AARES 52nd ANNUAL CONFERENCE

February 2008

Measuring Regional Productivity Differences in the Australian Wool Industry: A Metafrontier Approach

Renato Villano, Pauline Fleming and Euan Fleming

School of Business, Economics and Public Policy

University of New England, Armidale, NSW, 2351

Abstract

Using panel data, we estimate technology gaps for four distinct sheep-producing regions in Eastern Australia (Northern New South Wales, Central and South-Eastern New South Wales, South-Western New South Wales and South-West Victoria) that reflect spatial environmental and technological differences in wool production. A deterministic stochastic metafrontier production function model is estimated that envelops the stochastic frontiers of the four regions. This metafrontier approach enables us to estimate the environment-technology gap ratio that reflects these spatial differences in the environment and variations in production technologies in the wool enterprise for benchmarked farmers in each region. As a result, a more accurate estimation is possible of changes in total factor productivity on farms in the different regions. The major findings are that environment-technology gaps do exist between regions but they are relatively small. Greater variation is apparent within regions. Variation in technical efficiency seems to depend on the harshness of the production environment and whether consultancy advice is regularly received by the benchmarking group.

Keywords: Efficiency, Productivity, Metafrontier, Technology Gaps, Wool Production, Spatial

Corresponding author: Renato Villano

Email: rvillan2@une.edu.au Telephone: 02-67732027

Introduction

We would expect a significant technology gap to exist between producers operating in different regions of Australia for most agricultural enterprises. Whether one exists for wool production is problematic given the long history of various modes of adaptation to regional conditions that have taken place in the industry over the past two centuries.

Physical conditions have historically favoured wool production in wide areas of rural Australia given the nature of exogenous factors such as soil, climate, vegetation, location, pests and diseases (Williams 1973). In the early period of European settlement, the wool enterprise was well suited to managing the risks associated with agricultural production and marketing, saving scarce labour resources, and avoiding the need for large amounts of capital expenditure. Limited labour supply and high land-labour ratios encouraged industries that did not rely on intensive labour use, and encouraged labour-saving production methods that were suited to a pastoral activity such as wool production rather than the more intensive activities found on small farms in European agriculture at the time. Capital supply was initially restricted in agriculture in general, encouraging the use of on-farm capital accumulation in pastoral industries, such as post-and-rail fences cut from timber on the property. The storability and high value-weight ratio of wool has made it especially suitable as an export product that could be produced in remote areas.

We analyse the environment-technology gaps caused by spatial differences in the environment in which wool is grown on benchmarked farms in four sheep-producing regions of New South Wales and Victoria.

Environmental and technological constraints on wool production

Although wool output is less sensitive to environmental conditions than many other agricultural products, the production environment varies considerably for wool in Australia. Environmental differences in wool production are a function of spatial and temporal variations in the production conditions such as soil, vegetation, topography and climate. They also affect technology choice as wool producers have long been adjusting their production and marketing technologies to suit their operational environment. As a result, wool produced in Australia is not a homogeneous product, with farmers opting to produce wools of different qualities. But it is doubtful whether producers are able to adjust their production technology fully to the environment to bridge the productivity gap between a producer operating in a favourable environment and one operating in a difficult environment because of the often extreme difficulties imposed by adverse and variable conditions. Yet we expect the technology gap that exists between wool producers operating in different regions of New South Wales and Victoria to be relatively small because of the various adaptations and innovations that have occurred in the industry over a long period.

The wool industry is based mainly on Merino sheep, which are especially well suited to Australian production conditions, even the harsher environments. Further adaptations and innovations that have increased the productive capacity of the wool enterprise include (Duncan 1972, Peel 1973, Sturgess 1973, Stafford Smith and McKeon, 1998, ABARE 2007, Abel and Langston n.d., Howden et al. n.d.):

