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ASKBILL as a web-based program to enhance sheep wellbeing and productivity

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Short title: ASKBILL web-based program: Animal growth model

Abstract. ASKBILL is a web-based program that uses farm measurements, climate data and information on genetics to predict pasture growth, animal performance and animal health and climate risks. The program uses several biophysical models, which are customized by user inputs, localized daily weather updates and a dynamical probabilistic 90-day climate forecast to enhance sheep wellbeing and productivity. This approach can minimize the requirement for manual, auto and remote measurements, thus reducing labour requirements and complexity. In this article, the animal growth model provides an example of a biophysical model used to provide predictions. This is an energy-based model and the model parameterization is designed to be physiologically meaningful and able to be customized for the genetic merit of the animal using a growth coefficient that calibrates growth of body components and energy requirements. A key feature of the animal growth model is its forecast projections, which are based on an ensemble of simulations. The model can estimate supplementary feeding rates required to achieve target live weights and body condition scores and stocking rates required to achieve target pasture levels. The model can be customized for a farm and its livestock and is updated daily in response to climate data. This dynamic feature enables it to provide early-stage alerts to users when animal production targets are unlikely to be met.

Additional keywords: sheep, wellbeing, productivity, animal growth, climate, simulation model, forecast.

Introduction

The most economically important endemic diseases that impact on sheep wellbeing and productivity in the Australian sheep industry include neonatal mortality, internal parasites, dystocia, weaner ill thrift and mortality, and flystrike (Lane *et al.* 2015). These conditions can be the end result of a number of complex factors of which nutrition, body condition score, live weight and weather stress are of key importance. Combined, these diseases cost the sheep industry more than $1.5 billion per annum in 2015 as a result of production loss, costs of prevention and costs of treatment (Lane et al. 2015).

Effective management of these conditions relies on prediction and early detection in order to implement preventative actions and timely treatment. When management tactics rely on the detection of visual symptoms, the effects of subclinical under nutrition and disease will already have had a negative impact on wellbeing and productivity. The alternative approach of using forecasts of pasture availability, animal performance and disease risks to implement management plans and take preventative action consistently results in benefits from better productivity and improved wellbeing.

A key issue driving the need for a predictive approach to help sheep producers better manage their sheep production systems is the limitation of existing strategies for managing wellbeing and productivity. A review of the potential for new technologies to improve decision-making in southern livestock industries (Henry *et al*. 2012) identified 10 areas in which better information would benefit decision-making. Of these, information to aid with allocation of pasture feed and control of animal production were estimated to offer annual on-farm benefits of $81–$96/ha. Examples of better parasite management and improved ewe nutrition are as follows.

- Kelly (2011) demonstrated that in summer rainfall regions, the annual cost of gastrointestinal nematode parasites under typical management was $11/ewe. Providing extra information in the form of drench efficacy, worm tests, live weight, condition score, sheep genetics and grazing management reduced this annual cost to $6/ewe.
- The Lifetime Ewe Management program (http://www.lifetimewool.com.au/economics.aspx) has demonstrated the annual cost of not managing ewe condition score to meet recognised targets is $3−$5/ewe. Key to meeting these targets is the matching of pasture availability and supplements to changing animal requirements during the annual reproductive cycle.

Prediction to improve management

Prediction to improve the management of sheep wellbeing and productivity requires information about the current (known) situation and the probability of future events. For example, susceptibility to flystrike is controlled by known animal factors such as mulesing status, breech and body wrinkle and dag score, known management factors such as dates of shearing, crutching and treatments, and climate forecasts of temperature, rainfall and humidity (Horton and Hogan 2010). Risks of future flystrike are influenced by these known factors and by future climatic events, many of which can be accurately forecast.

Pasture provides the nutritional base for much of Australia's sheep production, and its growth, although dependent on a range of factors, is highly dependent on the availability of moisture. When accounting for moisture in forecasts of pasture growth, data on current plant-available water stored in the soil profile and forecast climate elements such as daily rainfall are both important.

Current events

The known information that contributes to the prediction of future events needs to be current, and this requires regular observation and measurements of animal, pasture and health status, which can be conducted manually or using auto- or remote-monitoring systems. Manual measurements of animal, pasture and health status such as the weighing of livestock, estimation of condition score and pasture availability and sampling to determine the status of major parasitic diseases have not been extensively adopted by sheep producers (Hooper 2007; Reeve and Walkden-Brown 2014), largely because of the labour-intensive nature of these activities and the complexities of data collection, storage and utilisation. Automatic and remote systems designed to monitor sheep and their health status are at various stages of development (Brown *et al.* 2015) and remain relatively expensive and complex.

