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A COMPARISON OF RISK EFFICIENCY CRITERIA IN EVALUATING GROUNDNUT PERFORMANCE IN DROUGHT-PRONE AREAS

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This paper contributes to an evaluation of the performance of groundnuts in drought-prone areas by estimating yield response functions to water from experimental data. They are combined with meteorological data to simulate yields by location. Efficient genotypes are identified by several risk criteria. Genotype rankings based on these risk criteria and simulated yields are different from those based on experimental data and plant scientists' traditional methods of evaluation.

A major source of risk facing farmers in the semi-arid tropics is the year-to-year variation in crop production. Such variability can be largely attributed to fluctuations in environmental factors that affect plant growth and yield, particularly available moisture. To help stabilise agricultural yields, the international agricultural research centres are working to develop higher-yielding varieties that also perform well in variable environments (Hazell 1986). The International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), for example, has an extensive ongoing programme to evaluate the performance of groundnut (peanut) genotypes under a range of drought conditions.

The evaluation of varieties has, in general, been based on data from multi-site, multi-season nursery trials. The analysis of such data typically follows the approach developed by Finlay and Wilkinson (1963), in which the yields of each genotype at each site are regressed on an environmental index, the mean yield of all genotypes at each site. The slope coefficient is regarded as a measure of a genotype's yield stability and genotypes are assessed according to their stability and

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their mean yield. The use of multi-locational trial data presumes that the spatial replication reflects the actual distribution of environmental conditions in producing areas. If this presumption is invalid, the evaluations may be of less value to farmers concerned with how a genotype will perform over time in their region. In Finlay and Wilkinson's (1963) approach, the environments in the trials are classified according to mean genotype performance; results cannot be extrapolated to other locations as no independent measure of the environment exists. Furthermore, data from such trials are often incomplete and, thus, results may be biased.

To deal with the data problems, plant scientists at ICRISAT have undertaken extensive experiments involving 22 groundnut genotypes and 96 drought treatments. The purpose of this paper is to extend their statistical and physiological analysis of the data and contribute further to an evaluation of the performance of groundnuts in drought-prone areas by incorporating economic concepts of risk efficiency. Yield response functions are estimated from the experimental data. These response functions are unique in that they account for the effects of both the quantity and timing of water application. They are combined with historical meteorological data from three sites in two of India's major groundnut-producing regions to simulate yield distributions for each genotype in each location. Having generated yield distributions, the efficient genotypes identified by various risk criteria are compared. The results have implications both for specific genotype selection by location and for the design of future experiments.

Experimental Data and Study Regions

The results from a single-site experiment conducted by ICRISAT, in which 22 genotypes of groundnut were subjected to a range of drought conditions (Nageswara Rao and Williams 1985), are used to estimate the relationship between yield and available moisture.[1] Groundnut genotypes of comparable maturity were selected to include lines found to be tolerant, average or susceptible to drought in previous screening. These included established commercial and Indian cultivars and advanced breeding lines. Drought patterns were developed in relation to four phenological phases in the groundnut growing cycle: 1) seedling–flowering; 2) pegging; 3) podset; and 4) podfilling to maturity. The treatments varied in the timing, duration and intensity of water stress, ranging from non-stressed control plots to plots in which the crop received virtually no water for the duration of the growing season.

In selecting the study locations, attention was focused on the two major groundnut-producing regions in India: Gujarat and Andhra Pradesh. These two states accounted for just under half of India's groundnut production in 1984 (Bailey 1988). One site was selected from Gujarat and two sites, Hyderabad and Anantapur, from Andhra Pradesh. The sites differ climatically. Hyderabad is fairly well assured of adequate rainfall during the growing season; Anantapur has a lower rainfall with a high and variable incidence of drought. While Gujarat

[1]For this present study, the unpublished data from this trial were obtained from ICRISAT.

TABLE 1

Summary Statistics on Distributions of RAW

	Growth phases			
RAW	G1	G2	G3	G4
Experiment				
Maximum	1·00	1·00	0·72	0·79
Minimum	0·50	0·01	0·02	0·01
Mean	0·94	0·80	0·51	0·57
Std. dev.	0·15	0·28	0·19	0·27
Skewness	−2·11	−1·29	−0·97	−0·94
$P(RAW \leq 0{\cdot}5)$	0·01	0·18	0·39	0·33
Hyderabad				
Maximum	1·00	1·00	1·00	1·00
Minimum	0·39	0·28	0·37	0·00
Mean	0·98	0·93	0·90	0·92
Std. dev.	0·10	0·14	0·17	0·20
Skewness	−5·17	−3·06	−1·52	−3·22
$P(RAW \leq 0{\cdot}5)$	0·01	0·02	0·04	0·05
Anantapur				
Maximum	1·00	1·00	1·00	1·00
Minimum	0·00	0·00	0·00	0·00
Mean	0·44	0·35	0·45	0·56
Std. dev.	0·30	0·29	0·32	0·39
Skewness	0·47	0·68	0·52	−0·27
$P(RAW \leq 0{\cdot}5)$	0·60	0·73	0·64	0·41
Gujarat				
Maximum	1·00	1·00	1·00	1·00
Minimum	0·55	0·03	0·01	0·00
Mean	0·99	0·94	0·79	0·60
Std. dev.	0·08	0·19	0·30	0·47
Skewness	−5·65	−4·17	−1·20	−0·39
$P(RAW \leq 0{\cdot}5)$	0	0·03	0·25	0·41

has a relatively high rainfall, its rainy season is much shorter, resulting in a high incidence of late season drought. About 80 years of daily meteorological data for Hyderabad and Anantapur, and 30 years of weekly data for Gujarat, were also provided in unpublished form by ICRISAT.