- Further genetic improvements and selection of sheep breeds and sires to suit particular production environments, such as genetic improvements for blowfly resistance and the trend to produce finer wool.
- Management of pasture and grazing pressure, such as the introduction of improved pasture species, rotations, fertiliser application, aerial sowing and fertiliser application in hilly farming areas, and better use of native pastures.
- Managing pests, diseases and weeds.
- Development and management of on-farm water supply.
- Animal husbandry and health management, such as drenching, modified timing of mating to suit seasonal conditions and aerial mustering.
- Flexibility in farming operations to manage environmental risk, including enterprise diversification and stocking rate changes in response to rainfall and the strategic trading in sheep.
- Greater ecological understanding by graziers.
- Use of decision support tools, such as those that help to make better predictions about future production conditions.
- Institutional support, such as wool research and development, the role of the family farm and local support networks, structural adjustment programs, drought assistance and the provision of extension advice and materials.
- Development of the transport and marketing infrastructure.

These different forms of adaptation and innovation have varied in relative importance between regions (for instance, the development of on-farm water supply have been particularly important in the Pastoral Zone), but have generally had the effect of reducing the influence of the natural environment on productivity. Rainfall is often considered a major factor placing different limitations on production possibilities in agricultural production between regions. But it has not had such a dominant effect on wool production as other factors often combine to diminish its effect. In their analysis of pasture growth in sheep production, Sanford et al. (2003) found that annual rainfall was a poor predictor of annual herbage accumulation in the High-Rainfall Zone.

Conversely, degradation that reduces the landscape function, scrub encroachment, salinity and loss of biodiversity (Abel and Langston n.d.) may have accentuated differences in productive capacity between regions by having differential effects on the natural resource base. As Abel and Langston (n.d., p. 22) pointed out in respect of the Pastoral Zone, ‘Much of the adaptive capacity [of rangelands] resides in its biodiversity.’

Study regions

The sheep production environment chosen for analysis covers most of New South Wales and parts of Victoria (and a small portion of South Australia). It is divided into four regions, as shown in Figure 1:

- Northern New South Wales (R1)
- South-Western New South Wales (R2)
- Central and South-Eastern New South Wales (including a small part of North-Eastern Victoria) (R3)
- South-Western Victoria (including a small part of South-Eastern South Australia) (R4)

