What impact do producer measured inputs have on the prediction accuracy of BeefSpecs?

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Abstract: The BeefSpecs fat calculator is a decision support tool created to help the beef industry increase compliance rates with carcass specifications. BeefSpecs combines the predictive powers of animal growth and body compositional models with experimental information relating to animal growth and fatness in response to changes in production environment. To facilitate producer acceptance and adoption, BeefSpecs makes explicit use of inputs that are easily recorded on-farm but still provide effective information to the modelling systems to enable accurate prediction. These inputs include: sex, breed type, initial live weight (kg), frame score, initial P8 fat depth (mm), hormonal growth promotant use, feed type, length of feeding period (days), growth rate (kg/day), and dressing percentage. BeefSpecs provides three outputs that are relevant to commercial production systems, namely final live weight, final subcutaneous rump fat depth (P8 fat), and hot standard carcass weight (HSCW). Most inputs are considered relatively easy to record on-farm but some require a degree of technical expertise (e.g. frame score and estimated P8 fat) or equipment (e.g. scales to record weight or ultrasonic measurement of P8 fat depth).

Although the structure of BeefSpecs represents one of its strengths via the linkage of easily recorded on-farm inputs to producer language, it also represents a potential weakness. The reliance on on-farm inputs dictates that the accuracy of BeefSpecs' predictions is contingent on the accuracy with which these inputs are able to be recorded. The impact inputs have on the prediction accuracy of BeefSpecs has not been reported previously. Sensitivity analysis is used to explore the relationships between information that flows in and out of modelling systems. A sensitivity analysis provides the opportunity to identify and quantify the key interactions present in BeefSpecs and thus provide information concerning where effort should be directed to most accurately record inputs and maximise predictive accuracy.

When investigating the non-linear, and in some cases chaotic, behaviour of models it is critical to measure sensitivities over the whole spectrum of inputs that may be encountered. Many designs have been proposed for testing sensitivity when models are expensive or lengthy to run. However, a complete factorial array of all variables provides the most comprehensive and safest coverage. The simplicity and low computational cost of running BeefSpecs lends itself to a complete factorial sensitivity analysis. The traditional 'one-at-a-time' (OAT) sensitivity analysis was not used because it is fundamentally flawed, as it does not investigate the typically complex and interactive behaviour of biological models. In the OAT approach, the model is configured to an 'average' or baseline scenario, from where each input is tested sequentially making these sensitivities only applicable at the selected baseline scenario.

The sensitivity analysis conducted in this study used a complete factorial array of all BeefSpecs input variables, to provide the most comprehensive coverage. This array of inputs was created by changing each input one variable at a time and required a total of 57,600 model runs. The dominant effects and interactions were identified by conducting an analysis of variance (ANOVA) on the 9-way factorial matrix of inputs.

Frame score was found to have significant impacts on BeefSpecs predictions of final P8 fat depth including errors of up to 2.3 mm P8 fat depth per unit error in frame score. Errors in initial live weight were found to have less impact on P8 fat predictions (e.g. 0.5 mm per 10 kg live weight error). Initial P8 fat depth was also found to have significant impacts on final P8 predictions, particularly at low initial live weights (e.g. up to 1.5 mm P8 fat depth per 1 mm error in initial P8 fat). Analysis of HSCW sensitivity to BeefSpecs inputs found, as would be expected, that HSCW is dependent only on initial live weight, feeding period, growth rate and dressing percentage, and is thus insensitive to other inputs such as frame score and initial P8 fat. These findings indicate that the accuracy of BeefSpecs inputs, particularly frame score and initial P8 fat depth, have critical impacts on prediction accuracy, which in turn impact on the tool's utility and potential adoption rates. These results also provide support for the development of new technologies that will increase the accuracy and ease of recording such inputs in the future.

