Pathways to Truth:
Rates of Reduction of Yield Uncertainty
Following Trials of a New Crop

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Introduction

At CLIMA (Centre for Legumes in Mediterranean Agriculture) considerable resources are being invested in breeding, testing and economic assessment of new species of grain legumes for Australian growers. A crucial element in the success of this effort is adoption of the resulting crops by growers, which is strongly influenced by growers' perceptions of the riskiness of the crop. Existing grain legumes are seen by farmers as being more risky than other available enterprises such as wheat and sheep. Many farmers state that this riskiness constrains their adoption of the crops, especially field peas. However there is currently little information anywhere in the world on what influences the perceived riskiness of a crop or on the impact of perceived riskiness on adoption of a new enterprise. In addition, there is little information on how important risk is to Western Australian growers' adoption decisions in general.

The aim of this project is to investigate in detail the adoption process for grain legumes such as chick peas, faba beans and lentils, with emphasis on the role of risk. In particular the projects aims are to identify:

- How risky are particular grain legumes perceived to be?
- How do these perceptions change over time with new information or experience?
- How do risk perceptions affect adoption behaviour?
- How can perceptions be influenced so that farmers do not unnecessarily reject beneficial grain legumes?
- How can farmers manage grain legumes to reduce risk?

In this paper we report on a study that investigated one aspect of the role of risk in adoption, namely the rate at which uncertainty about the yield distribution of a crop is reduced following the farmer's experience with it. We first present the results of a 1995 survey of farmers which elicited probability distributions of chick pea yields and farmers' perception of riskiness of grain legume crops. We then describe a Bayesian model of probability revisions that used the survey data as inputs. This model was used as a basis for a simulation model that was used to investigate the rate of reduction in uncertainty as a function of initial ('priors") perceptions and the objectively true distribution.

Background on Legumes

World grain trade of 6.4 million tonnes in 1991 was about 11 percent of world production of grain legumes. Australia's share of the trade market in 1991 was only about 11 percent (ABARE, 1993).
The FAO (Food and Agriculture Organisation) forecasts an annual growth rate of six percent for feed market and three percent for the human consumption market for grain legumes. Australian grain legume industry expanded rapidly during the 1980s and 1990s. Total production of grain legumes in Australia has risen by 220 percent since 1986. ABARE estimated that Australia produced 1,265 kilo-tonnes of grain legumes in the 1994-5 season. Australia's grain legume production consists mainly of lupins (67 percent), field peas (18 percent) and chick peas (six percent). Other grain legume crops produced in Australia include faba beans, cow peas, lentils, mung beans, navy beans and albus (Kiev) lupins. Western Australia, where 90 percent of Australia's lupins were grown in the 1994-5 season, produces only 11 percent of Australia's chick pea crop and 15 percent of the faba bean crop (ABARE 1994). Western Australia produces less than one percent of all other grain legume crops. Therefore, crops like lentils and albus lupins are new to most West Australian farmers.

Lupin production has had one of the highest growth rates in the grain legumes industry and the lowest year to year variation in yield. Initially lupins were not well suited to the existing farming systems, particularly in the northern sandplains of Western Australia, but a farming system was successfully developed around it (Wood *et al.* 1994). There is some evidence, from a project in Western Australia that the high rate of adoption in WA can be directly linked to extension activities of the public and private sectors (Marsh *et al.*. 1996).

South Australia and Victoria are the major areas of field pea production. There is presently little growth in field pea production in any region of Australia. Chick pea production in Australia has increased significantly since 1983 particularly in Victoria even though crop yields have varied significantly from year to year. Faba bean production has grown in New South Wales, Victoria and South Australia with least yield variability in New South Wales and most variability in Victoria. Other minor grain legumes such as mung beans and navy beans have traditionally been considered to be more risky than other grain legumes. Their production has been concentrated in New South Wales and Queensland (Hassall and Associates, 1991).

Risk, Uncertainty and Adoption

Typically, there is a considerable time lag from the point when a decision maker learns of the existence of an innovation until they adopt it (Lindner *et al.*, 1979 and Saha *et al.*, 1994). Decisions to adopt a new crop species are based on probability distributions of its yield and profitability, and the probability distributions which matter are subjective. They are based on a farmer's best guess or hunch, which may or may not be correct. The adoption process can be broken down into several discrete stages:

(a) The discovery stage: the period up until the farmer becomes aware of the innovation, or at least of its potential relevance to their farm.

(b) Non-trial evaluation phase: the period when the farmer collects more information on the innovation before making a decision on whether to trial it.

(c) Trial evaluation phase: the period when the farmer undertakes a trial usage of the crop by experimenting with the crop on their own farm. A primary aim in this phase is to collect information about the performance of the crop. This phase was studied by Leathers and Smale (1991) who developed a Bayesian behavioural model which explained sequential adoption as a consequence of a rational learning behaviour by adopting farmers. This paper is mainly concerned with this phase of the adoption cycle.