Development of a Measure of Water Availability

To control the drought treatments through the application of irrigation without interference from rainfall, the trial was planted in the late post-rainy season and continued into the summer season under conditions that, meteorologically, are different from those in the rainy season. Furthermore, the trial is characterised by discrete applications of water, irrigation being applied at the first signs of wilting in the non-stressed control plots. This is in contrast to the essentially continuous nature of rainfall in the rainy season, when soil moisture may be continually replenished by rain showers. Thus, the problem of simulating yields in each of the three sample locations is compounded by the difficulties involved in translating results from the post-rainy season trial to rainy season conditions.

To do this, an index of relative water availability (RAW, available moisture relative to potential water requirements, $0 \leq RAW \leq 1$) was developed based on a simple daily soil moisture budgeting approach [see Bailey (1988) and Bailey and Boisvert (1989) for complete details]. It takes account of the soil moisture-holding capacity and the consumptive water use requirements of the plant, given potential evapotranspiration rates and stage of crop growth, and allows for the carryover of soil moisture from one period to another.

Potential evapotranspiration, measured by Class A pan evaporation and adjusted by crop growth coefficients from Stern (1986), is used to estimate daily potential crop water requirements (PWR_t). Available water (AW_t) is calculated as the sum of daily rainfall (or irrigation) and stored soil moisture from the previous day, less losses to run-off or deep drainage. Losses are assumed to occur when rainfall (irrigation) plus stored soil moisture exceed soil moisture storage capacity.

Evapotranspiration is assumed to proceed at the potential rate, available water permitting, and the remaining soil water (SW_t) is carried forward and used in calculating the following day's available moisture. Otherwise it is assumed soil moisture is depleted to zero:

(1) if $AW_t > PWR_t$ then $SW_t = AW_t - PWR_t$, otherwise $SW_t = 0$

In estimating soil water budgets from the historical meteorological data, a growing season was defined for each year for which data were available. This was done by setting planting dates according to decision rules based on rainfall received. To account specifically for the effect of timing of water application, the growing seasons were further divided into the four growth phases discussed earlier: 1) seedling–flowering vegetative phase; 2) pegging to beginning of podset; 3) podset to podfilling; and 4) podfilling to maturity.

A measure of the total available moisture during each of these growth phases (AW_i; $i = 1,2,3,4$) is obtained from the sum of daily available moisture plus the initial stored soil moisture less the soil moisture remaining at the end of the growth interval. Similarly, the total potential water requirements (PWR_i) in each growth interval, i, are the sum of the daily requirements. Relative available water (RAW_i) is then defined as:

(2) $RAW_i = AW_i / PWR_i$

RAW_i is a measure of the degree to which the crop's requirements for water during each growth phase are satisfied. It is not proposed that this approach gives an accurate representation of the soil water regimes in the different sites and seasons; it simply provides a means of determining a relative measure of available water that is comparable across sites and seasons. A value of $RAW_i = 1$ indicates that sufficient water was available to meet the potential water requirements of the crop during the interval; a value less than unity indicates that available water was insufficient to meet potential water requirements. No notion of the degree of stress experienced by the plant is attached to the values of RAW_i.

Distributions of RAW in the four growth stages highlight differences between the sites. Table 1 presents summary statistics on RAW_i in the trial and in each of the three sites. Due to low temperatures early in the trial season, PWR during the early growth phase was relatively low.

Moreover, because the trial was adequately irrigated before the drought patterns were imposed, stored soil moisture was sufficient to maintain high levels of AW during the early growth phase, and, consequently, $RAW_1 \geq 0 \cdot 5$. PWR increased over the experimental season and this is reflected in the values of RAW in later growth stages.

In Hyderabad, the location of the trial, there was relatively little variation in total available water, which in many years was sufficient to meet total water requirements. This fact is reflected in the mean values and negatively skewed distributions of RAW_i in Table 1. Total water requirements in Anantapur were far higher due to higher temperatures, while total rainfall was lower, than in Hyderabad. Consequently, mean values of RAW_i are far lower, the probability of RAW_i falling below 0·5 far higher, and, except for growth phase G4, the distributions are positively skewed. In Gujarat, the variation in total rainfall was associated with date of planting; years in which drought occurred were those with low rainfall or those in which planting was delayed due to the late onset of rains. Mean values of RAW_i are similar to those in Hyderabad, except for RAW_4. The shorter rainy season in Gujarat increases the probability of late season droughts and, consequently, the distribution of RAW_4 is less negatively skewed than that for RAW_1, RAW_2 and RAW_3.

The relationships between genotype yields and relative available water (RAW_i) in the four phases ($i = 1, \ldots, 4$) were estimated using data from the experiment. The estimated coefficients from each genotype-specific response function were then used, along with estimates of RAW from the sample site meteorological data, to simulate yields for a series of years in each location.