Biophysical models provide a means of simulating the current situation in a manner that minimizes the requirement for manual, automatic or remote measurements. A biophysical model is a mathematical description of a biological system constructed using experimentally derived, causative relationships to predict the influence of biotic and abiotic factors on complex systems. Examples relevant to Australia's sheep production system include the SGS Pasture Model (Johnson *et al.* 2003), GrazFeed (Freer *et al.* 1997), Agricultural Production Systems Simulator (Holzworth *et al.* 2014) and WormWorld (Barnes *et al.* 1995).

Future events

Once current information has been recorded, climate becomes the most important predictor of the future status of sheep production and health. Future decisions including those about stocking rate, the type and level of supplemental feeds, the type and timing of animal health treatments and avoidance of extreme weather events are informed by prediction of the future climate. The Bureau of Meteorology provides dynamical deterministic weather forecasts for lead-times of 1–7 days using the Australian Digital Forecast Database (ADFD) and for lead-times of 8–90 days using the Predictive Ocean Atmosphere Model for Australia (POAMA).

Whereas ADFD forecasts are useful at a local level because the grid size has a resolution of 3–6 km, the local value of POAMA forecasts is reduced because of a resolution of 250 km. Nevertheless, POAMA forecasts have been demonstrated to provide greater accuracy in the prediction of growth rates of perennial ryegrass when compared with statistical forecasts that rely on historic climate data (Rawnsley *et al.* 2015). Predictions of intra-seasonal climate outlooks made by the Bureau of Meteorology are likely to become more useful at a local level with the implementation of Australian Community Climate and Earth-System Simulator Seasonal models (ACCESS-S), which have a resolution of 60 km (Anon 2017). Collaborative work between the Bureau of Meteorology and the Sheep Cooperative Research Centre has led to the planned release of a 5 km resolution output from ACCESS-S, which is likely to further improve the usefulness of the forecasts for agricultural applications.

Incorporation of climate elements into biophysical models has facilitated integration of historic and forecast climate data. However, historic climate is by nature deterministic (i.e., a single value for each element) and climate forecasts are probabilistic. For example, ACCESS-S will provide an ensemble of 11 forecasts for each day (members) from which both probability and magnitude can be calculated. Utilisation of this daily ensemble enables biophysical models to output a range of future scenarios that can be described using percentiles to indicate the likelihood of the output.

ASKBILL: a tool to enhance sheep wellbeing and productivity

ASKBILL is a web-based program that has been developed by the Sheep Cooperative Research Centre to provide accurate forecasts to help sheep producers better manage their sheep production systems. It represents a new approach that collates farm and industry data and information on climate and genetics to predict pasture growth, animal performance and the risks of flystrike, worm infection and weather stress (Fig. 1).

ASKBILL models process data with a daily time-step in response to updated climate data or changes in user-defined inputs. Farm data such as live weight, condition score, pregnancy status, pasture availability, health treatments and livestock inventory are combined with historic and forecast climate data and Australian Sheep Breeding Values (through RamSelect) to provide long-term average values (i.e., based on climate data collected over the last 30 years) and 90-day forecasts for the following information:

- The amount and quality of pasture across a whole farm or for specific areas of particular interest
- Live weight and body condition score for each stock class within the sheep flock
- The level of risk of worm and sheep blowfly infestations
- The risk of extreme cold and heat

Fig. 1 near here

The models also provide estimates of

- Stocking rates required to reach pasture availability targets
- Pasture area required to support a desired number of animals
- Supplementary feeding rates required to reach live weight and body condition score targets
- Changes in the risk of worm infection and fly strike following treatment

In this paper, the first that describes the components of ASKBILL, the animal growth model is discussed as an example of a biophysical model where forecast projections are based on an ensemble of simulations.

