm level conditions. Thus, it is important to be able to assess new technologies at the farm level.

Typically, experiment station yields have been adjusted to predict farm conditions by multiplying station yields by a factor less than one (Perrin et al., 1976; Adesina, 1988). While this method may adjust adequately for mean effects, it cannot be used to predict variance effects since farm yield variation may be due to factors not present in experiment station trials.

The advantage of on-farm trials, compared to experiment station trials, is that new technologies can be tested under a variety of conditions including soil, weather, farmer management skills, and labor and land availability. To analyze observations from farm trials, standard statistical tests such as analysis of variance used for controlled station experiments may not be appropriate for less controlled farm trials.

The purpose of this paper is to demonstrate analytic methods which can be applied to analyze the risk effects of new technologies from on-farm trials for such variable conditions. In particular, we are concerned with the effects of new technologies on income risk.

Some mathematical programming models used for farm planning under risky conditions (Hazell and Norton, 1986) defined income risk in terms of mean and variance and used historical income data to define objective functions, capturing the joint distribution of yield and price (Niang, 1980; Elamin, 1987). Farmer income was assumed to be normally distributed in early work on measuring income risk (Hazell, 1971), implying equal probability weights for sampled incomes.

Recent applications of risk programming in dryland agriculture have focussed on weather risk (Ensink, 1989; Adesina, 1988) for which weather is generally not normally distributed since years of alternative weather types (dry, normal, wet, etc.) may not be equally likely. Because there are long weather cycles (Thompson, 1988), a time series of about twenty to thirty years would be needed to capture the effects of weather risk adequately. Such a long time series for income data would rarely be available even for traditional technologies. Therefore, a different approach from direct use of historical yield or income data is needed to capture risk in dryland agriculture. This paper proposes such an approach.

The method presented here uses regression techniques and statistical modelling to provide the basis for measuring yield and income risk for alternative technologies. Two sources of yield and income variance are identified and measured separately: weather variance and cross-sectional variance. The latter includes sources of variation other than weather resulting from differences among farmers and farms. This type of decomposition of variance was also suggested by Carter (1989) who studied cross-sectional and intertemporal variance for millet, sorghum, and maize for traditional technologies and found cross-sectional variance to be large relative to intertemporal variance.

The production modelling approach provides an alternative to the use of historical income data. A long time series for weather (used to describe weather risk) is combined with a short time series for farm yields observations (used to model yield-technology-weather relationships). The combination produces a model of yield risk for newly available technologies from farm-level observations.

A brief description is given below of the SAFGRAD project which collected data used for this study. Measurement of mean, variance, and covariance effects of new technologies is demonstrated here based on data from this project.

SAFGRAD Project and Characteristics of the Description of Study Area

Data used in this study are from the Semi-Arid Food Grain Research and Development Farming Systems Program (SAFGRAD). This program was carried out by the government of Cameroon and the Scientific and Technical Research Commission of the Organization of African Unity and was funded by the International Fund for Agricultural Development. The objectives of the program included development of agricultural production technologies adapted to the conditions and needs of small farmers in the semi-arid zones of Northern Cameroon. A more complete description of this project can be found in Ngambeki, et al, 1989.

Data on yield collected for this project were obtained for the years 1986, 1987, and 1988. Included were farms in two climatic regions: an area with average annual rainfall of 800-1000 mm (Region 1 in this paper) during the growing season (April through October) and an area with average annual rainfall of 600-800 mm (Region 2 in this paper). Also included are farms of two predominant soil types: clayey soils and sandy soils.

Farms participating in this study included those using traditional technologies, those using extension techniques and varieties, and those using SAFGRAD techniques and varieties. Crops included are maize, cotton, groundnut, red sorghum, white sorghum, transplant sorghum (muskwari), and cowpea. In this paper, results for maize and groundnut are presented to demonstrate the methodology.

The technologies tested for maize include improved practices combined with use of either low or high levels of fertilizer (the high level was 90 kg/ha of nitrogen and the low level was 35 kgN/ha combined with either crop residues or manure); simple ridges or ridges tied at 2m; and alternative varieties. Improved practices include lower planting density (62,000 plants/ha.), thinning plants to 1-2 plant/hill, weeding twice, seed treatment, and fertilization applied in two doses at planting and weeding. Three varieties of maize were tested: Mexican 17E (a traditional long-cycle variety in widespread current use), TZPB-K81 (a long-cycle variety recommended by the Extension Service in North Cameroon), and CMS8501 (a short-cycle variety developed by SAFGRAD). (Appendix A shows the combinations tested in field experiments.)