Simulating Yield Response

A number of difficulties were encountered in modelling the response of groundnut to RAW_i, particularly in the early vegetative and flowering phase. Groundnut has the ability at this stage of growth to lie dormant until soil water is replenished. Initial analysis of the experimental data (Nageswara Rao and Williams 1985) indicated that, over some range, water stress in the early phase actually has a positive effect on yield, that is, marginal productivity of RAW in this early phase may be negative. Moreover, sensitivity to droughts later in the season is modified according to whether or not drought occurred in the early phase. Further, drought treatments in the experiment did not cover the full range of $0 \leq RAW_i \leq 1$ in all growth phases ($i = 1, \ldots, 4$) and difficulties were encountered with predicting outside the range of drought conditions in the trial.

In finding an appropriate response relation, a number of model specifications were examined, including: (a) a general Cobb–Douglas type function, and an alternative specification of the general form proposed by Minhas, Parikh and Srinivasan (1973) in estimating crop response to relative evapotranspiration; (b) a generalised quadratic and a third order polynomial; and (c) a generalisation of Mitscherlich's model (Hexem and Heady 1978) which is based on the law of diminishing returns, with yields increasing with inputs and asymptotic to the maximum attainable yield. The same type of relationship is represented by the generalised logistic and Gompertz growth curves, which were also examined.

The results from the experimentation with these functions are reported in detail in Bailey (1988). In general, these functions were too inflexible to model the lower tails of the distribution and did not predict well outside the range of the data, or, in the case of the Mitscherlich and other growth functions, the non-linear estimation process did not converge. In addition, both linear and quadratic response and plateau functions were estimated (Lanzer and Paris 1981); inflexion points for the first three growth phases were at $RAW > 1$. No inflexion point could be established for the fourth growth phase.

As an alternative, the more flexible translog function was estimated:

$$(3) \quad Y = a_0 \prod_i RAW_i^{a_i} \prod_i RAW_i^{\frac{1}{2}\sum_j b_{ij} \ln RAW_j}$$

or in logarithmic form:

$$(4) \quad \ln Y = \ln a_0 + \sum_i a_i \ln RAW_i + \tfrac{1}{2} \sum_i \sum_j b_{ij} \ln RAW_i \ln RAW_j$$

The translog function has been most often used in modelling production processes at the firm or aggregate level but to our knowledge has not been used in estimating response relations. However, it has some important advantages for the case at hand, allowing for positive and negative marginal products over an input range (Boisvert 1982). It accounts for the interaction between water available at different stages of growth and prohibits estimated yields from being negative. The elasticities of substitution between inputs (in this case, water at different stages) are not constant, but vary with the level of inputs (Boisvert 1982). Recalling that $0 \leq RAW_i \leq 1$, then $\ln RAW_i \leq 0$. The marginal productivity,

$$(5) \quad f_i = (\mathrm{d}\ln Y/\mathrm{d}\ln RAW_i)(Y/RAW_i) = \big(a_i + \sum_j b_{ij} \ln RAW_j\big)\, Y/RAW_i$$

can be positive for a range of values of RAW_j if $b_{ij} < 0$, but can also be negative if $b_{ij} > 0$. The range will depend on the relative sizes of b_{ij} and $\ln RAW_i$ compared to a_i.

The translog model was estimated in logarithmic form by ordinary least squares. The models fit well, with $\bar{R}^2$ above 0·8 for 16 genotypes. [See Bailey (1988) and Bailey and Boisvert (1989) for complete details.] Within the experimental range, predicted yields were close to actual yields for all patterns, particularly in the lower-yielding patterns. The function did not overestimate yields in the higher intensities of the early drought pattern, a problem with many of the other functions. Collinearity diagnostics (Belsley, Kuh and Welsch 1980) revealed that the matrix of independent variables was ill conditioned. Because there is little variation in RAW_1, terms involving RAW_1 were highly collinear, resulting in large standard errors for estimated coefficients. One potential solution is to remove selectively those squared and cross-product terms whose t-ratios are below some critical value. Without *a priori* rationale for deleting terms, this strategy could ultimately destroy the flexibility of the function. One of our concerns is with the prediction of yields when values of RAW_i are outside the experimental range, and particularly when $RAW_1 \rightarrow 0$. In the initial estimation of the full translog models, there were differences between genotypes in the sign and magnitude of estimated coefficients on terms involving RAW_1. As $RAW_1 \rightarrow 0$, $\ln RAW_1 \rightarrow -\infty$ and $(\ln RAW_1)^2 \rightarrow \infty$. A large positive coefficient on $(\ln RAW_1)^2$, relative to that on $\ln RAW_1$, or a large negative coefficient on $\ln RAW_1$, relative to that on $(\ln RAW_1)^2$, will lead to high predicted yields. Therefore, for those genotypes that had large, positive, non-significant coefficients on $(\ln RAW_1)^2$ the term was deleted.

A translog is attractive because of its flexibility; it places no restrictions on marginal productivity and the elasticities of substitution between inputs are not constant. Because of this flexibility, it is difficult to make general statements regarding response to RAW in different growth phases. However, in Table 2, it is evident that the positive effect on yield of an early drought is reflected through the negative marginal products on RAW_1.

