Rangeland cattle production in Uruguay: single-output versus multi-output efficiency measures

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Abstract:

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Acknowledegment:

JEL Codes: Q1, D24

#1225

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Key words: stochastic production frontier, stochastic ray frontier, rangeland cattle production.

JEL Classification: Q12, Q19, D24

1 Introduction

Rangeland cattle production is the largest agricultural sector of Uruguay. Based on natural pastures, grazing is usually made by cows and sheeps with three main products: beef, sheep meat, and wool. Ranching has shown a slow improvement in productivity over the last three decades. The combined production of beef-cattle and sheep (including meat and wool) has improved the productivity 1.7% on average between 1981-2010 (Bervejillo et al. (2011)). A widly used index of sector's performance is the equivalent meat produced by hectare ($EM\ ha^{-1}$). The evolution of $EM\ ha^{-1}$ has undergone a slow progress over the years, from 86 $kg\ ha^{-1}$ in triennium 1994-1996 to 95 in 2011-2013.

Equivalent meat index has been under scrutiny since the assumptions made to compare wool and meat are based on energy requirements. The main objection, is that cow-sheep grazing is in some way complementary rather than competitive and eventhough energy requirements is comparable, grazing occurs at different hights meaning different usage. At some extent there is a substitution effect between the two species but also a complement on grass usage.

A particular aspect of the rangeland cattle production is that the main feed base is of natural pastures being highly dependent on net primary production. Additionally, over the last 20 years rangeland cattle production has faced competition for available land from other activities, like forest and soybeans production. In this context, cattle production growth obtained by an increase in productivity seems to be key. One way of improving productivity is increasing the efficiency with which inputs are used. The overall objective of this study is to contribute to the knowledge of ranches' efficiency performance, and to better understand the relationship between the resources used in beef-cattle production and the obtained output. We propose a comparison between two methodologies: a stochastic production frontier (SPF) estimatation of equivalent meat (index) and a multi-output (beef, sheep-meat, and wool) stochastic ray frontier (SRF) for technical efficiency measures of ranches in Uruguay.

The SPF methodology has been widly applied to measuring technical efficiency in studies related to agricultural sector (Coelli and Battese (1996)). Usually efficiency studies focus on unique output farms or single crop analysis. When multi-output is present, alternatives are non-parametric approaches as DEA or parametric approaches as output distance functions. The later approach is not well suited for cases in which some outputs present zero values (Henningsen et al. (2015)), which is the case for cattle production in Uruguay where some ranches do not have sheeps.

Many studies that applied SPF methodology can be found in Bravo-Ureta et al. (2007). However, most of published studies involve dairy farms, and a few of them focus on beef cattle production. Trestini (2006) estimated a stochastic production frontier to measure the technical efficiency of an unbalanced panel of beef cattle farms in Italy. Qushim et al. (2013) studied the scale and technical efficiency of southeastern U.S. cow-calf farm. In Argentina Gatti et al. (2015) applied a meta-frontier methodology to measuring technical efficiency and technology gaps in beef cattle production for three distinct regions.

The stochastic ray production model has been applied in other multi-output settings since it was developed by Löthgren (1997). The model was used by Löthgren (2000) for specification and estimation of multi-output production frontier and technical efficiency of a panel data of Swedish County Councils which provided health-care. The study of Fousekis (2002) compares technical efficiency scores, structure of the underlying technology, and technical efficiency determinants obtained from the stochastic multi-output distance function and stochastic ray production function. Managi et al. (2006) estimated a stochastic ray frontier to analyze the effect of technological change on the offshore oil and gas industry in the Gulf of Mexico. The multi-output efficiency for Irish farm households obtained from estimating stochastic distance function frontier, stochastic ray frontier and data envelopment analysis are compared by Zhang and Garvey (2008). Niquidet and Nelson (2010) analyzed the productive efficiency of the interior sawmilling in British Columbia using the stochastic ray production function for a panel dataset.

Our study contributes to the rangeland cattle production efficiency and productivity literature available in Uruguay because it applies the SPF methodology for panel data for the first time. Moreover, we incorportae multi-outputs into the analysis of rangeland cattle production using the stochastic ray frontier approach. The data used for empirical estimation is an unbalanced panel that is derived from a yearly farm management records collected by 'Instituto Plan Agropecuario' (IPA).

