



SCIENTIFIC CONTRIBUTIONS OF THE PU FOR CHE

Series H: Inaugural Address nr. 124

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OF ECOLOGICAL AND
AGRICULTURAL DATA**

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Inaugural Address on 30 August 1991

Central Publications Department
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Having much respect for the vision of Potchefstroom University for CHE, and for its faculty and staff, it gives me great pleasure to be appointed in the Department of Plant and Soil Sciences. For several years, I have enjoyed collaborating with the faculty here, especially with Prof. Ockie Bosch on a major research project concerning ecologically sound management of grazed pastures. In this inaugural address, I would like to explain my speciality and interests, and indicate how I hope to contribute to the future work to be done here.

For the past two decades, my research at Cornell University has focused upon the statistical analysis of ecological and agricultural data. Accordingly, Part I of this address concerns multivariate analysis in community ecology, and Part II the analysis of regional yield trials. Furthermore, because I think it vital to connect specialized knowledge with the broader features of human knowledge, Part III draws general implications for the scientific method and philosophy of science. This is a natural extension because statistics is essentially inductive logic, and logic is crucial in science, philosophy, and theology — in all knowledge. Unfortunately, many of the world's universities lack the vision to truly integrate human knowledge across specialities, or lack the freedom to pursue the distinctively Christian understanding which alone can see reality as it is. Accordingly, Christian universities have a great opportunity and a high calling. But before considering these broader issues in Part III, let us begin with the more immediate matters of statistical analysis, first considering ecological applications.

I. MULTIVARIATE ANALYSIS IN COMMUNITY ECOLOGY

Community ecology concerns assemblages of plants and animals living together, and the environmental and historical factors with which they interact. Plant community ecology is also termed 'phytosociology.' Phytosociologists study a great diversity of plant communities. At each site, the abundance of each plant species is estimated in terms of some index, such as the percentage of the ground covered. The result is a two-way, species-by-samples data matrix. The two-way factorial experiment, replicated or not, is the principal data structure addressed in my work. *Multivariate analysis* is that branch of statistics which examines numerous variables simultaneously, including the two-way matrix. Multivariate data arise commonly in science because scientists are often interested in more than one trait of more than one individual, or like-

wise the performance of more than one thing in more than one situation.

Broadly speaking, the purposes of multivariate analysis are to address four difficulties or challenges. First, biological data are noisy: replicate samples are usually not identical. Some variation is interesting and repeatable, caused by environmental and other factors; but also some variation is idiosyncratic and unrepeatable, constituting merely sampling variation or noise. Multivariate analysis of a large data set in order to partition the total variation into a pattern-rich model and a noise-rich discarded residual. This increases accuracy and efficiency. Second, biological data are usually partially redundant — not every sample or species is tremendously unlike everything else. For example, although an ecological survey may have several hundred samples, it probably will have no more than a dozen or so substantially different kinds of samples. Multivariate methods can describe trends and clusters in the data, thereby grouping similar entities and generating compact summaries. Third, biological data typically have numerous complex relationships among the samples, among the species, and among the samples and species considered jointly. The plant distributions also have additional relationships with environmental and historical causal factors. Multivariate methods can produce informative statistics and graphs that reveal important biological patterns, which humans simply cannot grasp from enormous tables of raw data often containing many thousands of numbers. Fourth, biological data sometimes contain outliers — peculiar samples resulting from disturbed or odd situations, or even from technical or transcribing errors. Multivariate analysis can detect outliers, allowing them to be handled separately or appropriately.

Multivariate methods useful in ecology are of three basic kinds: direct gradient analysis, ordination, and classification.