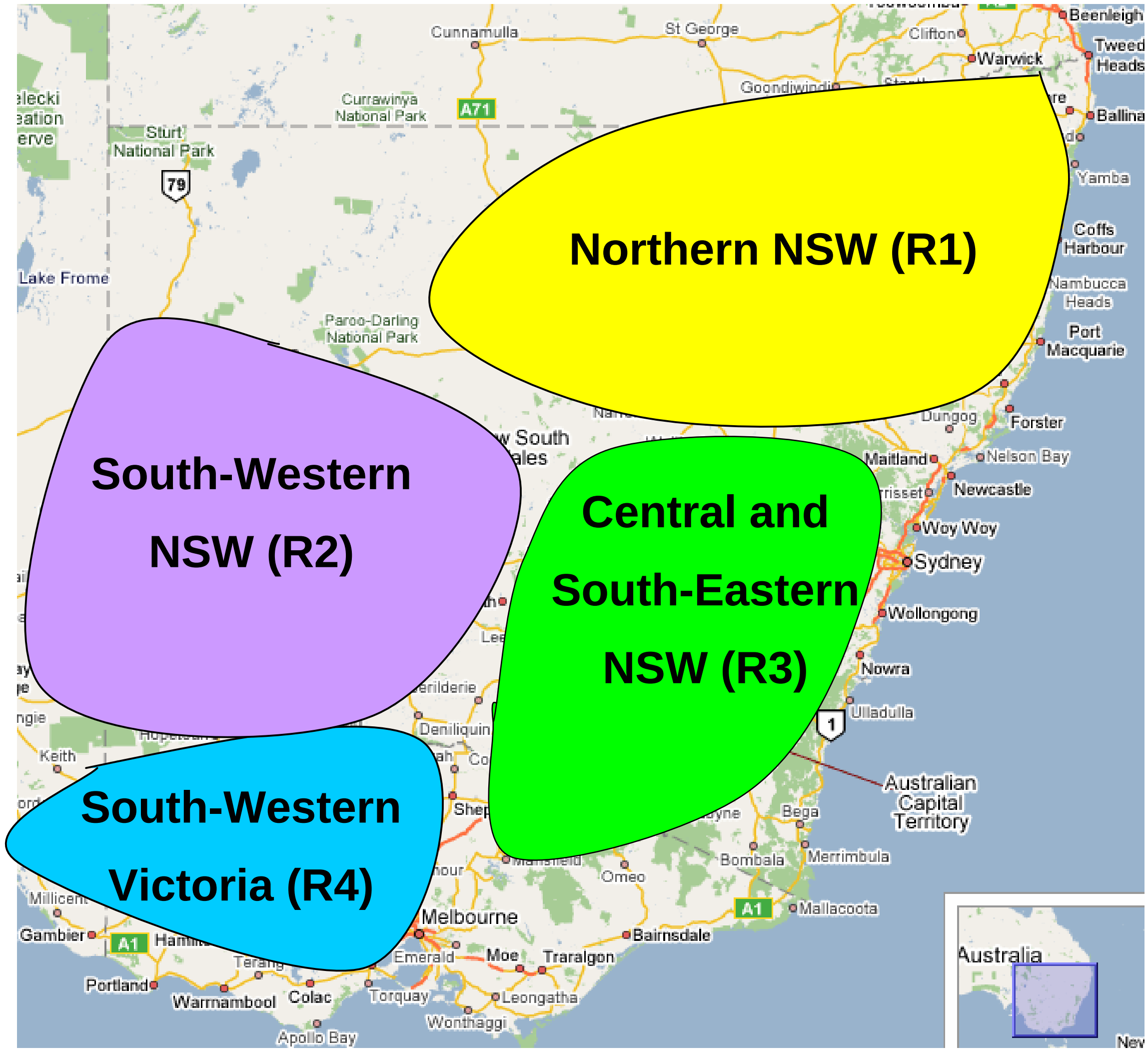

Figure 1 Regions of sheep production covered in the analysis.

Northern New South Wales (R1) has summer rainfall and is a mixture of High-Rainfall Zone and Wheat-Sheep Zone, with a small area of Pastoral Zone. Climatic conditions tend to be variable over time and soils, topography and climate conditions vary across space. These conditions make it difficult for producers to bridge the productivity gap. If they can, it is considered hard to do so on a regular basis.

South-Western New South Wales (R2) is in the pastoral zone with low winter rainfall. Rainfall tends to be extremely variable over time and across space. Once again, these conditions should make it difficult for producers in this region to bridge the productivity gap and, if so, it is hard to achieve on a regular basis.

Central and South-Eastern New South Wales (R3) is mainly in the Wheat-Sheep Zone, but contains small areas of Pastoral Zone and High Rainfall Zone. It has evenly spread to winter rainfall. These conditions are more favourable for wool production, which should make it easier for producers to operate at high levels of technical performance.

South-Western Victoria (R4) is in the High Rainfall Zone with winter rainfall. Environmental conditions tend to be favourable for wool production.

Propositions

We examine the following three propositions by estimating environment/technology gap ratios (ETGRs) and technical efficiency (TE-R) scores for wool producers in the four regions:

1. Variations in ETGRs between regions are expected to exist.
2. ETGRs are expected to be more widely distributed in the more environmentally challenging areas of Northern New South Wales (R1) and South-Western New South Wales (R2).
3. TE-R scores are expected to be more widely distributed in R4, due to lack of consultancy advice to some of the producers in this region.

Data

We use pooled farm-level data obtained over ten years from two benchmarking groups:

1. A commercial organisation provides consulting advice to all farmers in regions R1, R2 and R3 but only some farmers in R4. Farms in these regions are expected to have higher technical efficiency scores with lower variances.
2. A government-based organisation collects benchmarking data but does not provide any consultancy advice to most farmers in R4. Farms in this region are expected to have lower technical efficiency scores with higher variances.

