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OPPORTUNITIES FOR ECONOMIC ANALYSIS OF COMPONENT TECHNOLOGY AT FIELD SITES

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Introduction

Yields averaged across locations within a research site (adjusted for harvest and storage reductions) are normally used as the single productivity measure when evaluating the benefits of alternative bio-technical innovations. Most budget analyses compare the average return per unit of land between cropping patterns or practices. Unfortunately, reporting in terms of averages provides no information on the stability of a practice or the environment over which it is relevant. Indeed, an average is about the best way to hide information. In most situations, it makes sense to analyze the budget results in more detail to provide insights to the stability of alternative innovations, their comparative advantage for different target groups of farmers (e.g. owners or tenants), and on different aspects of the landscape at the site, and if possible, identify why the productivity of specific practices vary over space and time.

The purpose of this paper is to discuss some of the ways economic analysis may be extended beyond a first round budget-comparison of averages. Hopefully, economists working in production-focused research will be encouraged to pursue the analysis of agronomic trials in greater depth and not regard an average budget analysis as a satisfactory end-point of their activities. The suggestions of course, are not exhaustive, but are those feasible with a calculating capacity met by less than a $50 electronic calculator, graph paper, and any standard statistical textbook.

However, before addressing these issues. There are several points which should be addressed related to the conduct of budget analysis; they are not considered here, but are flagged nonetheless. (The interested reader is referred to Perrin et al (1976) and Rae (1977) for a discussion of some of the considerations that enter the budget process.) First, the harvested yield recorded for a crop or pattern even from on-farm trial tends to represent a highly optimistic estimate of the output which will accrue to the farmer. Tenure and harvest arrangements, processing, cartage and storage losses, for

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example, may result in the economic benefit to the decision maker being considerably less than inferred from the harvest yield. Second, input costs, particularly for labor and capital, may vary for different target groups of farmers. Third, economists have a propensity to estimate benefits per unit of land. This is appropriate when land is really the scarce resource. The analyst should be careful to identify what is the limiting resource, it may be labor, capital, possibly irrigation water, power capacity, or time, as reflected in the length of the growing season. Further, the effective constraint may be the resource requirement at a specific and critical period rather than the total use of the input. Fourth, the time sequence of costs and returns may vary between cropping patterns and technologies. If this is so, gains and costs may need to be discounted to a common point to enable alternatives to be compared on the same basis, at the same point in time.[1] This becomes more important, the more different are the time sequences of costs and returns.

Variability of Net Benefits

Profit stability of cropping patterns are usually compared in terms of their central tendency (usually the mean), and the dispersion around that value (usually the variance). The assumption of course, is that the data are normally distributed -- in which case the mean and the variance provide a precise description of the distribution.

Table 1 provides an example of an analysis of the net benefits of five methods of applying nitrogen to rice (No N, urea, mudballs, SCU, and briquettes) in terms of the above measures of dispersion. The data used are drawn from 15 experiment station trials conducted by the INFER network in the Philippines (IRRI, 1979). The coefficients of variation across the 15 sites for each treatment suggests that the SCU yields are most stable, with zero N, urea, and briquettes making up another group, the mudballs being somewhat more variable. The cause of high variability in the net benefit of any treatment, in this case mudballs, should be explored.

Probably, the easiest way to gain an impression of the existence of extreme values, or "outliers," is to plot the observed values of each treatment as a histogram. Figure 1, by way of example, shows the histograms for three of the practices (No N, urea, and mudballs) and provides a quick and visual impression of the central tendency of yields (mode), their dispersion and symmetry, and outlying values. The extreme value in the case of the mudballs is apparent (the $-37/ha for Trial No. 76). The

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[1] See Chisholm and Dillon (1966) for an excellent treatment of discounting procedures. Add a copy of this publication to your calculator, graph paper, and statistical text.

reasons for such extreme values should be examined and a decision made as to whether these outliers are related to treatment effects, and whether the observation should be rejected to prevent unwarranted distortion of the subsequent analysis.[2] In this case the extreme value is rejected, and the mean and variance for the mudball treatment reestimated with this particular observation excluded.

The inclination may be to make the next step in the analysis a test of whether or not there is a significant difference between the economic returns of the various treatments. Using the "hand calculator" technology (as we already have the means and variances) the hypothesis can be tested (using the student distribution) whether or not pairs of means are likely to be significantly different. The necessary calculations are shown in Appendix B, while the estimated t-tests, and their probabilities of occurrence, are listed in Table 2. The "probability" intervals listed in the two right columns of Table 2 are the probabilities of the sample means of one method of applying N being the same as the other it is being compared with. For example, there is a less than a 1% chance (based on the observations) that the mean gross margin for No N will be the same as the urea treatment, alternatively, there is between a 50% to 60% likelihood of SCU gross margins exceeding that of the mudballs. In summary, in this case, the analysis suggests that while the mean net benefits of the zero N-plots are lower than those where N was applied, within this latter set of N-treatments, there is no significant difference due to the method of application.

Depicting Variability of Net Benefits

Figure 1 provided a visual impression of the variability of net benefits, however, of more interest are some of the relationships which can be inferred from these distributions. For example, from the mean and variance it is possible to calculate (among other):

(1) the minimum level of net benefits for specified levels of probability;

(2) the probability of achieving minimum defined levels of net benefits;

(3) the probability of losses of given magnitudes

for each practice being evaluated. An example is provided in Table 3 of the analysis of the N-application alternatives in terms of the variability criteria, assuming the observations are normally distributed (which they are not).

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[2] If the cause of the extreme value can be explained as being independent of treatment then theobservation may be rejected. If, as in this case we cannot explain why the yield was extreme, we may still be inclined to reject it if the probability of observing such a value is remote, given the number of observations to hand.

Are Net Benefits Normally Distributed?

The above sequence of analyses assumes that the economic returns of each practice are normally distributed, which may not necessarily be the case. If the distribution of net benefits are skewed -- which is often the case in practice (Day, 1965; Roumasset, 1976) -- then the above inferences from assuming normal distributions (Table 3) are biased. Thus, researchers should satisfy themselves that the assumption of normality is a reasonable one before proceeding with a detailed analysis.

In the field context, the easiest way to test whether the data approaches a normal distribution is to plot the observed points on "normal probability" graph paper. If the plot approximates a straight line, the assumption of normality is reasonable. If it is not, then it is often possible to transform the data[3] to gain a straight line on the normal probability paper.

The cumulative percentage frequencies for the zero N and briquettes treatments are plotted on normal probability graph paper in Figure 2. The cumulative frequencies do not appear to follow a straight line, hence it is unlikely that a normal probability process is operative with this specific set of rice data. If anything, the curves appear to be convex inferring that the distributions are negatively skewed as was also gleamed from Figure 1. (Such a negative skewness incidentally, is not normally expected from crop-yield data.)