Direct Gradient Analysis

Direct gradient analysis displays the distribution of organisms along gradients of important environmental factors. For example, an ecologist may sample the vegetation along a moisture gradient — caused by undulating topography or whatever — and then graph the abundances of the species along this gradient. Some species are partial to the wet areas, others to intermediate moisture, and yet others to dry areas. Likewise, along a gradient of grazing pressure, some species flourish in lightly grazed places, some in intermediate conditions, and some unpalatable

species invade severely overgrazed areas. Hundreds of such analysis in a great diversity of plant and animal communities reveal that species typically have approximately Gaussian or bell-shaped distributions along an environmental gradient. Each species does best at some particular level of moisture or temperature or whatever, whereas its population declines to either side of its preferred mode.

Direct gradient analysis is the simplest multivariate method, and has been enormously effective in many ecological studies. However, its focus on a known environmental gradient limits its use in situations where environmental factors are poorly understood. Furthermore, an alternative perspective is to begin with analysis of the community data alone, and later use environmental data for interpretation of the results. For these and other reasons, ecologists complement direct gradient analysis with additional multivariate methodologies.

Ordination

A two-way data matrix may be conceived geometrically with the samples as axes and the species as points (or the converse). The matrix and geometric representations contain identical information. The challenge is that given perhaps hundreds of samples and species, the resulting space with hundreds of dimensions cannot be graphed or imagined. *Ordination* projects the points in an incomprehensible high-dimensional space into a manageable low-dimensional space, while in that process still minimizing the distortion of the distances between the points. Frequently, ordination results are ecologically meaningful for the profoundly significant reason that although the community data are intrinsically high-dimensional — with numerous species and numerous samples — nevertheless the important underlying environmental causal factors are ordinarily relatively few. Thus high-dimensional data contain a low-dimensional story. Consequently, ordination results frequently summarize complex, large data sets quite successfully. Furthermore, these results are useful for generating hypotheses about the identity and relative influence of the underlying environmental causal factors.

One specific statistical method for ordination is principal components analysis. It projects a high-dimensional cloud of points onto a space with fewer dimensions in such a manner as to maximize the sum of squares of the points in the principal components solution (or equivalently to minimize the sum of squares of the residuals). In other words, the first

principal components axis defines the least-square line through the multidimensional cloud of points, the first two principal components axes define the least-square plane, and so on.

The principal components analysis calculation is entirely objective in that a two-way data matrix is supplied, but nothing else is chosen or specified. Being objective and defining a least-square subspace might make principal components analysis sound ideal. However, like all statistical methods, principal components analysis has and presumes a particular underlying model. Consequently, only if this model happens to fit the data reasonably well in a given instance can the results be satisfying. Its main assumption is that the species respond to the underlying environmental causal factors in a linear fashion. But given the above result from direct gradient analysis that species responses are typically bell-shaped, this assumption of linearity is unrealistic unless a data set happens to sample only a relatively short gradient. This limitation has motivated ecologists to employ additional ordination procedures which can handle longer gradients successfully, such as reciprocal averaging and detrended correspondence analysis.

Ordination has been an enormously important method in community ecology. In some cases, however, research purposes call for results stated in terms of classes or groups, rather than a spatial or graphical model. For example, a manager may want to classify pastures into one of several kinds. Consequently, the methodologies discussed so far — direct gradient analysis and ordination — are complemented by a third methodology, namely classification.

Classification

Classification is the assignment of entities to classes or groups. Classification is a fundamental, ubiquitous mental activity. Accordingly, it is natural that the first conceptual framework for organizing community data was classification. However, the methods of early phytosociologists were informal and subjective, required an extended apprenticeship, and demanded long hours of tedious manipulations. When computers became widely available to ecologists around 1960, numerical classification methods were developed which were suitable for computer implementation and were more objective.

In community ecology, the input data constitute a species-by-samples

matrix of species abundances, and the resultant output may classify the species or the samples or both. A non-hierarchical classification merely partitions entities into a number of classes, but hierarchical classification merely partitions entities into a number of classes, but a hierarchical classification also places the classes into an overall arrangement which shows the relative similarity or dissimilarity between any pair of classes.