Animal growth model

The animal growth model as implemented in ASKBILL is based on Johnson *et al.* (2012), who described an energy-based model with body composition comprising fat, protein and water. A key underlying approach in the development of the model was to ensure that all parameters have a physiological interpretation. This enables model parameterization to be based on information about the genetic merit of the animal. The core parameters in the model are related to animal weight at birth and maturity (standard reference weight), as well as to the associated fat composition. There are additional parameters for the rate of protein degradation, heat maintenance, activity and, for situations in which intake is less than the requirement, fat catabolism. Simulations of body composition in response to energy supply as presented by Johnson *et al.* (2012) demonstrate close agreement with empirical curves.

The model contains a growth coefficient that is readily adjusted in response to information about weight-for-age and calibrates growth of body components and energy requirements. For example, using the model defaults, the user can define the body weight at 12 weeks to be 20 kg or 30 kg. The model then adjusts the growth coefficient. The resulting growth curves are shown in Fig. 2a and the corresponding metabolizable energy (ME) requirements (using 20 kg at 12 weeks as an example) are shown in Fig. 2b. Peak energy requirement for protein growth precedes that for fat, which is a later maturing component (Butterfield *et al.* 1983), but energy requirements to maintain protein account for a significant proportion of total energy requirements as animals mature.

Fig. 2a and Fig. 2b

The model can be used to assess the ME required for a target growth rate for animals at different live weights using the growth and energy dynamics as shown in Fig. 2. The growth rate underlying the growth curve (20 kg in Fig. 2a) is provided in Fig. 3a and ME requirements for growth as a function of animal weight are provided in Fig. 3b. Two aspects of Fig. 3b deserve special mention. Firstly, energy requirements for growth increase with weight as a consequence of a greater relative deposition of fat than protein (fat has a higher energy density than protein; Rattray and Joyce 1973). Secondly, as the target growth rate increases, the weight at which animals can achieve it declines and this is apparent in the slight curvature of the lines. This is due to the decline in growth rate as the animal approaches maturity.

Fig. 3a and Fig. 3b

Although these examples are for a growing sheep, the model also accommodates pregnant and lactating ewes, for which the framework was adapted from the lactating dairy cow model described by Johnson *et al.* (2016). The stock-class options in ASKBILL include mature dry wethers, weaners and reproductive ewes.

Simulating pasture growth and utilization by grazing sheep

As well as describing animal growth, the model also describes pasture growth and soil water dynamics in relation to daily climatic inputs for rainfall, maximum and minimum temperature, solar radiation, vapour pressure and wind speed. The focus is on analysis of historical pasture growth as it relates to animal production and projection of likely future growth. The beta release of ASKBILL (as described here) will use historical climate data to assess possible future management strategies (statistical model). Subsequent releases will use forecasts from the dynamical ACCESS-S model.

As an example of simulating pasture growth and utilisation by grazing sheep, consider mature dry sheep grazing at 10 wethers/hectare on a typical long-term improved pasture at Armidale, NSW (30.5016° S, 151.6662° E) containing a mixture of native and introduced species. The focus of this simulation is to run the model to 1 September 2015 and then assess feeding strategies for the next 3 months, as if today were 1 September 2015. Such hindcast analyses enable comparison of simulated and actual data. In this example, the model runs to 1 September 2015 and then continues an ensemble of simulations from that date, using historical climate data, for all the three-month periods starting on 1 September from 1986 to 2014. These simulation results are used to inform future management decisions.

Live weight (Fig. 4a) and body condition score (Fig. 4b) are modelled, with known climate informing pasture growth, for the 9 months preceding 1 September 2015. From July to September, there was a steady decline in live weight, which is reflected in a noticeable drop in condition score. Although not shown here, this change is due to a decline in pasture availability to approximately 0.5 t/ha. Following that date, the projections are based on the ensemble of simulations with the 25th, 50th (median) and 75th percentile ranges providing a spread of future outcomes.

Fig. 4a and Fig. 4b

On 1 September, the condition score was estimated to be 2.6 and the simulations suggest there was a 50% chance of it being in the range of 2.0–2.2 by November; the actual (based on climate data for that year) condition score was 2.1, although this would not have been known at the time. Outside of this range, there remained a 25% chance that the condition score would fall below 2.0. It can also be seen that there was little variation in the expected change in condition score during the first 3 weeks after 1 September, suggesting limited expected pasture growth, and hence feed availability, during that time. This, in itself, is valuable predictive information from the model. To explore the effect of providing supplemental feed, the model was then run with different levels of a daily supplement, starting on the projection date of 1 September, to evaluate the likely response of condition score. Fig. 5 shows the condition score corresponding to Fig. 4b, but with either 100 g/d or 200 g/d of an 80% digestible supplement being fed.