The genotype yield distributions based on these response functions were quite different across regions. In addition to the means and standard deviations being different (Table 2), there are a number of years in Hyderabad in which no drought was recorded, $RAW_i = 1$ in all growth phases, and consequently, the distributions of yields in Hyderabad are highly skewed to the left. Gujarat has a shorter rainy season. While there were a number of years in which no drought was recorded, there were also a number of years where late season drought severely reduced yields. Yield distributions are also negatively skewed but not to the extent of those in Hyderabad; yields tend toward a bimodal type of distribution, observations being concentrated in the upper and lower ranges. Anantapur not only experiences drought more often, but is also more prone to long-term droughts, increasing the probability of crop failure. Yield distributions in Anantapur are positively skewed; the degree of skewness is also more variable, across genotypes, than in the other two sites.

Risk Analysis

Having generated yield distributions for each genotype at each location, the genotypes can be evaluated by a number of risk decision criteria. The same criteria are applied to the results from the experiment using predicted yields from the response functions. In effect, this is a similar strategy to an analysis based on multi-site trials, with 'sites' being represented by the drought treatments in the experiment. Assuming no variation in product price between genotypes, and no variation in production costs, rainfall being the only variable input, then yields provide a reasonable surrogate for the argument of the implicit utility function (Anderson 1974). For each genotype, each observation on yield is regarded as a single element of a discrete non-parametric sample probability density function, each having equal probability of occurring.

Decision criteria

An entire efficiency frontier is generated by mean–variance (EV), mean–Gini (MG), and second and third degree stochastic dominance

TABLE 2

Marginal Products for RAW and Simulated Yields of Genotype by Site

	Marginal products (at means)[b]				Simulated yields (kg/ha)							
					Experiment		Hyderabad		Anantapur		Gujarat	
Genotype[a]	RAW_1	RAW_2	RAW_3	RAW_4	Mean	STD[c]	Mean	STD	Mean	STD	Mean	STD
1	−114	197	286	132	1604	882	3612	1189	964	1141	2760	2040
2	−83	230	375	115	1873	1032	4272	1401	1034	1229	3405	2304
3	−55	143	393	104	1922	958	4431	1444	1170	1355	3535	2320
4	−69	166	438	123	2192	1127	5106	1650	1142	1260	3983	2605
5	−244	114	310	96	1739	784	3631	1002	1156	1024	3082	1536
6	−47	154	373	125	1992	1011	4610	1465	1330	1428	3679	2243
7	−504	165	220	71	1623	691	2444	606	843	913	1889	1065
8	−61	160	395	122	1564	964	5171	2046	1192	1631	4171	2895
9	−144	97	204	110	1705	679	3004	817	975	843	2236	1445
10	−638	237	272	58	1689	769	2767	757	742	928	2142	1258
11	−239	180	394	125	1916	986	4545	1597	935	993	3540	2424
12	−183	196	237	98	1804	856	3255	963	727	778	2452	1628
13	−258	192	338	125	1913	966	3843	1111	967	1172	2917	1986
14	−207	186	395	116	2009	998	4347	1381	1064	1115	3458	2154
15	−49	64	312	90	1570	714	3451	1122	971	901	2700	1760
16	−23	67	232	67	1436	587	2737	804	813	673	2200	1233
17	−58	223	392	117	1996	1038	5013	1763	1382	1715	4035	2646
18	−151	118	370	134	2046	956	4354	1335	1059	1048	3373	2122
19	−62	179	356	77	1773	891	4169	1409	1055	1214	3297	2185
20	−17	155	387	129	1622	973	4577	1634	1012	1345	3728	2503
21	−323	138	206	99	1633	705	2568	675	827	942	1909	1158
22	112	177	249	92	1429	828	3257	1158	764	941	2539	1852

[a]Genotypes 3, 4, 5, 6 and 7 are ICRISAT high-yielding advanced breeding lines; 2, 10, 12, 15 and 22 are established Indian cultivars; 8, 9, 19 and 20 are high-yielding commercial cultivars or crosses with commercial cultivars; 13, 14, 16, 17, 18 and 21 are recent acquisitions identified as high yielding and/or drought tolerant in screening trials.
[b]Marginal products are the change, in kg/ha, for a change in RAW_i of 0·1.
[c]STD = standard deviation.

(SSD and TSD) criteria. Other methods reduce the size of the efficient sets either by limiting the efficiency analysis to specified intervals of risk aversion [stochastic dominance with respect to a function (SDWRF) and extended MG criteria] or through a complete ranking (exponential utility, empirical moment-generating function approach).

Despite its widespread application, there are some important objections to the EV criterion: it is consistent with the expected utility hypothesis only when yields are assumed to be normally distributed, or when a quadratic utility function is assumed. It equates risk with variance which means that extreme gains, as well as extreme losses, are considered undesirable. There may be cases when an increase in variance is not undesirable, for instance, if it is accompanied by an upward shift in the location of the distribution.

The stochastic dominance criteria provide a means of selecting alternatives that are optimal, according to expected utility maximisation, for a specified set of utility functions. Initially, two such criteria were developed (Hadar and Russell 1969, 1971; Hanoch and Levy 1969). For first degree stochastic dominance (FSD), preferences are restricted to the set of utility functions, U_1, that are monotonically increasing: $U_1=\{u(x):u'(x)>0\}$; it follows that $-\infty\leq r(x)\leq\infty$ where $r(x)$ is the absolute risk aversion function. The ordering rule for FSD is: F dominates G by FSD if, and only if, $F(x)\geq G(x)$ with a strict inequality for at least one value of x.

