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Yield Risk, Risk Aversion, and Genotype Selection: Conceptual Issues and Approaches

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Yield Risk, Risk Aversion, and Genotype Selection: Conceptual Issues and Approaches

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Yield Risk, Risk Aversion, and Genotype Selection: Conceptual Issues and Approaches

H.P. Binswanger and B.C. Barah

Abstract

In this paper, we have discussed several methods of stability and adaptability analysis where stability here has a risk connotation. For risk analysis we have proposed to measure stability by standard deviation and risk preferences by the tradeoff between standard deviation and mean yield. This leads to a unique preference-based ranking for choosing among genotypes for decision makers with given risk preferences. This ranking takes into account both (temporal) stability and mean yield. A practical way of measuring risk with several years of co-ordinated yield trial data is then proposed. We have also demonstrated why the joint regression approach to stability analysis cannot be used in the context of a stability analysis in the risk sense.

We then note that our proposed analysis is subject to a certain amount of nursery and region specificity and explore regression approaches on plant independent variables to overcome this problem. Clearly this approach has potential that has not so far been realized. Finally we discuss the relationship of stability and adaptability in the context of the regression framework.

This paper deals with yield risks of different genotypes or, conversely, their stability over time. It also deals with adaptability of genotypes over space. The distinction between temporal stability of genotypes and adaptability is due to Evenson et al. (1978).[1] A genotype is said to be "stable" if at a given location, its yield varies little from year to year. On the other hand, a genotype is said to be "adaptable" if its yield (average yield over years at a given location) varies little across locations. The distinction is important, because farmers who have to decide whether to adopt a genotype are only interested in how stable the genotype is at their location for a given yield level or conversely in how much risk they have to take. They do not care about the (average) yield potential of the genotype in locations other than their own and are therefore not interested in adaptability. On the other hand, breeding pro-

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1. Their method of measuring stability and adaptability is discussed in Appendix 2.

grams, though also interested in high stability, are at least as much interested in high levels of adaptability. It may be pointed out that the term "stability analysis" is used in a somewhat different sense in the genotype x environment interaction literature (G-E literature) which is discussed in more detail in Section 5 and Appendix 1.

The first section of this paper is devoted to the concept of risk or stability and their measurement with an ideal, but usually nonexistent, data set. Section 2 is an exposition of a well known choice-theoretic criterion from economics which can be used to rank genotypes in a unique way, taking account of farmers' attitudes towards both risk and mean yield. Section 3 explains how to measure stability (or risk) with a real world data set such as several years data from yield trials across locations. An adaptability measure is defined as a bye-product and its potential use is discussed.

All methods in the first three sections are based on variances and variance analysis. Section 4 then discusses why findings from such methods may not be generalizable for other agroclimatic regions than those where the experiments were carried out. Furthermore the results are specific to the nurseries used in the experiments. Regression analysis on plant-independent variables, discussed in Section 5, appears to provide the most promising approach to overcome these problems and to at least partially understand the physiological-structural reasons behind the presence or lack of stability and adaptability of genotypes. Section 6 then uses the regression framework to explore the conditions under which high levels of adaptability should also lead to high levels of stability. More technical matters are discussed in Appendixes 1 and 2.

1. Measure of Stability and the Concept of Risk Efficiency

Consider the problem of choosing at a particular location from a set of genotypes $i = A, B, C. \ldots K$ – the "best" genotype, taking account both of its yield[2] and stability. Assume for the moment that we have an ideal (but hypothetical) data set in which yield has been measured for these genotypes for many years $t = 1, \ldots \ldots, T$. Furthermore, to simplify the exposition, neglect the replications and consider only the mean yields of genotype i in each year across replication, i.e., write $\overline{Y}_{it} = Y_{it}$.[3]

In the notation of Table 1 the following yield model applies.

$$Y_{it} = \mu_i + \tau_{it} \qquad (1)$$

$$\sigma_i^2 = \sigma_{i\tau}^2 \qquad (2)$$

2. For farmers' choice the relevant criterion is not yield but profits. In this paper we deal with the analysis of yield nurseries where costs do not differ across genotypes. Yield and profit criteria will therefore lead to identical results. Price variation is excluded from the analysis as well.

3. Since the methods in Sections 1 to 3 are all based on variance analysis, an extension to include replications is straightforward.

where μ_i is expected yield, $\sigma^2_{i\tau}$ is the temporal variance and $\bar{Y}_i$, and $S^2_{i\tau}$ are their estimates. Since rankings by variance and standard deviation are related in a one-to-one fashion and in later sections we need to consider the standard deviation, Figure 1 plots the standard deviations against the mean yields. One typically finds that higher yielding genotypes tend to have higher standard deviation.

Risk as a Measure of Stability

Figure 1 can be used to rank the genotypes according to different criteria and the rankings are given in Table 2.