For groundnut, the traditional variety and practices were compared to improved practices with two new varieties, the SAFGRAD variety K1-441-77 and the extension variety 28-206.

Another management tool is planting date. Because of labor scarcity during normal planting periods, labor constraints can be eased by staggering planting activities. However, there can be yield penalties associated with early or late planting. When early planting is followed by poor rainfall, yield can be reduced, but with later good weather, plants may "catchup". By delaying planting, there may also be a reduction in yield if early weather is good.

Weather Probabilities

Alternative weather conditions were classified in terms of rainfall for critical periods of the growing season. Early season rainfall was represented by cumulative rainfall for the period from April to June 10 and mid-season weather was represented by cumulative rainfall through July 20. Rainfall patterns for the two periods were then grouped as shown below, to designate "drier", "intermediate", and "wetter" rainfall conditions.

Probabilities of "drier", "intermediate", and "wetter" conditions, were based on 24 years of historical rainfall data by agroclimatic region. To obtain probabilities, rainfall observations for three representative sites were used for each region for 1965-1988, for a total of 72 rainfall observations per region. (See Appendix B for observed frequencies of rainfall events by region.)

Note that the probability distribution for rainfall conditions is not normal in either region. The distribution for Region 2 is heavily skewed toward low rainfall, whereas for Region 1, it is skewed toward intermediate to wetter rainfall conditions.

Growing Period Rainfall (mm)

Early (before June 10)		Later (before July 20)	
low	≤ 150	low	≤ 250
medium	151 - 230	medium	251 - 350
high	≥ 231	high	≥ 351

Classsification of Rainfall Conditions

as Related to Early/Later Rainfall

Drier: low/low; low/medium; medium/low

Intermediate: medium/medium; low/high; high/low

Wetter: high/high; medium/high; high/medium

Probabilities of Rainfall Conditions by Weather Region.

	Drier	Intermediate	Wetter
Region 1:	.3055	.3472	.3472
Region 2:	.6528	.3194	.0278

Yield Modelling

Field experiments could not test each possible combination of planting date, soil, fertilizer level, variety, and ridges. Therefore, regression models were used to infer yield for combinations not directly tested.

The production function approach models yield (y) as related to technology inputs (x), soil (s), and weather (w). Because of weather and other sources of randomness, yield is a random variable. Here we represent the random nature of yield by the relationship

$$y = f(x,s,\omega) + \epsilon \tag{1}$$

where $f(\cdot)$ is the mean production function for given weather, soil, and technology and ϵ is a random variable representing deviation from this mean by individual farmers. ϵ can be identified with cross-sectional sources of variation; therefore a normal distribution with zero mean is an appropriate specification. The relationship between ϵ and ω may be a conditional one; that is, the probability of observing any given deviation from the mean yield may depend on weather and inputs. For example the use of fertilizer and tied ridges may reduce yield variation among farmers with different types of soil.

Separate yield regressions were estimated for each type of weather condition because the effect of a given technology may depend on the weather in a nonlinear way. For example, tied ridges may increase yield for intermediate rainfall conditions but could decrease yield for wetter conditions, especially with clayey soils. Or, a new drought tolerant variety may increase yield more for lower rainfall conditions than for higher rainfall conditions.

Farm yield observations for each type of weather condition are regressed in terms of technology choices, planting dates, and soil. The regression is of the form:

$$y_{ik}^{\omega} = y_{io}^{\omega} + \sum_{\ell} \alpha_{i\ell}^{\omega} D_{i\ell} + \alpha_{is}^{\omega} D_S + \epsilon_{ik}^{\omega}. \tag{2}$$

where y_{ik}^{ω} is the yield for crop i, farmer k, weather ω. y_{io}^{ω}, the constant term, is the mean yield for the traditional technology in weather state ω. $D_{i\ell}$ denotes a dummy variable indicating a nontraditional technology choice; a value of one means that the technology is applied whereas a value of zero means it is not applied: D_S indicates a dummy variable for soil type, a value of zero or one differentiates between soil types. The coefficient $(\alpha_{i\ell}^{\omega})$ of a factor (ℓ) tells how the application of a new technology will affect yield for the average farmer for weather state ω. By assumption the error term for the regression (ϵ^{ω}_{ik}) has a normal distribution with mean zero.