SSD assumes a further restriction, that of decreasing marginal utility. $U_2=\{u(x):u'(x)>0,\ u''(x)<0\}$ represents all risk-averse individuals by restricting $0\leq r(x)\leq\infty$. The ordering rule for SSD is: F dominates G by SSD if, and only if, $F_2(x)\leq G_2(x)$ with a strict inequality for at least one value of x, where

$$F_2(x)=\int_0^x F(t)\,\mathrm{d}t$$

TSD, developed by Whitmore (1970), imposes a further restriction, a positive third derivative, on the admissible set of utility functions, such that $U_3=\{u:u'>0, u''<0, u'''>0\}$. F dominates G by TSD if, and only if,

(a) $F_3(x)\leq G_3(x)$, with strict inequality for at least one value of $0\leq x\leq b$, where

$$F_3(x)=\int_0^x F_2(t)\,\mathrm{d}t, \text{ and}$$

(b) $F_2(b)\leq G_2(b)$

The analysis of first, second, and third degree stochastic dominance was carried out using the Fortran program presented in Anderson, Dillon and Hardaker (1977, p. 313), which treats the probability specification as linearly segmented cumulative density functions (CDFs). The discrete observation points were used as successive coordinates on the implied linearly segmented CDFs.

Stochastic dominance criteria also have some shortcomings. They may not be discriminating enough and one is left with a large efficient set of choices. Any further reductions in the efficient set will require the imposition of further restrictions on $u(x)$ for which there may be no theoretical justification. There is, therefore, a need for a criterion that offers greater flexibility and discriminatory power. While SSD and TSD describe classes of admissible preferences by placing restrictions on the form of the utility function, SDWRF, developed by Meyer (1977*a*, *b*), orders risky actions for a particular group of decision makers by placing assumed, or measured, restrictions on the bounds of the absolute risk aversion function $r(x)$. This more general approach allows the ranking of distributions that could not be ranked by ordinary stochastic dominance and, by varying the specified bounds on $r(x)$, the effects on choice of genotype of changes in the degree of risk aversion can be examined.

In this study, the upper and lower bounds on $r(x)$ were derived from results reported by Binswanger (1978, 1980) of games where Indian farmers were asked to choose between a number of gambles each with two payoffs of equal probability.[2] Following Raskin and Cochran (1986), the bounds on $r(x)$ estimated from the payoffs in the game must be transformed so that they correspond to payoffs in terms of kg/ha of groundnuts. The transformation involved a conversion factor based on the average area sown to groundnuts, and the average product price of groundnuts, thus converting yields in kg/ha to an equivalent monetary payoff [see Bailey (1988) for details]. The SDWRF analysis was carried out using a program written by Meyer, reported in King and Robison (1981) and modified by Tauer.

The popularity of the EV approach to choice under uncertainty is attributable to its ease of application; one need only calculate and compare means and variances. An alternative approach, the MG criterion, developed by Yitzhaki (1982), is based on a function of Gini's mean absolute difference. The approach has the convenience of the EV approach but does not equate risk with variance.

Yitzhaki (1982) shows that a necessary condition for a distribution F_1 to dominate another, F_2, by FSD and SSD is: $\mu_1 \geq \mu_2$ and $\mu_1 - \Gamma_1 \geq \mu_2 - \Gamma_2$, with at least one strict inequality, where Γ_i is defined as one-half Gini's mean difference:

$$(6) \quad \Gamma_i = 1/2 \int\int |x-y| \, \mathrm{d}F_i(x) \mathrm{d}F_i(y)$$

which can be written as:

$$(7) \quad \Gamma_i = \int F_i(x)[1-F_i(x)] \, \mathrm{d}x$$

[2]Binswanger estimated the bounds on risk aversion implied by the choices in the game, using a utility function with constant partial risk aversion. The partial risk aversion function $P(W, z) = z[u''(W+z)/u'(w+z)]$, where W=initial wealth, z=gain or loss from gamble and $W+z=x$=total assets after the gamble. $P(W, z)$ is a function of the absolute risk aversion function of total assets: $P(W, z) = zr(W+z) = zr(x)$. P measures aversion to risk as risk is varied, wealth remaining fixed, while the absolute risk aversion coefficient, r, measures aversion to risk as wealth is varied (Menezes and Hanson 1970). Bounds on r were estimated from Binswanger's results using the certainty equivalents at the points of indifference between two gambles (Bailey 1988).

If cumulative distributions cross only once, this is a sufficient condition for SSD; however, examination of the simulated yield data revealed that many distributions cross more than once.

The same conditions are also derived from Yitzhaki's development of an extended Gini inequality index. Yitzhaki (1983) defines the absolute parametric Gini index of equality for a distribution F defined over the range $[a \geq 0, b]$ as:

$$(8) \quad \delta(v) = \int_0^b [1 - F(x)]^v \mathrm{d}x, \; v \geq 0 = \mu - \Gamma(v)$$

The least variable distribution is that which maximises the Gini index of equality $\delta(v)$. This index is a weighted integration of the area under the CDF. A risk-averse decision maker will place more weight on values in the lower tail than in the upper tail. Changing the value of v affects the weights attached to the points on the distribution; increasing v will increase the weights attached to the lower tails and decrease those attached to the upper tails. Thus, v can be regarded as a measure of aversion to inequality: $0 \leq v < 1$ represents aversion to equality, $v = 1$ represents indifference, and $v > 1$ represents inequality aversion (Yitzhaki 1983). Under the assumption of risk aversity, $u''(x) \leq 0$, the necessary condition, for F_1 to dominate F_2, is $\delta_1(v) \geq \delta_2(v)$ for all $v \geq 1$. When $v = 2$, this mean–extended Gini criterion is equal to the MG criterion.