Rather than iterate to find the level of supplemental feed that will achieve the target condition score, the user has the option to use the model to estimate the level of feed required to achieve the target. For example, if the target condition score by the end of the 90-day projection period were 2.8, the median level of supplement required would have been 170 g/d. Although not presented here, similar analyses can be done to estimate risk associated with achievement of a target body condition score in ewes or a target sale weight in weaners.

These analyses show how the pasture and animal simulation model in ASKBILL can be used to assess likely risk in relation to possible future climate scenarios and management decisions. Working with the 25th to 75th percentile range does not give the full risk profile but it is likely to be a useful indicator for producers. An important feature is the model's daily time-step with the next day's simulation informed by the previous day's weather. In this manner, the 90-day projection extends out from 2 September, followed by 3 September and so forth with the breadth of historic data extending at the same time. With the example discussed above, this time-step facilitates continual re-evaluation of feeding levels in response to known changes in pasture and animal condition.

Other functions are provided for each stock class. Feed budgets are a recognised approach to managing animal and pasture condition and are a useful component for forecasting seasonal stocking rates. Automatic calculation, and daily updates, of the feed budget are likely to assist planning. The animal growth model is able to link with the pasture model in ASKBILL to calculate stocking rates over a 90-day projection period (Fig. 6). In this example, sheep are grazed at 10 dry sheep units per hectare on a typical long-term improved pasture at Armidale, NSW as described earlier. From July to April, there was a decline in pasture availability. The projections commencing on 1 April 2014 indicate pasture availability in the range 0.9–1.1 t DM/ha by 1 July. Here, the user has indicated a pasture target of 1.3 t DM/ha by 1 July, which the model calculates can be achieved if the stocking rate is reduced to 7.5 dry sheep units per hectare.

Fig. 5 and Fig 6

Conclusion

Automated downloads of climatic data and daily recalculation of actual and forecast production information are designed to make it easier for producers and their advisors to use the power of the predictive biophysical models. This predictive functionality, combined with the comprehensive biophysical and physiological nature of the ASKBILL models, is expected to be particularly useful in managing risks and production opportunities that involve the interaction of nutritional status and climatic or parasite events.

Nutritional intervention often involves a considerable lead-time in order to have an impact on a production variable related to live weight or body condition score. Even short-term supplementary feeding requires gradual introduction and there is often a delay of several weeks before a feeding regimen has an impact on live weight change. For these reasons the long-range forecasting and predictions available through ASKBILL are expected to have a positive impact on sheep wellbeing and productivity.

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Captions for Figures

Fig. 1. Schematic of the flow of data and information through predictive biophysical models that underpin the ASKBILL program to provide alerts and 'what-if' options to assist management decisions.

Fig. 2a. Calibrated growth curve for total (solid), protein (dashes) and fat (dots) mass of a sheep with birth weight 4 kg and mature standard reference weight 60 kg at 20 kg (grey) or 30 kg (black) at 12 weeks of age. Note: protein includes the water component.

Fig. 2b. Metabolizable energy requirements;total (black solid), maintenance (black dashes) and growth (black dots) with components for protein maintenance (grey dash) and growth (grey dot), fat (black long dash dot) and heat (black long dash dot dot) also provided. Note: requirements were calculated for the 20 kg example shown in Fig 2a.

Fig. 3a. Growth rate corresponding to Fig 2a for an animal weighing 20 kg at 12 weeks of age.

Fig. 3b. Metabolizable energy required to achieve daily growth rates (g/d) of 200 (solid), 150 (dash), 100 (dot), 50 (long dash dot) and 0 (long dash dot dot) in relation to animal live weight. Note that 0 g/d corresponds to maintenance.

Fig. 4a. Simulated live weight of mature dry sheep grazing pasture. Live weight values prior to 1 September 2015 were simulated using known climate data to inform the model. After that date, an ensemble of simulations provided a range of 90-day projections and 75th (upper grey solid), 50th (black dots) and 25th (lower grey solid) percentiles.

Fig. 4b. Simulated body condition score of mature dry sheep grazing pasture. Condition score values prior to 1 September 2015 were simulated using known climate data to inform the model. After that date, an ensemble of simulations provided a range of 90-day projections and 75th (upper grey solid), 50th (black dots) and 25th (lower grey solid) percentiles.