Regression (1) should be corrected for heteroscedasticity by the method of moments (Antle, 1983). Cross-sectional variance is estimated as related to alternative technologies by regressing the squared residual in (1) on the same explanatory variables. The cross-sectional variance regression is of the form

$$SE^{\omega}_{ik} = V^{\omega}_{io} + \Sigma\beta^{\omega}_{i\ell}\, D_{i\ell} + \beta^{\omega}_{is}\, D_s + \eta^{\omega}_{ik} \tag{3}$$

for the sum of squared error $SE^{\omega}_{ik} = (\epsilon^{\omega}_{ik})^2$. V^{ω}_{io} represents the cross-sectional variance for the traditional technology and η^{ω}_{ik} is the regression error term having mean zero. $\beta^{\omega}_{i\ell}$ shows how a technology (ℓ) affects cross-sectional variance for weather state ω. Weights for generalized least squares (GLS) are obtained from (3) and used to obtain consistent parameter estimates for (2) having minimum variance.

Table 1 shows GLS regressions for maize yield by weather condition. The constant term in the mean yield regression represents the yield for the average farmer with traditional technology for weather conditions at the indicated level. Note that this traditional yield increases as the weather improves, increasing from 1310 kg/ha to 2161 kg/ha to 2673 kg/ha.

The effects of new technologies, planting date, and soil on mean yield are indicated by the coefficients of the corresponding dummy variables. Use of improved agronomic practices and low fertilizer for maize increases yield for the driest rainfall pattern. In comparison, the combination of high fertilizer and the CMS variety produces a smaller yield increase of 3588 for the driest weather.

For intermediate weather, using high fertilizer significantly increases yield. The combination of TZPB, high fertilizer, and tied ridges produces an average yield of about 5372 kg/ha. With wetter weather, the maximum yield of 4086 kg/ha is obtained from the combination of high fertilizer and the CMS variety.

Considering the significance of the coefficients for RIDGE, use of tied ridges can complement improved agronomic practices when rainfall conditions are in the intermediate range. Use of simple ridges (RID) does not significantly increase average yields in any period. Planting late (after June 20) reduces yields significantly for the intermediate rainfall condition.

Technologies can also affect cross-sectional variance. Fertilizer, simple ridges, and late planting have significant effects on cross-sectional variance for drier weather. Simple ridges and late planting reduce variance. Except for soil, cross-sectional variance is not otherwise significantly affected for intermediate and wetter conditions by maize technologies.

Similar results for groundnut are shown in Table 2. Planting early or late has a significantly negative effect for yield in wetter rainfall conditions. Both new varieties have a significant positive effect on yields for both intermediate and wetter rainfall conditions. Cross-sectional variance results show that both planting early and planting late reduce variance. Use of the new variety 28-206 also reduces cross-sectional variance.

Measurement of Mean and Variance for Optimization Models

The purpose of optimization is to choose the number of units of land to be planted in each crop, given price and variable cost per yield unit for each crop. Using variance as a measure of riskiness, technologies are preferred which reduce variance, or which have mean effects offsetting variance effects. Crop combinations which exhibit negative correlations (or have a negative covariance) may be combined to produce preferred crop portfolios in terms of risk.

As will be shown below, income variance can be expressed in terms of weather variance for each crop, cross-sectional variance for each crop, and covariances for each pair of crops grown. Yield regressions as those given above, can be used to measure yield risk in such optimization models.

Each farmer (k) in a cross-sectional study provides sample yield observations for each crop (i) grown. We now show, with the assumption that ϵ in (1) is conditional on weather, that yield variance can be decomposed into two terms: weather variance for the average farmer and cross-sectional variance. Let y_{ik}^{ω} denote yield observed for crop i for farmer k and weather state ω. Let π^{ω} denote the probability of weather state ω and N^{ω} denote the number of farms with observations in weather state ω. (In the derivation below, we assume each farm sampled grows each crop, but the number of farms sampled each year may differ.)