Cumulative Frequency Distributions

Instead of trying to identify a transformation which will normalize a given data set, a better approach when in the field with limited facilities may be to plot the cumulative frequencies and derive the probabilities of interest directly from the graphs. The (first order) cumulative probability distributions for four of the N treatments are sketched in Figure 3, the fifth (that with mudballs) is left out to prevent the diagram becoming excessively cluttered. From the frequency distribution for any treatment, it is possible to directly read:

(1) the probability of the gross margin exceeding any target value;

(2) the minimum level of gross margin expected for any desired level of probability;

(3) the probability of net benefits falling within a desired range.

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[3] The most common transformations used are logarithmic, semi-logarithmic and square root transformations.

The results from this analysis are compared to the estimates derived when assuming a normal distribution (i.e. Table 3) in Table 4. In this case, the estimated income levels for a given level of probability (below the mode) are lower when estimated directly from cumulative frequency distribution than when derived from the assumed normal distribution. Conversely, the estimated probability of achieving a target income above the mode is higher. These results -- and directions of biases -- are as anticipated. Had the underlying distributions been positively skewed, then the biases would have been in the opposite directions from the normal distribution estimates.

Of equal interest to the probability inferences which can be drawn from the individual probability distributions is to compare the entire probability distributions of alternative practices, on the one diagram, as in Figure 3. This comparison underlies the concepts of stochastic dominance which provides a means of identifying technologies which have a greater probability of a higher net benefit than alternative technologies (Anderson, 1974). Thus, in Figure 3, the Urea, Briquette and SCU treatments, at any level of cumulative frequency, have a higher gross margin than the No N. (That is, the cumulative frequency distributions for the plus-N treatments always lie to the right of the zero N.) For this reason, the treatments with applied N are "risk efficient" when compared to the zero-N treatment and are therefore preferred to it.[4] However, in many situations the concepts of stochastic dominance if strictly applied does not so neatly differentiate treatments as was the case in Figure 3. The problem occurs because the cumulative distributions of two treatments may cross - possibly more than once - in which case, for some levels of income one technology may be "best," and for income levels, the alternative technology would be identified as superior.

Limited Observations (Sparce Data)[5]

Rarely are researchers in the fortunate position of having large numbers of observations to work with, normally decisions must be based on a limited number of observations. This is referred to as a sparce data situation. Fortunately, as demonstrated by Anderson et al (1977, p. 42), a distribution rule exists which can be used to approximate the parent distribution from the few observations which is valied irrespective of the nature of the underlying probability distribution. Suppose only a small number of observations, n, are available on the net benefits of a technology. When arranged in ascending order,

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[4] Also, given the sketch, the briquette treatment is stochastically dominant to urea.

[5] This particular section draws heavily on this subject matter as presented in Anderson et al (1977, pp. 42-44).

the k-th observation is a reasonable estimate of the k/ (n + 1) fractile. This rule is reasonable in the sense that the expected fraction of all values of the random variable falling below the k-th order statistic is k/n (n + 1) (Barnet, 1975).

The fractile estimates from the sparce data rule can be plotted and a cumulative distribution smoothed though these coordinates and other points incorporating any additional information available. For example, the researcher may be confident that the zero-N treatment for rice will yield at least 1 ton/ha but certainly not more than 5 tons; also, the cumulative distribution of a unimodal two-tailed distribution is S shaped.

Suppose for example, we have 5 observations on the rice yields: 2.2, 3.5, 2.0, 4.1, 2.8 tons/ha. To apply the sparce data rule, first arrange the observations in order: 2.0, 2.2, 2.8, 3.5, 4.1, which then serve as the estimates of the 1/6, 2/6, 3/6, 4/6 and 5/6 fractiles, respectively. To provide an estimate of the distribution, smooth a subjective cumulative distribution though these points, making use of the data on extreme values which is also available (Figure 4).

As pointed out by Anderson (1974), the sparce data approach is nothing more than a subjective approximation of the underlying distribution. Nonetheless, the approach is found to provide a better stochastic representation than obtained by assuming for example, that the mean and the variance of the population is adequately estimated from a few observations. Perry and Greig (1975) demonstrate how the mean and variance of a distribution can be estimated from smoothed distribution functions.

Within and Between Site Comparisons

The preceding analysis has operated on all data being pooled and no provision made for the comparative performance of alternatives within and between sites. Further, the pooled analysis may infer that there is "no significant difference" between two treatments, yet inspection of the data may suggest that one treatment tends to be superior to another, site by site. It is worthwhile exploring these impressions.

For example, consider the gross margins of urea and briquettes. The means across sites were not judged as significantly different (based on the t-test), yet in 12 of the 15 sites, the briquette yield exceeded that of the straight urea. A simple visual starting point

to compare treatments over sites is to plot the paired comparisons, then compare their scatter to a 45° line (Figure 5). On the plotted comparison, it is evident that in most cases, site by site, that applying N as briquette results in a higher net revenue than when applied as urea. This observation should be tested statistically.

One straightforward way of testing paired comparisons -- which does not require the assumption of normality -- is the Wilcoson sum[6] (Bliss, 1967, p. 290). The approach is as follows. If the two samples come from the same population, then the sum of the expected differences $(Y_1 - Y_2)$ is computed for each pair of observations. The z's are then ranked in order of increasing size (ignoring the sign) with zero differences omitted. The positive and negative ranks are then summed, and the smallest sum, h, compared with its expected critical value (Appendix C) for the n differences in the sample.

Consider the urea and briqueetes case again. The arithmetic to estimate the Wilcoxon sum test for this data is shown in Table 5. Since the absolute total of the three ranks with the negative sign, h = 18, is less than its expectation (25.3) at a 5 percent level of probability with 15 cases being compared, we conclude that the briquettes do indeed have a significantly higher economic return than urea alone.

Performance and Environmental Indices

The analysis of the cumulative distributions and the paired comparisons, while adding greater insights than an analysis of average yields over sites does not address the question of whether there is any relationship between the performance of a treatment and the environment of the site. That is, is there treatment-by-site interaction, or in other words, do some treatments perform better in some environments than others?

Plant breeders have been concerned with this class of question for many years (e.g. Finlay and Wilkinson, 1963; Eberhart and Russell, 1966; Evenson et. al, 1978). Their approach (shile simplistic, it remains within the realm of our pocket-calculator technology) relates the productivity of each treatment at a site to an environmental index for that site. In the absence of other site descriptors, Finlay and Wilkinson (1963) and Eberhart and Russell (1966) used the mean yield of all treatments in the experiment at a site to provide a numerical grading for each site, and define this as the environment index for that site. The model fitted is:

$$Y_{ij} = a + b_i \; X_{ij} + u_{ij}$$

where

Y_{ij} = yield of treatment i in environment j;

X_{ij} = the mean yield of all treatments at site j, i.e., the environmental index;

u_{ij} = error term (deviation from trend line),

which can be readily estimated with our hand calculator.

The methods of nitrogen application data from the INFER trials were analyzed in this manner, the results are plotted in Figure 6 and recorded in Table 6.