Keywords: *Sensitivity analysis, beef cattle, prediction error, body composition*

1. INTRODUCTION

Beef cattle producers are constantly making management decisions in response to production pressures that impact on the profitability of their beef businesses. Many of these decisions have either a direct or indirect impact on the capacity of cattle to meet market specifications and thus maximise financial returns to the enterprise. Until recently there has been only limited experimental data (Edmondston et al. 2006; Polkinghorne 2006; McKiernan et al. 2007) to support anecdotal evidence that a significant proportion of Australian cattle fail to comply with market specifications. An analysis of 20,000 feedlot records for short-fed cattle supported this anecdotal evidence by demonstrating that 28% of carcasses failed to meet carcass weight specifications costing \$5.50/carcass, and 16% failed to meet subcutaneous rump fat depth (P8 fat) specifications costing \$17.50/carcass (Slack-smith et al. 2009). A more recent analysis of grass-fed records containing 18,860 steers and 13,118 heifers demonstrated 17.4% of steers and 15.6% of heifers failed to meet carcass weight specifications, costing \$25.97/carcass and \$7.28/carcass, respectively (McPhee and Walmsley, 2013). A similar pattern was found for fat specifications with 13.0% of steers and 19.1% of heifers failing to comply with specifications, costing \$10.94/carcass and \$24.82/carcass, respectively.

A program was initiated within the Cooperative Research Centre for Beef Genetic Technologies aimed at addressing this issue of non-compliance in the beef industry. The BeefSpecs fat calculator (Walmsley et al. 2011) is a decision support system (DSS) developed by this program which is designed to assist producers increase compliance rates with target market specifications by predicting the end-point fatness of carcasses, specifically P8 fat. To achieve this objective BeefSpecs combines the predictive powers of animal growth and body compositional models (Keele et al. 1992; Williams and Jenkins 1998) with experimental information relating to animal growth and fatness in response to changes in production environment. Merging animal growth and body compositional models with experimental data in this manner has allowed BeefSpecs to be developed to be functional across a wide range of production environments.

One primary objective during the development of BeefSpecs was to address the concerns raised by Newman et al. (2000) that many DSS developed for agricultural industries are perceived as too complex and have thus achieved limited acceptance and adoption. In order to overcome these perceived impediments, BeefSpecs has combined the computational power of animal growth and body compositional models with easily recorded on-farm inputs and terminology familiar to beef cattle producers. These on-farm inputs are focused on animal and production characteristics that are relatively simple and inexpensive to record whilst still providing effective information to the modelling systems to facilitate prediction. These developments to allow the integration of on-farm inputs have occurred while maintaining the integrity of the base modelling systems.

Although BeefSpecs use of easily recorded on-farm inputs and familiar terminology provides a point of strength that helps overcome the perception of DSS being too complicated, they also represent a potential weakness. The sensitivity of the BeefSpecs predictions to the accuracy with which inputs are collected and the contribution that each input makes to this sensitivity is unclear. It is regarded by modellers and practitioners from various disciplines that a sensitivity analysis is a key ingredient of the quality of any model-based system (Saltelli and Annoni 2010). Conducting a sensitivity analysis to explore the relationships BeefSpecs inputs have with predictions will allow the impacts that inputs have on predictive accuracy to be quantified. These findings will identify those inputs which BeefSpecs users need to ensure are collected with the highest accuracy to gain the greatest predictive accuracy. Focusing on these inputs and maximising the accuracy of their collection will deliver the highest level of functionality and adoption of BeefSpecs within the Australian beef industry.

This paper describes a sensitivity analysis conducted with the objective of determining the extent to which the BeefSpecs inputs affect the accuracy of final P8 fat prediction. The impact these findings have on the collection of inputs and the implementation of the BeefSpecs calculator will also be discussed.

2. BACKGROUND

There have been many modelling systems developed for describing cattle growth and development (Oltjen et al. 1986; Keele et al. 1992; Williams and Jenkins 1998; Hoch and Agabriel 2004). However, these models have generally failed to gain any real traction and adoption in the form of DSS within the commercial beef industry. This lack of adoption has been partially attributed to DSS being perceived as overly complex and requiring extensive inputs, having limited end-user input during development, and a mismatch between DSS outputs and the language used by end-users, amongst other important factors (Newman et al. 2000). The development of BeefSpecs to create a DSS to help producers increase compliance rates with market specifications specifically addressed these perceived shortcomings (Walmsley et al. 2011).