(d) Full adoption phase: the period when the farmer uses the innovation primarily because of its perceived direct benefits.

(e) Disadoption phase: the period when the crop is superseded and its use is reduced over time, eventually to zero.

Wood *et al.* (1994) identified production risk as one factor which has a negative influence on farmers' decisions to adopt crops like chick peas. A survey of New South Wales farmers found that one quarter of farmers surveyed believed chick peas had a high chance of failure and were unlikely to profitably fit into their farming system. Such attitudes towards new crops are also likely to exist in farmers from other states as well (Vancaly and Lockie, 1994). Saha *et al.* (1994) showed that perception of riskiness of an innovation influenced the degree of its adoption. Farmers vary in their attitudes toward risk and in their perception of riskiness of various enterprises (Anderson *et al.* 1979, Feder 1980, Kingwell 1994). Feder (1980) showed that the optimal allocation of land for new crops declines with higher degrees of risk aversion.

In this paper we make a distinction between risk and uncertainty. We define risk as environmental or economic variability. If the farmer knew the probability distributions of yield for each crop they would be making a purely risky decision. On the other hand uncertainty is due to the ignorance of the farmers. They do not know the probability distributions exactly. In this case a risky variable such as yield of a crop has a probability distribution. If we ask a farmer for the probability distribution of yield for a new crop, the answer they give will include both risk and uncertainty. Therefore, a farmer who has had more experience with crop A than B may report a larger variance of yield of B even though in, reality, they may both have the same level of risk (Feder, 1980).

Adesina and Baidu-Forson (1995) found that farmers' perceptions of technology characteristics significantly affect their adoption decisions. They pointed to a clear lack of studies that have used a Bayesian framework to model the influence of farmers' subjective assessment of the technology characteristics on their adoption decisions. Lindner *et al.* (1979) found that the adoption time is directly related to farmers pessimism about relative profitability of an innovation like a grain legume and also directly related to their conservatism or the degree of conviction with which they hold this initial expectation. Perception of riskiness of a crop relates to the variance of the perceived probability distribution of yield. But attitude to risk relates to whether the decision maker cares about the size of the variance or only the mean of the distribution.

The adoption process involves a reduction in uncertainty over time as the farmer gains more information about the crop. The level of risk may change little or not at all depending on whether the technical efficiency of the farmer can be improved through learning. Feder and Slade (1984) point to several studies which have modelled innovation diffusion as a Bayesian learning process, where each period's experience is used to update initial beliefs about the characteristics of the new technology. Some of these studies indicate that individual farmers are willing to bear the cost of obtaining such information directly. In the case of Western Australian farmers considering adoption of new grain legume crops they may consider the value of information generated by trialing a new crop on their own farm to be worthwhile.

A farmer's initial perception of the yield distribution of a new crop may range anywhere from optimistic to pessimistic depending on how informed they are. These perceptions may or may not be correct when judged against the actual yield distribution of a crop (Smith and Mandac, 1995) but they are rational (Lindner, 1986). From a Bayesian framework perspective a farmer who enters the trial phase with a certain perceived yield distribution of a crop carries out the trials on their own farm in order to hone in on or narrow the gap between their perception and the crop's true or objective distribution of yield.

It is hypothesised in this study that the further a farmer's perceptions deviate from the truth, the longer the trial phase will take before they are within an acceptable range of the true distribution of the crop yield. We hypothesis that this mechanism will operate in both directions. When a farmer considering a crop that has a yield distribution in the low yield range may be optimistic or in other words perceive the crop to have a yield distribution in higher yield range and visa versa. This hypothesis has important ramifications for the adoption and diffusion of innovations like new grain legumes. Being able to assist farmers in forming a realistic perception of the performance of a crop on their farm will reduce the time and costs in the trial phase, reduce the time to optimal adoption and speed up the rate of diffusion of grain legumes.

Survey

A survey of 120 farmers in the central, eastern and northern wheatbelt of Western Australia was conducted between February and March 1995. These farmers were selected at random from a mailing list of "On the Pulse" newsletter, the official journal of the Grain Legume Association of Australia. To test the impact of this selection bias in our sample we also chose at random a group of farmers who delivered wheat to the Australian Wheat Board. A written questionnaire was filled out in a structured interview and consisted of questions on the following general topics:

- Age, experience, family/business structure and prospects in farming;
- Farm resources, cropping and flock history and pasture quality;
- Attitude towards risk, use of insurance, time and discount rate preferences;
- Agronomic and marketing knowledge and experience with grain legumes;
- Current and previous adoption history and pattern;
- Perception of the riskiness of legume crops and subjective yield and price distributions;
- Perception of the interactions of legume crops with other enterprises and covariance relationships;
- Factors affecting adoption of grain legumes, including use of information.