The final approach, the exponential utility moment-generating function (EUMGF) approach, leads to a complete ordering of uncertain choices, according to expected utility. The EUMGF approach was developed by Hammond (1974) who observed that the negative exponential utility function yields a simple expression for expected utility in terms of the moment-generating function (MGF) of the random variable. The EUMGF approach leads to a complete ordering according to EU maximisation and, by varying the absolute risk aversion coefficient, r, in the exponential utility function, it allows actions to be ranked under varying degrees of risk aversion.

The use of the EUMGF approach also has its shortcomings. First, it depends critically on whether the assumption of a negative exponential utility function is an acceptable representation of preferences. The negative exponential utility function exhibits constant absolute risk aversion; it has been argued that most individuals exhibit decreasing absolute risk aversion. Second, Hammond's approach is restricted to specified parametric distributions with finite MGFs. A recent development of the approach, by Collender and Chalfant (1986), circumvents this second problem by replacing the parametric MGF with a nonparametric estimator, the empirical MGF. The selection criterion can be written:

$$(9) \quad \text{maximise } CE = -(1/r)\ln\left[N^{-1} \sum_{i=1}^{N} \exp(-rX_i)\right]$$

where CE is the certainty equivalent, r is the absolute risk aversion coefficient, and N is the number of observations (X_i) in the distributions.

The EUMGF criterion represents an attempt to circumvent the major criticism of stochastic dominance or any other efficiency criterion in which genotypes may be inefficient, but inefficient by only a small degree. It is attractive in that, by ranking genotypes in terms of their certainty equivalents, it allows one to assess the extent of the differences in performance of genotypes at different levels of risk aversion.

Results

Results from applying these various criteria are given in Tables 3 and 4. Within each location, results are more or less consistent across the alternative approaches to risk analysis. SSD analysis is effective in considerably reducing the set of genotypes under consideration to five genotypes in Hyderabad and seven in Gujarat, both of which have relatively less variable environments than Anantapur which has a greater frequency of severe droughts and an SSD efficient set of nine genotypes. TSD is ineffective in reducing the size of the SSD set except in Anantapur. The EV efficient sets differ by location and contain four to five genotypes including the lowest yielding, most stable genotype. These latter genotypes are not found in the SSD sets. The SSD efficient sets contain a larger number of the most highly ranked (in terms of mean yield) genotypes than the EV efficient sets, particularly in Hyderabad and Gujarat. This supports Anderson's (1974) proposition that as the environmental scope becomes more restricted, the greater the chance that only very highly ranked varieties will appear in the SSD or TSD sets.

The MG criterion exhibits greater discriminatory power than the SSD and EV criteria. The MG efficient set in Gujarat contains only the highest yielding genotype and in Hyderabad the two highest yielding genotypes. In Anantapur, the MG efficient set contains two high-yielding genotypes plus a lower-yielding, more stable one. The implications of this greater discriminatory power, in terms of the degree of risk aversion, are not known exactly. However, the results correspond with those from the SDWRF analysis for slight to moderate risk aversion and support Buccola and Subai's (1974) hypothesis that the MG criterion represents the preferences of relatively weakly risk-averse decision makers.

To obtain additional insight into this issue, similar comparisons can also be made between extended mean–Gini (MEG) efficient genotypes and those efficient by SDWRF. Extended MG calculations were made for integer values of v from 3 to 10, and for arbitrarily selected higher values of $v=20$, 25 and 50. Selected results are presented in Table 4. From these results, it is clear that while the MG efficient set ($v=2$) from the trial corresponds to the risk intervals, $0 \leq r(x) \leq 0{\cdot}00037$ in the SDWRF analysis, the MEG sets for $v=3, 4, 5, 6$ correspond to the set, $0{\cdot}00037 \leq r \leq 0{\cdot}00198$. At the extreme value of $v=50$, genotype number (GNO) 5 is included and corresponds to interval, $0{\cdot}00198 \leq r \leq 0{\cdot}005$. The union of all MEG efficient sets for $v=3, 4, \ldots, 50$ corresponds to that from SDWRF for the full range of r. For Hyderabad, efficient sets from MG analysis and MEG analysis for values of $v=3, 4, \ldots, 10$, contain GNO4 and GNO8 corresponding to SDWRF results for interval $0{\cdot}00005 < r < 0{\cdot}00015$. Only when $v > 10$, does the MEG set include GNO6 and GNO5, representing the higher risk-averse intervals, $r > 0{\cdot}00037$.