Fig. 5. Simulated body condition score of mature dry sheep grazing pasture (as in Fig. 4b). Ninety-day projections of condition score when an 80% digestible supplement was fed at a level of 0 g/d (A), 100 g/d (B) or 200 g/d (C) and associated 75th (upper grey solid), 50th (black dots) and 25th (lower grey solid) percentiles.

Fig. 6. Simulated pasture availability of a typical long-term improved pasture at Armidale, NSW in response to a stocking rate of 10 dry stock unit/ha. From 1 April 2014, an ensemble of simulations provided a range of 90-day projections and 75th (upper grey solid), 50th (black dots) and 25th (lower grey solid) percentiles. The 50th percentile projection is shown for a stocking rate of 7.5 dry stock units /ha (black dashes).

Figures

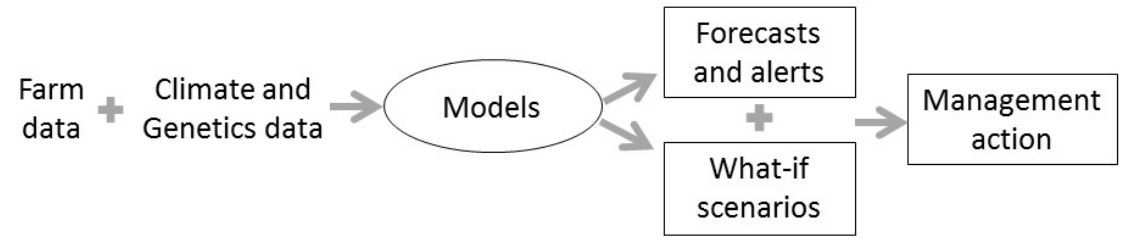


Fig. 1

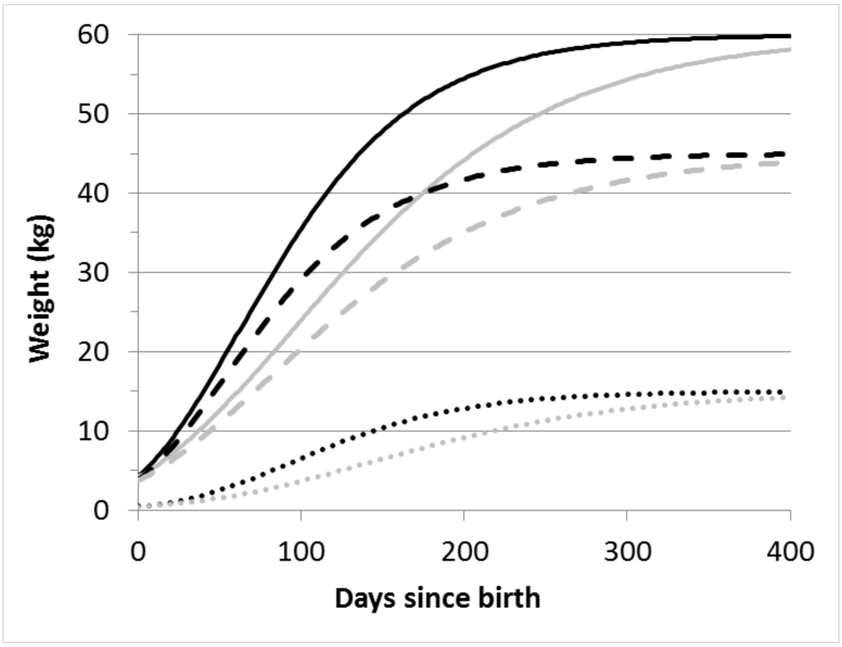


Fig. 2a

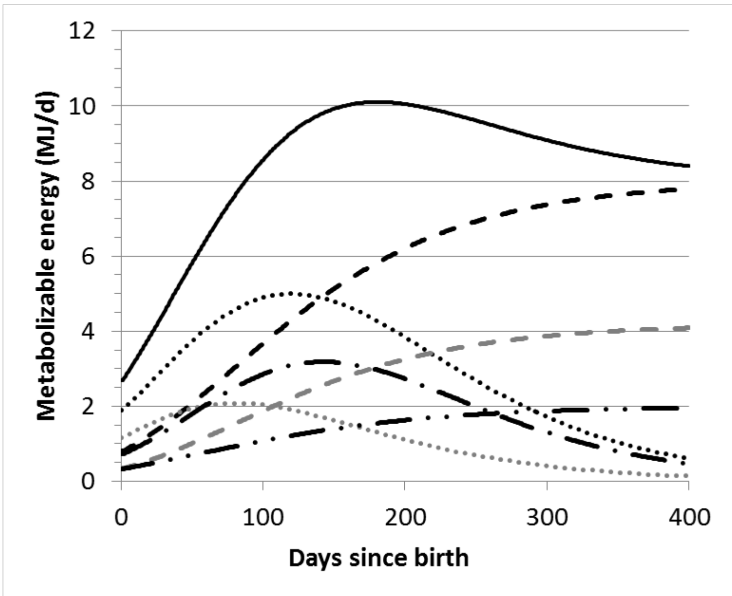