During the interview we elicited the farmer's Subjective Estimate of Yield (SEY) for wheat, chick peas and lupins. This data was used as inputs for the simulation model described below. We used a modified version of the visual impact method referred to in Anderson *et al.* (1975) as a practical way of eliciting the farmers SEYs. The farmer was first asked to consider a paddock on their farm that would be suitable for chick peas but which had not previously grown it. They were then asked to describe the soil type, history and the arable area of this paddock. Next, we asked the farmer for their perception of the long term average yield of wheat, chick peas and lupins on that paddock. They were asked to think about planting the crop in 1996. The question was framed in the context of the 1996 season because they had no idea then (pre seeding in 1995) what the weather would be like in 1996 as it was then two seasons away and this prevented the farmer from giving conditional probabilities as influenced by the 1994 season. The farmer was then asked to estimate the highest and the lowest possible yield for the crop in question in 1996 on the nominated paddock. This range was used to construct the intervals of a discrete yield distribution. The farmer was asked to distribute twenty counters between seven squares representing the range of yields to indicate their perceived probability distribution.

Survey Results

Table one shows a sample of three elicited yield distributions for chick peas. The results in Table 1 highlight the wide diversity that exists amongst farmers in their perception of the yield distribution for chick peas. Subjective yield distributions similar to these were used in the simulation model as inputs.

Table 1. Subjective yield distribution for chick peas.

Farmer		Very poor	Poor	Below average	Average	Above average	Good	Very good
1	Yield	0.1	0.2	0.3	0.4	0.47	0.53	0.6
	Probability	0.4	0.2	0.1	0.1	0.1	0.05	0.05
2	Yield	0.3	0.53	0.77	1.0	1.13	1.27	1.4
	Probability	0.1	0.15	0.25	0.25	0.15	0.05	0.05
3	Yield	0.5	0.67	0.83	1.0	1.5	2.0	2.5
	Probability	0.05	0.1	0.25	0.25	0.2	0.1	0.05

The farmer was also asked to rate the relative riskiness of chick peas as compared to wheat on that paddock. The mean of the responses shown in Table 2 indicate that farmers perceive chick peas to be 51 percent more risky in yield and 44 percent more risky in profit compared to wheat. This was in response to the question; "If the risks associated with growing a wheat crop on this paddock can be shown by the length of a line drawn on the page, could you draw a line the length of which represents how risky you think chick peas are?" Although the farmers' responses to this question is unclear, results clearly indicate that farmers consider chick peas to be more "risky".

Table 2. Subjective estimates of riskiness of yield and profit of chick peas compared to wheat.

	Riskiness of yield (relative to wheat)	Riskiness of profit (relative to wheat)
Mean response	151%	144%

The farmers' expectation of long term average yields of legume crops is shown in Table 3. It is shown that, in general, farmers believe that faba beans will out-yield the other legumes. However a 42 percent coefficient of variation (c.v.) for faba beans shows that there is also a wide range of responses about the yield of this crop. A handful of farmers expect the long term average yield of faba beans to be as low as 0.1 t/ha and some think that they can yield as high as 2 t/ha. On the other hand the mean subjective yield for field peas is 0.87 t/ha but the c.v. of subjective yields amongst farmers is 9 percent less than for faba beans. This could reflect the fact that since field peas have been around for longer, more farmers are likely to have either grown them or seen others grow them over the years.

Table 3. Perception of expected long term average yield of legume crops

Legume crop	Field pea	Chick pea	Faba bean	Lentil	Albus lupins
Expected yield (t/ha)	0.87	0.76	0.92	0.56	0.87
c.v. (%)	(33%)	(31%)	(42%)	(38%)	(32%)

Bayesian Framework for the Simulation Model

The surveyed farmers were asked to give their perception of the probability distribution for chick peas. These elicited distributions were used as the starting point for a simulation model of changing yield perceptions over time.

It was hypothesised that the elicited distributions include both risk and uncertainty. There are many possible probability distributions which might be the true distribution for chick peas. The fact that these potentially true distributions have variances greater than zero reflects their riskiness. The fact that the farmer does not know which of the possible distributions is true reflects uncertainty. It is assumed that the uncertainty can be represented as a subjective probability that any of the risky distributions is the true distribution.

Throughout the study, discrete distributions based on seven yields are used. Thirty risky distributions were specified to represent the full range of possible distributions (Figure 1 and Table 4). Three different uncertain distributions were specified across the 30 risk distributions. These represent low, medium, and high initial yield perceptions (Figure 2).

Table 4. Risky probability distributions of yield used in the simulation model.