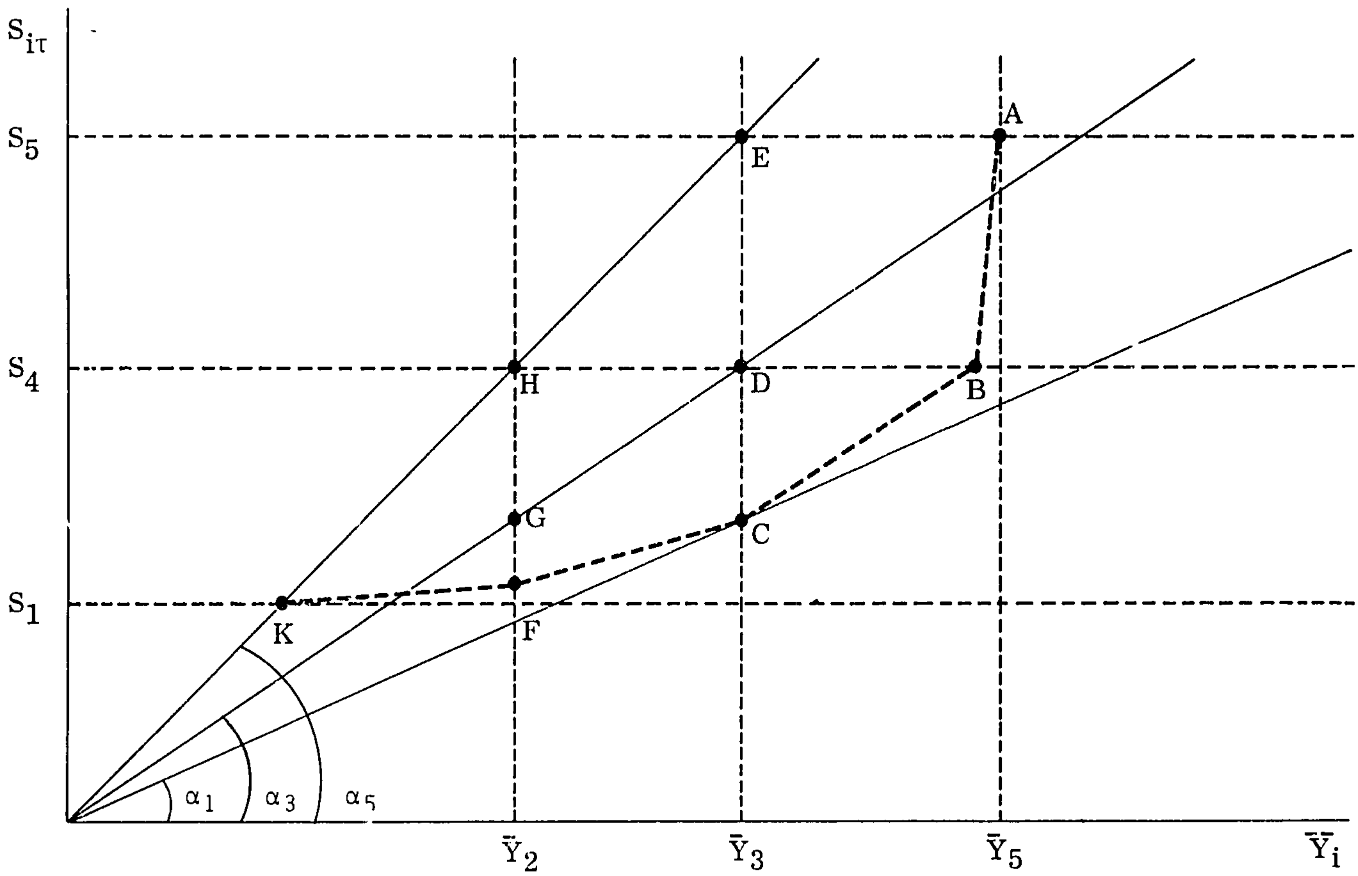

Figure 1. Mean yield, standard deviation, coefficient of variation and risk efficiency.

Key: A to H are locations of the genotypes in the yield (Y) and standard deviation space.

Mean yield ranks the genotypes according to their position on the horizontal axis, i.e., relative to a set of vertical lines through the graph, and therefore ranks them in alphabetical order A to K with several genotypes tying for rank.

Table 1. Notations and normalizations

1. Indices

$i = 1, \ldots\ldots\ldots, V$ = genotypes

$j = 1, \ldots\ldots\ldots, J$ = environments, general notation

$j = \ell t = 1, \ldots\ldots LT$ = environments with a time x season distinction

$\ell = 1, \ldots\ldots\ldots, L$ = locations

$t = 1, \ldots\ldots\ldots, T$ = seasons, years

$h = 1, \ldots\ldots\ldots, H$ = Index for plant-independent environmental variables

2. Yields

Y_{ij} = yield of genotype i in environment j

$\bar{Y}_{i.}$ = average yield of genotype i across the dotted subscript

3. Symbols

Symbols	Effects	Variances and variance component
(a) μ_i	genotype i effect	
(b) γ_{ij} =	environment j x genotype i interaction	σ^2_{ij} = overall variance
$\gamma_{ij} = \lambda_{i\ell} + \tau_{i\ell t}$		
$\lambda_{i\ell}$	Location x genotype i interaction	$\sigma^2_{i\lambda}$ = adaptability component
τ_{it}	time x location interaction	$\sigma^2_{i\tau}$ = stability component
$\tau_{i\ell t} = \nu_{it} + \eta_{i\ell t}$		
ν_{it}	time effect (average)	$\sigma^2_{i\nu}$
$\eta_{i\ell t}$	residual time x location effect	$\sigma^2_{i\eta}$

4. Normalization

$$\sum_j \gamma_{ij} = \sum_\ell \lambda_{i\ell} = \sum\sum_{\ell t} \tau_{i\ell t} = \sum\sum_{\ell t} \eta_{i\ell t} = \sum_t \nu_{it} = 0$$

5. Independence assumptions

$$\text{Cov}(\lambda\tau) = \text{Cov}(\lambda\eta) = \text{Cov}(\tau\eta) = \text{Cov}(\nu\eta) = 0$$

Standard deviation (SD) or variance ranks genotypes according to their position on the vertical axis, i.e., relative to a set of horizontal lines; K has highest and E and A have lowest rank. The objection to standard deviation is that it is not mean independent. Therefore, one can rank according to coefficient of variation (CV).

Coefficient of variation (CV) This criterion ranks genotypes according to their position relative to a set of rays from the zero point. The lower the slope α of that ray, the higher the rank.

Table 2. Ranking by mean yield, standard deviation, coefficient of variation, and risk efficiency

Genotype	Mean yield	Standard deviation	Coefficient of variation	Risk Efficiency	Preference ranking
A	1	5	4	*	2
B	2	4	2	*	1
C	3	3	1	*	3
D	3	4	3		4
E	3	5	5		5
F	4	2	2	*	5
G	4	3	3		6
H	4	4	5		7
K	5	1	5	*	8

* The genotype is in the risk-efficient set.

However, these approaches have the following problems:

a. Both SD and CV are measures of "stability" and they rank genotypes differently.[4] We therefore lack a unique measure of stability (or risk). For choice-theoretic reasons discussed in the next section we will choose SD as

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4. Given a data set like the one discussed, many more measures of stability (or its opposite, risk, the lack of stability) can be defined. For a thorough theoretical discussion see Roumasset (1979) or Rothschild and Stiglitz (1970). Variance or SD is an appropriate measure if the utility approach of decision theory is to be used and probability distributions of yield are normal.

the measure of stability, but we also note that for other purposes the CV remains useful.

b. The yield rankings differ from both the SD and CV rankings. These measurements and rankings alone are therefore insufficient, and a criterion must be developed which gives weight to both yield and stability, however one may define stability.

Risk Efficiency and the Risk Efficiency Frontier.[5]

A first approach to taking into account both yield and stability is risk efficiency : Consider genotype D : Every risk-averse decision maker would prefer it over genotype E because it achieves the same yield with lower SD. Similarly every risk-averse decision maker would prefer D over H because it achieves a higher yield with equal SD. On the other hand relative to D, the decision maker would prefer C or B for similar reasons. The concept of risk efficiency is therefore defined as follows:

> A genotype is risk efficient if no other genotype in the tested set can achieve (a) the same average yield with lower standard deviation or (b) the same standard deviation with higher average yield.

The genotypes D, E, G, H are risk inefficient, while the genotypes A, B, C, F, K are risk efficient, which is indicated in Table 2 by an asterisk. They are therefore on the Risk Efficiency Frontier (REF) which is the broken line from A to K in Figures 1 and 2. Risk efficiency allows us to divide the genotypes into two sets, the risk-inefficient and the risk-efficient ones.

But would one really want to consider such a low-yielding genotype as K for adoption? More generally how does one choose between genotypes on the efficiency frontier? Rules for weighting stability and yield to make such a choice must come from decision theory as developed in statistics and economics.[6]

2. Risk Aversion and Preference-Based Rankings

A choice between any genotypes on the REF involves a weighting or a tradeoff between yield and SD or Variance. The simplest choice-theoretic model used for such choices

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5. Another term used for "risk efficiency" is "stochastic dominance." Anderson (1974) shows that second-order stochastic dominance is equivalent of risk-efficiency in EV analysis for normally distributed yields. We have not pursued stochastic dominance further in this paper. Note, however, that when yield distributions deviate substantially from normality, one would want to shift to stochastic dominance analysis.