The dynamic steer growth model called the Meat Animal Research Centre (MARC) model, originally developed by Keele et al. (1992) and subsequently modified by Willams and Jenkins (1998), forms the basis of the BeefSpecs fat calculator. The development of BeefSpecs has been described by Walmsley et al. (2011). In brief, BeefSpecs requires a series of easily recorded on-farm inputs to both initialise starting body composition in terms of fat and lean content and predict changes in these components as animals grow. Inputs used to initialise BeefSpecs include a description of animal type using sex (e.g. steer or heifer), breed type and an estimate of mature size termed 'frame score' which are combined with initial live weight (kg) and initial P8 fat depth (mm). The performance inputs namely growth rate (kg/day) and feeding period (DOF – days on feed), are used to drive the prediction of body composition across time which is also influenced by the management inputs; feed type (e.g. grass or grain) and hormonal growth promotant (HGP) use. Predicted body composition is used in conjunction with sex, breed type and live weight to predict final P8 fat (mm) (Walmsley et al., 2010) which can be compared directly with market specifications used within the Australian beef industry. BeefSpecs also calculates final live weight based on DOF, initial live weight and growth rate which are subsequently multiplied by estimated dressing percent to calculate hot standard carcass weight (HSCW). The easily recorded on-farm inputs and model predicted outputs are combined with a simple user interface to provide an interaction that encourages on-farm use (Figure 1). The breed type input shown in Figure 1 is generated by the user moving the cursor to produce a visual output on the interface that best matches the user's live animals.

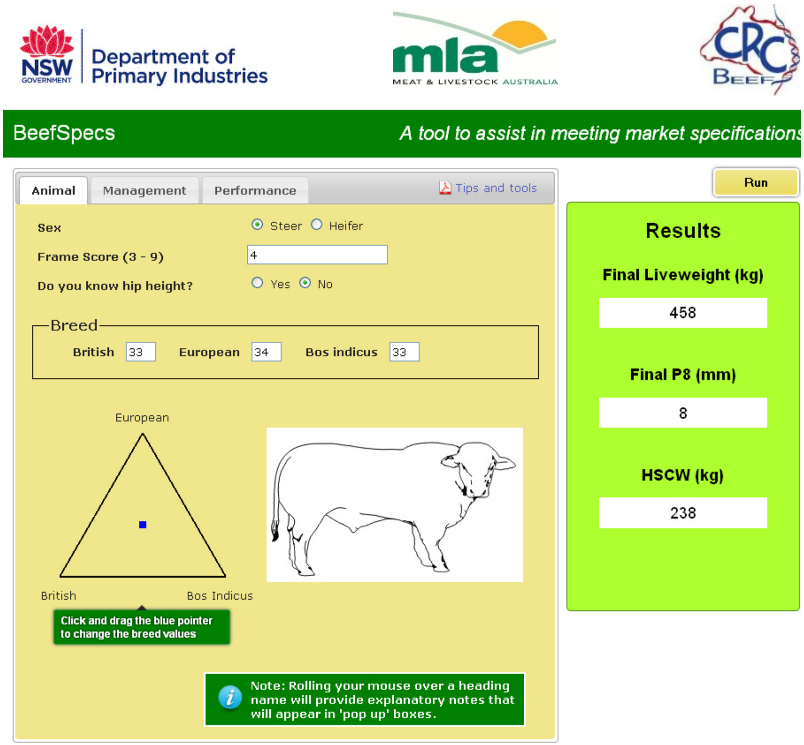

Figure 1. A screen capture of the BeefSpecs web user interface hosted by New South Wales Department of Primary Industries.

Although the inputs to BeefSpecs are considered easily recorded on-farm measurements, some inputs do require a level of technical expertise (e.g. estimating initial P8 fat) and the ability of beef producers to accurately record these is unclear. Consequently, the impact such inputs to BeefSpecs have on the accuracy of outputs is also unclear. A sensitivity analysis explores the relationships between information flowing in and out of a model (Saltelli et al. 2000, page 4). Saltelli et al. (2000, page 5) define this mathematically as;

$$S_{i,j} = \partial Y_i / \partial X_j$$

where X_j is the model input variable j, Y_i is the model output variable i, and $S_{i,j}$ is the sensitivity of the output Y_i relative to the input X_j. A sensitivity analysis will allow the impact each input to BeefSpecs has on the accuracy of prediction to be quantified. This will turn allow inputs to be identified that require particular attention to maximise their accuracy of recording and provide guidance as to where effort needs to be placed to determine the potential for developing methods to assist users record these inputs.

Saltelli et al. (2000) outlined a wide range of methods for conducting a sensitivity analysis. The most important message they delivered, which is strongly reiterated in Saltelli and Annoni (2010), is that the traditional 'one-at-a-time' (OAT) sensitivity analysis is flawed, despite being used quite extensively. In the OAT approach, the model is configured to an 'average' or baseline scenario, and each input (X_j) is tested sequentially. This usually occurs by applying an upward and downward deviation to X_j, and averaging the responses in the output (Y_i). Whilst this does in fact measure sensitivities, these are only applicable at the selected baseline scenario.