Computer Implementation

The Cornell Ecology Programs series, which has gone to over four thousand laboratories, offers programs for ordination, non-hierarchical classification, and hierarchical classification. Versions are available for both mainframe computers and microcomputers. A distinctive feature of this series is that most programs are implemented by algorithms with a linear workload, meaning that the amount of memory and time required rises only linearly with the amount of data. Consequently, even microcomputers can handle quite large data sets readily.

From a historical perspective, plant community ecology — as well as the multivariate statistics used in ecology — have emphasized relatively undisturbed, natural ecosystems. By contrast, disturbed, managed ecosystems are far more complex. Although it is natural that plant ecology began with the simpler systems, the practical need to manage grazed pastures calls for tackling complex ecosystems often disturbed by overgrazing. During the past several years, Prof. Bosch, Dr. Booyesen, and I have had to develop some new ecological models and new statistical methods in order to understand these complex ecosystems better.

This year we will be working to finalize the first release of the Integrated System for Plant Dynamics (ISPD) program for grazed pasture management. Applications to various ecosystems throughout the world, together with possible extensions of its predictive component and economics component, will present us with much challenge and work for many years. I expect this project to make a positive contribution to the agricultural needs of this and many other countries.

II. STATISTICAL ANALYSIS OF REGIONAL YIELD TRIALS

Agricultural research helps farmers to produce a greater quantity, quality, and diversity of products within constraints of acceptable profitability and risk. The central experiment in this research is the yield trial. Yield trials have proven informative for agronomic recommendations and breeding selections, but their value is often limited by inaccuracy and other problems. Although relatively new to agriculturalists, the Additive Main effects and Multiplicative Interaction (AMMI) model has proven helpful for achieving accurate yield estimates, reliable selections, insightful models, and efficient designs. This model begins with ordinary analysis of variance for the additive main effects, and then analyzes the residual non-additive interaction with principal components which is a multiplicative model. Typically yield is measured for G genotypes grown in E environments with R replications, resulting in GER observations. These 'environments' are usually site and year combinations such as Ithaca in 1990. Here each genotype environment combination is termed a 'treatment', so there are GE treatments. Thus the typical yield trial's design is a genotypes-by-environments two-way factorial experiment, with replication.

Agronomists and breeders use yield trials for a variety of research purposes, which may be collected under four headings: accurate estimates, reliable selections, insightful models, and efficient designs. Individual research projects vary in the relative importance of these four purposes, as well as in the inherent strength of the data for accomplishing these varied purposes.

Accurate Estimates

The most obvious and fundamental purpose for yield trial research is to provide accurate yield estimates for each genotype in each environment. Naturally, the practical value of a yield trial is critically dependent upon its accuracy. Accurate yield estimates permit reliable recommendations and good selections, but inaccurate estimates may be misleading and practically worthless.

But this simple term, 'accuracy', can be understood statistically in two different senses: accuracy in *postdicting* a yield observation already used in constructing a statistical model; and accuracy in *predicting* an observation not used in constructing the model, but instead used in

validating the model's success in fitting new or independent observations. This may sound like merely a philosophical distinction. In fact, this distinction leads to different model choices and hence to different yield estimates. Typically these AMMI refined estimates are as accurate as are ordinary estimates based upon several times as much field data. However, the cost of running a microcomputer briefly in order to perform AMMI calculations is trivial compared to the cost of actually collecting several times as much field data. Hence AMMI offers a remarkably cost-effective means for gaining accuracy. In short, what begins sounding like a philosophical distinction between prediction and postdiction turns out in the end to mean better research and more money in the pocket.

Reliable Selections

AMMI produces adjusted yield estimates, in general differing from the raw means. AMMI's different estimates often lead to different rankings of the genotypes within each environment, and hence to different selections of the best material. The greater AMMI accuracy implies better selections, even with less field data requirements. Furthermore, promising material can be identified earlier, so genetic gain can be achieved faster. In a typical scenario, AMMI selections can offer in just two years the same genetic gain as can regular selections in three years. Likewise, agronomic recommendations can be more reliable with AMMI.