6. Note that the confusion surrounding various measures of stability in the plant breeding literature derives from the fact that these measures have never been linked to any theory of choice.

is Expected Returns - Variance Analysis (E-V Analysis).[7] It assumes that the farmer has a weighting or utility function

$$U = f(\mu_i, \sigma^2_{i\tau}) \qquad (3)$$

that relates his level of utility (satisfaction) to both the expected yield of a genotype μ and its variance.[8] The problems associated with measuring such utility functions have occupied economists for the past 150 years, and need not concern us here. All we need to know is that various combinations of expected return and variance can lead to the same level of satisfaction (utility). In Figure 2 these combinations can

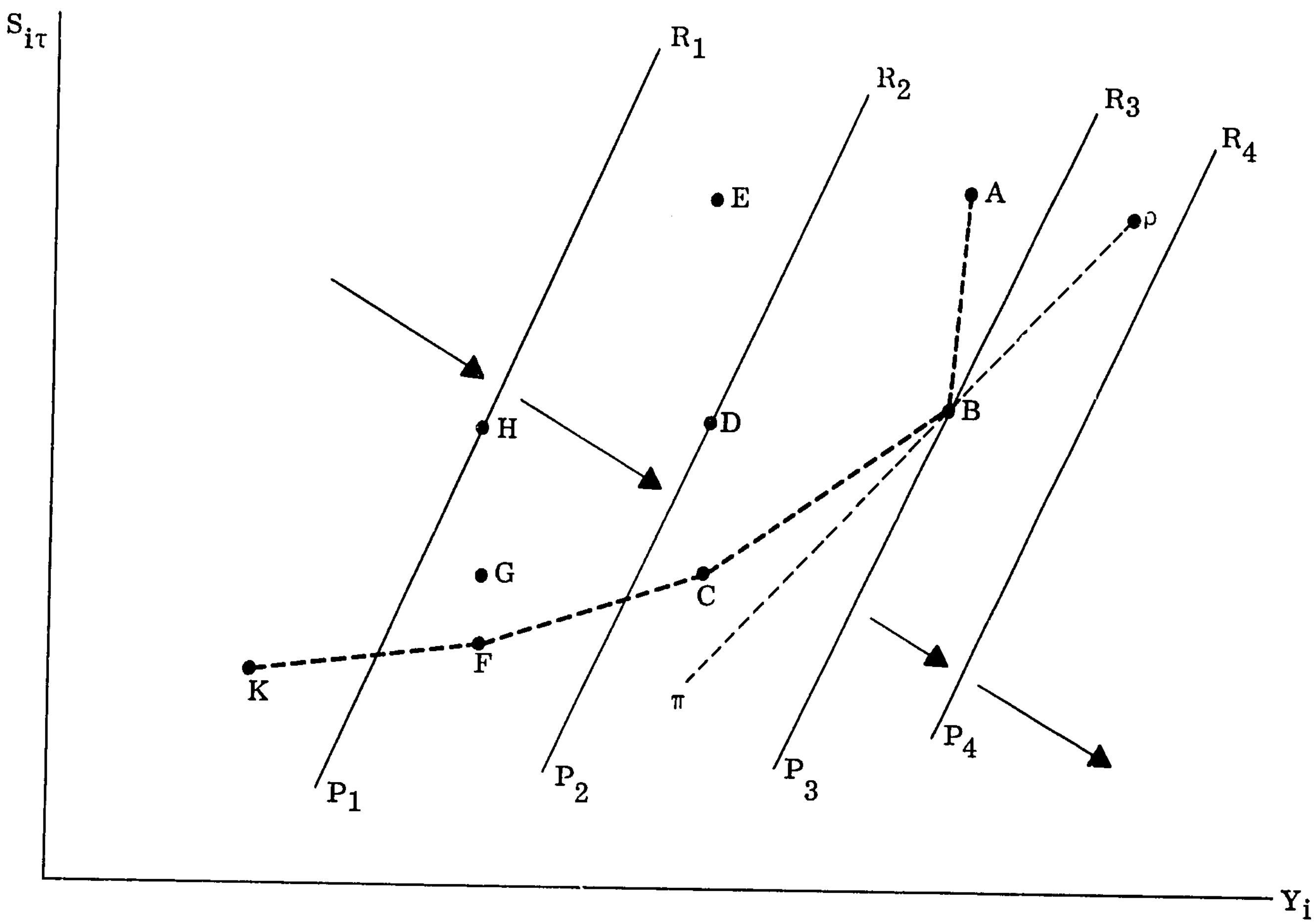

Figure 2. Risk aversion and preference-based choice.

Key: P_1 R_1 --- P_4 R_4 are iso-utility curves.
A to H are locations of genotypes on the mean-yield/standard deviation space.
Arrows specify direction of increased utility.

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7. The choice of this framework is the reason for choosing SD as a measure of risk or stability in the last section. At a more complex level one can use the Benoullian Expected Utility Model; see Anderson et al (1977) or Dillon (1979) for reviews. However, complexities increase rapidly, and the fuller model is necessary only if yield or profit distributions depart substantially from normality.

8. See Footnote 2 for a discussion why yield is used here rather than profit.

be plotted on lines such as P_1R_1 to P_4R_4, which are called iso-utility curves.[9] Since individuals have a preference for lower variance and higher yields, the utility or satisfaction level associated with P_4R_4 is higher than the one with P_3R_3. Farmers attempt to choose the genotype that allows them to reach the iso-utility curve which lies farthest in the direction of the arrows to the lower right corner of Figure 2. The lowest such parallel line can be reached by choosing genotype B. With genotype H only the line P_1R_1 can be reached, which corresponds to a lower level of satisfaction.

With a series of psychological experiments, Binswanger (1980) has estimated the slope of the PR lines. This slope $\Delta S/\Delta \bar{Y}$ is a measure of risk aversion. He found that it lies close to 2.0 for the semi-arid tropical farmers of Maharashtra and Andhra Pradesh.[10] This information thus allows one to rank genotypes according to the average risk-preference of farmers involved in a unique preference-based ranking, which is given in the last column of Table 2. We propose this ranking as the solution to the problem posed at the outset of Section 1.

However, two caveats are in order. First Binswanger (1978) found a relatively modest spread of risk aversion slopes: for 85% of the farmer population these slopes lie between a value of 1.5 and 3.0, with a mean value of roughly 2. (Note that the higher the slope, the lower the risk aversion.) Each slope gives rise to a separate preference based ranking, although, since the upper bound and lower bound of risk aversion slopes are close together, the rankings are unlikely to differ very much.

Secondly, farmers may not consider each particular crop as a separate enterprise, but be interested in the riskiness of farming as a whole, which, as long as yields of different crops are not the same, will be lower for all crops together than for each one individually. Furthermore they may have access to various means of self-insurance and self-protection to help them even out their consumption levels over the years in the face of risky production.[11] Despite the fact that their iso-utility curve may look like the line P_iR_i, they may prefer to take more risk for higher returns because of the fact. Nevertheless we can then look at the risk aversion slope of 1.5 as an upper bound of risk aversion, which in Figure 1 is drawn as the line Πp.

9. Mathematically the iso-utility curve is defined as $\mu_i|_U = g(\sigma^2)$ Because of the functional relationship of σ and σ^2 we can also rewrite this as $\mu_i|_U = h(\sigma)$ which is used in Figure 2.

10. In Binswanger (1978) the discussion is in terms of $\Delta\bar{Y}/\Delta S$ instead of $\Delta S/\Delta\bar{Y}$; therefore the relevant range in that paper is 0.66 to 0.33. Note that the lower the value of the slope – i.e., the less steep it is – the higher the extent of risk aversion.