Most modelling systems tend to behave non-linearly, and in some cases chaotically, meaning it is critical to measure sensitivities over the whole spectrum of inputs that may be encountered. Importantly, an approach is needed which will identify and quantify the key interactions present in the behaviour of BeefSpecs across the full range of the input variables. Saltelli and Annoni (2010) list a number of efficient statistically-based designs for achieving this. However, these designs are needed only when a model is expensive or lengthy to run, and as pointed out by Saltelli and Annoni (2010) conducting a complete factorial array of all variables provides the most comprehensive and safest coverage. The simplicity and low computational cost of running BeefSpecs lends itself to a sensitivity analysis involving a complete factorial array of inputs.

3. METHODS

This study conducted a sensitivity analysis using the techniques described by Saltelli et al (2000, page 4) which included a complete factorial design of the BeefSpecs input variables. The inputs and outputs could have been standardised to provide an indication of 'relative importance' which would have allowed a comparison across all variables. However, preference was to retain the original definition, which uses the actual units of measurement for each variable and thus gives estimates of the direct impact on model outputs that is attributable to the variability in the respective input parameters (i.e. due to uncertainty, or errors in recording).

Table 1. Input variables for the factorial sensitivity analysis of BeefSpecs

Inputs	Levels
Sex	Steer, Heifer
Feed Type	Grass, Grain
Hormone growth promotant	None, Oestrogen, Androgen
Breed Type	British, European, Bos indicus, 3-way cross
Days on feed	60, 120, 180
Frame Score	2, 4, 6, 8
Initial P8 Fat (mm)	2, 4, 6, 8, 10
Initial Live Weight (kg)	200, 250, 300, 350, 400
Growth rate (kg/day)	0.5, 1.0, 1.5, 2.0

The BeefSpecs model described by Walmsley et al. (2011) was used to create a matrix of BeefSpecs inputs and outputs. The array of inputs analysed during the sensitivity analysis included sex, feed type, HGP, breed type, DOF, frame score, initial P8 fat, initial live weight and growth rate. The levels of the inputs analysed are given in Table 1 and produced an array of 57,600 model runs. This matrix was created by incrementally changing each input one variable at a time as well as including BeefSpecs final P8 fat and HSCW predictions, along with calculations performed using the equation described above as additional columns. An analysis of variance (ANOVA) on the 9-way factorial matrix of inputs was conducted using Genstat (2011) to investigate the dominant effects and interactions.

4. RESULTS AND DISCUSSION

Gaining an understanding of the dominant effects and interactions present in the 9-way factorial analysis of BeefSpecs inputs is not straight forward. Using an ANOVA for each Y_i can help but even estimating only to the 7-way interactions results in 501 individual F-tests being considered by the ANOVA table. A further complication is simulation output (particularly with deterministic models like BeefSpecs) tends to be rather consistent meaning the residual error can be quite small. The presence of 'many' degrees of freedom from the comprehensive factorial design also results in a high proportion of the F-tests being statistically significant, even when using the $P < 0.01$ level. For example, when considering the BeefSpecs output of final P8 fat depth, the 7-way 'DOF by frame score by HGP by initial P8 fat by initial live weight by sex by growth rate' interaction has $F_{(576,\ 9504)} = 10.5$ ($P < 0.001$), but is virtually impossible to interpret.

Table 2. Summary of the ANOVA output for predicted P8 fat depth.

ANOVA Terms	Avg. F-values	Multiplier (vs. next level)	Cum. R^2 (%)
Main effects	248,889,111	48	84.822
2-way	5,157,629	111	99.342
3-way	46,433	85	99.942
4-way	544	5	99.977
5-way	118	8	99.998
6-way	14	8	99.999
7-way	2		100.000

When analysing simulation output, it is the relative sizes of the F-values that need to be considered, rather than the formal statistical significance levels (Mayer et al. 1994). Table 2 lists a summation of the ANOVA table for final P8 fat depth, including R^2 (as in Saltelli et al. 2000), which measures the cumulative amounts of total variation accounted for at each step. Table 2 demonstrates that the majority of information is contained at the 3 or 4-way interaction level. The dominant 4-way interaction was 'DOF by frame score by initial live weight by sex', with $F_{(24, 9504)} = 11{,}231$. This interaction contains two input variables (frame score and initial live weight) that require either some technical expertise or technical equipment (e.g. cattle scales). The estimated sensitivities of final P8 fat depth relative to these inputs are shown in Tables 3 and 4, respectively.