2 Methods

Stochastic frontier analysis independently and simultaneously proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) is the underlying methodology of single output SPF and multi-output SRF. The single output SPF is defined by the following time-varying model for panel data proposed by Battese and Coelli (1992):

$$y_{it} = f(\mathrm{x}_{it}; \beta) exp(v_{it} - u_{it}) \tag{1}$$

where y_{it} is the output of the i-firm in period t; $f(\mathrm{x}_{it}; \beta)$ is a function that represents an input vector x_{it} for i-firm in period t, and a vector of parameters β to be estimated; and v_{it} is the random error assumed to be distributed independent and identical following $\mathrm{N}(0,\sigma_v^2)$. The term u_{it} is the non-negative random error that captures technical inefficiency. It can follow different distributional forms, being the most common the truncated normal and the half-normal distribution. A more detailed analysis of inefficiency error term distributional forms can be found in Kumbhakar and Knox Lovell (2000).

According to Battese and Coelli (1992), u_{it} is treated as time-variant depending on specific function as follows:

$$u_{it} = \eta_{it} u_i = \{\exp[-\eta(t - T)]\} u_i$$

Inefficiency variation comes from the interaction between time and an unknow parameter

(η). The sign of η defines the inefficiency variation, if η is positive this means that TE is increasing along time, η is equal zero means no change in efficiency, and if η is negative TE decreases over time.

The multi-output stochastic ray frontier was proposed by Löthgren (1997) to accomodate the cases where multi-output cannot be analyzed in a dual form, and to handle zero values in the output quantities. The multi-output frontier is closelly related to Shepard's output distance function and according to Henningsen et al. (2015) can be modeled in two ways. One is to divide all outputs by numeraire output using a transformation of the distance function (Coelli and Perelman (1996)). The second way, is to use the stochastic ray production function proposed by Löthgren (1997). According to Henningsen et al. (2015) the SRF proposed by Löthgren (1997) outperforms the approach presented in Coelli and Perelman (1996) in cases where zeros are present in some outputs. The multiple output model can be represented by the output vector as:

$$y = \|y\| \cdot m(\theta)$$

where $\|y\| = (\sum_{k=1}^{n} y_i^2)^{1/2}$ is the Euclidean norm of outputs y, and $m(\theta)$ represents the output mix $(y/\|y\|)$ as a transformation of the polar coordinates angles (θ) following the formula:

$$m_k(\theta) = \cos\theta_k \prod_{j=0}^{i-1} \sin\theta_j \qquad k = 1, \ldots, K$$

Löthgren (2000) shows that being $P(x)$ a closed, bounded, and non-empty production set a production function can be represented as

$$f(x) = \max\{y \geq 0 : y \in P(x)\} \tag{2}$$

The multi-output ray production function can be represented as a transformation of equation 2:

$$f(x, \theta) = \max\{\iota \geq 0 : \iota \cdot m(\theta) \in P(x)\}$$

Therefore, the multi-output production function exhibits the maximum output norm given factors and the coordinates of the output vector. Equation (1) can be transformed to accomodate the multi-output SRF in the following way

$$y_{it} = f(x_{it}, \theta_{it}) exp(v_{it} - u_{it}) m(\theta)$$

taking the norm at both sides, using the fact that $\|m(\theta)\| = 1$, and $exp(v_{it} - u_i)$ is a scalar we obtain:

$$\|y_{it}\| = f(x_{it}, \theta_{it}) exp(v_{it} - u_{it}) \tag{3}$$

Then applying logs to equation (3) the stochastic ray production frontier is obtained,

$$\ln \|y_{it}\| = \ln f(x_{it}, \theta_{it}) + v_{it} - u_{it}$$

We use maximum likelihood (ML) method to estimate the parameters in the single output SPF and in the multi-output SRF. Accroding to Battese and Corra (1977) the log-likelihood function is parameterized in terms of the variance ratio $\gamma = \sigma_u^2/\sigma^2$, where $\sigma^2 = \sigma_v^2 + \sigma_u^2$. The variance ratio γ reflects which part of the total variance in the model is attributed to technical inefficiency variance. All the estimations were done using the package Frontier for R which provides ML estimates for the parameters.

In order to obtain an estimation of firm-specific technical inefficiencies we follow the approach proposed by Jondrow et al. (1982). He used the mean or the mode of the conditional distribution (u_{it}/ϵ_{it}) where $\epsilon_{it} = v_{it} - u_{it}$ is the composed error. This idea was generalized to panel data models by Battese and Coelli (1988).