As shown in Figure 6, for each environmental index, the treatments which have N-applied yielded higher gross margins than the zero-N treatment. Further, under adverse environmental conditions (i.e. environmental index of 300 for the site) SCU performed better than urea, with briquettes and (while not shown) mudballs in between. However, in the best environments sampled (environmental index of approximately 550), the briquettes resulted in a higher net revenue per ha than the other forms of nitrogen tested. Inspection of the slope coefficients (b_1 in Table 6), also shows that as the environment "improves," so does the profit-performance of urea and briquettes, vis-a-vis the other treatments (P .05). It would be instructive to have sufficient site-related information to determine what were the key environmental factors causing these differences in performance (moisture regimes, soil texture?).

Technology Performance and Site Factors

The environmental index used in the analysis reported in Table 5 suffers from the limitation of being treatment related (ideally it should be treatment independent), and does not provide the researcher with a usable characterization of the environments in which the trials were located. However, if no site-related data is available, then the index does provide a working approximation to rank the productivity of sites.

However, what is more important is to identify the causes of yield variability between sites. An often used approach to tackle this

task is to use regression techniques to relate observed yields to managed and non-managed site related factors.[7] Sometimes, even a minimal description of a site (e.g. planting dates, crop density, number of weedings, soil analysis, and yields) may go a long way towards explaining the variability of yields between sites (e.g. Flinn and Lagemann, 1976). More detailed site descriptions of course enables more complete models to be constructed with purpose to estimate among other, the economic levels of inputs to use, and the importance of managed and non-managed inputs (both weather, soil pest and disease related) in explaining yield differences between sites and years (Figure 7). An excellent example of the inclusion of site-related and management variables in the analysis of on-farm experiment is provided in the work of Herdt and Mandac (1979) and Mandac (1978), Table 7.

Multi-variate regression analysis is of course beyond the scope of the pocket-calculator technology of this paper. Nonetheless, the questions of which site descriptors are the priority ones and which should be collected for different agroecological zones is a critically important issue -- irrespective of our calculating capacity in the field. The cost of collecting massive quantities of site-related data is large and in many cases difficult; similarly the penalty (opportunity cost) of not collecting the priority variables is equally high. Suffice it to submit that the production economists could be far more innovative in addressing, in collaboration with biological scientists, the question of why yields differ between sites, and quantifying the impact of both managed and site-related factors on the appropriateness of a technology.

Evaluating Innovations Within Farm Plans

Budgeting procedures, supplemented by returns to the scarcest resources and by measures of variability, in the majority of cases provides the end point of the economic analysis and comparison of new innovations with old. Some additional comparative analysis, recognizing the importance of site-related variables, have also been suggested in this paper. The above procedures have the strength of being relatively simple and are usually sufficient to identify new cropping patterns and practices which have a real chance of being adopted.

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[7] In situations where most of the data is qualitative, e.g. (N, S, E, W facing aspect; wet, dry; position on landscape, weedy or clean field) discriminate analysis offers a possible alternative.

The above analyses are of course partial in the sense that the technologies are not evaluated as an integral component of a farming system. In particular, it is difficult to judge whether the input requirements for the technology are managerially feasible, and the output economically attractive to the farmer, given his resource base, existing technologies, and the alternative uses which the family commit these resources. One way of internalizing many of these issues is to analyze the proposed and existing production opportunities at the same time in a simulated whole-farm framework.

A commonly used whole farm analytical approach used by researchers to evaluate technological opportunities is linear programming and its extensions. Jayasuriya (1979) has discussed this technique. Suffice it to point out that linear programming is certainly not a field-based, pocket-calculator technology. However, more simple approaches do exist which enable the analyst to evaluate a new technique within a farm planning framework, at least in terms of the one or two most limiting constraints. The potential for example, of using gross margin planning and simplified programming (Richards and McCornell, 1967; Weathers, 1964) as a field aide in farm level evaluation of innovations should be more seriously examined than seems to have been the case in the Network.

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Table 1. Gross margins ($/ha) for 5 methods of applying N, INFER trials, Philippines, wet season, 1978.[a]

INFER Trial No.	Method of N application				
	No N	Urea	Indian	SCU	Briquettes
68	359.00	425.72	354.63	375.98	337.63
69	197.00	317.72	435.63	375.98	391.63
70	170.00	304.22	327.63	402.98	391.63
71	413.00	533.72	530.13	551.48	607.63
72	372.50	547.22	543.63	537.98	621.13
75	399.50	560.72	543.66	551.43	621.13
76	278.00	385.22	-36.37	402.98	418.63
79	291.50	317.72	341.13	416.43	337.63
80	452.50	479.72	408.62	443.48	525.62
82	318.50	452.72	462.63	470.48	445.63
84	345.50	501.72	557.13	537.98	567.13
86	305.00	493.22	449.13	524.48	435.13
87	372.50	547.22	516.63	551.48	607.63
90	278.00	479.72	449.13	470.48	513.13
92	372.50	547.22	543.63	605.48	594.13
$\bar{X}$	328.46	459.92	428.43	481.28	497.83
$S_{\bar{X}}$	77.63	90.25	150.41	75.03	104.43
CV (%)	24	20	35	16	21

[a]Source: The INFER yield data is listed as Appendix A.

Prices used in the analysis were:

Paddy	$0.135/kg	Labor	$0.311/day
Urea	$0.495/kg	SCU	$0.651/kg

Other assumptions as found in IRRI (1979).

Table 2. Tests for significance between mean gross margins of N application methods, INFER trials, Philippines, wet season, 1973.

Comparison between					Probability interval	
Method	$\bar{X}_i$	Method	$\bar{X}_j$	t	lower[b]	higher
No N	323.4	Urea	459.9	4.28	-	.01
	"	Mudball[a]	461.7	3.40	-	.01
	"	SCU	481.3	5.49	-	.01
	"	Briquettes	497.8	5.04	-	.01
Urea	459.9	Mudball[a]	461.7	0.05	.9	-
	"	SCU	481.2	0.71	.4	.5
	"	Briquettes	497.3	1.06	.3	.4
Mudball[a]	461.7	SCU	481.3	0.68	.5	.6
	"	Briquettes	497.8	1.04	.3	.4
SCU	481.3	Briquettes	497.3	0.50	.6	.7

[a]14 mudball observations, extreme value deleted, adjust $\bar{X}$ = 461.66, S = 80.74, CV = 17%.

[b]the - implies a less than one percent likelihood of occurrence.

Table 3. Comparison of net benefits of methods of N application, INFER trials, Philippines, wet season, 1978.

	Units	Method of N application				
		No N	Urea	Mudball	SCU	Briquettes
Mean net benefit	$/ha	323	460	462	481	498
Standard deviation		78	90	81	75	104
Degrees of freedom	n-1	14	14	13	14	14
Min. benefits, P ≥ 90	$/ha	223	345	358	385	365
Min. benefits, P ≥ 70	$/ha	275	399	407	430	423
Prob. of at least $500/ha	%	1	33	32	40	42

Table 4. Probability estimates derived from cumulative frequency distribution of N application methods to rice.