11. For a discussion how insurance will alter the criterion of choice in favor of expected return see Binswanger et al. (1979).

3. Estimating Stability and the Concept of Adaptability-Efficiency

A farmer or breeding programs can obviously not wait for 10 or 20 years of uniform genotype trials in a location to make a choice among genotypes. One must make use of multilocation trials carried out over at least 2 years to estimate the time component of variability.

The Estimation of the Stability-Variance from a Multilocation Multiyear Trial

Assume the following additive model of crop yields

$$Y_{i\ell t} = \mu_i + \lambda_{i\ell} + \tau_{i\ell t} \tag{4}$$

where $\lambda_{i\ell}$ is the location effect and $\tau_{i\ell t}$ is the location x year interaction effect.

For the variance analysis below and especially the covariance analysis of Section 5 it will be necessary to split the location-year interaction up into two components with the corresponding variance component.

$$\tau_{it} = \nu_{it} + \eta_{i\ell t} \tag{5}$$

$$\sigma^2_{i\tau} = \sigma^2_{i\nu} + \sigma^2_{i\eta} \tag{6}$$

where ν_{it} is the average time effect across locations with its associated variance component $\sigma^2_{i\nu}$ and $\eta_{i\ell t}$ is the residual location x time interaction. Therefore, the model will read.

$$Y_{i\ell t} = \mu_i + \lambda_{i\ell} + \nu_{it} + \eta_{i\ell t} \tag{7}$$

With the genotype variance σ^2_i composed of the following components.

$$\sigma^2_i = \sigma^2_{i\lambda} + \sigma^2_{i\nu} + \sigma^2_{i\eta} \tag{8}$$

$\sigma^2_{i\tau} = \sigma^2_{i\nu} + \sigma^2_{i\eta}$ is the stability relevant variance component since a farmer at a given location experiences both variations. This variance component is estimated from the corresponding mean squares (MS) of the associated variance analysis tables of genotype i by solving the expected mean square expressions for $\sigma^2_{i\gamma}$ $\sigma^2_{i\eta}$

$$S^2_{i\tau} = \frac{MS_{years} + (L-1)\, MS_{residual}}{L} \tag{9}$$

where L is the number of locations, $S_{i\tau}$ can then directly be used in figures such as 1 and 2.

This analysis requires the following assumptions : Normalizations (4) and independence assumption (5) from Table 1, which are straightforward.

However, the following homogeneity of variance assumption is not trivial.

$$\sigma^2_{i\tau\ell} = \sigma^2_{i\tau} \qquad (10)$$

This implies that (for each genotype) the variance of yields over time is the same in all locations. If this assumption is violated, it is impossible to estimate the over-time components of the overall genotypic variation from a multilocation trial in a restricted number of years. As will be discussed in Section 4, the homogeneity of variance assumption requires that the time components of variance will be estimated from locations that are not too different from each other.

Adaptability-Efficient Genotypes

Variance analysis according to the model of equations (3.4) and (3.5) also provides an estimate of $\sigma^2_{i\lambda}$, the adaptability-relevant variance which is the variance of the average crop yield (over years) across locations.

It is estimated from the corresponding Mean Squares as

$$S^2_{i\tau} = \frac{MS_{location} - MS_{residual}}{T} \qquad (11)$$

where T is the number of years.

Clearly we can plot mean yields against adaptability-relevant standard deviations $S_{i\lambda}$ in graphs similar to Figures 1 and 2, and define the concept of adaptability efficiency:

> A genotype is adaptability-efficient if no other genotype in the tested set can achieve (a) the same average yield with lower adaptability-relevant standard deviation or (b) the same adaptability-relevant standard deviation with higher average yield.

This definition will divide genotypes into an adaptability-inefficient set and an adaptability-efficient set. Note that the adaptability efficient set will usually not coincide with the stability-efficient set. How similar these two sets are is an empirical question.

What are the criteria by which one should choose from an adaptability-efficient set, i.e., how should one, in breeding program trade-off adaptability against yield potential? Note that the criterion cannot be the same as for choosing from the stability-efficient set. First of all we cannot speak of the "nonadoption risk" in the same way as of a temporal risk and therefore cannot use an idea of a breeders risk aversion. Secondly, a genotype will only be adopted in environments where it outperforms the currently available genotype. The loss of nonadoption, therefore, is not the difference between a genotype's overall mean yield and its actual yield at a location, as in the inter-temporal context, but the fact that a genotype that outperforms the existing one, is not becoming available at that location.

A criterion for choosing a genotype from an adaptability-efficient set -- or more broadly of choosing between one research program aimed at developing widely adaptable genotypes and several programs aimed at developing more location-specific varieties, therefore, must come from a comparison of the costs and potential for success of two such different research strategies. We have not yet developed such a criterion, but will direct our attention to it in the future.

Single-Year Data and the Concept of Variability Efficiency

Breeding programs often need to take quick decisions on genotypes after 1 year of multilocation testing. What can be inferred from 1 year's data? Each yield at a particular location is a realization of equation (4), where the subscript t refers to the fact that a particular year's outcome of the equation is considered.

$$Y_{i\ell 1} = \mu_i + \lambda_{i\ell} + \tau_{i\ell 1} = Y_{ij} = \mu_i + \gamma_{ij} \qquad (12)$$

However, from the data we cannot separately observe realizations of $\lambda_{i\ell}$ and $\tau_{i\ell 1}$ but only their sum $\gamma_{ij} = \lambda_{i\ell} + \tau_{i\ell 1}$. Therefore, it is impossible to estimate the stability and adaptability components of the overall variance separately. All that we can estimate is the overall variance $\sigma_i^2 = \sigma_{ij}^2$ the overall variability. Of course, we can now define the concept of variability of efficiency by plotting $\overline{Y}_{i\cdot}$ against S_{ij} and analyze it in the same way as in Figure 1 or 2. Defining variability efficient sets in this particular way may make sense because the stability variance and the adaptability variance both enter the overall variance, which is thus a weighted sum of stability and adaptability. But it exaggerates riskiness of a genotype in the sense used in this paper.

4. The Problem of Nursery- and Region-Specificity of EV-Analysis

Models derived from variance analysis have the limitation that the stability efficient and adaptability-efficient sets so identified are specific to the nursery in which they were tested and to the agroclimatic region within which the multilocation trial was carried out. This can best be illustrated by reference to Figures 3a and 3b.

Suppose as before that Figure 3(a) identifies genotypes A to E as risk-efficient on the basis of a multiyear and multilocation experiment. Suppose now

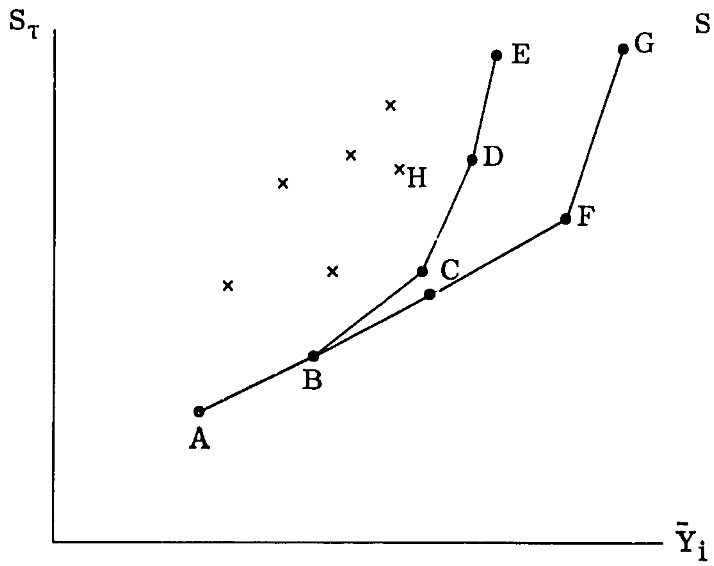

Figure 3(a). Nursery-specificity of result.