The unbalanced panel data set contains 1157 observations from 372 farmers covering the ten-year period from 1994/95 to 2003/04. The data set contains farm-level input and output data for farm enterprises including wool, beef, prime lamb and some crops. We confine our analysis to wool enterprise only. The wool output variable was calculated as the sum of deflated wool revenue, to measure implicit wool output, and net trading profit or loss on adult sheep. Implicit output was obtained by dividing wool revenue in each year by the wool price index published by ABARE (2004). Lamb output is the value of lamb sales deflated by the lamb price index, also published by ABARE (2004). Both outputs were calculated per dry sheep equivalent (DSE).

Seven input variables were included in the estimated models: agistment, health, pasture, selling, shearing, labour and overheads. All input variables were calculated per DSE and deflated with the index of prices paid by farmers (ABARE 2004). Basic information about the data set and variables are provided in Table 1.

Table 1: Basic information and descriptive statistics of output and input variables ($/ DSE)*

Items	R1	R2	R3	R4	ALL
No. of observations	221	307	123	506	1157
No of cross-sections	98	109	42	123	372
Wool income	21.33 (7.069)	17.97 (4.91)	19.97 (5.97)	22.55 (11.53)	21.15 (9.05)
Agistment (X_1)	1.99 (3.23)	2.53 (4.69)	2.27 (3.61)	2.33 (2.35)	2.27 (3.20)
Health (X_2)	1.51 (0.74)	1.30 (0.74)	1.34 (0.92)	1.056 (0.62)	1.25 (0.77)
Pasture/Feed (X_3)	2.19 (1.29)	1.08 (1.72)	2.81 (1.67)	2.55 (1.23)	2.37 (1.50)
Overhead (X_4)	4.91 (1.76)	5.78 (2.78)	4.80 (1.90)	8.74 (5.90)	6.65 (4.59)
Shearing (X_5)	3.88 (1.23)	3.83 (1.24)	3.47 (1.16)	3.066 (1.093)	3.41 (1.20)
Selling (X_6)	1.97 (0.94)	1.84 (0.79)	1.89 (1.16)	1.90 (0.82)	1.90 (0.94)
Labour (X_7)	4.83 (2.29)	5.84 (3.58)	4.94 (2.00)	4.96 (3.53)	5.02 (2.99)

* Figures in parentheses are standard deviations.

Method of Analysis

Several approaches are used to accommodate potential environmental and regional variations of agricultural production and obtain comparable technical efficiencies. Efficiency estimation in stochastic frontier models typically assumes that the underlying production technology is the same for all farms. Unobserved differences in technologies might be inappropriately labelled as inefficiency if variations in technology are not taken into account. A number of methods could be used to address this issue. They include the stochastic metafrontier framework (Battese and Rao 2002, Battese, Rao and O'Donnell 2004, O'Donnell, Rao and Battese 2007), latent class model (Greene 2004), random parameter model (Greene 2004) and switching regression model (Sriboonchitta and Wiboonpongse 2004). O'Donnell and Griffiths (2006) used a state-contingent frontier where states of nature for different environments are treated as a latent variable and estimated using a finite mixture model. Results from the applications of the above models reveal that failure to account for environmental variables can lead to biased estimators of the parameters of the frontier and technical efficiency inefficiencies. Among these approaches, we chose the metafrontier framework because of a lack of data needed to apply the other models and its ability to estimate the technology-gap ratios, in addition to estimated parameters of frontiers and technical inefficiencies. Under the metafrontier framework, the following approaches are followed:

- A standard stochastic frontier production function was estimated for each region.
- A pooled-stochastic frontier model was then estimated to test whether the application of a metafrontier is warranted.
- Once it was established that a metafrontier needs to be estimated, linear programming was used to accomplish this task.