Metabolizable energy (MJ/d)
Days since birth
0
2
4
6
8
10
12
0
100
200
300
400

Fig. 2b

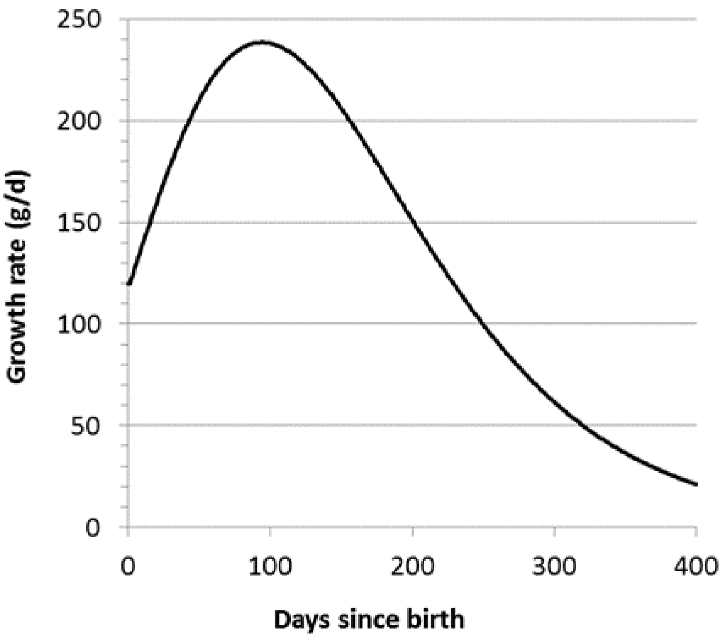

Growth rate (g/d)
Days since birth
0
50
100
150
200
250
0
100
200
300
400

Fig. 3a

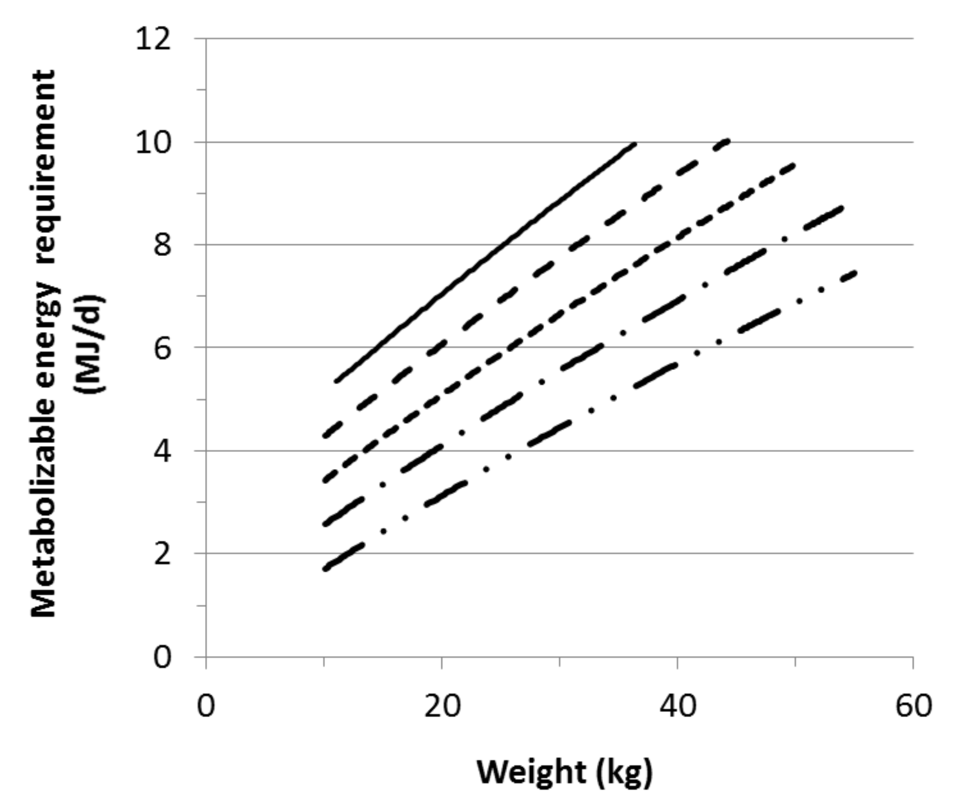

Metabolizable energy requirement (MJ/d)
Weight (kg)
0
2
4
6
8
10
12
0
20
40
60

Fig. 3b

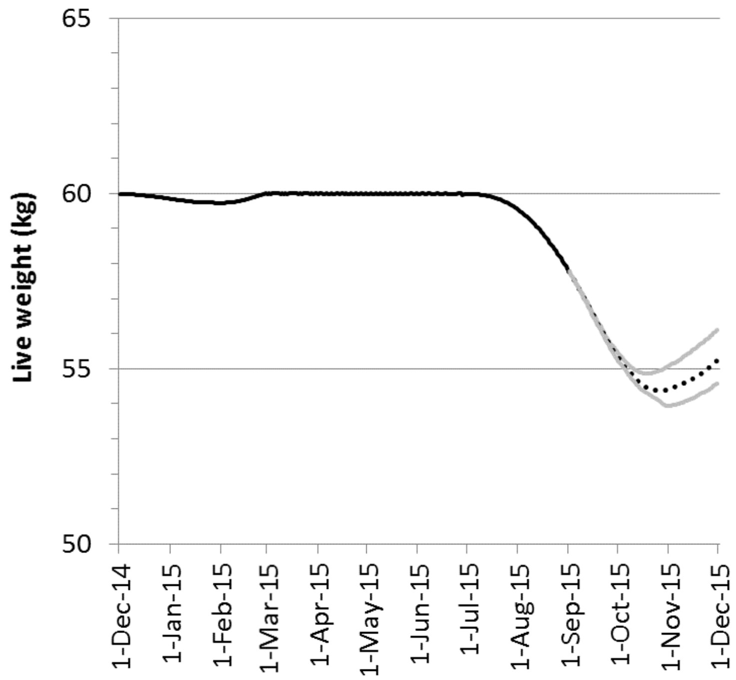
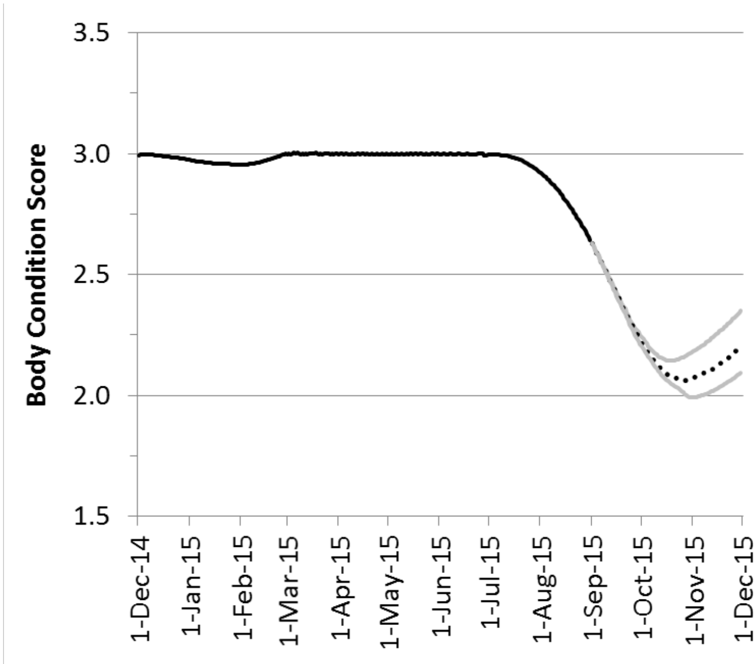