Insightful Models

Estimation and selection, as just considered, address questions which are conceptually simple, focusing upon just one or several yields at a time. By contrast, other important research questions address a regional yield trial as a whole. AMMI results can provide various summary statistics and graphical displays that have proven effective for answering these broad research questions. The major contribution is the biplot graph, so named because it contains two kinds of points to represent the genotypes and the environments respectively. A biplot can be remarkably informative, showing both additive and interaction effects for both genotypes and environments. This effective display may make obvious by a moment's glance numerous complex yield patterns which will never be comprehended by even many days of tedious study of large tables containing thousands of numbers. Furthermore, a biplot often captures 90% or more of the treatment variation. Especially considering that often

at least 5% to 10% of the treatment variation is noise, relegated by AMMI to a discarded residual, biplots often capture essentially all of the real pattern in a yield trial data set.

Efficient Designs

From a practical perspective, effective yield trial research is largely a matter of allocating limited resources in an efficient manner. The goal is to optimize agricultural progress *relative to* research costs. The cost of a yield trial depends upon many factors, but to a first approximation it is a function of the number of yield plots. Given G genotypes, E environments, and R replications, a trial has GER yield plots. However, given some practical limit on the number of plots, researchers face a difficult choice between increasing replications R or else increasing treatments GE . Increasing R increases the *accuracy* of a yield trial. For example, an agronomist would prefer to plant eight replications rather than only two, since the resulting yield estimates would be twice as accurate. On the other hand, increasing GE increases the *scope* of a yield trial. For example, a breeder would prefer to screen 300 plant introductions rather than only 50. Likewise, an agronomist would prefer to test a new variety in ten sites rather than only three, and over five years rather than only two. More generally, given inevitable limitations in overall resources, yield plots allocated to one experiment preclude other experiments. Which choice of experiments will maximize agricultural progress? This choice deserves more consideration than it generally receives. Much more could be said, but the present point is simply that a more efficient AMMI statistical analysis, delivering equivalent accuracy with fewer replications, can generate valuable new options for increasing the scope or number of experiments. Better analysis at the end can call for a different and better design at the start.

At Cornell University, Prof. Richard Zobel and I have been developing agricultural applications of AMMI. Last year a sabbatical visitor from Pretoria, Dr. Benjamin Eisenberg, greatly augmented our work. Prof. Zobel and I consider ourselves fortunate to have numerous helpful collaborators from South Africa and many other nations. This year my main project at Cornell is to write a book on AMMI, which is to appear in both English and Chinese editions.

III. GENERAL IMPLICATIONS: PHILOSOPHY OF SCIENCE

At present, most scientists are highly specialized. This is understandable and necessary because of the enormous quantity of scientific information available in the modern world. In order to master the available knowledge and then make some new contribution, a scientist's effort must be focused narrowly. By contrast, my great-grandfather was a professor of 'Natural Science'. He lectured on everything from geology to agriculture to engineering to veterinary and human medicine. But again, now it is a life's work just to master a speciality such as propeller design, crop fertilization, or silicon compounds.

On balance, however, much greater intellectual strength can result if specialized knowledge is combined with an accurate and insightful general understanding of the scientific method. This broad base lies at the interface between science and philosophy, and is called 'Philosophy of Science' at English-speaking universities. Philosophy of science seeks to describe the proper methods of scientific inquiry, to define science's prospects and limits, and to interrelate science with other branches of knowledge such as philosophy. Incidentally, my field of statistics has applications in science, but foundations in logic and philosophy, so it quite naturally involves philosophy of science.

Now I submit that scientists would profit greatly from a minor effort in learning some basic philosophy of science. What I mean by a 'minor effort' is that, of the many courses required for a bachelor's degree in science, merely one such course would suffice. It might be team taught by faculty from several departments in the sciences and humanities, and likewise listed by several departments in order to allow students with diverse majors to meet their course requirements readily. This call for merely a few percent of a science student's curriculum to be in philosophy of science should not hinder the required acquisition of specialized scientific knowledge. And yet even this minor call represents a significant departure from the customary practices of many universities since most students who graduate with even a Doctor of Philosophy degree in science have never taken even a single course in philosophy.