Suppose we have k regions in the industry. We can estimate the stochastic region-k frontier using the standard stochastic frontier model defined as:

$$Y_{i(k)} = f(X_{i(k)}, \beta_{(k)}) e^{V_{i(k)} - U_{i(k)}} \qquad i = 1, 2, \ldots, N_{(k)} \tag{1}$$

where $Y_i(k)$ denotes the output of the i-th firm for k-th region; $X_{i(k)}$ denotes a vector of functions of the inputs used by the i-th firm in the k-th region; $\beta_{(k)}$ is a vector of unknown parameters to be estimated associated with the k-th region; $V_{i(k)}$ represents statistical noise assumed to be independently and identically distributed as $N(0,\sigma_{Vk}^2)$ random variables; and $U_{i(k)}$ are non-negative random variables assumed to account for technical inefficiency in production and assumed to be independently distributed as truncations at zero of the $N(\mu_i(k),\sigma_{U(k)}^2)$ distribution. Using data on outputs and inputs of firms in the k-th region a maximum-likelihood estimates of the unknown parameters, $\beta_{(k)}$, can be estimated using FRONTIER (Coelli, 1996a). Accordingly, the technical efficiency of the *i*-th firm with respect to the region-*k* frontier can be obtained using the result:

$$TE_{i(k)} = \frac{Y_{i(k)}}{f(X_{i(k)}, \beta_{(k)})e^{V_{i(k)}}} = e^{-U_{i(k)}} \tag{2}$$

Equation (2) allows us to examine the performance of the *i*-th firm relative to the individual region frontier. In order to examine the performance of the *i*-th firm relative to the metafrontier, the stochastic metafrontier production function approach is used. The metafrontier is considered to be an envelope function of the stochastic frontiers of the different regions such that it is defined by all observations in the different regions in a way that is consistent with the specifications of a stochastic frontier model (Battese and Rao, 2002, p. 89).

Following, Battese and Rao (2002) and Battese, Rao and O'Donnell (2004), a deterministic stochastic metafrontier production function model in the industry can be expressed as:

$$Y_i^* = f(X_i, \beta^*) \qquad i = 1, 2, \ldots, N \tag{3}$$

where ($f(.)$) is a specified functional form; Y_i^* is the metafrontier output; and β^* denotes the vector of metafrontier parameters satisfying the constraints

$$f(X_i, \beta^*) \geq f(X_i, \beta_{(k)}) \text{ for all } k = 1, 2, \ldots, K. \tag{4}$$

Equation (4) indicates that the metafrontier dominates all region frontiers. For equation (4) to hold, the metafrontier production function is obtained by solving the optimisation problem that minimises the sum of the absolute deviations of the metafrontier values from those of the region frontiers, as discussed in more detail by Battese, Rao and O'Donnell (2004). The optimisation problem is defined as:

$$\min_{\beta} \quad \sum_{i=1}^{N}\left[\ln f(X_i,\beta^*) - \ln f(X_i,\beta_{(k)})\right]$$
$$s.t. \qquad \ln f(X_i,\beta^*) \geq \ln f(X_i,\beta_{(k)}) \tag{5}$$

where $\beta_{(k)}$ is the estimated coefficient vector associated with the region-*k* stochastic frontier. The standard errors for the estimators for the metafrontier parameters are obtained using bootstrapping methods. The method draws a vector from a multivariate normal distribution using the maximum-likelihood estimate of the region frontier and associated covariance matrix. Each draw is used to estimate the metafrontier, and the sample standard deviations of the metafrontier parameters are estimates of the standard errors.

The observed output defined by the stochastic frontier for the *k*-th region in equation (1) can be alternatively expressed in terms of the metafrontier function in equation (3), such that

$$Y_i = e^{-U_{i(k)}} \times \frac{f(X_i,\beta_{(k)})}{f(X_i,\beta^*)} \times f(X_i,\beta^*)e^{V_{i(k)}} \tag{6}$$

The first term on the right-hand side of equation (6) is the same as that in equation (2), which denotes the technical efficiency of the *i*-th firm relative to the region-*k* frontier. The second term is what Battese and Rao (2002) term the technology gap ratio (TGR). In view of the environmental constraints in wool production, we call this ratio the environment-technology gap ratio (ETGR), which is expressed as

$$ETGR_i = \frac{f(X_i,\beta_{(k)})}{f(X_i,\beta^*)} \tag{7}$$

The *ETGR* measures the ratio of the output for the frontier production function for the *k*-th region relative to the potential output that is defined by the metafrontier function, given the observed inputs (Battese and Rao 2002, Battese, Rao and O'Donnell 2004). The TGR has values between zero and one.