Risky distributions	0.15	0.30	0.45	0.60	0.87	1.13	1.40	Mean	Standard deviation
1	0.345	0.345	0.243	0.034	0.014	0.014	0.007	0.321	0.194
2	0.209	0.307	0.279	0.184	0.008	0.008	0.004	0.382	0.185
3	0.138	0.260	0.347	0.230	0.010	0.010	0.005	0.420	0.183
4	0.154	0.226	0.301	0.256	0.054	0.006	0.003	0.438	0.199
5	0.095	0.180	0.352	0.299	0.063	0.007	0.004	0.474	0.190
6	0.181	0.231	0.241	0.216	0.052	0.052	0.026	0.476	0.175
7	0.227	0.227	0.217	0.165	0.066	0.066	0.033	0.476	0.288
8	0.152	0.195	0.260	0.254	0.073	0.044	0.022	0.495	0.274
9	0.144	0.201	0.268	0.241	0.058	0.058	0.029	0.505	0.231
10	0.119	0.166	0.284	0.277	0.080	0.048	0.024	0.520	0.289
11	0.076	0.143	0.281	0.351	0.096	0.051	0.003	0.535	0.272
12	0.015	0.132	0.333	0.417	0.088	0.010	0.005	0.536	0.317
13	0.105	0.146	0.249	0.312	0.097	0.070	0.021	0.552	0.275
14	0.086	0.142	0.263	0.329	0.094	0.057	0.029	0.558	0.215
15	0.074	0.121	0.225	0.361	0.113	0.081	0.025	0.589	0.279
16	0.011	0.098	0.246	0.453	0.123	0.065	0.004	0.599	0.279
17	0.091	0.091	0.200	0.348	0.139	0.100	0.030	0.616	0.298
18	0.068	0.112	0.209	0.335	0.134	0.104	0.037	0.626	0.225
19	0.083	0.083	0.182	0.317	0.163	0.127	0.046	0.658	0.302
20	0.009	0.085	0.215	0.396	0.158	0.108	0.028	0.660	0.266
21	0.017	0.017	0.200	0.472	0.189	0.100	0.006	0.666	0.319
22	0.103	0.103	0.138	0.283	0.158	0.158	0.057	0.674	0.336
23	0.079	0.079	0.173	0.301	0.154	0.154	0.060	0.687	0.347
24	0.119	0.119	0.159	0.199	0.131	0.182	0.091	0.692	0.272
25	0.097	0.097	0.129	0.266	0.148	0.190	0.074	0.708	0.363
26	0.014	0.014	0.164	0.386	0.227	0.155	0.041	0.741	0.387
27	0.012	0.012	0.148	0.348	0.205	0.205	0.070	0.788	0.298
28	0.023	0.023	0.030	0.341	0.258	0.258	0.068	0.839	0.292
29	0.019	0.019	0.026	0.288	0.218	0.321	0.109	0.898	0.306
30	0.036	0.036	0.048	0.060	0.214	0.405	0.202	1.001	0.333

In any particular run of the simulation model, one of the 30 risky distributions was specified as being the true distribution. Random yields were generated from this distribution and used with Bayes' rule to adjust the perceived probabilities of each of the 30 distributions being the true one. This was repeated for 20 years in order to observe the change over time in yield perceptions of a "Bayesian" farmer.

[Figure 1 and 2 about here]

Results and Discussion

Figure 3 shows some examples of the pattern of change for the mean of the perceived distributions of yield over 20 years. Three different sample runs of the simulation model are shown, all based on the same parameters but with different random samples of yields. These runs were done with the true distribution set to number 15 with a mean of 0.59 tonnes per hectare and the farmer's initial yield perception was set at the medium. As each year's yield was generated at random from distribution 15, there is a degree of variability in yields between years.

[Figure 3 about here]

Figure 4 shows how the degree of error in farmer's perception are reduced over 20 years of trialing where the farmer holds a pessimistic view of the likely distribution of the yields but the true distribution is number 15. The error term is expressed in terms of the percentage difference between the mean yield and also the standard deviation of the yield of the true distribution and those of the of the prior distribution. In year 1 the error in farmer's perception of the mean and the standard deviation of the yield of the crop was at around 18% and 10% respectively. But over the trial period as the farmer collects more information about the crop and observes the yields they revise their knowledge of the possible true distribution, eventually reducing the error in their perception of reality to around 4%. This is shown by the general downward trend from year 1 to year 20. This downward trend, however, is not smooth since the yields from one year to the next are selected at random from the true distribution. For example, the low yields of around 0.3 (t/ha) in years 10 and 11 cause the farmer to revise their perception of the crop yield downward to an extent which increases their error in judgement about the mean and standard deviation of the true distribution.

[Figure 4 about here]

The data presented in Figure 4 is only for a single run of the simulation. Given the random nature of yields in each trial year, it is difficult to determine from Figure 3 whether the trends would be similar under a different set of random yields generated for each trial. To assess whether the trends are similar over a extended set of runs, the simulation model was run repeatedly 30 times and the results averaged for each year. The assumptions relating to the true distribution and the initial prior distribution were as for Figure 4, where the true distribution was number 15 and the farmers initial perception was assumed to be pessimistic. Figure 5 shows a smoother downward trend line as the error in perception of the true distribution of yield is reduced through yield information in every year. Over the 20 years of trialing the crop the level of error in perception of the mean yield was halved, dropping from around 14% in the first year to about 6% in year 20. The average level of error associated with the perception of the standard deviation of crop yield remained relatively constant at around 7 to 8%, increasing marginally towards the final years.