3 Data and empirical model

The data base available consist of an unbalanced panel of 70 famers over 3 years, totalizing 201 individual observations. Summary statistics of variables that describes the sector are presented in table 1. Equivalent meat by hectare ($EM\ ha^{-1}$) is constructed as the sum of beef meat, sheep meat, and wool converted by a factor of 2.54. This factor reflects the relation between the energy needed to produce a kg of wool relative to a kg of meat. All meat variables are constructed as:

$$\text{Meat production} = \text{Total sales - Total purchases} \pm \text{Stock difference}$$

As table 1 shows is clear that the ranches included in the database are heterogeneous. For example, the range of land in hectares runs from 79 to 10,497 ha. This result in different strategies of production that might explain differences in our estimation. Given that some ranches do not produce sheeps the minimum wool production is zero. The negative minimum value for ovine meat production is explained by a very negative year in terms of stock changes due to low lambing. Improved pastures reflects the percentage of area with cultivated pastures or improved natural grass (exotic species or fertilization). The mean value of 16.7% does not fully capture the high variation of improved pastures (from 0 to 99%). This variable has the weakness of aggregating different types of practices that are not always fully comparable.

Stocking reflect the number of animals by hectare, bovine and ovine, by feed intake capacity relative to the necessary grass intake made by a pregnant cow weighting 480 kg. Each stocking category is measured relative to this pattern and it is presented as units per hectare. Labor measures the number of equivalent workers to a 2100 hours per year worker. Total expenditure is the sum of pasture, grain-feed and veterinary expenditures. Pasture expenditure reflects the yearly expenditure in improved pastures. Grain-feed accounts for the expenditure in grain for feeding cattle. Veterinary inputs represents the expenditure in veterinary products.

Improved pastures reflects the percentage of area that has some level of intervention. It ranges from fertilizer application to natural grass-land to completelly cultivated pastures. Most of the ranches have less than 40% of area under some type of improvement and there is not a clear and straight definition for each type of improvement. Therefore, improved pastures is a variable that is not a good fit explaining production differences.

Of the 70 ranches in the data set, there are 37 cow-calf producing systems characterized by a herd of cows and main products are calf for finishing and cows for slaugther. There are 33 complete cycle systems in the data set that produce steers for industry from their own calf production.

For empirical estimation of technical efficiency we use Stochastic Frontier Analysis (SFA) and Stochastic Ray Frontier approach. We introduce SRF in order to have measures of product response besides technical efficiency. The SPF is a benchmark for comparison using a widly and traditional product index for cattle production in Uruguay. Comparing allows us to better analyse the results specially in the case of technical efficency scores.

In order to measure efficiency we have to take into account two weaknesses. First, the main input of the system, natural pasture, is not a marketeable input but a natural resource making the efficiency estimation a difficult task. The second weakness comes from the lack of consistent and widly collected information on production input decisions. One institution dedicated to rangeland cattle production in Uruguay is the IPA. This institute yearly collects management information from cattle ranches and presents management indicators. Ranchers participation is voluntary and depending upon the presence of an agronomist processing data. However, these ranchers do not have a special management system.

Following Battese and Coelli (1992) and using a translog (TL) specification, the single output SPF model (Mod 1) is represented as:

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j \ln x_{jit} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln x_{jit} \ln x_{kit} + \lambda_1 d_{1it} + \lambda_2 d_{2it} + \lambda_3 t + v_{it} - u_{it}$$

where the sub-indexes j represent the $j - th$ explanatory variable, i is a specific farm and $t - th$ is the time period.

The dependent variable y_{it} represents total equivalent meat in kg. The inputs included in the analysis are labor (LB), total veterinary, pasture and grain-feed expenditure (EX), bovine stock (UG), and total land used for cattle production (LD). Given that the estimation is performed in levels, stocking is included as total bovine-cattle stock units and not in the traditional way of measure of carrying capacity. To consider differences in production systems we include a dummy variable d_{1it} equals 1 if it is a complete cycle system, and an ordinal variable that accounts for the number of grazing fields d_{2it}. The number of fields into that a ranch is divided, defines the way stocking is managed. When the number of fields is low there is a tendency of continuos grazing affecting grass production, which in turn result in lower productivity. Finally, a tendency variable (t) is included to capture technological change.