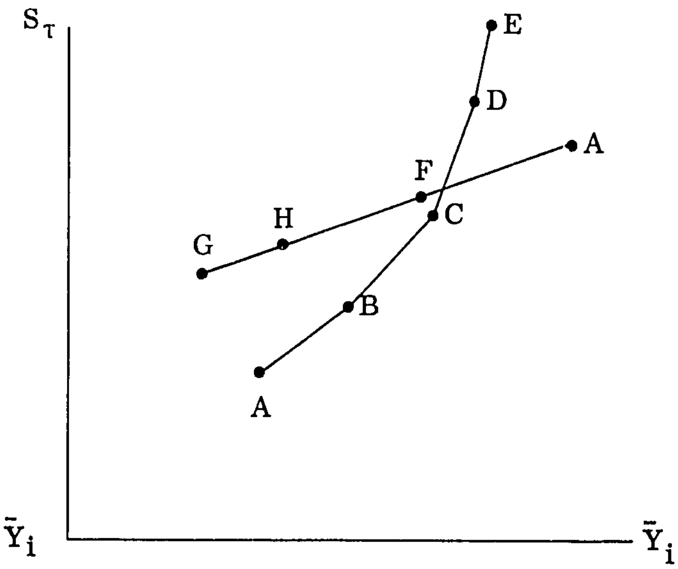

Figure 3(b). Region-specificity of result.

the nursery tested had also included a genotype F and G. The risk-efficient set would then have consisted of genotypes A, B, C, F, and G. On the other hand, inclusion of genotype H would not have altered the results. Conclusions as to risk efficiency (or adaptability and variability efficiency) must therefore stress that the genotypes identified as efficient are efficient compared with those tested in the same nursery. It is not possible to speak of an efficient genotype per se.

Region-specificity of the results is illustrated in Figure 3(b). Suppose the same nursery had been tested in multilocation and multiyear trials in two different agroclimatic zones, such as India and Africa. In the Indian trials the genotypes A, B, C, D, E were found to be stability-efficient, but genotype A, of African origin, was found to do poorly in terms of yields in India. In Africa, therefore, it is likely that it might outyield all others and be in the risk-efficient set with genotypes G, H, and F. On the other hand, a genotype, say E, might be inefficient in the African context despite its relative risk-efficiency in India. Again all findings of efficiency can apply only to agroclimatic zones similar to the ones in which the multilocation trials were initially conducted.

Conclusions that are not nursery- or region-specific, should be based on physiological/structural models in which components of stability or adaptability are specifically identified such as drought tolerance, photoperiod insensitivity, or disease and pest resistance. One approach to such structural identification is regression or covariance analysis, which will be discussed in the next section.

5. Structural-Physiological Models and the Use of Regression Analysis

As discussed in the previous section, the major drawback of the EV-based models discussed so far is the nursery- and region-specificity of the results.

The Joint Regression Approach

Attempts to overcome such specificity have a long history in the Environment x Genotype interaction (GE) literature, which is based on one-variable regressions of genotype performance on environmental indices. The environmental indices are almost always the mean yields of all genotypes within a given location (Yates and Cochran 1938, Findlay and Wilkinson 1963, Perkins and Jinks 1968a, Eberhardt and Russel 1966). A more detailed discussion of these approaches is given in Appendix 1. Here we note the following problems with the approach in the context of stability and adaptability analysis as defined in this paper.

a. Consider the case of a nursery grown over many years, at a given location. Then the traditional concept of stability of the GE literature coincides with the concept of stability used here, but the measures are not the same. However, we have seen that it is impossible to rank genotypes in a unique way as "stability optimal" in the absence of knowledge about the decision makers' preferences in yield and (measured) stability, however that concept may be measured. The GE literature fails to explicitly recognize and discuss how that tradeoff is to be made; therefore it is not surprising that the debate about the best concept or measure of stability and risk continues.

b. The GE literature treats every dimension of the environment in the same way. It does not distinguish between a time and a location dimension of environmental differences.[12] Therefore, it is not capable of distinguishing between adaptability and stability as defined in this paper.

c. The ultimate aim of these regression methods is to derive a measure of "stability" that is independent of the nursery as well as the set of environments in which it was conducted. However, the regression coefficient found in a regression of the yield of genotype i on the mean yields of all genotypes in a given location is of course specific to the nursery within which genotype i was tested. Thus the method does not overcome nursery specificity.

Furthermore the use of deviations around a regression line as an additional measure of stability proposed by Eberhardt and Russel (1966) makes the method as region specific as the methods based on EV analysis, since these deviations are variance components similar to the ones used above.

We therefore reject the traditional joint regression approach to measure the concept of stability of this paper, recognizing that in other contexts the approach has many merits.

A method with many similarities to the joint regression approach is that

12. In fact, often different soil types or cultural practices at the same location are treated as different environments in the same way as genuine location and time differences.

of Evenson et al. (1978) to which we owe the distinction between stability and adaptability. It overcomes problem (b) of the joint regression approach and is discussed in Appendix 2.

Regression Analysis on Plant Independent Variables with Single-Year Data

Hardwick and Wood (1972) have extensively discussed the use of regressions of mean yields (over replications)[13] on plant-independent variables of the environment such as latitude, soil moisture stress, or fertilizer levels. The models have the form

$$Y_{ij} = \mu_i + \sum_{h=1}^{H} \beta_i^h E_j^h + \gamma^*_{ij} \qquad (13)$$

where, as long as the E_j variables are deviations of the environmental variables from their means across locations, the μ_i effects are the same as those described in the previous section. However, the γ^*_{ij} are residual variations around the regression line, whereas the γ_{ij} are differences from mean yields. We may call γ_{ij} the residual genotype × environment interaction. For the one-variable case this is shown graphically in Figure 4. Hardwick and Wood (1972) call the class of models in (13) physiological models and show the relationship of these regression models to regressions on environmental means (See Appendix 1).