The technical efficiency of the *i*-th firm, relative to the metafrontier, is denoted by TE_i^* and is defined in a similar way to equation (2). It is the ratio of the observed output relative to the last term on the right-hand side of equation (6), which is the metafrontier output, adjusted for the corresponding random error, such that

$$TE_i^* = \frac{Y_i}{f(X_i, \beta^*) e^{V_{i(k)}}} \quad (8)$$

Accordingly, following equations (2), (6) and (7), TE_i^* can be expressed as

$$TE_i^* = TE_{i(k)} \times TGR_i \ .$$

Stochastic frontier models defined by equations (1) and (3) were estimated assuming a translog functional form:

$$\ln Y_{i(k)} = \beta_{0(k)} + \sum_{j=1}^{7} \beta_{j(k)} \ln X_{ij(k)} + \frac{1}{2} \sum_{j=1}^{7} \sum_{s=1}^{7} \beta_{js(k)} \ln X_{ij(k)} \ln X_{is(k)} + V_{i(k)} - U_{i(k)} \quad (10)$$

where *j* represents the *j*-th input (*j* = 1, 2, …, 7) of the *i*-th firm (1, 2,…, N_k) in the *k*-th region (*k* =1, 2, …, 5); $\beta_{ij(k)} = \beta_{ji(k)}$ for all *j* and *k*; Y_i represents the wool income; and X_{ij} are as defined in the Table 1. All variables are mean-corrected to zero, which implies that the first-order estimates of the model represent the corresponding elasticities.

Results

On fitting the stochastic production frontier to individual regions and the pooled data set, the likelihood ratio test results suggest that we cannot reject the frontier models for each region and in the pooled sample. In addition, our generalised-likelihood ratio test result suggests that the group frontiers are not identical (p-value = 0.0000). Accordingly, the estimation of the metafrontier production model is justified.

The estimates of the metafrontier estimations are presented in Table 2 (parameter estimates of the group frontiers and pooled frontier are available upon request). The standard deviations of the metafrontier estimates were calculated using parametric bootstrapping as Battese, Rao and O'Donnell (2004) suggested. Apart from labour and pasture/feed, estimated coefficients of the stochastic metafrontier production function were found to be significant and of expected sign.

Table 2: Estimates of Parameters of the Metafrontier Production Function

Variable	Coefficient	Standard error	*t*-statistic
Constant	0.539	0.042	12.79[a]
Agistment	-0.034	0.008	-4.44 [a]
Health	0.053	0.035	1.54[c]
Pasture/Feed	0.016	0.014	1.16
Overhead	0.250	0.043	5.87 [a]
Shearing	0.076	0.039	1.96[b]
Selling	0.215	0.032	6.78 [a]
Labour	0.035	0.037	0.96

Note: This is an abridged version of the translog model.

[a,b,c] indicate significant at 1, 5 and 10 per cent levels, respectively.

Estimated ETGRs and technical efficiencies with respect to regional frontiers and metafrontier are presented in Table 3. The value of ETGR ranges from 0.20 to 1. The maximum value of 1, which was observed in all regions, indicates that all regional frontiers were tangent to the metafrontier. The mean values of the ETGRs vary from 0.72 (R2) to 0.80 (R3). This result implies that, on average, wool farmers in R2 produce only 72 per cent of the potential wool output given the technology available and most suitable environmental conditions in the industry as a whole. The average ETGRs were found to be significantly different for all regions.

On average, farmers in R1 and R2 achieved higher technical efficiencies relative to their respective regional frontiers but they tended to be furthest from the potential output as indicated by their lower ETGRs. This is expected given the harsher environment in these regions. Results of statistical tests indicate that the mean ETGRs and TE-Rs for R1 and R2 are not statistically different.