What benefits would accrue from science pursued with a deeper philosophical understanding? I submit that two specific benefits would accrue: better science, and better integration of science with philosophy and theology.

Better Science

A few years ago, I was enjoying a trip in the Karoo to see the field sites of a graduate student in ecology from another university. While explaining his thesis research project, he began to describe their plans for checking their model's predictive accuracy. I was quite surprised and pleased because rather few ecological projects consider or check predictive accuracy. However, I asked him, "Why are you interested in predictive accuracy — why are you bothering to measure it?" The result was complete bewilderment and silence. I offered the suggestion that predictive accuracy is important because it provides evidence of getting at the truth, and because it gives a realistic assessment of the accuracy that can be expected in future applications of the model. Furthermore, I wanted to discuss the technical details of his research design because scientists use the English word 'prediction' with diverse usages, and I wanted to make sure that his experiment concerned real prediction and not merely postdiction. Also, I suspected that a proper and energetic assessment of prediction might confer several choices and strengths not yet understood by this graduate student. Anyway, the present point is just that students often develop much technical knowledge, but with an unfortunate lack of a broader scientific understanding. A little philosophy of science could give such a student a much deeper understanding of science in general, and of his own research in particular.

As another example, my recent research with applying AMMI to yield trials has opened new possibilities for efficient experiments. The bottom line is greater agricultural progress relative to research costs, and yet the point of departure is a philosophical distinction between prediction and postdiction. I feel that my contribution to this area of agricultural research was largely due to my acquaintance with the literature in philosophy of science.

I hope that Potchefstroom University of CHE can increase somewhat its teaching of the foundations of scientific methodology. The result can be better scientists. I like to envision a group of twenty engineers working on some difficult problem, and a graduate from Potch gets the key insight because he or she can really understand science in depth. I like to envision a Potch graduate seeing how to redesign a big experiment with only a third of the original cost because he or she is really a scientist, not merely a technician. Most fundamentally of all, I like to envision

a Potch graduate perceiving that the question circulating in a research group is somewhat tangential or vague relative to the real question that can stimulate great progress. In a word, I think that a little philosophy of science can make scientists better scientists.

Better Integration of Knowledge

This university has had a sustained effort for many years, involving all of its faculty and students, to integrate all human knowledge, and more specifically to look at all academic disciplines from a distinctively Christian perspective. Through numerous courses and publications, much has been accomplished, and yet still more remains to be done. Because “Reality is in Christ,” as St. Paul declares (Colossians 2:17), this noble effort is both right and important. It is doubly important because so few of the world’s universities pursue this vision.

Space does not allow here for a systematic exploration of the relationships between science, philosophy, and theology. Instead, we must settle for just one extended example. Consider Christian apologetics — that branch of theology which defends the truth of the Christian faith or religion. Three points follow regarding Christian apologetics: first, that a historical review reveals three main approaches; second, that philosophical analysis can explain why there are exactly three approaches, and third, that a historical and philosophical overview can illuminate possibilities for making Christian apologetics stronger.

First, the three main approaches are evidentialist, presuppositionalist, and philosophical apologetics. Evidentialist apologetics emphasizes historical and other evidence for the truth of Christianity. This approach dominated the first eighteen centuries of Christian apologetics, with Eusebius’ “Proof of the Gospels” being representative. Evidentialists claim that Christianity alone matches up with the objective facts of history and reality. By contrast, presuppositionalistic apologetics emphasizes the faith or unprovable presuppositions which lie at the base of every worldview, including Christianity. It has come to be the most popular approach in the present century, especially in Reformed circles. Presuppositionalists argue that Christianity provides the most comprehensive and satisfying view of life. Regarding yet another approach, philosophical apologetics attempts to prove that God exists by means of arguments whose premises are essentially logical or rational, as contrasted with premises making substantial appeal to empirical facts from history or

science. Thomas Aquinas, Anselm, and others proposed several such arguments which continue to this day to have some influence, especially in Roman Catholic circles.