	Method of N application							
	No N		Urea		SCU		Briquettes	
	CD[a]	ND[b]	CD[a]	ND[b]	CD[a]	ND[b]	CD[a]	ND[b]
Min. benefits, P ≥ 90%	200	228	315	345	380	385	340	365
Min. benefits, P ≥ 75%	272	275	385	399	400	430	400	428
Prob. of Y ≥ $500/ha	0	1	40	33	45	40	50	42

[a]Derived directly from Figure 3 using the actual Cumulative Distributions shown there.

[b]Derived by assuming the distribution is normally distributed as in Table 3.

Table 5. Wilcoxon sum test for briquettes and urea, INFER trials, wet season, Philippines, 1973.

Trial No.	Y_1 Briquette	Y_2 Urea	$Y_1 - Y_2$)	Rank
63	337.63	425.72	-88.09	-15
69	391.63	317.72	73.91	12
70	391.63	304.22	87.41	14
71	607.63	533.72	73.9	12
72	621.13	547.22	73.91	12
75	621.13	560.72	60.41	9
76	418.63	385.22	33.41	4.5
79	337.63	317.72	19.91	3
80	526.63	479.72	46.91	6.5
82	445.63	452.75	-7.12	-2
84	567.13	506.72	60.41	9
86	486.13	493.22	-7.09	-1
87	607.63	547.22	60.41	9
90	513.13	479.72	33.41	4.5
92	594.13	547.22	46.91	6.5

N = 15 For negative difference Σ /ranks/ = 18
For positive difference Σ /ranks/ = 102

for N = 15, h = 18, .02 $\geq$ P $\geq$ .01

Table 6. Gross margins per hectare of five methods of applying N as related to environment.[a]

N source	Partial regression coefficient[b]				$\bar{R}^2$	F
	b_o	(t)	b_1	(t)		
Zero N	-9.506	(0.12)	0.759	(4.44)	.57	20
Urea	-29.969	(0.84)	1.100	(13.97)	.93	195
Mudball	37.721	(0.74)	0.938	(8.33)	.83	69
SCU	90.351	(2.07)	0.878	(9.08)	.85	82
Briquette	-64.205	(1.39)	1.262	(12.37)	.92	153

[a]Source INFER wet season trials, Philippines, 1978.

Fitted model: $Y = b_o + b_1 I + e$

where: Y is gross margin/ha

I is the environmental index

e are deviations from trend line.

[b]LSD ($P < .05$) for slope coefficients is 0.342.

Table 7. Production function estimated from combined all sites, Nueva Ecija, 1974 wet season to 1977 dry season.

Independent variables	Symbol	Regression coefficient	
		Equation 1	Equation 2
Constant		2422	1248
Applied fertilizer (linear)	F	-5.18876	
Applied fertilizer (quadratic)	F^2	-0.02986*	-0.02907***
Insect control cost (linear)	I	-1.68886***	0.47209***
Insect control cost (quadratic)	I^2	0.00232***	
I x F	IF	0.00675**	
I^2 x F	I^2F	-0.0000083**	
Weed control cost (linear)	W	0.85781	0.69068**
Weed control cost (quadratic)	W^2	0.01264*	
W x F	WF	-0.00894	
Age of seedlings	A	-15.61711***	-10.14466***
A x F	AF	0.08966**	
Pest damage index	P	1.47486	
P x F	PF	-0.13196***	-0.11468***
Disease incidence index	D	-27.33710***	-25.76919***
D x F	DF	-0.26612***	-0.25110***
Soil organic matter (linear)	OM	3111.28400***	184.06790***
Soil organic matter (quadratic)	OM^2	-657.80790***	
OM x F	OMF	0.22347	
OM x F^2	OMF^2	0.00147	
Soil texture (linear)	T	-106.29080***	
Soil texture (quadratic)	T^2	0.71679***	
Soil extractable P	EP	5.68052	2.45482***
EP x F	EPF	-0.01764**	
Late water stress	SL	-44.19641	
SL x F	SLF	0.04427	-0.20722***
Solar radiation	SR	89.35734***	99.49221***
SR x F	SRF	0.92762***	0.82938***
SR x SL	SRSL	1.17469	
Dummy variable for typhoon occurence	DT	-471.31890***	-416.37120***
Average F efficiency	DFF	-1.97364***	-1.99634***
Average I efficiency	DII	-0.47455**	-0.46925***
Average W efficiency	DWW	-1.56297**	
$\bar{R}^2$		0.658	0.640
F		179.087	388.934

* is significant at the 10% level (t=1.645)
** is significant at the 5% level (t=1.960)
*** is significant at the 1% level (t=2.576)

Source: Mandac and Herdt, 1979.