In Anantapur, from the SDWRF analysis, GNO17 alone dominates over mild to moderate ranges of absolute risk aversion; from MG and

TABLE 3

Efficient Genotypes for Alternative Approaches to Risk Analysis[a]

Criterion	Location			
	Experiment	Hyderabad	Anantapur	Gujarat
EV[b]	4, 18, 9, 16	8, 4, 5, 7	17, 6, 5, 16	8, 17, 4, 5, 7
Stochastic dominance:				
SSD	4, 18, 6, 11, 5, 9	8, 4, 17, 6, 5	17, 6, 8, 3, 5, 4, 14, 9, 11	8, 17, 4, 6, 14, 18, 5
TSD	4, 18, 6, 11, 5, 9	8, 4, 17, 6, 5	17, 6, 5, 9	8, 17, 4, 6, 14, 18, 5
Mean–Gini	4	8, 4	17, 6, 5	8
SDWRF				
$r \leq 0$	4	8	17	8
$0 \leq r \leq 0{\cdot}00005$	4	8	17	8
$0{\cdot}00005 \leq r \leq 0{\cdot}00015$	4	8, 4	17, 6	8
$0{\cdot}00015 \leq r \leq 0{\cdot}00037$	4	4	6	8, 17
$0{\cdot}00037 \leq r \leq 0{\cdot}00198$	4, 18	4, 6	6, 5	17, 4, 6, 5
$0{\cdot}00198 \leq r \leq 0{\cdot}005$	4, 18, 5, 9	6, 5	5, 9	4, 5
EUMGF (top 5 ranked, by CE)				
$r = 0$	4, 18, 14, 17, 6	8, 4, 17, 6, 20	17, 6, 8, 3, 5	8, 17, 4, 20, 6
$r = 0{\cdot}00005$	4, 18, 14, 17, 6	8, 4, 17, 6, 20	17, 6, 5, 8, 3	8, 17, 4, 20, 6
$r = 0{\cdot}00015$	4, 18, 14, 17, 6	8, 4, 17, 6, 20	6, 17, 5, 3, 4	8, 17, 4, 6, 20
$r = 0{\cdot}00037$	4, 18, 14, 6, 17	4, 17, 8, 6, 20	6, 5, 17, 4, 3	17, 4, 6, 8, 20
$r = 0{\cdot}00198$	18, 9, 4, 14, 17	6, 5, 4, 18, 17	5, 9, 6, 18, 15	5, 6, 18, 4, 14
$r = 0{\cdot}005$	9, 5, 18, 11, 16	5, 6, 8, 20, 17	9, 5, 6, 18, 16	4, 5, 6, 3, 18

[a] Numbers refer to genotypes. See Table 2 above and Bailey (1988) for descriptions. Genotypes are ranked according to their mean yield, except for EUMGF results which are ranked by CEs. The specific computer program and methods used in generating these efficient sets from the empirical data are discussed specifically in Bailey (1988).
[b] Only those genotypes lying on the efficiency frontier are reported.

TABLE 4

Extended Gini-Efficient Genotypes[a]

v[b]	Experiment	Hyderabad	Anantapur	Gujarat
2	4	8, 4	17, 6, 5	8
3	4, 18	8, 4	17, 6, 5	8, 17
4	4, 18	8, 4	17, 6, 5	8, 17, 5
5	4, 18	8, 4	17, 6, 5	8, 17, 6, 5
6	4, 18	8, 4	17, 6, 5	8, 17, 6, 5
7	4, 18, 9	8, 4	17, 6, 5	8, 17, 6, 5
8	4, 18, 9	8, 4	17, 6, 5, 9	8, 17, 4, 6, 5
9	4, 18, 9	8, 4	17, 6, 5, 9	8, 17, 4, 5
10	4, 18, 9	8, 4	17, 6, 5, 9	8, 17, 4, 5
20	4, 18, 9	8, 4, 6, 5	n.a.[c]	8, 17, 4
25	4, 18, 9	8, 4, 6, 5	n.a.	n.a.
50	4, 18, 5, 9	8, 4, 6, 5	n.a.	n.a.

[a] Numbers in the table are genotypes (GNO). The procedures for conducting the extended Gini analysis based on the empirical data are described in detail in Bailey (1988).
[b] Exponent on the absolute Gini index of equality.
[c] Not applicable.

MEG analysis, all values of $v \geq 2$ appear to represent severe or extreme risk aversion ($r > 0{\cdot}00037$). In Gujarat the MG efficient genotype GNO8 is the dominant genotype when $r < 0{\cdot}00015$; a value of $v = 3$ appears to correspond to intermediate levels of risk aversion, and values of $v = 5$, 6 correspond to higher risk aversion intervals ($r > 0{\cdot}00037$). At higher values of v, $v = 9$, GNO18 enters the MEG efficient set; under SDWRF analysis, GNO18 is always dominated by another genotype. The end result is that a single value of v cannot be used to evaluate genotypes for a given level of risk aversion in all locations; different values of v correspond to different values in the different locations and there is no way of specifying, *ex ante*, the degree of risk aversion represented by a particular value of v.

Somewhat in contrast to these efficiency criteria, the final alternative discussed is the EUMGF approach. Only the top five ranked genotypes are presented for each specified level of r [the full range of results is in Bailey (1988)]. The results generally support those from SDWRF but also indicate the order in which genotypes enter and leave the efficient set as the degree of risk aversion increases.

To interpret these results, however, it is important to remember that the values for r were generated from an experiment by Binswanger. He finds that when payoffs in the game played with farmers rise to levels equivalent to agricultural investments (as in the 50 Rupee game from which the bounds on r used in this analysis are derived), most farmers have similar pure attitudes toward risk and were largely concentrated in the moderate and intermediate risk aversion classes (35 per cent and 40 per cent, respectively). Approximately 10 per cent were in the risk-neutral and risk-preferring classes and 8 per cent were in the severe and extreme classes (Binswanger 1978, p. A-55).