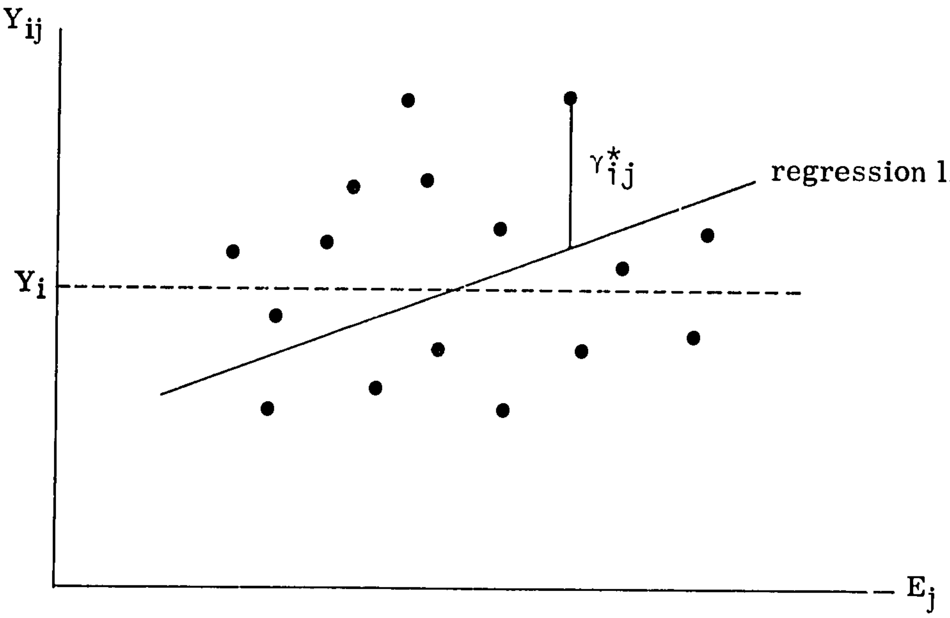

Figure 4. Genotype x environment interactions and residual genotype x environment interactions.

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13. Unless the error variance is the same as the variance across location i.e., $\sigma^2_{i\varepsilon} = \sigma^2_{i\gamma}$ Ordinary Least Squares estimators (OLS) of the β coefficient in equation (13) are consistent (i.e., unbiased in large samples) but not most efficient and therefore, as long as OLS methods are to be used, it is better to neglect the replication and work directly with means across replications.

The regression coefficients β_i^h have the following stability or adaptability interpretation: There are three types of plant-independent variables: "control" variables C, such as fertilizer levels; "site" variables Z, which vary only across locations but not years, such as latitude or soil type; and "weather" variables W, which vary over sites as well as over years, such as rainfall, or soil moisture. Consider the case in which a regression contains one of each:[14]

$$Y_{ij} = \mu_i + \beta_i^c C_j + \beta_i^z Z_j + \beta_i^W W_j + \gamma_{ij}^* \tag{14}$$

Clearly, with respect to a "weather" variable W, high <u>stability</u> must imply that the regression coefficient β_i^W be close to zero, i.e., that the genotype be insensitive to weather. With respect to "location" variables such as latitude or soil types, a highly adaptable genotype would again have a regression coefficient β_i^z close to zero. For both measures we are looking for low explanatory power of the regression. On the other hand, for certain "control" variables such as fertilizer, highly responsive genotypes are preferred and we are looking for high β_i^C coefficients. Therefore whether a high or a low regression coefficient is desirable depends on the variable factor considered. To repeat, <u>low</u> regression coefficients of crop yields on "weather" and "location" variables are indications of high degrees of stability or adaptability of a genotype with respect to that particular measured factor.

If properly measured, regression coefficients as "stability" parameters should not be nursery- or region-specific. Fertilizer responsiveness, photoperiod insensitivity, drought tolerance, and other specific physiological components of adaptability and stability are inherited and are therefore transferable from one region to another. This is the case even though new diseases in another region may make a given genotype as a package of such physiological components unattractive. Breeding programs can break up the physiological package of a genotype and incorporate the identified desired components into the genotypes of another region through cross-breeding. Regression analysis on plant-independent variables may help identify such components, although breeding programs also have other methods to identify such components.

The regression approach can clearly be used with single-year data to identify both stability and adaptability components. As long as each year contains at least some variation in E^h across locations, β_i^h coefficient can be measured. Of course, a single year trial at only a few locations can estimate the impact of only a few β^h coefficients, and multiyear data sets may still be required to overcome degree-of-freedom problems.

<u>Can one also use residual sums of squares and coefficients of determination (R^2) as measures of stability and adaptability?</u> In the notation of equations (13) and

14. Alternatively there can be several C, Z, and W variables, in which case β_i^C, β_i^Z and β_i^W are vectors of coefficients and C_j, Z_j, and W_j are matrixes.

(14) Residual sums of squares can be written as $RSS_i = \sum_j Y^{*2}_{ij}$ where Y^*_{ij} are the estimated residuals, $Y^*_{ij} = Y_{ij} - Y_{i.} - \sum_h b^h_i E^h_j$. Residual variance then is $S_{iY}{}^* = \sum_j \hat{Y}_{ij}{}^*/J-H-1$. Thus RSS_i or $S^2_{iY}{}^*$ are estimators of the unexplained portion of total variability, and in some circumstances it may be useful to compare genotypes according to how much of their total variability remains unexplained after regression. But it is not possible to use these measures as criteria for choices among genotypes because (1) they are not independent of the β^h_i measures and (2) no choice theoretical basis can be found which would justify the use of these measures. Even in the simplest case when the regression (13) is performed on a single location over many years, so that the residual variance would clearly be a residual stability variance it is not possible to justify RSS_i or $S^2_{iY^*}$ (which in that case should rather be written as $S^2_{i\tau^*}$) as measures of stability. This is because the farmer who would adopt a genotype is concerned with the total variability of the genotype and not just the unexplained portion. The proper measure to define variability-efficient sets remains $S^2_{i\tau}$ i.e., the total variance, rather than $S^2_{iY^*}$, the residual variance.

The coefficient of determination $R^2 = \frac{RSS_i}{TSS_i}$ where TSS_i is the total sums of squares, tells us the proportion of the total variance which the plant independent variables can explain. But first note that it is a relative measure, not an absolute one and therefore can vary both because of changes in TSS as well as RSS. Second, since it has been shown above that stable or widely adaptable genotypes should have low β^Z_i and β^W_i coefficients, a high R^2_i is not necessarily a desirable characteristic of a genotype.

If the plant-independent variables contain control variables, R^2 becomes an even less useful measure, because -- as in the case of fertilizers--one may be looking for genotypes with high β^C_i coefficients, i.e., one wants to explain as much as possible. If a regression contains both C, Z, and W variables, then one does not know whether to look for a high or a low R^2. R^2, therefore, should not be used as a criterion in the context of adaptability and stability analysis.

Regression analysis on plant-independent variables has its pitfalls, however, one reason why it has been used so little is that the number of environments is often quite small and one cannot hope to fit regressions with many variables for lack of degrees of freedom. An alternative is to collapse the environment into single variables by using genotype means[15].

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15. An alternative way of reducing the number of environmental variables and finding an index of the environment is provided by principle component analysis.

Another problem is the issue of left-out variables[16]. Plant growth is determined by a large array of variables and it will always be impossible to include more than, say, eight or ten variables in such a regression. It is well known that, if we leave out of the regression equation (13) an environmental variable that is correlated with variables included in the regression, then the coefficient estimate of the variables included in the regression will be biased. If latitude, for example, were correlated with temperature but temperature were left out, the regression coefficient of latitude would reflect photoperiod sensitivity as well as the temperature effect to some degree. Investigators thus need good knowledge of the nature of their data sets and the physiological importance of what may not have been measured.