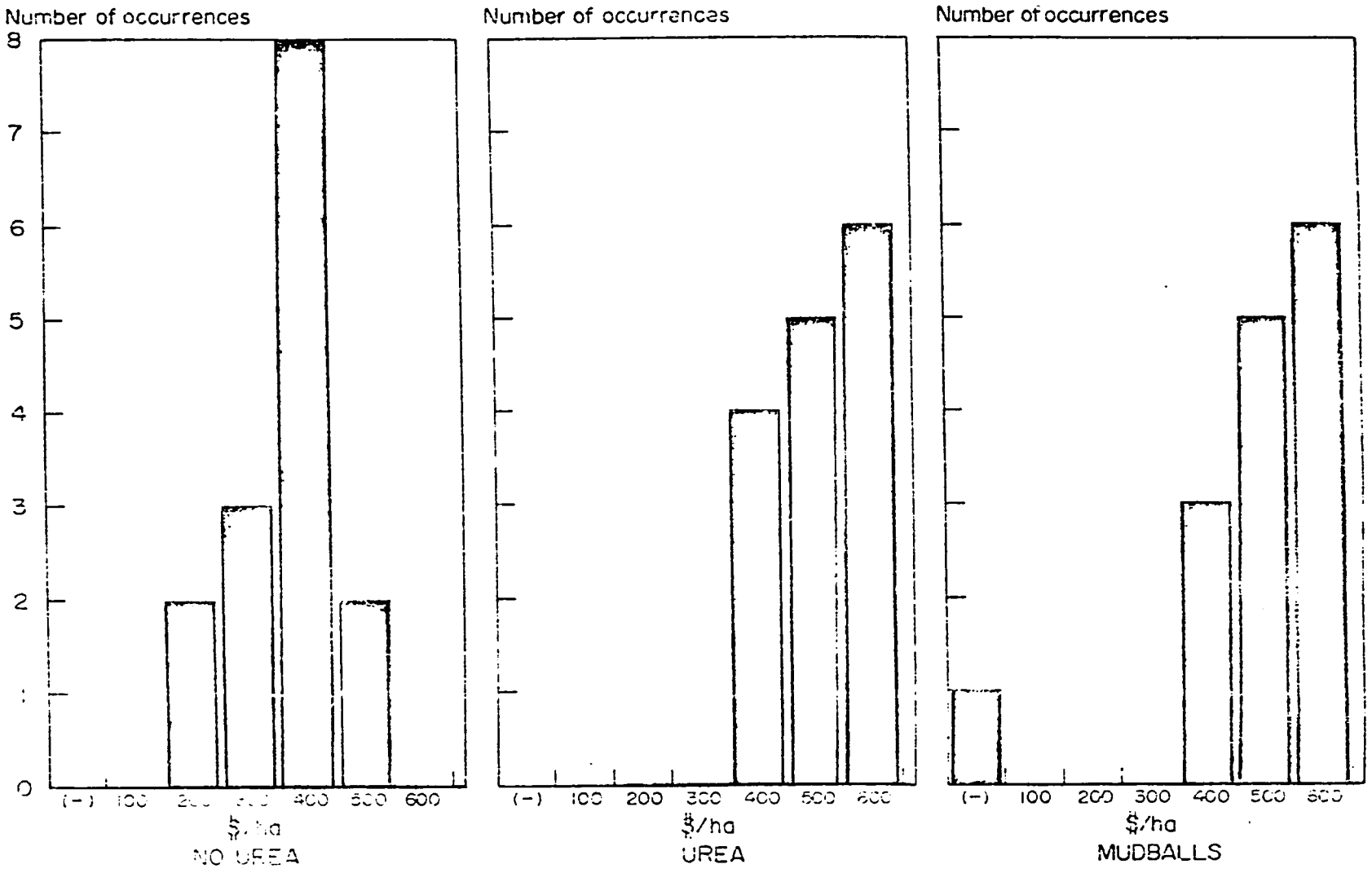

Fig. 1. Frequency distribution of net benefits for rice, three methods of nitrogen application, INFER trials, Philippines, wet season 1978.

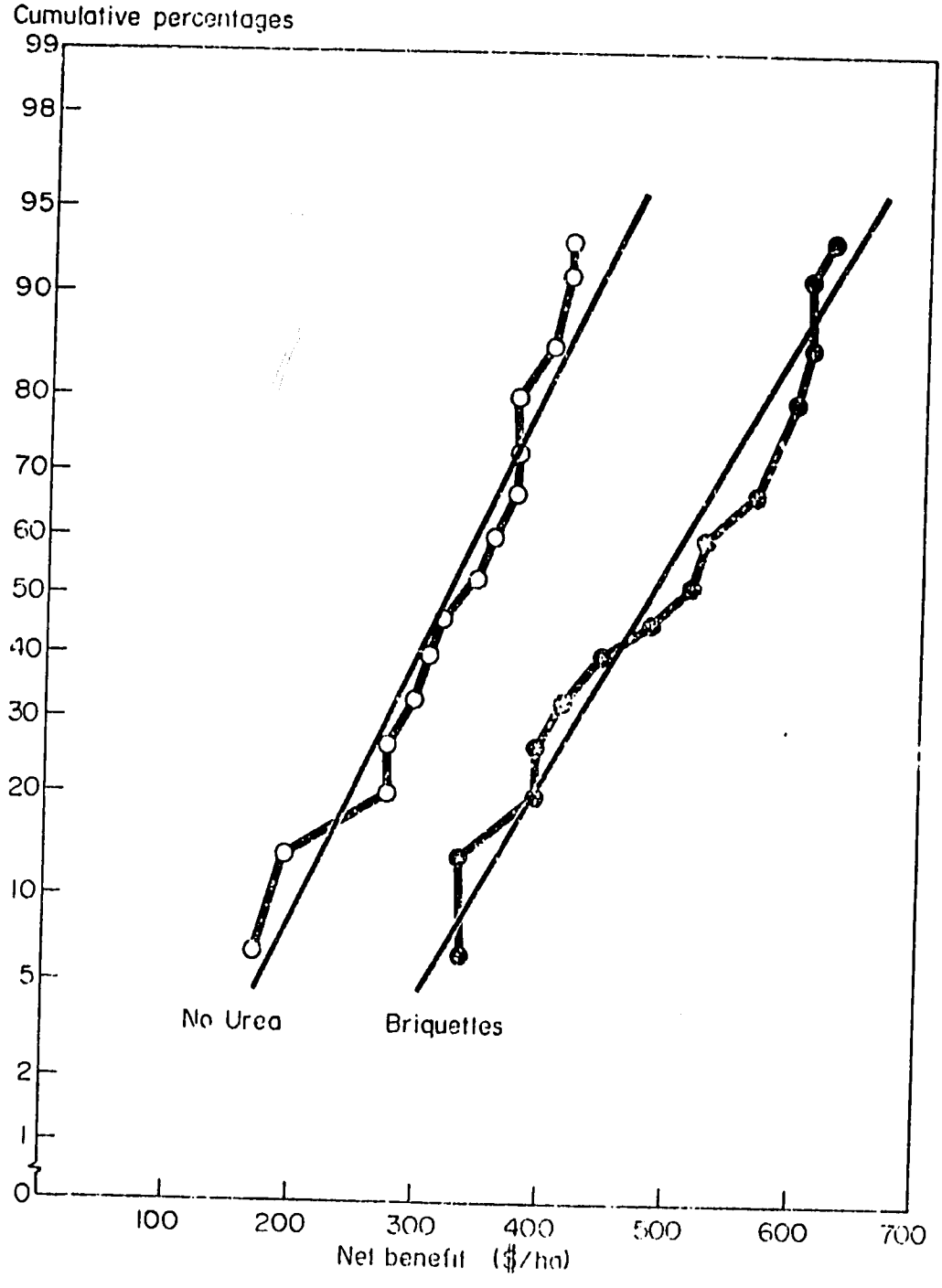

Fig. 2. Cumulative distribution of rice net revenues, plotted on normal probability paper.