The multi-output SRF model (Mod 2) is also defined as a TL function according to Löthgren (1997). However, we do not take the logarithm of the polar coordinates proposed by Henningsen et al. (2017). They argue that the polar coordinates angle range between $[0, \pi/2]$ and taking logarithms increase the range to $[-\infty, \ln(\pi/2)]$ besides a tendency to be left skewed.

$$\begin{aligned}\ln ||y_{it}|| =& \beta_0 + \sum_{j=1}^{4} \beta_j \ln x_{jit} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln x_{jit} \ln x_{kit} + \sum_{m=1}^{2} \alpha_m \theta_{mit} + \frac{1}{2}\sum_{m=1}^{2}\sum_{l=1}^{2} \alpha_{ml}\theta_{mit}\theta_{lit} \\ &+ \sum_{m=1}^{2}\sum_{j=1}^{4} \delta_{mj}\theta_{mit} \ln x_{jit} + \lambda_1 d_{1it} + \lambda_2 d_{2it} + \lambda_3 t + v_{it} - u_{it}\end{aligned}$$

where $||y_{it}||$ is the Euclidean output norm for the i farm at time t. The output vector is defined by (y_1, y_2, y_3), where y_1 is total ovine meat, y_2 is total wool, and y_3 total bovine meat. The explanatory variables used are the same as in the single output model, and d_{1it}, d_{2it}, and the tendency variables are also included.

To calculate the polar coordinate angles (θ) we followed the the formula proposed by Henningsen et al. (2017), that avoids the rounding errors of the recursive structure proposed by Löthgren (1997). The formula for θ's calculation is

$$\theta_m(y) = \arccos\left(\frac{y_m}{\sqrt{\sum_{j=m}^{M} y_j^2}}\right)$$

In both models (1 and 2), u_{it} follows a half-normal distribution $N^+(0, \sigma_u^2)$, and it is time-varying according to Battese and Coelli (1992).

Kumbhakar et al. (2014) discuss that Battese and Coelli (1992) is a restrictive model since the inefficiency only varies over time following an exponential function. To overcome this restriction Battese and Coelli (1995) can be implemented. The authors models the inefficiency as a function of exogenous variables that explain the inefficiency variation. Technical efficiency is associated with the role of management in the production process, the famers' ability to use the inputs to obtain the maximum output. According to Bravo-Ureta and Pinheiro (1993) the most used variables to explain technical efficiency are farm specific variables like education, age, farm size or access to credit. In our data base, we have three dummies variables related to farm's management capacity: if farmer pays for veterinary or agronomic assistance, if farmer is part of a group which gives him some kind of support, and if farmer uses gestation diagnosis techniques. We tried to model the inefficiency term using these variables but non of them were suitable.

Both Battese and Coelli (1992) and Battese and Coelli (1995) are models that mix inefficiency with specific firm effects (Kumbhakar et al. (2014)). Alternatives to surpass this limitation where proposed by Green (2005a) and Green (2005b), considered as 'truefixed' and 'true-random' effects models. Given the nature of our panel structure (unbalanced and short) these two models do not fit properly.

4 Results

Likelihood ratio tests were implemented to better understand the structure of production technology and the nature of technical inefficiency present in the two defined models, which share the same results[1]. To represent the frontier we choosed a Translog specification, preferred over a Cobb-Douglas functional form for the two models defined. A likelihood ratio test (LR) was used to confirm which functional form fits the data significantly better. The null hypothesis that the restricted form of the Translog is suitable ($H_{01} : \beta_{jk} = 0, j \leq k = 1 \ldots 4$), is rejected. The LR test results are presented in table 2.

We also tested the variation nature of the model by looking at a ratio of variances. As we already mentioned, the total variance of the model can be expressed as $\sigma^2 = \sigma_v^2 + \sigma_u^2$ being the γ parameter defined as $\gamma = \sigma_u^2/\sigma^2$. If $\gamma = 0$ then the inefficiency term is negligible meaning that the results are equivalent to an OLS estimation, and $\gamma = 1$ means that all the variance is explained by the inefficiency term (the model is equivalent to a deterministic approach). Under the null hypothesis ($H_{02} : \gamma = 0$ –no inefficiency) the test statistic follows a mixed χ^2-distribution (Coelli (1995)), and critical values can be obtained from Kodde and Palm (1986). The null hypothesis was rejected as table 2 shows. Moreover, we obtained an estimated γ equal to 0.931 and 0.941 in Mod 1 and Mod 2, respectively (table 3). These results comfirm that both statistical noise and inefficiency are important for explaining deviations from the production frontier. Therefore, the stochastic production frontier and the stochastic ray frontier are more suitable than OLS model.

[1]The test statistic $LR = -2[\ln L(H_0 - L(H_1)]$ where $\ln L(H_1)$ and $\ln L(H_0)$ are the log-likelihood values under the alternative and the null hypothesis, respectively, follows the χ^2-distribution with defree of freedom equal to the number of restrictions imposed

Since we have a 3 year panel structure we tested the hypothesis of varying efficiency over time. That means testing u_{it} against u_i on the models. Given the LR test result, we rejected the null hypothesis of time invariant inefficiency ($H_{03} : \eta = 0$).