Live weight (kg)
50
55
60
65
1-Dec-14
1-Jan-15
1-Feb-15
1-Mar-15
1-Apr-15
1-May-15
1-Jun-15
1-Jul-15
1-Aug-15
1-Sep-15
1-Oct-15
1-Nov-15
1-Dec-15

Fig. 4a


Body Condition Score
3.5
3.0
2.5
2.0
1.5
1-Dec-14
1-Jan-15
1-Feb-15
1-Mar-15
1-Apr-15
1-May-15
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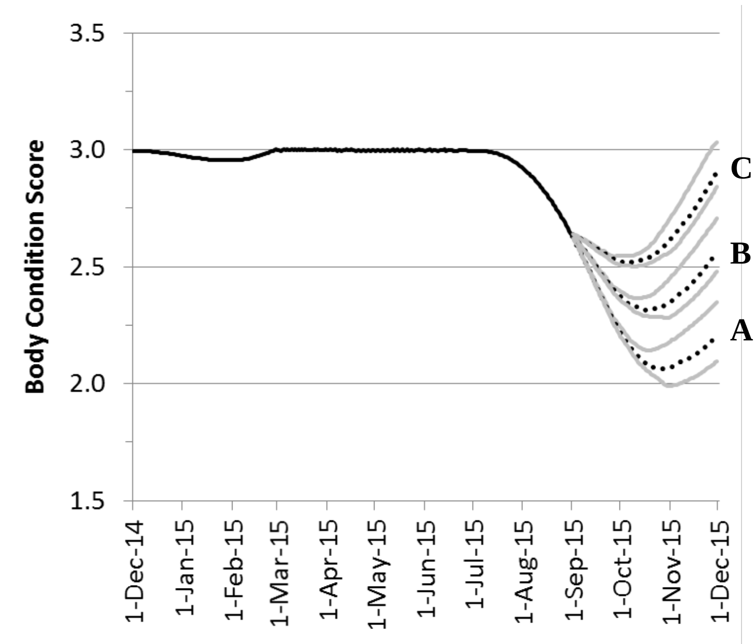
1-Oct-15
1-Nov-15
1-Dec-15

Fig. 4b


Body Condition Score
3.5
3.0
2.5
2.0
1.5
C
B
A
1-Dec-14
1-Jan-15
1-Feb-15
1-Mar-15
1-Apr-15
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1-Nov-15
1-Dec-15

Fig. 5

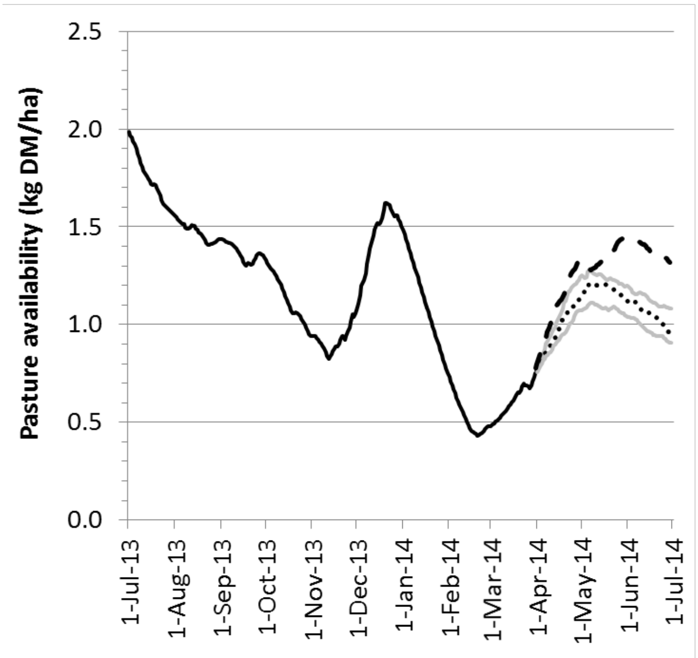
Pasture availability (kg DM/ha)
2.5
2.0
1.5
1.0
0.5
0.0
1-Jul-13
1-Aug-13
1-Sep-13
1-Oct-13
1-Nov-13
1-Dec-13
1-Jan-14
1-Feb-14
1-Mar-14
1-Apr-14
1-May-14
1-Jun-14
1-Jul-14

Fig. 6