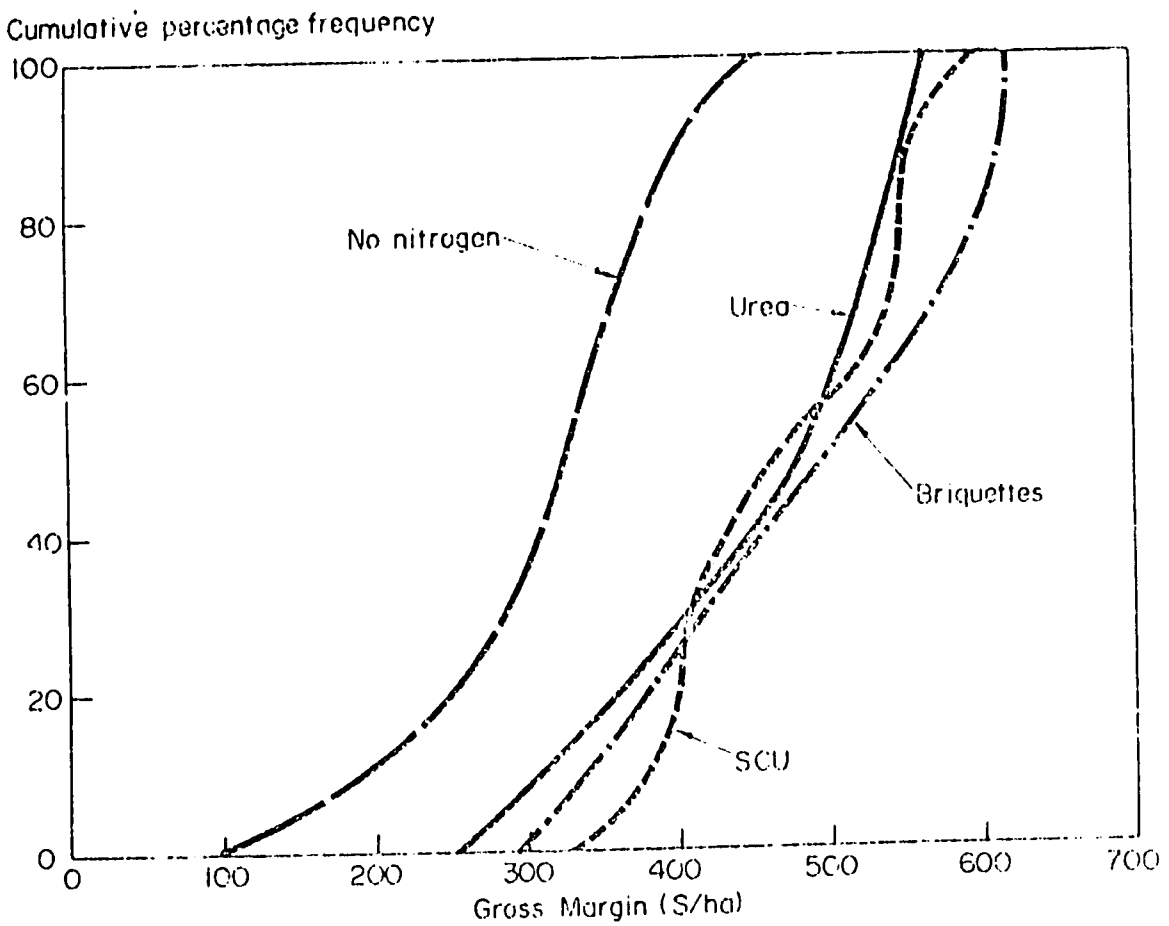

Fig. 3. Cumulative distribution of net benefits, INFEP trials, Philippines, wet season 1978.

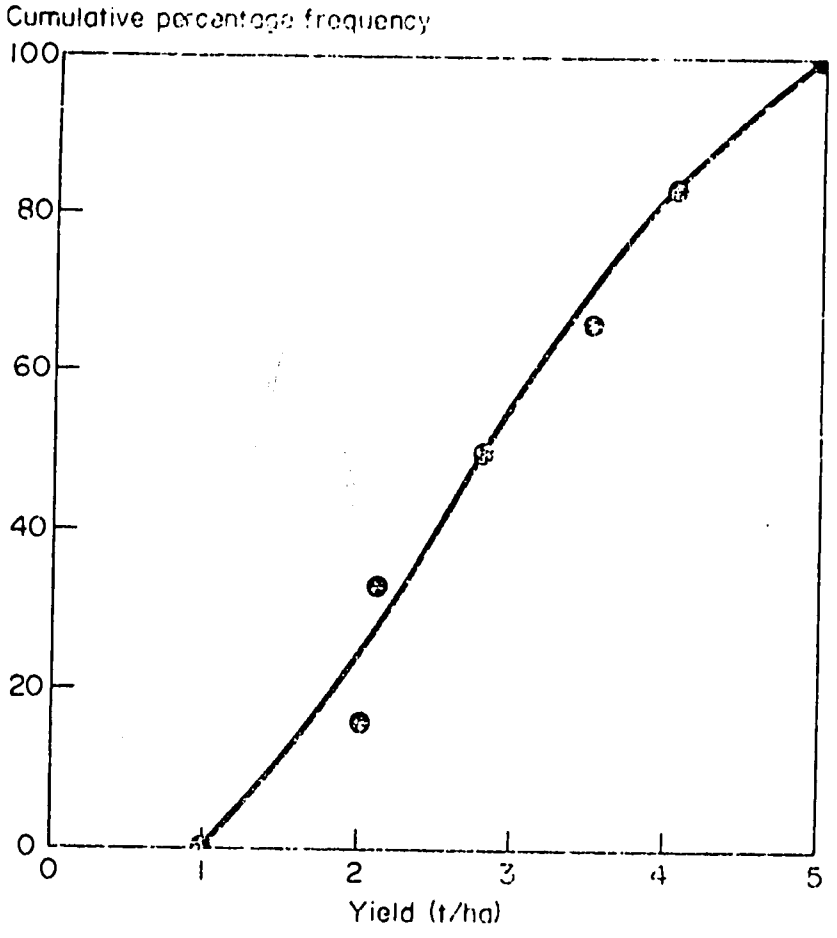

Fig. 4. Subjective cumulative distribution based on sparce data rule fractiles.