Additionally, we tested neutral linear technological change using a LR test rejecting the null hypothesis of no technological change ($H_{04} : \lambda_3 = 0$). Even the short and unbalanced panel data structure, the technical change appears to capture part of the variation of the data. Testing for non-constant non-neutral technical change was not possible given the number of parameters involved and the length of the panel.

The overall efficiency score for Mod 1 is 0.769 and for the Mod 2 the mean efficiency score is 0.779. The difference is almost negligible, being the Pearson's product-moment correlation coefficient for technical efficiency scores equal to 0.957, and statistically significant. This result is confirmed by the graphical relation between both TE estimates shown in figure 1. Table 4 shows the summary statistics for TE estimates by year for both models. We can see that the statistics follow a decreasing trend in the two models, and mean TE reaches its maximum in the agricultural year 2013-2014. Therefore, the equivalent meat index is in some sense useful to compare ranches efficiency. Technical efficiency mean scores are in line with those obtained by Trestini (2006) and Qushim et al. (2013), and are larger than those obtained by Gatti et al. (2015).

However, the two models exhibit differences if we consider the frontier coefficients. Mod 2 shows more significant coefficients than Mod 1 and a larger log-likelihood value. Mod 1 shows 9 out of 18 significant variables, while in Mod 2 there are 18 significant variables out of 31 (Table 3). The coefficient estimate of polar coordinate angle θ_2, θ_1^2 and most of the input-polar coordinate angle interaction variables are significant. Therefore, the output mix have effects on the frontier output norm for a given input vector. Regarding to labor variable, it only results significative in the interaction with total expenditure in Mod 1. Given the nature of the labor variable (total equivalent man workers) it is no surprise that it is not significant. This form of measuring labor does not capture differences in quality that can be better expressed in terms of labor expenditure. One might expect that better paying results in improved productivity or in better quality hiring.

Technical change captured by the time trend results significative and shows a positive sign close to 5% in both models. At the same time the value of η is negative equal to -0.254 and -0.251 in Mod 1 and Mod 2, respectively, meaning that technical efficiency is decreasing over time. This result can be explaining that production measured as EM $kg\ ha^{-1}$ is decreasing over the period, meaning that even when technical change appears to be positive an increase in inefficiency offsets the improvement. Also, beef-cattle production based on natural pasture is largely dependent on net primary production (NPP) which is highly correlated with weather conditions. In figures 2 and 3 the relation between TE scores are compared with equivalent meat by hectare. As can be seen the distribution of 2015/16 year values appears to be below the other two years showing consistency with the decreasing behavior of efficiency.

The output elasticity with respect to the inputs and the polar coordinate angles are presented in Table 5. Of all inputs variables, bovine stock have the highest effect on the dependent variable in each model. In Mod 1 bovine stock (UG) and land (LD) elasticities present the largest positive values. The elasticities mean that a 1% increase in any of these variables results in an estimated increase in total equivalent meat of 0.507% and 0.377%, respectively. In Mod 2, bovine stock and land influence the Euclidean output norm. An increase of 1% of these variables lead to an estimated increase in the output norm of 0.578% and 0.309%, respectively.

Considering polar coordinate elasiticities ($\partial \ln(\|y\|)/\partial \ln \theta_i$) results show that for θ_1 is equal to 0.620, and for θ_2 is 3.919. The elasticity with respect to θ_1 represents the percentage change in the output norm with respecto to a change in y_1 with fixed proportions of y_2 and y_3. The elasticity with respect to θ_2 represents the change in the output norm when y_1

remain constant. Being positive both elasticities values reflects that changing the output mix from mixed systems (ovine and bovine) to more bovine specialized systems results in a higher output. These results are consistent with the bovine specialization of ranches in Uruguay over the last 20+ years.

Since we have two type of ranches in the data base (complete cycle vs cow-calf), it is interesting to analyze the efficiency scores by system type. The mean values of TE obtained from Mod 1 and Mod 2 are presented by type and year in table 6. On average, both systems show very similar efficiency result, which can be showing that ranchers choose the best system for the natural environment that they have available. Complete cycle systems is associated to larger land size than cow-calf systems, but from an efficiency analysis there are no difference between systems. Hence, the production system is not a significant determinant on efficiency performance.

5 Conclusion

This study estimated a single output SPF and a multi-output SRF to obtain and compare technical efficiency measures of ranches in Uruguay. Since equivalent meat index has been under scrutiny because of how it is defined, we estimated a multi-output frontier allowing to consider all outputs in efficiency analysis. However, it is important to note that beef-cattle production in Uruguay remains to be highly dependent on net primary production, which impose limitations on stochastic production functions estimation due to limited use of external inputs.