Table 3. Sensitivity (mm/unit) of final P8 fat predicted by BeefSpecs to the frame score input.

Frame Score	Initial Weight (kg)	60 Days on Feed		120 Days on Feed		180 Days on Feed	
		Heifer	Steer	Heifer	Steer	Heifer	Steer
Low	200	*-0.45*[*]	*-0.29*	-0.77	-0.60	-1.23	-0.71
(2 to 4)	250	-0.56	*-0.32*	-1.00	-0.67	**-1.61**	-0.87
	300	-0.65	*-0.38*	-1.32	-0.73	**-2.01**	-1.10
	350	-0.83	*-0.47*	**-1.63**	-0.87	**-2.29**	-1.38
	400	-0.83	-0.56	-1.49	-1.09	**-2.11**	**-1.66**
High	200	*-0.26*	*-0.17*	-0.56	*-0.35*	-0.67	-0.56
(6 to 8)	250	*-0.30*	*-0.18*	-0.61	*-0.39*	-0.83	-0.59
	300	*-0.36*	*-0.19*	-0.68	*-0.45*	-1.08	-0.61
	350	*-0.45*	*-0.22*	-0.86	-0.51	-1.34	-0.68
	400	-0.53	*-0.27*	-1.07	-0.58	**-1.60**	-0.82

[*] Bolded values are > 1.50 (absolute values); italicised are < 0.50 (absolute values).

Table 3 shows that final P8 is most sensitive to measurement error in frame score when animals undertake longer feeding periods (e.g. 180 days). This sensitivity is particularly evident in low frame-score heifers that begin at higher initial live weights. For each unit of error in estimating frame score BeefSpecs will predict final P8 with an error of up to 2.3 mm in heifers and up to 1.7 mm in steers. Also evident is that during shorter feeding periods (e.g. 60 days) any inaccuracies in the estimation of frame score result in smaller errors in the prediction of final P8 fat, particularly when animals have higher frame scores.

Despite the positive and negative impact errors in initial live weight can have on predicted final P8 fat depth, the results in Table 4 indicate that highly accurate recording of live weight is not essential. A 10 kg error in initial live weight will result in a maximum error of approximately 0.5 mm in predicted final P8 fat depth.

Table 4. Sensitivity (mm/10 kg) of final P8 fat predicted by BeefSpecs to the initial weight input.

Initial Weight (kg)	Frame Score	60 Days on Feed		120 Days on Feed		180 Days on Feed	
		Heifer	Steer	Heifer	Steer	Heifer	Steer
Low	2	*-0.09*[*]	*-0.15*	0.03	-0.09	0.28	-0.01
(200 to 250)	4	*-0.13*	*-0.16*	-0.06	*-0.11*	0.13	-0.08
	6	*-0.16*	*-0.17*	-0.09	*-0.14*	0.01	-0.09
	8	*-0.17*	*-0.17*	*-0.11*	*-0.16*	-0.05	-0.10
High	2	0.21	0.12	0.35	0.25	**0.48**	0.38
(350 to 400)	4	0.21	0.09	**0.41**	0.16	**0.55**	0.27
	6	0.15	0.06	0.31	0.12	**0.47**	0.18
	8	0.12	0.04	0.22	0.10	0.36	0.13

[*] Bolded values are > 0.40 (absolute values); italicised are < -0.10 (absolute values).

Initial P8 fat depth, which is one BeefSpecs input that requires some technical expertise to estimate, was also present in a dominant 4-way interaction; 'frame score by initial live weight by sex by initial P8 fat', with $F_{(48, 9504)} = 6{,}255$. It was apparent in this interaction that the sensitivities of animals with low initial fat depths (e.g. 2 to 4mm) were higher than those of animals with higher initial fat depths (e.g. 8 to 10mm). Table 5 shows that animals (irrespective of sex) which have lower initial live weights and fat depths are most sensitive to errors in initial fat depth, with this sensitivity following a slightly increasing trend as frame score increases. Although not presented in Table 5 these sensitivities were found to be more evident for shorter feeding periods (60 or 120 days). The average sensitivity of animals across sexes and frame scores with an initial live weight of 200 kg and initial fat depth of 2 mm was 1.51. This result means an error in the estimation of initial fat depth of 2 mm will result in an error of up to 3 mm in the prediction of final P8 fat depth.