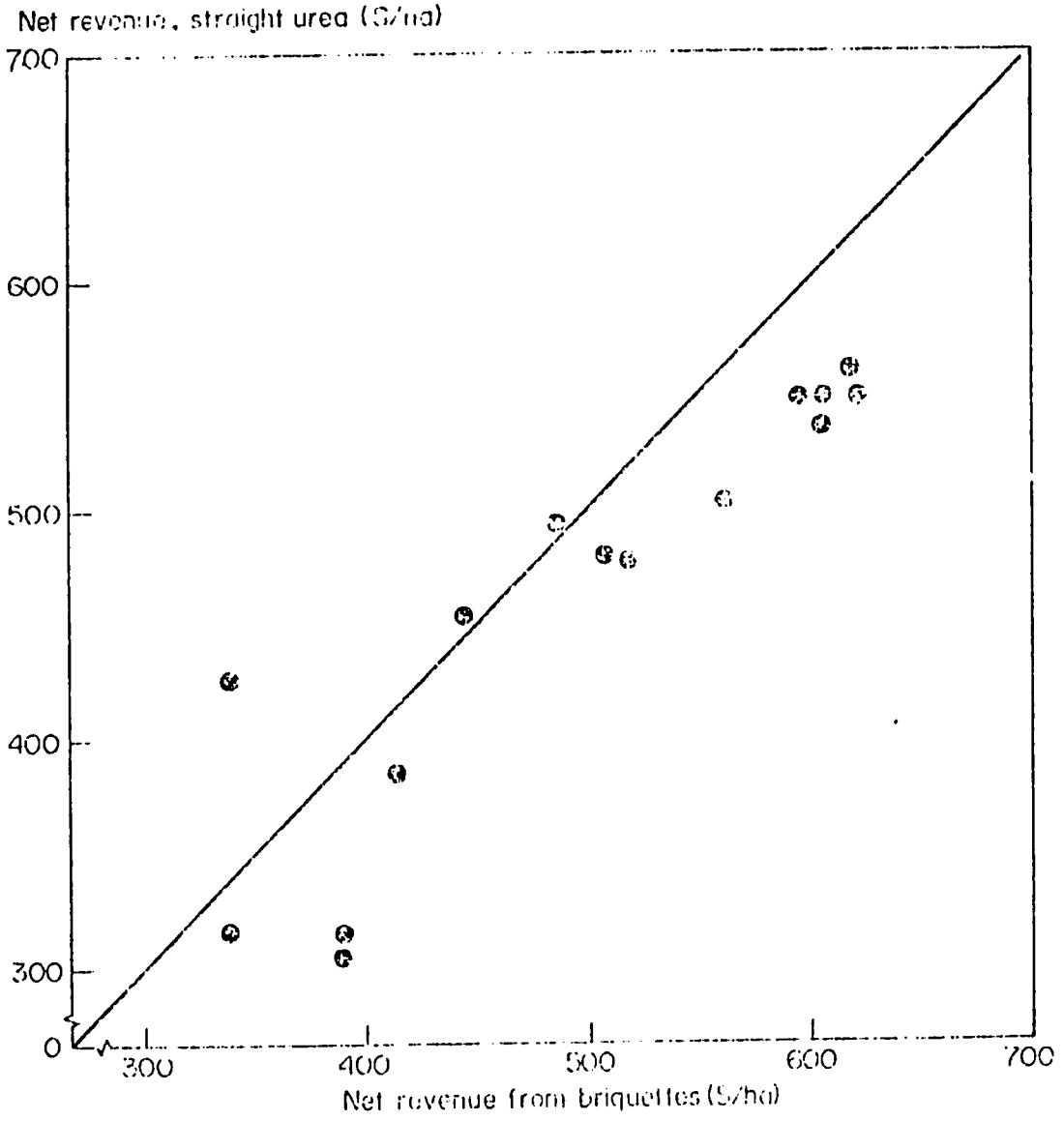

Fig. 5. Comparative yield of briquettes and urea.

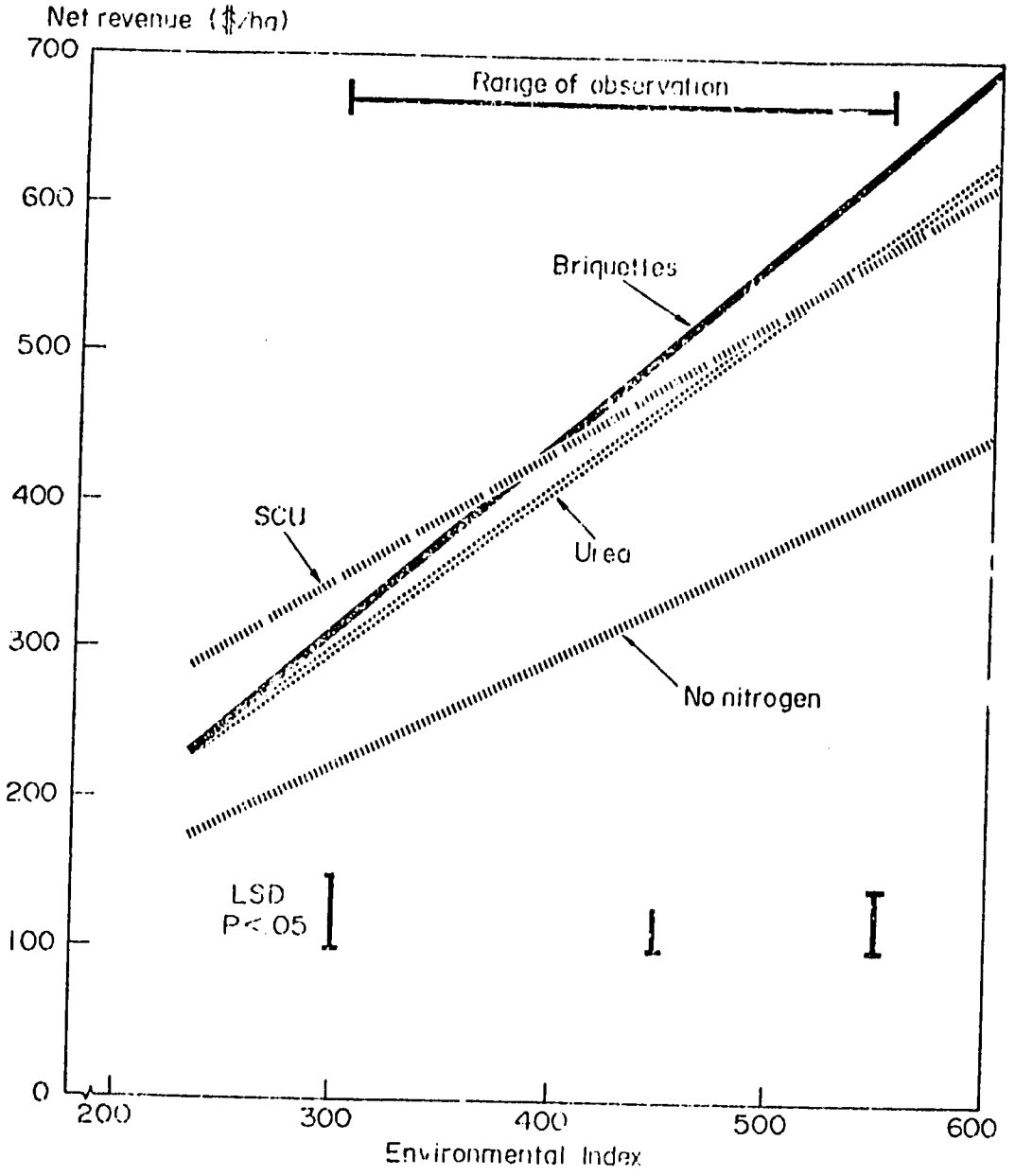

Fig. 6. The response of four means of applying N to rice to varying environmental INFER data, 1978.