Regression analysis with several years' data

To overcome the lack of degrees of freedom it is useful to combine several years' data into the following model

$$Y_{i\ell t} = \mu_i + \sum_{h=1}^{H} \beta_i^h E_{\ell t}^h + \lambda^*_{i\ell} + \tau^*_{it} + \eta^*_{i\ell t} \tag{15}$$

which has an overall residual variance

$$\sigma_i^{2*} = \sigma^2_{i\lambda^*} + \sigma^2_{i\tau^*} + \sigma^2_{i\eta^*} \tag{16}$$

The interpretation of the β_i^h coefficients as measures of stability or adaptability remains the same as discussed before. But statistical problems arise from the fact that one should not use Ordinary Least Squares (OLS) regression on a data set that combines several years' data[17]. While the OLS method leads to consistent estimators of the β_i^h coefficients, these estimators are not efficient. (A consistent estimator is one that is unbiased for large samples; an efficient estimator is one with the lowest possible standard error of the β_i^h coefficients among all possible linear estimators.)

Several methods are possible to get more efficient estimators than the OLS ones. First one can treat $\lambda^*_{i\ell}$ and τ^*_{it} as fixed effects and introduce dummy variables for each location and each site. This is most easily done by transforming all the data in the following way, if the data set is balanced.

$$Y_{i\ell t} = Y_{i\ell t} - Y_{i\ell .} - (\overline{Y})_{i.t} + (\overline{Y})_{i..} \tag{17}$$

$$e_{i\ell t} = E_{i\ell t} - \overline{E}_{i\ell .} - \overline{E}_{i.t} + \overline{E}_{i..} \tag{18}$$

Assuming that $\sum_{\ell} \lambda_{i\ell} = \sum_{t} \tau_{it} = 0$ one then

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16. For a discussion see Johnston (1972), p 168.

17. In the econometric literature this problem is known as "combining cross sections and time series" and a solution to its efficient estimation was first proposed by Wallace and Hussain (1969).

performs an OLS regression as follows

$$Y_{i\ell t} = \sum_h \beta_i^h e_{i\ell t}^h + \eta_{i\ell t} \qquad (19)$$

However, the Generalized Least Square techniques (GLS) due to Wallace and Hussain (1969) is even more efficient. This technique first estimates the variance components in equation (16) from the residuals of a first stage regression and then uses these estimates to further transform the Y and E data and finally runs a second stage regression which leads to efficient estimators[18]. A third approach is the use of Maximum Likelihood Estimators (MLE) in which the βs and the variance components are estimated simultaneously. However MLE programs are most often not available in developing countries.

6. The Relationship between Stability and Adaptability

The conceptualization of this relationship can come from equation (16) rewritten here with one control (C), site (Z) and "weather" (W) variable respectively, although there can of course be several in each class.

$$Y_{i\ell t} = \mu_i + \beta_i^C C_{\ell t} + \beta_i^Z Z_{\ell t} + \beta_i^W W_{\ell t} + \lambda_{i\ell}^* + \tau_{it}^* + \eta_{i\ell t}^* \qquad (20)$$

Consider the case of the overall adaptability variance which is a function of both the β_i^Z coefficients and the variance of λ_i^* the unexplained component of the overall adaptability variance.

If, for example, a genotype is photoperiod-insensitive, as measured by a zero β_i^Z where Z is latitude, then we cannot expect that fact to contribute to the stability of the genotype at a given location over years. Similarly if the unexplained location effects $\lambda_{i\ell}^*$ are large, say, because some locations have saline soils, and that fact has not been measured and not been included as a regression variable, high sensitivity to salinity will not contribute to low stability of the genotype over years in locations where it is well adapted. Thus if low overall variability comes primarily from insensitivity to measured and unmeasured site variables, then high adaptability does not imply high stability.

On the other hand, if a genotype is found to be stable because of low sensitivity to measured and unmeasured "weather" variables, which vary across locations as well as over years, high stability also contributes to high adaptability. For example, if moisture stress has been measured as a variable and its regression coefficient is found to be low, then this will enable easy transfer from more

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18. At ICRISAT the COMTAC program performs these computations using a procedure of Amemiya's (1971) to estimate the variance components of equation (16) in which the first stage regression is the one of equation (19). For a detailed discussion see Barah (1976).

humid climates to dry areas as well as high stability. Even in humid areas the plant can be subject to as much drought stress in a particular year as can be encountered more often in a dry area. As another example, disease or pest resistance of a genotype should lead to a low unexplained variance component of ${}^{*}\eta_{i\ell t}$ because pest and disease incidence varies across locations as well as within a particular location from year to year. Therefore -- as is well known -- disease resistance should increase stability as well as adaptability.

To sum up, stability and adaptability should be strongly related if they come from insensitivity to "weather" variables that vary across locations as well as years, but not if adaptability arises from insensitivity to measured and unmeasured, variables that vary only across locations.

Appendix 1: Relationships to other genotype x environment interaction models

In this appendix we will discuss the classic joint regression approach to genotype x environment interaction, which consists of regressions of individual genotype yields on the means of all genotypes in each environment. These models have been developed and/or popularized by Yates and Cochran (1938), Findlay and Wilkinson (1963), Perkins and Jinks (1968), and Eberhart and Russel (1966).

Hardwick and Wood (1972) have closely compared regressions of the type of equation (13) with those on environmental means. In notation of our paper they assume that $\gamma_{ij} = \beta_i \bar{\gamma}_{.j} + \gamma_{ij}^{**}$ and γ_{ij} is the original γ_{ij} in equation (12), which is broken down into a regression effect and another residual around the regression line, γ_{ij}^{**}. The environment is measured as the average deviation of yields over genotypes in environment j, i.e., as $\bar{\gamma}_{.j}$. This leads to the equation

$$\gamma_{ij} = \mu_i + \beta_i \bar{\gamma}_{.j} + \gamma_{ij}^{**} \qquad \text{(A-1.1)}$$ [19]

Hardwick and Wood demonstrate first that in OLS regressions, as proposed in the genotype x environment literature, b_i is a biased estimator of β_i, with the bias declining as the number of genotypes in a nursery increases. Secondly, and much more importantly, they show that one can try to equate models (13) and A-1.1 to each other. If for genotype i the β_i^h differ from $\bar{b}^h$ (the average regression coefficient across genotype) by the same constant for all environmental variables h, then model A-1.1 is an exact condensation of the more complicated model (13). This condition means that there cannot be substantial response differences among genotypes for more than one environmental factor. For example, the sensitivity of genotype i to drought stress should differ from the average sensitivity of all genotypes to drought stress by the same constant as its sensitivity to day length differs from that of the average genotype. This condition is indeed a difficult one to meet.