Table 3: Estimated ETGRs, TE-Rs and TE-Ms

Statistic	Region	Mean	Standard deviation	Minimum	Maximum
Environment-technology gap ratios (ETGRs)	R1	0.73	0.10	0.31	1.00
	R2	0.72	0.17	0.20	1.00
	R3	0.80	0.12	0.35	1.00
	R4	0.77	0.13	0.27	1.00
Technical efficiency with respect to the regional frontiers (TE-Rs)	R1	0.86	0.08	0.33	0.96
	R2	0.86	0.09	0.54	0.97
	R3	0.80	0.13	0.30	0.97
	R4	0.74	0.15	0.09	0.94
Technical efficiency with respect to the metafrontier (TE-M)	R1	0.63	0.11	0.23	0.95
	R2	0.62	0.16	0.17	0.93
	R3	0.64	0.14	0.16	0.94
	R4	0.57	0.15	0.08	0.91

Distributions of ETGRs, TE-R and TE-M scores are presented in Figure 2. Results support the three propositions outlined above. Higher mean ETGRs were found to exist in R4 (0.77) and R3 (0.80) than in R1 (0.73) and R2 (0.72). Both R3 and R4 have a substantial proportion of TE-R observations on or close to the metafrontier. R3 has relatively high mean ETGR and TE-R scores of 0.80, in line with expectations.

Observations are relatively widely spread in R4, with a mean TE-R score of 0.74, which we believe is a result of a lack of consultancy advice for all farmers in this region. A statistical test indicates that there is a significant difference in TE-R scores between those farms with consultancy advice and those that do not receive any advice, with the former having a higher mean technical efficiency. In contrast, R1 has very few observations on or near the metafrontier, but they are relatively closely grouped such that the mean TE-R score is high at 0.86. R2 recorded a relatively low mean ETGR of 0.72 and a high mean TE-R score of 0.86, similar to R1, but there were quite a few high individual ETGRs.

Variation in technical efficiency seems to depend on the severity of the production environment and whether consultancy advice is regularly received by the benchmarking group. While the inter-regional differences in ETGR were found to be present they were not large, ranging from 0.72 to 0.80. Greater variation is apparent within regions.

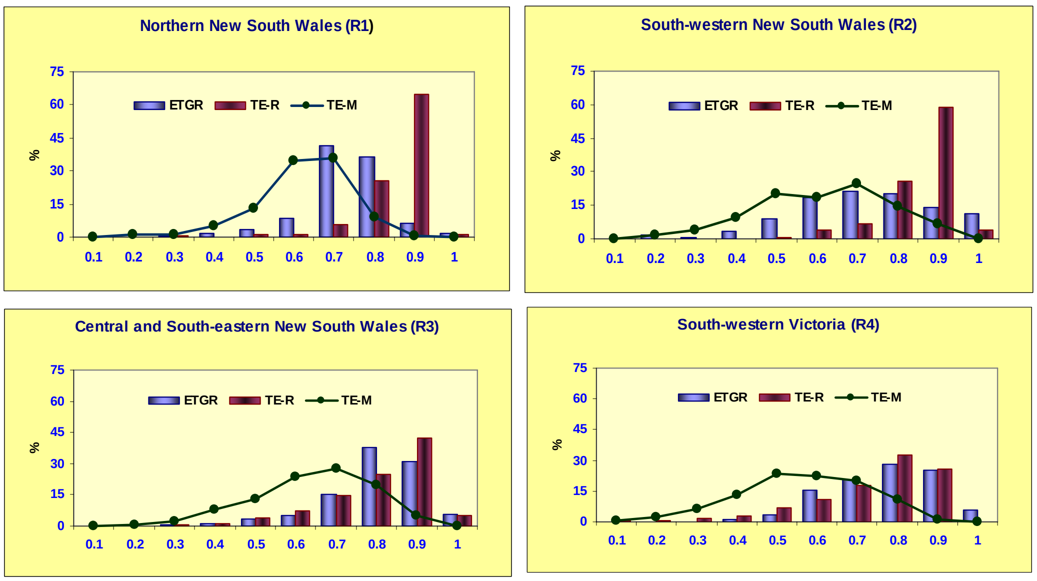

Figure 2 Distributions of ETGRs, TE-Rs and TE-Ms by region.