We find that the average level of TE is 0.769 for the single output SPF and 0.779 for the multi-output SRF, suggesting that ranches can expand cattle production using the current level of inputs and production technology available. TE is decreasing among the period considered and it reaches the lowest score in the last year (0.717 and 0.730 for SPF and

SRF, respectively). Both models show that production is more sensitive to bovine stock and land size rather than to expenditures cattle management or labor.

The comparison between the single output SPF and the multi-output SRF leads to very similar efficiency results. However, using an index to combine different products has some caveats since it does not allow to capture impacts of specialization. The stochastic ray frontier results indicates that specializing on beef catlle over sheep-cattle results in production improvements.

As a final comment, to improve the results in order to draw public policies recommendations, the program that collect the data of ranch management should be reinforced. This reinforcement implies encouraging ranchers to remain in the program allowing for the construction of long time panel structures. On the other hand, the tecnical efficiency analysis could be improved including explanatory variables associated with the role of management in the production process.

Table 1: Summary statistics of selected variables (n=201)

Variables	Units	Mean	Std. Dev.	Min	Max
Total EM	kg	104,949	128,226	8,505	934,233
Total ovine meat	kg	8,906	15,208	-1,838	104,970
Total wool	kg	3,293	5,373	0	38,839
Total bovine meat	kg	87,713	105,422	7,851	750,659
$\|\|y\|\|$	kg	88,790	106,175	7,856	756,000
Labor	Equivalent workers	3.3	2.9	0.3	20
Total expenditure	$	18,340	27,727	252	240,250
Bovine stock	kg	679	803	56	5,861
Land	ha	1,077	1,365	79	10,497
$EM\ ha^{-1}$	$kg\ ha^{-1}$	99.5	27	26	178
Improved pastures	%	16.7	18.1	0	99.2
Stocking	$UG\ ha^{-1}$	0.83	0.14	0.52	1.31

Table 2: Likelihood ratio tests (5%)

Null hypothesis	Test statistic	Critical value	Decision
Mod 1			
$H_{01}: \beta_{jk} = 0, j \leq k = 1 \ldots 4$	21.06	18.30	Reject
$H_{02}: \gamma = 0$	119.21	7.05	Reject
$H_{03}: \eta = 0$	18.91	3.84	Reject
$H_{04}: \lambda_3 = 0$	5.70	3.84	Reject
Mod 2			
$H_{01}: \beta_{jk} = 0, j \leq k = 1 \ldots 4$	53.71	32.70	Reject
$H_{02}: \gamma = 0$	108.19	7.05	Reject
$H_{03}: \eta = 0$	22.21	3.84	Reject
$H_{04}: \lambda_3 = 0$	6.07	3.84	Reject

Table 3: Stochastic Production Frontier and Stochastic Ray Frontier Estimates

	Mod 1			Mod 2		
Variable	Coef.	Signif.	Std. Err.	Coef.	Signif.	Std. Err.
Intercept	6.981	***	1.608	62.369	***	24.021
LB	0.398		0.421	0.818		1.550
EX	-0.232		0.237	-2.597	***	0.947
UG	3.097	***	0.832	16.032	***	4.009
LD	-2.248	**	0.910	-14.068	***	4.074
θ_1				0.011		6.375
θ_2				-62.884	**	32.023
LB^2	-0.053		0.107	-0.055		0.103
EX^2	-0.056		0.039	-0.079	**	0.034
UG^2	0.624	**	0.272	1.391	***	0.496
LD^2	0.988	***	0.310	1.642	***	0.506
θ_1^2				-4.144	**	2.032
θ_2^2				33.048		22.749
LB x EX	-0.085	*	0.045	-0.021		0.043
LB x UG	0.201		0.130	0.273		0.178
LB x LD	-0.108		0.133	-0.254		0.188
LB x θ_1				-0.329		0.439
LB x θ_2				-0.032		1.114
EX x UG	-0.066		0.079	-0.274	***	0.102
EX x LD	0.199	**	0.083	0.392	***	0.104
EX x θ_1				0.282		0.216
EX x θ_2				1.385	**	0.704
UG x LD	-0.914	***	0.253	-1.591	***	0.462
UG x θ_1				2.456	***	0.776
UG x θ_2				-9.713	***	2.828
LD x θ_1				-2.334	***	0.694
LD x θ_2				8.751	***	2.640
θ_1 x θ_2				2.862		4.703
d_1	0.003		0.062	-0.009		0.061
d_2	-0.002		0.003	-0.002		0.003
Time trend	0.047	**	0.020	0.046	**	0.018
σ^2	0.217	***	0.045	0.201	***	0.038
γ	0.931	***	0.018	0.941	***	0.015
η	-0.254	***	0.057	-0.251	***	0.057
Mean TE		0.769			0.779	
LL-Value		62.22			80.10	