Table 5. Sensitivity (mm/mm) of final P8 fat predicted by BeefSpecs to the initial P8 fat input.

Initial P8 Fat	Frame Score	Sex	Initial Weight (kg) 200	250	300	350	400
Low (2 to 4)	2	Heifer	1.45*	1.28	1.15	0.88	0.66
	2	Steer	**1.52**	1.37	1.31	1.18	0.81
	4	Heifer	**1.50**	1.35	1.23	0.91	*0.47*
	4	Steer	**1.52**	1.39	1.34	1.22	0.84
	6	Heifer	**1.52**	1.39	1.28	0.95	*0.47*
	6	Steer	**1.51**	1.38	1.34	1.23	0.87
	8	Heifer	**1.53**	1.40	1.31	0.99	*0.49*
	8	Steer	**1.53**	1.40	1.31	0.99	*0.49*
High (8 to 10)	2	Heifer	1.17	1.00	0.88	0.78	0.81
	2	Steer	1.27	1.13	1.03	0.96	0.87
	4	Heifer	1.23	1.06	0.98	0.87	0.79
	4	Steer	1.29	1.16	1.07	1.00	0.95
	6	Heifer	1.27	1.13	1.03	0.95	0.87
	6	Steer	1.31	1.17	1.08	1.03	0.98
	8	Heifer	1.30	1.16	1.07	1.00	0.94
	8	Steer	1.32	1.18	1.09	1.04	1.00

[*] Bolded values are > 1.50 (absolute values); italicised are < 0.50 (absolute values).

Analysis of the sensitivity of HSCW to BeefSpecs inputs provided little information. The final live weight is calculated directly (i.e., without any random variation) from initial live weight, growth rate and DOF. HSCW is then calculated directly by multiplying final live weight by dressing percentage. As would be expected, the ANOVA found HSCW is dependent on these factors only, and is insensitive to other inputs such as frame score and initial P8 fat. Also of note is the sensitivity of HSCW *vs.* initial live weight is simply equal to the assumed dressing percentage. This result suggests the ability of producers to estimate dressing percentage from past experience and/or data will determine the accuracy with which HSCW is calculated by BeefSpecs.

5. PRACTICAL IMPLICATIONS

A general finding from the sensitivity analysis conducted during this study is that the accuracy of the inputs into the BeefSpecs fat calculator has important implications for the quality of predictions made. The results have particularly highlighted the importance of recording frame score and initial P8 fat depth with the highest accuracy. Even though errors in some areas of the input parameter space produce less substantial errors in the predictions this should not be used as reason to not record inputs with as higher accuracy as practically possible. Recent unpublished data assessed the capability of manual P8 fat depth assessment by industry personnel. This data indicates the average difference between manually assessed P8 fat depth on live animals and carcasses was 4.55 mm (n=174). This inaccuracy presents a challenge for placing confidence in manually assessed P8 fat depths. A recent study has explored the use of 3D camera technology to estimate frame score and P8 fat depth in live animals in real-time with some very promising results (McPhee 2013). These results indicate P8 fat was estimated with a mean bias of 0.14 mm (root mean square error = 1.1 mm) in a group of steers used as a challenge dataset. The development of such technology for use in commercial enterprises will dramatically increase both the capability and accuracy of recording such data. Although the sensitivity results suggest predictive accuracy is less sensitive to initial live weight the recording of live weight should still be taken seriously (i.e. use cattle scales rather than guesstimate). The results demonstrate an error in live weight of 50 kg will produce an error of up to 2.5 mm in final P8 fat depth. The slightly different sensitivities between heifers and steers also highlight that the accuracy of other inputs should also not be overlooked.

6. CONCLUSIONS

The results of the sensitivity analysis indicate that the accuracy with which inputs into BeefSpecs are recorded, particularly initial P8 fat, frame score and to some degree initial live weight, has important implications for the accuracy of predictions made by BeefSpecs. For this reason the best effort should be made to maximise the accuracy with which BeefSpecs inputs are recorded. This in turn justifies future efforts to develop more accurate methods to record these inputs. Maximising the accuracy of inputs will result in

BeefSpecs making the most reliable predictions, which will in turn encourage higher rates of adoption than experienced by past DSS and maximise compliance to market specifications to improve beef profitability.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding support of Meat and Livestock Australia. The authors would also like to thank John Wilkins, Matthew McDonagh, Michael Atzeni and Aroon Parshotam for useful comments on the manuscript.

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