As a byproduct of this result these authors are able to demonstrate as a further result... "that the deviations (γ_{ij}^{**}), the sums of squares of which have been proposed by Eberhart and Russel (1966) as the second parameter of stability, are not independent

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19. Equation A-1.1 is often given in a somewhat different notation. One starts from a modified version of equation (4) and writes $Y_{ij} = \mu_i + \bar{Y}_{.j} + \delta_{ij}$ (A-1.2) where $\gamma_{ij} = \bar{\gamma}_{.j} + \delta_{ij}$, i.e., the genotype x environment interaction is first split up into an average environment effect $\bar{\gamma}_{.j}$ and a residual interaction. Then one writes $\delta_{ij} = \beta_i \bar{\gamma}_{.j} + \gamma_{ij}^{**}$ and substitutes into A-1.2. This leads to an equation equivalent to A-1.1: $Y_{ij} = \mu_i + (1+\beta') \bar{\gamma}_{.j} + \gamma_{ij}^{**}$ (A 1.3) "Stable" genotypes are those that have β coefficients close to 1, i.e., they perform almost as well as the average genotype in all environments. This corresponds to a β' coefficient of zero. All traditional definitions of "stability" set $\beta = 1$ or $\beta' = 0$ as the proper standard.

of the regression on the environmental mean but are rather a necessary adjunct of the line fitting procedure" (Hardwick and Wood, 1972, p 215, with γ_{ij}^{**} substituted for their notation δ_{ij}). Thus the regression slope and deviation sums of squares are not independent measures of stability.

Appendix 2: Regression of deviations from year means and location means

Evenson et.al. (1978) pioneered the distinction of stability and adaptability used in this paper. They borrowed from the G-E literature the use of yields as an environmental index. However they reason that mean yield of genotypes across environments is not a good measure of site or year potential. Instead, the yield potential should be better reflected in the yield of the highest-yielding genotype at that location or year, i.e., they define

$$M_{\ell t} = \max_i (Y_{\ell t}) = \text{yield potential of environment } \ell t.$$

Note that this will usually lead to the use of yields of different genotypes for different locations as measures of potential yield.

They then fit two regressions for each genotype of the form

$$Y_{i\ell t} = \mu_i + \alpha_i M_{\ell t} + \lambda^*_{i\ell} + \varepsilon_{i\ell t} \qquad \text{(A-2.1)}$$

$$Y_{i\ell t} = \mu_i + \alpha'_i M_{\ell t} + \nu^*_{it} + \varepsilon'_{i\ell t} \qquad \text{(A-2.2)}$$

where α_i and α'_i are regression coefficients on the environment ε and ε' are residuals and λ^* and ν^* are residual location and year effects, respectively, the asterisk indicating the residual nature, after regression, of these effects. λ_ℓ and ν^*_t are estimated by introducing dummy variables into the regression for each location or each year as necessary.

It is somewhat easier to see what these regressions are by subtracting the location and time means respectively from equation (A-2.1) and (A-2.2):

$$Y_{i\ell\cdot} = \mu_i + \alpha_i \overline{M}_{\ell.} + \lambda^*_{i\ell} + \overline{\varepsilon}_{i\ell.} \qquad \text{(A-2.3)}$$

$$Y_{it} = \mu_i + \alpha_i \overline{M}_{\cdot t} + \nu^*_{it} + \overline{\varepsilon}'_{i.t} \qquad \text{(A-2.4)}$$

Subtracting (A-2.3) from (A-2.1) and (A-2.4) from (A-2.2) leads to the disappearance of the time and location effects from the equations, i.e., to regressions in deviations from site means and from year means of the dependent and the independent variables:

$$(Y_{i\ell t} - Y_{i\ell.}) = \alpha_i (M_{i\ell t} - M_{i\ell.}) + \rho_{i\ell t} \qquad \text{(A-2.5)}$$

$$(Y_{i\ell t} - Y_{i.t}) = \alpha'_i (M_{i\ell t} - M_{i.t}) + \rho'_{i\ell t} \qquad \text{(A-2.6)}$$

where $\rho_{i\ell t}$ and $\rho'_{i\ell t}$ are deviations of the respective ε from the time and location means.

Since in equation (A-2.5) the location effects have been removed, the α_i coefficient captures the sensitivity of the genotypes to the remaining year-to-year variability and thus captures the stability in exactly the same sense as the β_i coefficients of the joint regression technique (A-1.1) captures stability, i.e., one wants to have the coefficient close to 1. Similarly, in equation (A-2.6) the year effects have been removed and the α_i' coefficient captures adaptability in the same sense that the Eberhardt and Russel coefficient captures insensitivity to environments. Again, it should be close to 1.

Evenson et al. make no use of the residual variability of ρ_{ijt} and ρ'_{ijt} in their stability and adaptability analysis.

The finding of Evenson et al. that β_i and β_i' are correlated must therefore be interpreted as saying that the systematic components of stability and adaptability are correlated. However, since the environment is not measured by plant-independent variables the objection (a) and (c) against this approach discussed in Section 5 still apply. Also the β coefficients explain only part of the total stability and adaptability variance discussed in Section 2, and fail to consider the size of the unexplained portion of these variance components.

References

AMEMIYA, P. 1971. The estimation of the variance in a variance component model. International Economic Review 12:1-13.

ANDERSON, J.R. 1974. Risk efficiency in the interpretation of agricultural production research. Review of Marketing and Agricultural Economics 42 (3):131-183.

ANDERSON, J.R., DILLON, J.L., and HARDAKER, J.B. 1977. Agricultural decision analysis. Ames (USA): Iowa State University Press.

BARAH, B.C. 1976. Combining Time-Series and Cross-Section Data in Regression Analysis. ICRISAT Discussion paper, Patancheru.

BINSWANGER, H.P. 1980. Attitudes towards risk: Experimental measurement in rural India. American Journal of Agricultural Economics (In Press).

DILLON, JOHN L. 1979. Bernoullian decision theory: Outline and problems. In Roumasset et al. (eds.), Chapter 2, pp 23-38.

EBERHART, S.A., and RUSSEL, W.A. 1966. Stability parameters for comparing varieties. Crop Science 6:p.36.

EVENSON, R.E., 1978. Risk and uncertainty as factors in crop improvement research. IRRI paper series 15, Manila, Philippines.

FINLAY, K.W., and WILKINSON, G.N. 1963. The analysis of adaptation in a plant breeding programme. Australian Journal of Agricultural Research 14:742-754.

HARDWICK, R.C., and WOOD, J.T. 1972. Regression methods for studying genotype-environment interaction. Heredity 28:209-222.

JOHNSTON, J. 1972. Econometrics methods. New York: McGraw-Hill.

KNIGHT, R. 1970. The measurement and interaction of genotype-environment interaction. Euphytica 19:225-235.

LAING, D.R., and FISHER, R.A. 1973. Preliminary study of adaptation of entries in 6th ISWN to non-irrigated conditions. CIMMYT, Mexico.

MARSHALL, D.R., and BROWN, A.H.D. 1973. Stability performance of mixtures and multilines. Euphytica 22:405.

PERKINS, J.M., and JINKS, J.L. 1968. Environmental and genotype environmental component of variability. Heredity 23:339-356, 525-535.

ROTHSCHILD, M., and STIGLITZ, J.E., 1970. Increasing risk, I: A definition. Journal of Economic Theory 2:225-243.

ROUMASSET, J.A., BOUSSARD, Jean-Marc., and INDERJIT SINGH (eds.). 1979. Risk, uncertainty and agricultural development. Laguna, Philippines, and New York : SEARCA and ADC.

ROUMASSET, J.A. 1979. Introduction and states of the arts. Pages 3-22 in Roumasset et al. (eds.).

WALLACE, T.D., and HUSSAIN, A. 1969. The use of error components model in combining cross-section with time series data. Econometrica 37:55-72.

YATES, F., and COCHRAN, W.G. 1938. The analysis of groups of experiments. Journal of Agricultural Sciences 28:556.