[Figure 5 about here]

Figure 6 displays the mean yield and the standard deviation of the yield for the same scenario as for Figure 5. The results show that the perception of the mean crop yield increased steadily towards the true mean as perceptions were revised each year as a result of new information from the trial in the previous season. The perceived mean yield moved from 0.51 (t/ha) in year 1 up to 0.55 (t/ha) in year 20. There was however little change in the perceived standard deviation of the true yield distribution.

[Figure 6 about here]

Perceptions of the likely performance of a crop is likely to vary amongst individuals. The simulation model was used to examine the effect of different initial perceptions on the rate of judgement revision. Figure 7 shows the changes in perception of the true mean yield of the crop for three types of prior beliefs about crop yield distribution. Once again the results are the average of 30 runs of the simulation model. In all of the runs we assumed the true distribution to be number 15 with a mean yield of 0.59 (t/ha). The results show that when decision maker's prior beliefs are close to the true distribution, trials will simply confirm the validity of the prior beliefs as depicted by the line labelled "medium". However when the prior beliefs about the yield distribution of the crop are pessimistic or optimistic the slopes of the lines in Figure 7 show the rate at which prior beliefs are modified over the 20 trial years. Where initial perceptions vary widely from reality the decision maker is still unable to perfectly predict the distribution of the crop yield even after 20 trials.

[Figure 7 about here]

The results of the simulations were used to estimate the number of years that would be required for a decision maker with their prior beliefs ranging from pessimistic to optimistic to revise their perception so that the means fall within 5, 10 and 15% of the mean of the true distribution. Figure 8 shows the results for a farmer whose prior beliefs about the yield distribution of the crop is "medium" or centrally positioned on the yield scale. The results show that for someone with this type of prior beliefs, it would take more than 20 years for them to get within 5% of the true distribution if the true distribution has a mean less than 0.6 (t/ha) and larger than 0.7 (t/ha). If we accept a 10% error margin between the mean yield of the perceived distribution and the true one, this range is widened to an extent where the decision maker's prior beliefs match the true distribution within a single trial year if the true distributions fell within the range of 0.55 (t/ha) and 0.67 (t/ha) mean yield. However if the tolerance for the error margin in perceptions were increased even further to 15%, the decision maker would be able to revise their perception to get within 15% error of most of the true distributions under 20 years unless the true distribution was at the very low end of the yield range with a mean of 0.45 (t/ha). For a farmer with prior beliefs centred around the middle of the yield range it would only take around 6 years to be able to identify the true distribution that had a mean of 0.8 t/ha with 85% accuracy, whereas, it would take more than 20 years to do the same with 95% accuracy.

[Figure 8 about here]

Figure 9 shows the impact of the degree of error in the initial perception of a decision maker about the true distribution of crop yields on the number of trial years required to be able to predict, with 90% accuracy, the shape of the true distribution. For instance, an optimistic decision maker with 25% initial error in their perception of the true distribution would require around 7 years to predict the shape of the true distribution with 90% accuracy, whereas a pessimistic DM with the same initial error would require 15 years to do the same.

[Figure 9 about here]

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Figure 2. Prior distributions of the true distributions

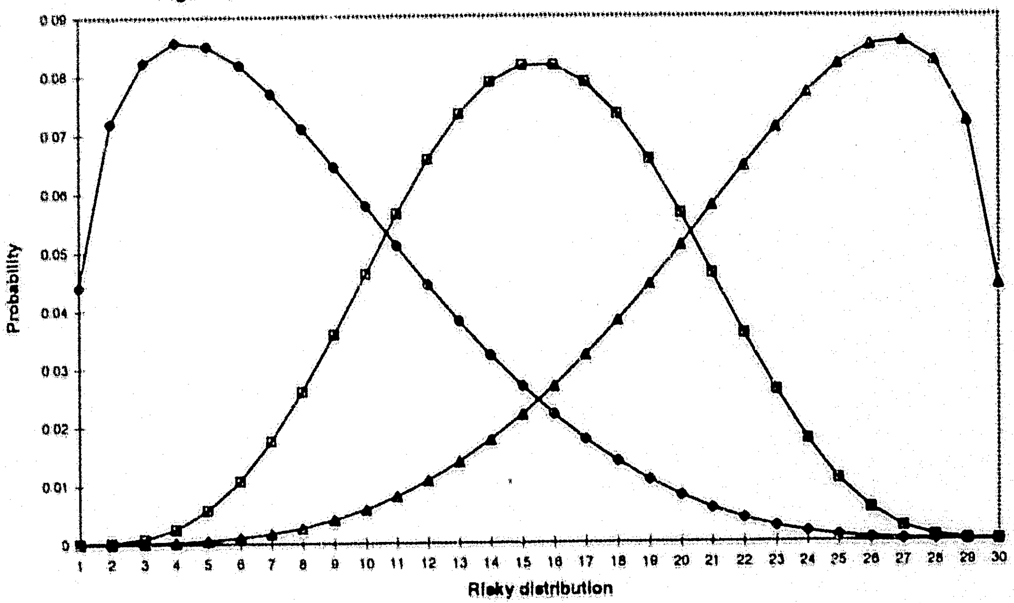

Figure 3. Mean yield over trial years for three simulations for a medium prior distribution