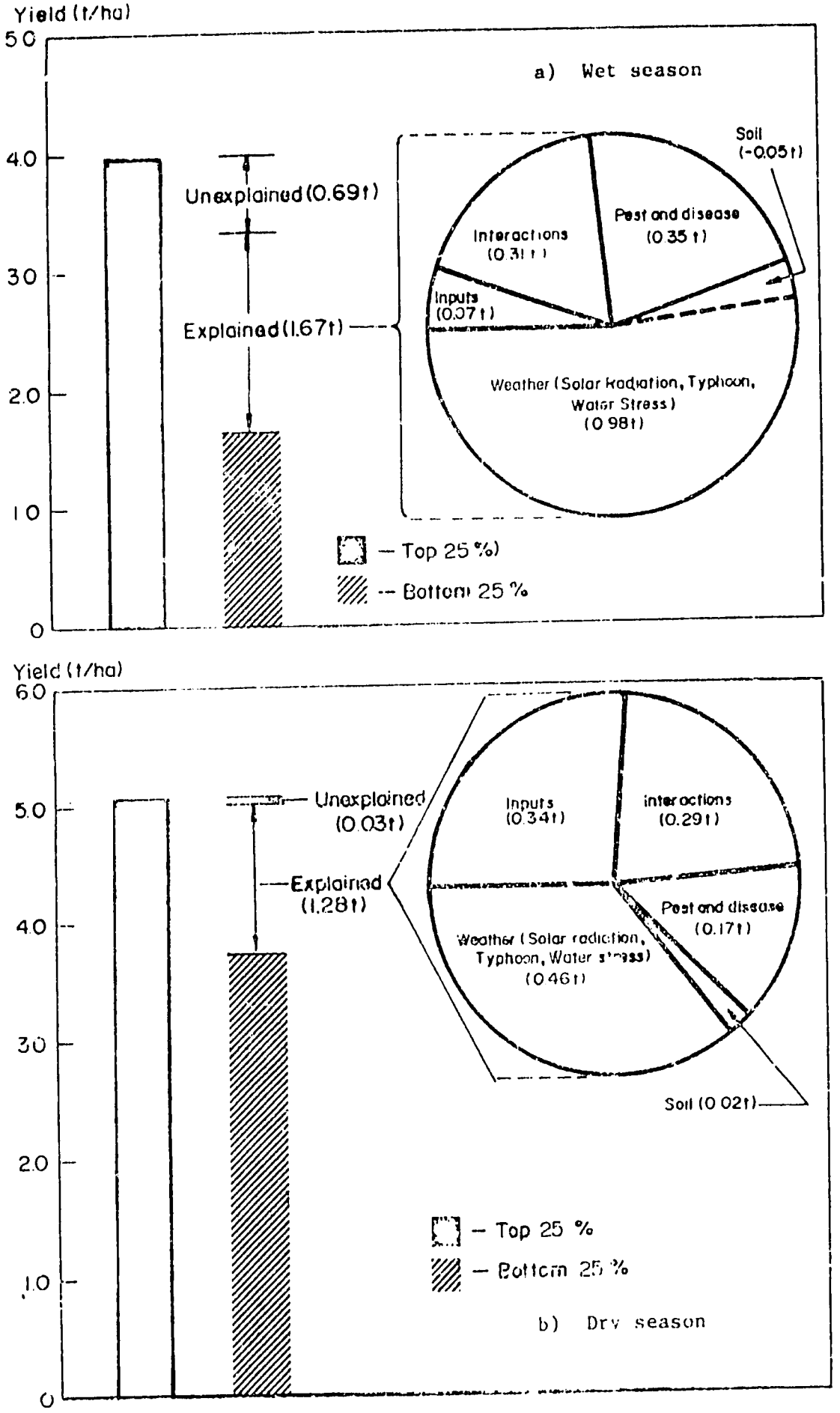

Figure 7. Accounting for differences between low and high yield farms, Nueva Ecija, Philippines. (Source: Mandac and Berdt, 1979).

Appendix A. Yield data, INFER trials, Philippines, wet season, 1978.[a]

INFER Trial No. Treatment No.	Method of N application				
	No N 1	Urea 7	Mudball 9	SCU 10	Briquettes 11
68	3.4	4.1	4.0	3.8	3.5
69	2.2	3.3	4.6	3.8	3.9
70	2.0	3.2	3.8	4.0	3.9
71	3.8	4.9	5.3	5.1	5.5
72	3.5	5.0	5.4	5.0	5.6
75	3.7	5.1	5.4	5.1	5.6
76	2.8	3.8	1.1	4.0	4.1
79	2.9	3.3	3.9	4.1	3.5
80	4.1	4.5	4.4	4.3	4.9
82	3.1	4.3	4.8	4.5	4.3
84	3.3	4.7	5.5	5.0	5.2
86	3.0	4.6	4.7	4.9	4.6
87	3.5	5.0	5.2	5.1	5.5
90	2.8	4.5	4.7	4.5	4.8
92	3.5	5.0	5.4	5.5	5.4

Prices: Urea $0.496/kg
Paddy $0.135
Labor $0.311
SCU $0.56
55 mandays/ha = $52.715

[a]Source IRRI (1979, Table 3 , p 58).

Appendix B. Estimating the significance of the difference between two sample means.

To test the hypothesis that the two samples come from the same population, we compute

$$|t| = \frac{|\bar{X}_1 - \bar{X}_2|}{S_{\bar{X}_1 - \bar{X}_2}}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the mean values of the two samples; $S_{\bar{X}_1 - \bar{X}_2}$ is the standard error of the pooled data.

$$S_{\bar{X}_1 - \bar{X}_2} = S\sqrt{\frac{1}{N_1} + \frac{1}{N_2}}$$

where N_1 and N_2 are the number of observations in each sample,

and

$$S = \sqrt{\frac{(N_1 - 1)S_1^2 + (N_2 - 1)S_2^2}{N_1 + N_2 - 2}}$$

where S_1^2 and S_2^2 are the variances of the two samples.

Example: No N $N_1 = 15$ $\bar{X}_1 = 328.4$ $S_1 = 77.63$

Urea $N_2 = 15$ $\bar{X}_2 = 459.9$ $S_2 = 90.25$

$$S = \sqrt{\frac{(14)(77.63)^2 + (14)(90.25)^2}{28}} = 84.18$$

$$S_{\bar{X}_1 - \bar{X}_2} = 84.18\sqrt{\frac{1}{15} + \frac{1}{15}} = 30.74$$

Ho: the two samples come from the same normal population.

Refer to the t-table with $N_1 + N_2 - 2$ degrees of freedom.

Test $|t| = \sqrt{\frac{131.50}{30.74}} = 4.28$

From the t-table, with N = 28, $P(|t| > 4.28) < .01$. The hypothesis is rejected so it is reasonable to assume the rice responds to the treatment with urea.

Appendix C. Wilcoxon sum.*

No. of cases N	P for two-sided tests of significance 0.10	0.05	0.02	0.01
5	0.6	-	-	-
6	2.1	0.6	-	-
7	3.7	2.1	0.3	-
8	5.7	3.7	1.6	0.3
9	8.1	5.7	3.1	1.6
10	10.8	8.1	5.1	3.1
11	13.9	10.8	7.2	5.1
12	17.5	13.8	9.8	7.3
13	21 4	17.2	12.7	9.8
14	25.7	21.1	15.9	12.7
15	30.4	25.3	19.6	15.9
16	35.6	29.9	23.6	19.5
17	41.2	34.9	28.0	23.4
18	47.2	40.3	32.7	27.7
19	53.6	46.1	37.8	32.4
20	60.4	52.3	43.4	37.5
21	67.5	58.9	49.3	42.9
22	75.3	66.0	55.6	48.7
23	83.9	73.4	62.3	54.9
24	91.9	81.3	69.4	61.5
25	100.9	89.5	76.9	68.5
	0.05	0.025	0.01	0.005
	P for one-sided tests of significance			

*Source: Bliss (1967) p. 512.