Conclusion

The major finding of the study is that, while environment-technology gaps were found to exist in wool production between four selected regions in Eastern Australia, they are not particularly great. This result can probably be attributed to the various processes of adaptation to suit environmental conditions facing producers that have taken place since the wool industry began in Australia. Another finding of interest is the wider distribution of technical efficiency scores within the South-Western Victoria region than in other regions, which is most likely due to the variation in consulting advice received by sampled farmers in this region.

References

ABARE 2004, *Australian Commodity Statistics 2004*, Australian Bureau of Agricultural and Resource Economics, Canberra.

Abel, N. and Langston, A. n.d., Evolution of a socio-ecological system: Adaptation and resilience in the New South Wales rangelands 1850 to 2020, Draft paper, Sustainable Use of Rangelands in the 21st Century, CSIRO. Downloaded on 9 January 2008 from:
http://www.cse.csiro.au/research/aglands/nswrangelands/pubs/index.htm

Battese, G.E. and Rao, D.S.P, 2002, 'Technology gap, efficiency, and a stochastic metafrontier function', *International Journal of Business and Economics* 1, 87-93.

Battese, G.E., Rao, D.S.P. and O'Donnell, C. 2004, 'A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies', *Journal of Productivity Analysis* 21, 91–103.

Coelli, T. 1996, A guide to frontier version 4.1: a computer program for stochastic frontier production and cost function estimation, CEPA Working Paper 96/07, Center for Efficiency and Productivity Analysis, University of New England, Armidale.

Duncan, R.C. 1972, 'Technological change in the arid zone of New South Wales', *Australian Journal of Agricultural Economics* 16, 22-30.

Greene, W. 2004, 'Reconsidering heterogeneity in panel data estimators of the stochastic frontier model', *Journal of Econometrics* 126, 269-303.

Howden, M. et al. n.d., *An Overview of the Adaptive Capacity of the Australian Agricultural Sector to Climate Change*, Sustainable Systems, CSIRO, Canberra. Downloaded on 10 January 2008 from:
http://www.cse.csiro.au/publications/2003/AGOAgClimateAdaptationReport.pdf

O'Donnell, C. and Griffiths, W. 2006, 'Estimating state-contingent production frontiers', *American Journal of Agricultural Economics* 88, 249-266.

O'Donnell, C., Rao, D. S. P., Battese, G. 2007, 'Metafrontier frameworks for the study of firm-level efficiencies and technology ratios', *Empirical Economics*, Online First http://www.springerlink.com/content.

Peel, L.J. 1973, 'History of the Australian pastoral industries to 1960', Ch. 2 G. Alexander and O.B. Williams (eds) 1973, *The Pastoral Industries of Australia: Practice and Technology of Sheep and Cattle Production*, Sydney University Press.

Sanford, P. et al. (2003), 'SGS pasture theme: effect of climate, soil factors and management on pasture production and stability across the high rainfall zone of southern Australia', *Australian Journal of Experimental Agriculture* 43, 945-959.

Sriboonchitta S. and Wiboonpongse, A. 2004, 'On estimation of stochastic production-frontiers with self-selectivity: Jasmine and non-Jasmine rice in Thailand, Paper presented at the 2004 Asia-Pacific Productivity Conference, Brisbane, July.

Stafford Smith, M. and McKeon, G.M. 1998, 'Assessing the historical frequency of drought events on grazing properties in Australian rangelands', *Agricultural Systems* 57, 271-299.

Sturgess, N.H. 1973, 'Management economics in the pastoral industries', Ch. 14 in G. Alexander and O.B. Williams (eds) 1973, *The Pastoral Industries of Australia: Practice and Technology of Sheep and Cattle Production*, Sydney University Press.

Williams, O.B. 1973, 'The environment', Ch. 1 in G. Alexander and O.B. Williams (eds) 1973, *The Pastoral Industries of Australia: Practice and Technology of Sheep and Cattle Production*, Sydney University Press.