One could, therefore, argue that if any selection of genotypes is to be made, it should be based on preferences in the intermediate and moderate risk aversion classes ($0{\cdot}00005 < r < 0{\cdot}00037$). If our decision were based on the SDWRF results for the trial only, then GNO4 would be identified as the preferable genotype. If the location-specific results from the sample sites are used, then GNO4 would be selected in Hyderabad, GNO6 in Anantapur, and GNO8 in Gujarat; the more stable, but lower yielding, genotypes such as GNO5 and GNO9 are excluded from consideration when attention is focused on the moderate and intermediate levels of risk aversion. The same conclusions would be drawn from the results from EUMGF analysis.

Binswanger's intervals of risk aversion were, however, determined by the game, and farmers were classed accordingly; the bounds on r were not elicited directly from farmers. The rescaling of the values of r for use in our analysis involved generalisations regarding average area, price, etc. We have also, inherently, assumed that farmers' attitudes towards the payoffs in the game are the same as towards actual returns from a groundnut crop. In short, the bounds on r used in the analysis must be regarded as more or less arbitrary. An alternative use of the SDWRF and EUMGF approaches would be to conduct a search over the intervals of r, sequentially subdividing each interval, to pinpoint the exact values of r at which the ordering of genotypes changes. However, it is unlikely that researchers will ever be able to measure either individuals' risk preferences or the distribution functions of outcomes with enough accuracy to make such a search useful. Thus, it is argued that the results contained here are sufficient to indicate how the ordering of genotypes changes as risk aversion increases.

Furthermore, care must be taken in interpreting the results of the EUMGF approach because it is based on the assumption of constant absolute risk aversion associated with the negative exponential utility function. Binswanger (1980, p. 400), however, finds evidence that suggests farmers have non-linear, risk-averse utility functions which exhibit increasing *partial* risk aversion. Zeckhauser and Keeler (1970) show that utility functions that exhibit constant absolute risk aversion also display increasing partial risk aversion. Thus, conditions for increasing partial risk aversion are satisfied by the negative exponential utility function $U(x) = -e^{-kx}$, where $x = W + Z$, the argument of the partial risk aversion function (see footnote 1). Therefore, the use of the EUMGF approach to order genotypes according to risk preferences of farmers such as those included in Binswanger's study is not inappropriate.

Conclusions

This research was prompted by concerns with the methodology currently employed in the evaluation of genotype performance under variable environmental conditions. The traditional approach, as developed by Finlay and Wilkinson (1963), has been to identify 'stable', yet high-yielding varieties, based on the analysis of results from multi-site multi-season variety testing trials. Such an approach does not distinguish between the temporal and locational dimensions of yield variability; farmers are not concerned with how widely adaptable a genotype is, but with how it will perform given the environmental conditions prevailing in their area. Second, the approach does not specify any criteria by which the trade-off between stability and yield is to be made.

In the alternative approach developed here, the combination of location-specific weather data with response functions, estimated from a suitably designed *single-site* experiment, allows the derivation of a time series of estimated yield data for different locations. By incorporating economic concepts of risk efficiency, it becomes possible to make comparisons of the relative riskiness of varieties in *specific locations.*

In evaluating the groundnut genotypes by the criteria used in this study, two major conclusions can be drawn, neither of which would be apparent through the plant scientists' traditional evaluation methods. First, the inclusion of location-specific meteorological information leads to different rankings of genotypes than would have been drawn from the trial results alone. Second, the plant scientists' approach has no explicit way of considering different risk preferences. Within each location, the results from the different risk criteria are quite consistent. The results, however, are perhaps not that surprising. High-yielding genotypes are preferred over the moderately risk-averse range, but they do not dominate at more severe levels of risk aversion. This is a result that earlier literature also found.

The limitation of the approach described here is that it can only be used for specific sources of risks, such as weather, for which a long time-series of data is available. It is unlikely that sufficient historical data exist to allow other environmental risks, such as pest and disease incidence, to be analysed in this way. However, varying levels of pest and disease control, as well as other inputs, could be included as treatments in a single-site trial, and a multivariate response function estimated. This would enable scientists to make recommendations on the choice of genotype for specific locations, given the historical weather conditions and specified levels of pest and disease control and other inputs. This more complete evaluation would also account for quality differences as reflected by differences in price for a given quantity by product.

Perhaps the most important result from the analysis is that the rankings of genotypes depend crucially on the simulation of yields and, therefore, on the estimation of the response to relative available water. That is, despite the fact that many of the translog functions fit quite well, others did not. This was primarily due to the nature of groundnut response to early drought and difficulties relating the artificial drought conditions simulated by the experiment to actual soil moisture in the regions. The consistency of results within each location suggests that future research should focus on the improved modelling of agrometeorological relationships and not with refining the choice of selection criteria. Through additional developments in modelling the factors determining available water and plant yield, one can better ensure that treatments in trials of the type conducted by ICRISAT would adequately represent the full range of conditions prevailing in the locations of interest. Classification of crop environments in terms of independent meteorological and other environmental factors would assist in the extrapolation of results from a suitably designed single-site trial.

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