The sample mean $(\bar{y}_i^{\omega})$ over farmers for a given weather state, with soil and technology held constant, is obtained by weighing each observation equally because of assumed normality of the ϵ distribution:

(4) $$\bar{y}_i^{\omega} = \sum_k y_{ik}^{\omega}/N^{\omega}.$$

$\bar{y}_i^{\omega}$ represents the yield for the average farmer in weather state ω.

The expected value of yield is obtained from the joint distribution of yield over both farmers and weather states. Because of the assumed conditional relationship of ϵ on ω, the joint probability of a farm yield observation and a given weather state is the product of the probabilities: $(1/N^{\omega})\ \pi^{\omega}$. First taking the mean over farmers and then over weather probabilities, the overall mean $(\bar{\bar{y}}_i)$ is the yield for the average farmer in each weather state ω weighted by the probability of each weather state:

(5) $$\bar{\bar{y}}_i = \sum_{\omega} \sum_k y_{ik}^{\omega}\ (1/N^{\omega})\ \pi^{\omega} = \sum_{\omega} \bar{y}_i^{\omega}\ \pi^{\omega}.$$

The sample variance of yield is obtained by squaring the difference between each farm observation and the overall mean yield, weighting by the joint probability, and then summing over farmers and weather states. Sample variance for a given crop and technology can be decomposed into two terms, as follows:

$$(6)\quad \text{Sample Var}\,(y^{\omega}_{ik}) = \sum_{\omega}\sum_{k} (y^{\omega}_{ik} - \bar{y}_i)^2 \frac{1}{N^{\omega}} \pi^{\omega}$$

$$= \sum_{\omega}\sum_{k} (y^{\omega}_{ik} - \bar{y}^{\omega}_i + \bar{y}^{\omega}_i - \bar{y}_i)^2 \frac{1}{N^{\omega}} \pi^{\omega}$$

$$= \sum_{\omega} (\bar{y}^{\omega}_i - \bar{y}_i)^2 \pi^{\omega} + \sum_{\omega}\sum_{k} (y^{\omega}_{ik} - \bar{y}^{\omega}_i)^2 \frac{1}{N^{\omega}} \pi^{\omega}$$

$$+ 2 \sum_{\omega} (\bar{y}^{\omega}_i - \bar{y}_i) \left(\sum_{k} (\bar{y}^{\omega}_{ik} - \bar{y}^{\omega}_i) \frac{1}{N^{\omega}}\right) \pi^{\omega}.$$

The first term in this decomposition is variance due to weather for the average farmer, and the second term is cross-sectional variance. The third term is zero by (4).

Taking expectations in (2) over both farmers and weather, the expected yield as related to technology and soil can be determined:

$$(7)\qquad \bar{y}_i = \sum_{\omega} \bar{y}^{\omega}_i \pi^{\omega} = \sum_{\omega} (y^{\omega}_{io} + \sum \alpha^{\omega}_{i\ell} D_{i\ell} + \alpha^{\omega}_{is} D_s) \pi^{\omega}.$$

Weather variance as related to use of technology by the average farmer (the first variance term in (6)) can also be measured by applying results of regression (2). As in the first term of (6), weather variance is obtained by subtracting the mean taken over all weather states ($\bar{y}_i$) from the mean for each weather state ($\bar{y}^{\omega}_i$), squaring each of these terms, and then weighting each by the weather probability. (This measure of variance is analogous to what would be obtained in an experiment station study of technologies in which only weather conditions would vary.)

The cross-sectional variance (CSV_i) over all weather conditions is obtained as related to technology, planting date, and soil by taking the expected value of over both farmers (to get SE_i^{ω}) and weather in (3):

$$(8) \qquad CSV_i = \sum_{\omega} (\overline{SE}_i^{\omega})\ \pi^{\omega} = \sum_{\omega} (V_{io}^{\omega} + \sum \beta_{i\ell}^{\omega}\ D_{i\ell} + \beta_{is}^{\omega}\ D_s)\ \pi^{\omega}.$$