*** 1% level of significance, ** 5% level of significance, * 10% level of significance

Figure 1: Technical efficiency socres for SPF versus SRF

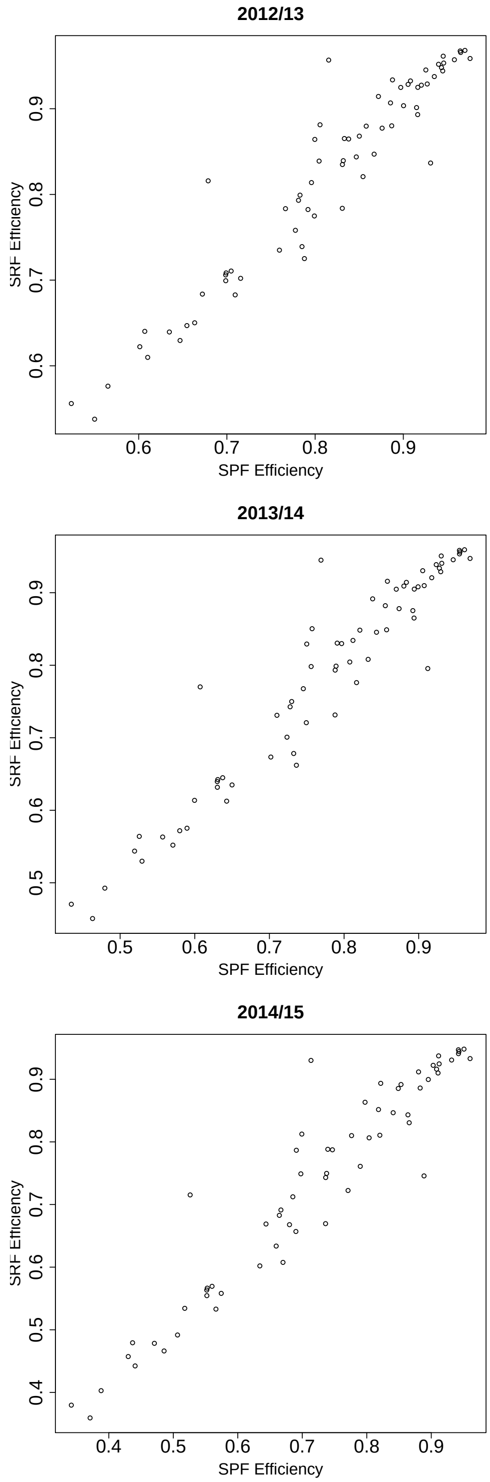


Table 4: Summary statistics for technical efficiency estimates by year for models 1 and 2

Mod 1						
Year	Min	Q1	Median	Mean	Q3	Max
2013-14	0.524	0.716	0.832	0.813	0.915	0.976
2014-15	0.435	0.650	0.791	0.772	0.894	0.969
2015-16	0.342	0.570	0.736	0.717	0.865	0.960
Mod 2						
2013-14	0.538	0.725	0.844	0.820	0.928	0.968
2014-15	0.451	0.662	0.808	0.782	0.909	0.959
2015-16	0.359	0.586	0.750	0.730	0.889	0.948

Table 5: Output elasticity with respect to the inputs and polar coordinate angles

Variable	Mod 1	Mod 2
LB	0.082	0.052
EX	0.070	0.088
UG	0.507	0.578
LD	0.377	0.309
θ_1	-	0.620
θ_2	-	3.919

Table 6: Mean value and standard deviation of technical efficiency estimates by production system

Mod 1 System	2013-14	2014-15	2015-16
Cow-calf	0.813	0.775	0.713
	0.124	0.149	0.177
Complete cycle	0.812	0.769	0.722
	0.112	0.134	0.164
Total	0.813	0.772	0.717
	0.117	0.142	0.170
Mod 2 System	**2013-14**	**2014-15**	**2015-16**
Cow-calf	0.820	0.783	0.723
	0.127	0.152	0.181
Complete cycle	0.820	0.780	0.738
	0.113	0.138	0.162
Total	0.820	0.782	0.730
	0.119	0.144	0.171