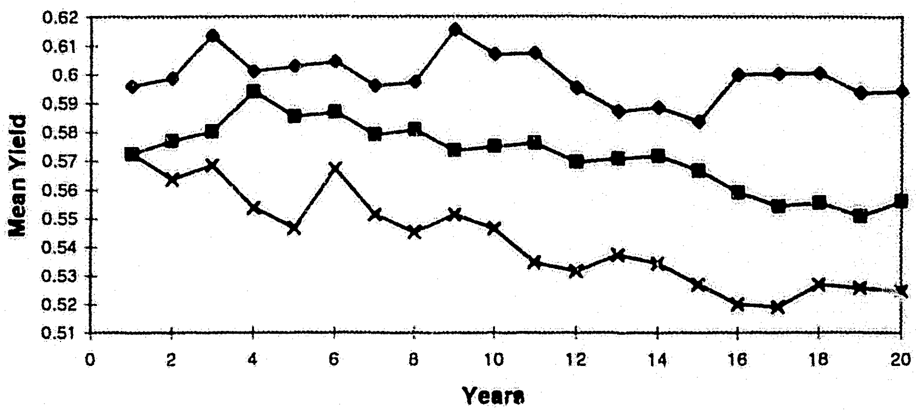

Figure 4. Error in decision maker's beliefs about the mean yield and the standard deviation of the crop yield when the true distribution is 15 and the decision maker is pessimistic with a low prior distribution.

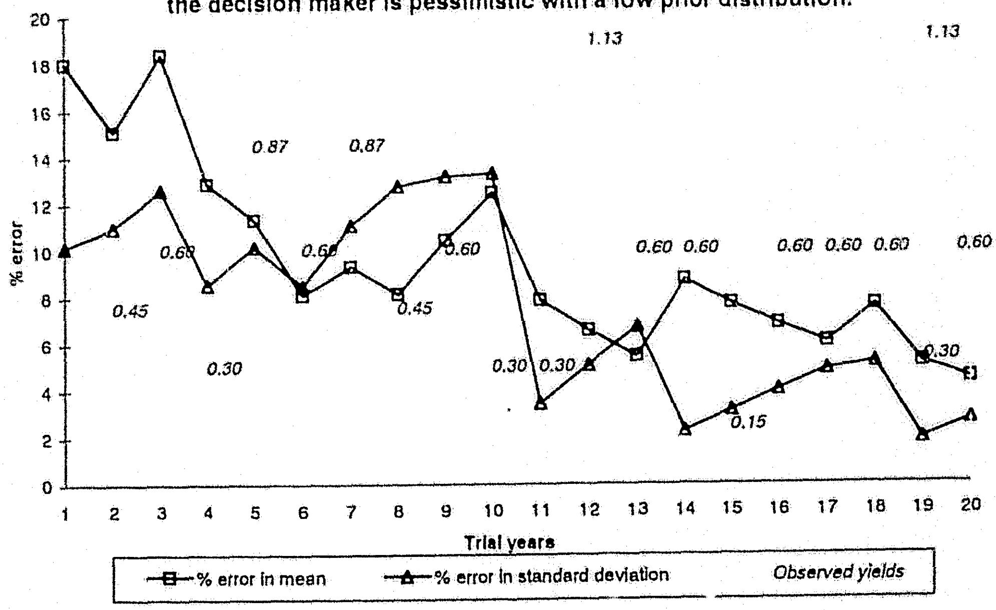

Figure 6. 30 run average mean yield and stndard deviation of yield over trial years for a pessimist when true distribution is 15

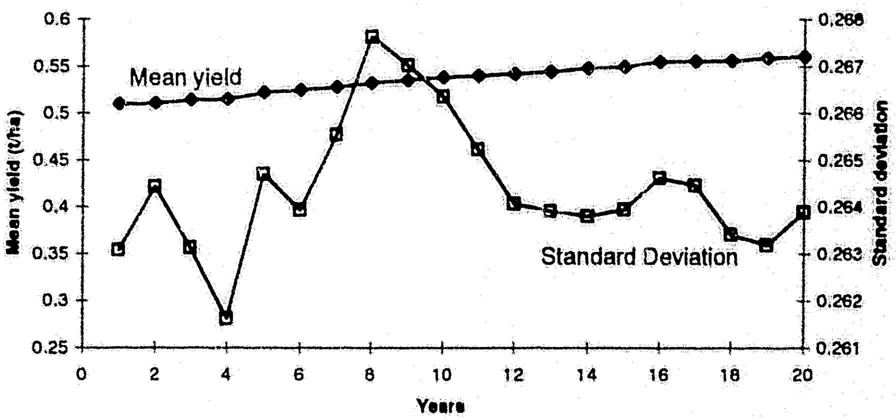

Figure 7. 30 run average mean yield for various perceptions when true distribution is 15 over 20 trial years