Based on the sampled yields, sample income for farmer k over all crops grown is:

$$(9) \qquad I_k^{\omega} = \sum_i [p_i\ y_{ik}^{\omega} - C_i]\ A_i$$

where C_i denotes variable cost per land unit planted for crop i, P_i denotes price for crop i, and A_i is land units planted. (Here, price is not random.) Sample income variance compared to the overall mean income $\bar{I}$ is:

$$(10) \quad \text{Sample Income Variance} = \sum_{\omega} \sum_{k} (I_k^{\omega} - \bar{I})^2 \frac{1}{N^{\omega}} \pi^{\omega}$$

$$= \sum_{\omega} \sum_{k} (\sum_{i} p_i^2\ A_i^2\ (y_{ik}^{\omega} - \bar{y}_i))^2 \frac{1}{N^{\omega}} \pi^{\omega}$$

$$= \sum_{i} p_i^2\ A_i^2\ [\sum_{\omega} \sum_{k}\ (y_{ik}^{\omega} - \bar{y}_i)^2 \frac{1}{N^{\omega}} \pi^{\omega}]$$

$$+ \sum_{i,j} p_i A_i\ p_j A_j\ [\sum_{\omega} \sum_{k} (y_{ik}^{\omega} - \bar{y}_i)(y_{jk}^{\omega} - \bar{y}_j) \frac{1}{N^{\omega}}\ \pi^{\omega}].$$

Considering the last equality in the decomposition of income variance, the expression in brackets in the first term is the sample yield variance for each crop. This term can be further decomposed to be the sum of weather variance and cross-sectional variance for each crop as shown above. The expression in brackets in the second term is the covariance for pairs of crops i and j. Similar to variance, covariance can be expressed as a sum of two terms, covariance due to weather for the average farmer and cross-sectional covariances for pairs of crops. Covariance for two crops can be related to the technology factors which affect yields for maize ($D_{M\ell}$) and groundnut ($D_{G\ell}$) separately from the regressions (2) and (3).

Estimated Mean, Variance, and Covariance Effects of New Technologies

Means and variances associated with alternative technologies for each of the two weather regions, obtained by applying the regression equations with the corresponding weather probabilities and the above formulas, are shown in Table 3 for maize and Table 4 for groundnut. Table 5 shows covariance for selected technology combinations for maize and groundnut.

Table 3 shows the expected values and variances of yield for four technology combinations for maize. These combinations are: traditional variety with traditional farming methods; traditional variety with improved methods and low fertilizer; traditional variety with improved methods, high fertilizer, and tied ridges; and the new variety (CMS8501) with improved methods, high fertilizer and tied ridges. (Results shown in Table 3 and 4 are in terms of a normal planting date and sandy soil.) Total variance in Table 3 is the sum of the two types, weather variance and cross-sectional variance. Note that the cross-sectional variance is a larger share of total variance for maize than the weather variance.

Weather variance is reduced by low fertilizer, in comparison to the traditional technology, but it is increased by high fertilizer in Region 1. The percent reduction in weather variance obtained by the use of low fertilizer is greater in Region 2 than in Region 1. All technologies increase cross-sectional variance but the effect due to using low fertilizer is relatively small. Total variance is reduced in both regions by low fertilizer use but is increased by other technologies.

Higher total variance for new technologies is offset by higher mean yields. All new technologies shown in Table 3 increase mean yield but a greater percent increase occurs for Region 2 because of the predominance of dry weather conditions for which new technologies are designed.

The coefficient of variation in yield (the standard deviation divided by mean) is the measure of riskiness. It is lower for all of the new technologies than for the traditional technology. Since all new technologies produce similar coefficients of variation, lower cost technologies (ie improved practices with low fertilizer) will be preferred. Region 2 becomes more like Region 1 in terms of yield risk when new technologies are introduced.

Table 4 shows similar information for groundnut. Use of the new variety increases mean yield in both regions, with a larger percent effect obtained in Region 2 because of its greater chance of having dry conditions. In this case, use of the new variety reduces cross-sectional variance but increases weather variance in Region 1. The total variance is reduced by the new variety. The coefficient of variation of yield is greatly reduced by use of the new variety, again with a larger effect in Region 2. Again, yield risk in Region 2 becomes more similar to that in Region 1 with the new technology.

In Table 5, covariance effects are shown for combinations of technologies for maize and groundnut. From a portfolio standpoint, negative covariance is preferred. (Covariance indicates correlation in yields; correlation is obtained from covariance by dividing by the product of standard deviations for each crop. For example the correlation coefficient between maize and groundnut yield for the traditional technologies in Region 1 is .86.) Covariance cannot be directly compared to variance of maize and groundnut without converting to common dollar units. However, since prices of maize and groundnut are similar (respectively $.30 and $.33 per kg), the magnitudes of income variance and covariance are roughly similar.