Figure 2: TE scores and Equivalent Meat ($kg\ ha^{-1}$) production by year for the single output SPF

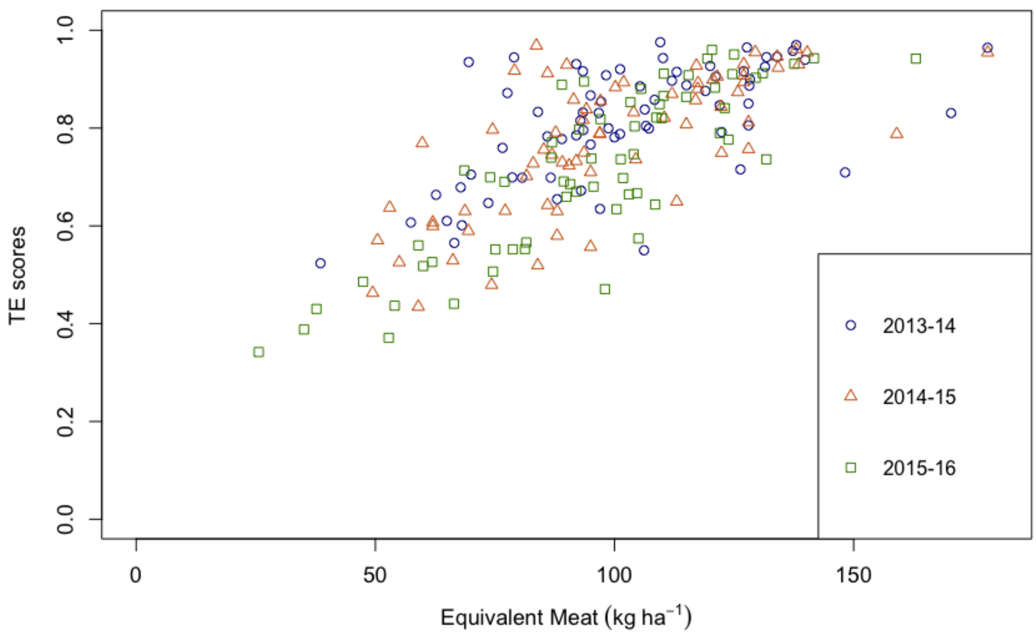
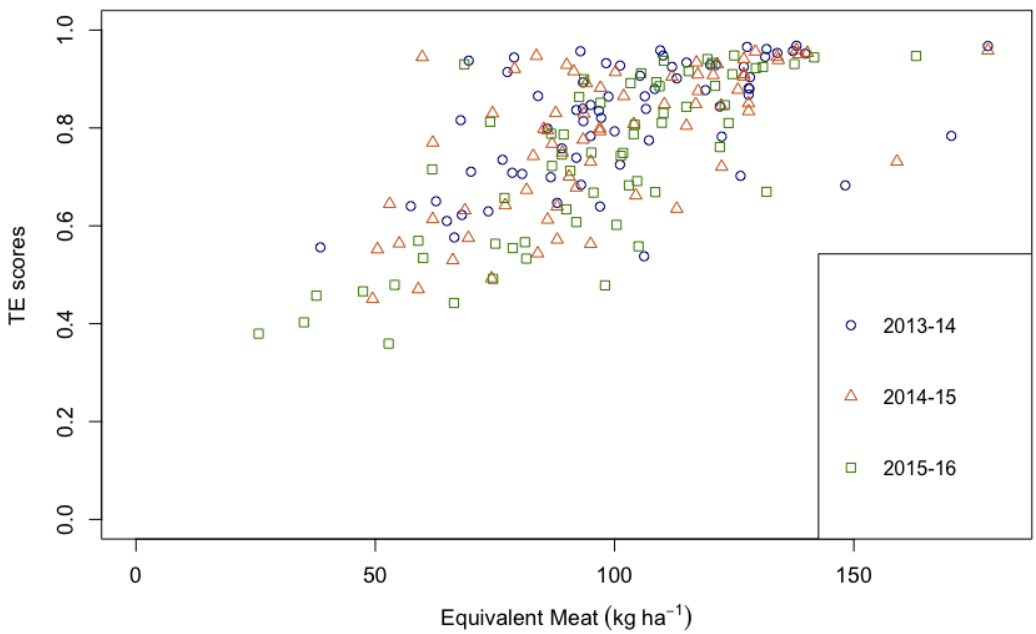


Figure 3: TE scores and Equivalent Meat ($kg\ ha^{-1}$) production by year for the multi output SRF



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