Second, the existence of these three approaches can be explained by understanding the general, pervading structure of any rational thought. It suffices to analyze a trivial common-sense question, namely “Does the jar contain cookies?” Using terminology from science, the roster of possible answers is the ‘hypothesis set’, here constituting the two possibilities “Yes” and “No”. Comparison of these two hypotheses reveals both dissimilarities and similarities. The dissimilarity is most striking: one hypothesis says that the jar contains cookies, and the other the opposite. Nevertheless, there are also similarities, and these are quite important: both hypotheses presume that the physical world and its jars and cookies actually exist, and both presume that human sense experience is reliable enough to satisfy our reaching some conclusion to this question.

The crucial goal sought here how is a *complete* argument for holding either of these hypotheses as one’s conclusion. Exactly how could one support the conclusion that, say, “Yes, the jar contains cookies,” giving a *complete* account? Now the common-sense reason is that some observation, such as “I just saw cookies in the jar,” would justify this conclusion. This argument has the structure “Seeing proves existence,” or “S; therefore E.” In common sense this works because “seeing is believing” as the saying has it; however, in logic this is an invalid *non sequitur* — the conclusion E does not follow from the premise S. To say the least, this argument is incomplete. The required additional premise is the presupposition that the physical world and its jars and cookies exist, that sense experience is generally reliable, and so on, which together amount to saying that “S implies E.” Thus amended, now the argument says “S; S implies E; therefore E,” which is an instance of the valid argument form *modus ponens*. However, in order to be really complete, the argument can add a third premise explicitly declaring that *modus ponens* is a valid inference rule. Finally, in order to give an absolutely complete disclosure of this entire argument, it could also be said that all of our knowledge deemed not relevant to the present question — which philosophers term the ‘background’ — contains or hides nothing which is relevant and thus could impact, or even-reverse, our conclusion.

This simple common-sense example suffices to reveal the basic structure of any rational justification: presuppositions plus evidence, operated upon by inference rules, produce a conclusion (while an irrelevant background is essentially ignored). This structure pervades rational thought in common sense, science, philosophy, and theology. Note the three inputs: presuppositions, evidence, and inferences. In essence, the presuppositions account for why we consider ourselves able to reach any conclusion at all to the question, the evidence accounts for why we select one particular conclusion over the other possibilities, and the inferences combine the various premises in order to produce the conclusion. Presuppositionalistic apologetics emphasizes presuppositions, evidentialistic apologetics emphasizes evidence, and philosophical apologetics emphasizes logic or inferences. Hence this general model of justification allows us to understand the existence of these three schools of Christian apologetics.

Third and finally, the inherent clarity and strength of a complete argument points to possibilities for combining the valid insight from these apologetics traditions into a new integrated approach with greater strength. Furthermore, by extending the same rational completeness into scientific reasoning, the relationship between science and theology can become more clear and more cordial. However, this is a longer story than can be pursued here.

The general point which this one example is intended to illustrate is that deeply integrating knowledge across fields can make each and every field stronger. My greatest hope is that Christian apologetics can be done better. Apologetics seeks to defend the faith — but whose faith? For many older persons their faith is reasonably secure. However, younger persons of the next generation will have to make their own choices. It is not principally for ourselves, but rather for others — especially for the next generation, and most especially for those in doubt or trial or unbelief — that Christian apologetics must be as strong as possible. It is not adequate for Christian apologetics to be good enough for us; rather it must be good enough for others who are not yet Christians. This will require much work by many Christian scholars. For several years I have been working on a book which I intend to complete within a year. I hope that it will contribute toward clearer philosophy of science, and even toward stronger Christian apologetics.

In conclusion, collaborations with this faculty over the past several

years have been very enriching to me, and I look forward to the continued collaboration made possible by my appointment here. A Christian university has a great calling; may God grant us grace.

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