In terms of total covariance, use of low fertilizer for maize and the new variety for groundnut produces the most negative covariance because maize yield is greatly increased by low fertilizer in drier weather whereas groundnut yield increases with wetter weather conditions. Cross-sectional covariance increases with new technologies.

Conclusions

In formulating objective functions for mathematical programming models to be used for farm planning in a risk context, historical income data may not represent weather risk correctly if a short time series is used. A long time series for income is rarely available for underdeveloped countries and, even if available, would not reflect new technologies.

The regression methodology based on the method of moments presented in this paper provides an alternative way to measure yield risk. Weather probabilities are obtained from historical weather data. Risk can be modelled for different weather regions by applying the appropriate probabilities.

This paper separately identified weather and cross-sectional variance as components of total variance. IFor the SAFGRAD technologies analyzed here, similar to Carter's (1989) results for traditional technologies, it was shown that cross-sectional variance, can an important source of yield variation in comparison to weather variance. New technologies can affect cross-sectional variance as well as weather variance. Our results indicate that, compared to high input or traditional practices, low input improvements together with improved varieties may have the most beneficial effects on yield input risk. Furthermore, covariance is of a magnitude similar to variance and it may be greatly reduced by use of new technologies.

Since experiment station tests of new technologies do not measure cross-sectional variance and covariance, it is important to test new technologies with farm-level trials in order to make appropriate recommendations about new technologies. Specific results about new technologies obtained here from farm-level data indicate that improved practices, low fertilizer use, and new varieties can help to reduce yield risk in drier climatic areas and also to reduce the disparity between wetter and drier climatic regions.

Future work will incorporate the regression method for a full spectrum of crops in mathematical programming models to consider the implications of new technologies for crop mix and total income risk.

Table 1a. GLS Estimate of Yield Model by Weather Pattern, Maize (kg/ha)

	Drier Weather		Inter. Weather		Wetter Weather	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Y_0^{ω}	1310.56	5.06*	2161.70	13.093*	2673.48	12.06*
DFH	1762.21	2.49*	1190.12	2.198*	1166.90	2.27*
RID	-149.38	-0.21	509.32	0.934	-198.82	-0.38
RIDGE	319.56	0.43	973.77	1.481*	-90.80	-0.15
DL	-30.00	-0.09	-753.62	-3.910*	-268.76	-1.31*
SD	40.48	0.15	287.65	1.720*	-362.49	-1.71*
DTZPB	110.11	0.27	1048.32	2.747*	-515.09	1.12
DCMS	516.47	1.84*	479.66	1.703*	246.18	0.79
DFL	2399.40	2.88*	41.72	0.061	402.03	0.64
R^2	.25		.52		.23	
N^{ω}	139		194		153	

Table 1b. Cross-Sectional Variance, Maize $(kg/ha)^2 \times 10^4$

	Drier Weather		Inter. Weather		Wetter Weather	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
V_0^{ω}	49.90	1.07	32.23	0.98	98.83	2.81*
DFH	260.93	2.66*	.58	0.00	55.98	0.72
RID	-213.65	-2.21*	113.32	1.02	35.40	0.46
RIDGE	-39.83	-0.40	35.48	0.27	-34.37	-0.39
DL	-85.83	-1.66*	14.38	0.43	-35.37	-1.09
SD	28.53	0.69	62.16	2.24*	-44.88	-1.31*
DTZPB	66.89	1.00	-37.04	-0.61	69.93	1.19
DCMS	33.35	0.69	17.47	0.43	-21.63	-0.49
DFL	186.69	1.35*	-110.98	-0.80	-16.86	-0.17
R^2	.15		.11		.09	
N-OBS	139		194		153	

Definition of Regression Variables for Maize:

Y_0^{ω} - yield for the average farmer with the traditional technology.

V_0^{ω} - variance of yield for the average farmer, traditional technology.

DFH - a dummy variable value of one indicates high fertilizer use.

RID - a dummy variable value of one indicates use of ridges.

RIDGE - a dummy variable value of one indicates use of tied ridges.

DL - a dummy variable value of one indicates maize planting after June 20.

SD - a dummy variable value of one indicates sandy soil (as opposed to clayey soil).

DTZPB - a dummy variable value of one indicates use of new variety TZPB.