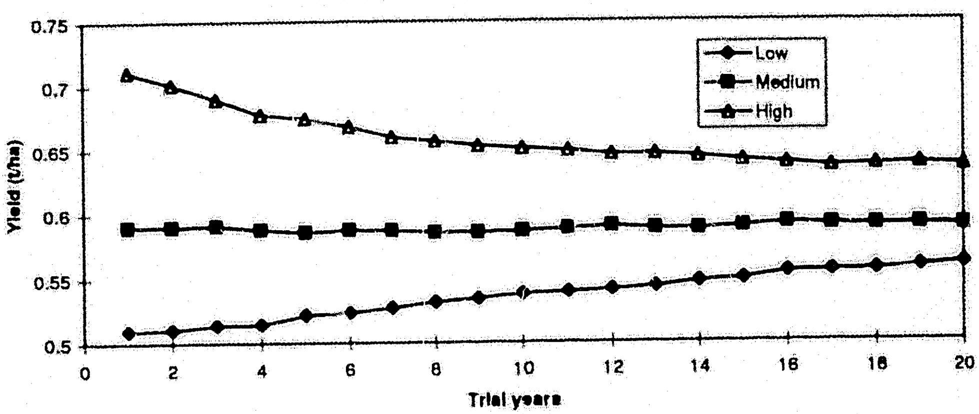

Figure 8. Number of years required to reach within 5, 10 and 15% error of the mean yield of each of the 30 true distributions (plotted as 5 year moving average)

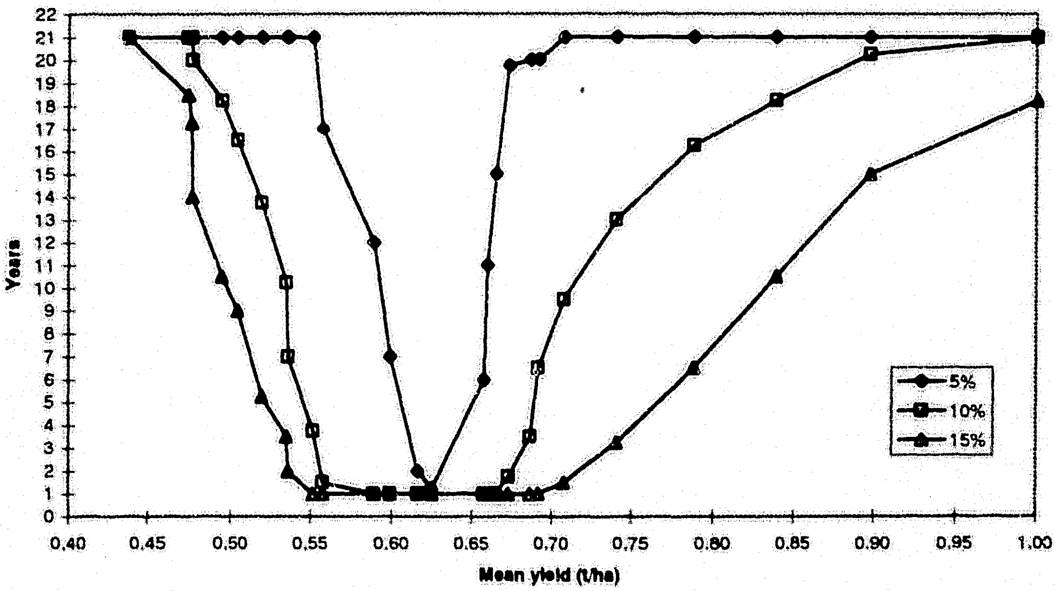

Figure 9. Impact of initial error in perception of crop yield on the number of years to reach within 10% error of the true distribution with priors ranging from low to high