DCMS - a dummy variable value of one indicates use of new variety CMS8501.

DFL - a dummy variable value of one indicates low fertilizer use.

*Significant at least at 90% level.

Table 2a. GLS Estimates of Yield Model by Weather Pattern, Groundnut (kg/ha)

	Drier Weather		Inter. Weather		Wetter Weather	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Y_o^{ω}	1026.75	10.36*	2060.19	12.17*	2269.02	9.70*
SD	-168.00	-1.46*	332.95	1.37*	1123.22	2.80*
DE	70.46	0.60	-242.37	-0.68	-685.68	-2.43*
DL	-57.85	-0.40	-500.13	-2.02*	-637.83	-1.65*
DK1	•	•	795.68	3.35*	981.98	2.51*
D28	•	•	844.37	3.83*	789.73	2.28*
R-SQUAR		0.04		0.30		0.59
N-OBS		66		97		42

Table 2b. Cross-Sectional Variance Effects, Groundnut $(kg/ha)^2 \times 10^4$

	Drier Weather		Inter. Weather		Wetter Weather	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
V_o^{ω}	29.65	5.78*	56.16	2.34*	70.12	3.95*
SD	-15.92	-2.50*	55.88	2.19*	-36.75	-1.44*
DE	-9.45	-1.14	-46.90	-1.37*	-52.25	-2.47*
DL	-10.06	-0.95	-60.40	-2.91*	-3.84	-0.16
DK1	•	•	-23.79	-0.81	-32.25	-1.23
D28	•	•	-39.30	-1.35*	-53.94	-2.07*
R-SQUAR		0.13		0.19		0.18
N-OBS		66		97		42

Definition of Regression Variables for Groundnut:

Y_0^{ω} - yield for the average farmer with the traditional technology.

V_0^{ω} - variance of yield for the average farmer, traditional technology.

DE - a dummy variable value of one indicates groundnut planting before May 30.
DL - a dummy variable value of one indicates groundnut planting after June 20.
DK1 - a dummy variable value of one indicates use of new variety GK1.
D28 - a dummy variable value of one indicates use of new variety G28.
SD - a dummy variable value of one indicates sandy soil (as opposed to clayey soil).

*Significant at least at 90% level

Table 3. Yield Mean and Variance by Weather Region, Maize[a]

Mean Yield by Technology (kg/ha)	Region 1	Region 2
Trad.	2065.54	1728.54
Trad. + Improved Prac. + low Fert.	2751.12	2903.42
Trad. + Improved Prac. + high Fert. + Ridge	4021.11	4224.55
CMS + Improved Prac. + high Fert. + Ridge	4430.91	4721.75

Weather Variance of Yield by Technology ($x 10^4$)	Region 1	Region 2
Trad.	18.14	26.84
Trad. + Improved Prac. + low Fert.	6.39	8.41
Trad. + Improved Prac. + high Fert. + Ridge	26.20	8.33
CMS + Improved Prac + high Fert. + Ridge	38.04	8.88

Cross-Sectional Variance by Technology ($x 10^4$)	Region 1	Region 2
Trad.	75.46	82.85
Trad. + Improved Prac. + low Fert.	75.80	83.21
Trad. + Improved Prac. + high Fert. + Ridge	140.36	190.85
CMS + Improved Prac. + high Fert. + Ridge	149.10	217.61

Total Variance of Yield by Technology ($x 10^4$)	Region 1	Region 2
Trad.	93.60	109.69
Trad. + Improved Prac. + low Fert.	82.19	91.62
Trad. + Improved Prac. + high Fert. + Ridge	166.56	199.18
CMS + Improved Prac. + high Fert. + Ridge	187.14	226.49

Coefficient of Variation of Yield by Technology	Region 1	Region 2
Trad.	.47	.61
Trad. + Improved Prac. + low Fert.	.32	.33
Trad. + Improved Prac. + high Fert. + Ridge	.32	.33
CMS + Improved Prac. + high Fert. + Ridge	.31	.32

[a] Normal planting date, sandy soil.

Table 4. Yield Mean and Variance by Weather Region, Groundnut[a]

	Region 1	Region 2
Mean Yield (kg/ha)		
Trad.	2271.03	1419.27
G28[b]	3058.00	2084.76
Weather Variance in Yield ($(kg/ha)^2 \times 10^4$)		
Trad.	105.09	61.62
G28[b]	143.14	3.85
Cross-Sectional Variance in Yield ($(kg/ha)^4 \times 10^4$)		
Trad.	53.40	45.17
G28[b]	8.60	3.85
Total Variance in Yield ($(kg/ha)^2 \times 10^4$)		
Trad.	158.49	106.79
G28[b]	151.74	86.53
Coefficient of Variation in Yield		
Trad.	.55	.73
G28[b]	.41	.44

[a] normal planting date, sandy soil.

[b] assumes the yield in ω = drier is 0.7 times yield in ω = intermediate, because of missing data.

Table 5. Covariance $((kg/ha)^2 \times 10^4)$ for Technology Combinations, Maize and Groundnut.[a]

Weather Covariance

Trad. G with:	Region 1	Region 2
Trad. M	41.21	69.40
Trad. M + low Fert.	-68.78	-115.82
Trad. M + high Fert. + Ridge	2.33	3.29
CMS + high Fert. + Ridge	-8.75	15.53
G28 with:		
Trad. M	46.19	76.71
Trad. + low Fert.	-77.06	-127.99
Trad. + high Fert. + Ridge	6.12	7.16
CMS + high Fert. + Ridge	-5.52	-12.86

Cross Sectional Covariance

Trad. G with:	Region 1	Region 2
Trad. M	63.41	61.07
Trad. M + low Fert.	63.50	61.19
Trad M + high Fert + Ridge	86.48	92.68
CMS + high Fert. + Ridge	89.13	98.96
G28 with:		
Trad. M	25.45	17.84
Trad. M + low Fert.	25.51	17.87
Trad. M + high Fert. + Ridge	34.71	27.07
CMS + high Fert. + Ridge	40.08	28.91

Total Covariance

Trad. G with	Region 1	Region 2
Trad. M	104.62	130.47
Trad. M + low Fert.	-5.28	-54.63
Trad. M + high Fert. + Ridge	88.81	95.97
CMS + high Fert. + Ridge	80.38	83.43
G 28 with:		
Trad. M	71.64	94.55
Trad. M + low Fert.	-13.56	-66.80
Trad. M + high Fert. + Ridge	92.60	100.28
CMS + high Fert + Ridge	83.61	86.10

[a]Normal planting date, sandy soil.

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Appendix Table A. Technology Combinations for Maize Experiments

Name	Variety	High Fert.	Low Fert.	RIDGE	TIED RIDGE	IMP. PRAC.
TRAD	mixed	0	0	0	0	0
M25	MEX .17	0	1 (manure)	1	0	1
MR25	MEX .17	0	1 (crop residue)	1	0	1
M100	MEX .17	1	0	1	0	1
M5T*	MEX .17	0	0 (very low)	1	0	1
MFPR*	MEX .17	0	0	1 (very simple)	0	0
MFLOT	MEX .17	1	0	0	0	1
MRID	mixed	1	0	1	0	1
M2RM	MEX .17	1	0	0	1	1
M3RM	MEX .17	1	0	0	1	1
MAX17	MEX .17	1	0	1	0	1
CMS501	CMS8501	1	0	1	0	1
TZPB	TZPB	1	0	1	0	1

**Data excluded from regression

**Note that in regressions, improved practices are applied whenever fertilizer and for ridges are applied. That is, we are not able to separate the effects of improved practices from fertilizer use and/or ridges.

Appendix Table B. Weather Probabilities by Rainfall Pattern, Region, and Weather

	Weather Region 1				Weather Region 2			
Rainfall	sect 1	sect 4	sect 5	prob.	sect 2	sect 3	sect 9	prob.
pattern*	freq.	freq.	freq.	prob.	freq.	freq.	freq.	prob.
ll	1	3	1	.0694	5	6	10	.2917
lm	5	6	4	.2083	6	10	10	.3611
lh	9	6	4	.2639	5	3	2	.1389
mm	1	1	3	.0694	2	2	0	.0555
ml	1	1	0	.0278	0	0	0	0
mh	2	3	5	.1389	4	0	1	.0139
hh	1	3	5	.1250	0	0	0	0
hm	4	0	2	.0833	0	3	1	.0139
hl	0	1	0	.0139	1	0	0	0

*l - low
m - medium
h - high