Risky	Low Priors		Medium Priors		High Priors	
Distribution	Initial error	Years	Initial error	Years	Initial error	Years
1	0.52	>20	0.84	>20	1.24	>20
2	0.28	>20	0.55	>20	0.89	>20
3	0.16	6	0.41	>20	0.71	>20
4	0.11	7	0.35	>20	0.64	>20
5	0.03	1	0.25	>20	0.52	>20
6	0.03	1	0.24	>20	0.51	>20
7	0.02	1	0.24	17	0.51	>20
8	0.01	1	0.20	14	0.46	>20
9	0.03	1	0.17	14	0.43	>20
10	0.06	1	0.14	10	0.38	>20
11	0.09	1	0.11	3	0.34	>20
12	0.09	1	0.10	1	0.34	18
13	0.12	2	0.07	1	0.31	19
14	0.13	4	0.06	1	0.29	19
15	0.17	9	0.00	1	0.22	14
16	0.19	6	0.01	1	0.20	6
17	0.21	14	0.04	1	0.17	4
18	0.22	16	0.05	1	0.15	3
19	0.26	>20	0.10	1	0.09	1
20	0.26	17	0.10	1	0.09	1
21	0.27	13	0.11	1	0.08	1
22	0.28	18	0.12	4	0.07	1
23	0.29	20	0.14	8	0.05	1
24	0.29	>20	0.14	13	0.04	1
25	0.31	>20	0.16	13	0.02	1
26	0.34	>20	0.20	18	0.03	1
27	0.38	>20	0.25	>20	0.09	1
28	0.42	>20	0.29	>20	0.14	2
29	0.46	>20	0.34	>20	0.20	6
30	0.51	>20	0.41	>20	0.28	8

A1 for test results).

Within Table 2 for the basis for analyses, the degrees of freedom for the estimated coefficients were either 51 or 52. For the type of analyses the degrees of freedom for the estimated coefficients are 45. For the regressions associated with sources of effectiveness, the degrees of freedom for the estimated coefficients are 77. The coefficients are largely significant, many at the 1% level. There was a large improvement in the significance of the estimated coefficients when the intercept was dropped from the regressions. The raw moment R^2 values were quite high for cross sectional data - they ranged from 38.9 to 75.37 percent. Just over half the regressions involved had Durbin-Watson statistics suggesting no autocorrelated errors, while for just under half the regressions involved the Durbin-Watson test was inconclusive. However, given that the surveys were from a cross-section autocorrelation is unlikely. Further analysis of their residual plots showed the errors to be random, that is autocorrelated errors are not likely to be a problem in Table 2. The inconclusive result may imply that the model imposed to replicate the Just and Rausser (1989) study is misspecified.

For type of analyses and source of effectiveness regressions either Breusch-Pagan tests or NR^2 statistics from auxiliary regressions failed to detect heteroscedastic errors at a =5 or 1%. However, for baris for analyses, the coefficients for secondary data are not minimum variance, that is the explanation of published secondary data sources has heteroscedastic errors. The significance of these coefficients must be questioned (see Appendix A-Table A2 for test results)

Within Table 3 for ideal coursework emphasis, the degrees of freedom associated with the estimated coefficients are 62. For the difference between ideal and actual coursework emphasis the degrees of freedom associated with the estimated coefficients are 64. The coefficients for ideal coursework emphasis are quite significant, although the estimated coefficients for the difference between ideal and actual emphasis are largely insignificant. The raw moment R^2 values range from 44.85 to 71.68 percent for ideal coursework emphasis. In contrast, for the difference between ideal and actual coursework emphasis the raw moment R^2

values range from 7.54 to 12.9 percent. Of the fourteen regressions run to form Table 3, twelve had Durbin-Watson statistics that rejected autocorrelated errors, while only two were inconclusive about the presence of autocorrelation.

For ideal coursework emphasis and the difference between ideal and actual coursework emphasis, Breusch-Pagan tests and NR^2 statistics from the auxiliary regressions of residuals squared on fitted values and residuals squared on fitted values squared were used to detect heteroscedasticity. For all regressions involved in Table 3 either the Breusch-Pagan or NR^2 statistics did not detect heteroscedastic errors at either a=5 or 1%. The estimated coefficients for Table 3 appear not to violate OLS assumptions (see Appendix A - Table A3 for results of tests).

For the initial regressions involved in Table 4, there were 20 degrees of freedom for the estimated coefficients associated with the number supervised, and there were 15 degrees of freedom for the coefficients associated with the level of influence. The coefficients for the regression explaining the number supervised are insignificant, and for the regression explaining the level of influence all coefficients except years since last degree are insignificant. Because the regressions in Table 4 contain intercepts, the appropriate measure of goodness of fit is R^2. The initial values of R^2 were 55.64 percent for the explanation of the number supervised, and 57.32 percent for the explanation of the level of influence.

The Durbin-Watson statistics led to inconclusive test results for autocorrelation, although it is unlikely in cross sectional data to find autocorrelated errors. Breusch-Pagan tests for heteroscedasticity at 5 percent significance accepted the null hypothesis of homoscedastic errors for both regressions [2].

Analysis of the correlation matrices of the original OLS regressions found extremely high correlation coefficients between several regressors - thus there is multicollinearity in the data

[2] For No. Supervised,
B-P stat = 24.439   chi-square 15df =24.9958
For Level of Influence,
B-P stat = 19.951   chi - square 15 df = 24.9958