final report

Project code: B.SBP.0125

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Date published: January 2015

ISBN: 9781741919608

PUBLISHED BY
Meat & Livestock Australia Limited
Locked Bag 991
NORTH SYDNEY NSW 2059

Algorithm for estimating producer carcass yield

Meat & Livestock Australia acknowledges the matching funds provided by the Australian Government to support the research and development detailed in this publication.

Abstract

The primary objective of this project was to estimate the producer carcass yield based on daily measurements of yield at the meat processing plant, which are derived from multiple producers. We found that it is feasible to estimate the average yields of individual producers from the ensemble measured by the processor. We tested the performance of the algorithm with simulated test data and real data from an Australian lamb meat processor and found that boning room yield for the top supplier to the processor was 83 ± 0.6%. The secondary objective of this project was to estimate the contribution of an individual sire group to carcass yield based on daily measurements of yield at the meat processing plant. Extending the methodology to deal with estimating meat yields of different sire families was also possible. This avoids the high phenotyping costs of measuring the yield of individual animals and will allow for more rapid genetic selection of yield and improved producer management of animals for yield. The algorithm will also allow for more rapid introduction of new sensor technology into meat processing plants. Future validation work will be required to benchmark the algorithm and develop a usable commercial product.

Executive summary

A meat processor is able to make daily measurements of the average meat yields of the carcasses processed. This measurement cannot directly discriminate differences in meat yield between individual producers because multiple producers are processed each day. However, a mathematical algorithm has been developed that can make this discrimination using the set of daily average meat yield estimates from the meat processor. Extending the methodology to deal with estimating meat yields of different sire families was also possible.

The algorithms applied in this project are based on bulk measurements of phenotype (yield from multiple carcasses as opposed to individual carcasses) in the processing plant. Such algorithms will therefore allow for more rapid introduction of new sensor technology into meat processing plants (bulk measurements from multiple carcasses are generally easier and cheaper than from individual carcasses).

We tested the performance of the algorithm with simulated test data and real data from an Australian lamb meat processor. Simulated data was based on best available information on the variability in producer yield and number of producers processed per day. For the simulated data the correlation between algorithm-estimated producer yield and actual producer yield after 2 years processing was r = 0.91 (based on 365 producers and a 1% yield sensor accuracy). The correlation between algorithm-estimated sire group yield and actual sire group yield after 2 years processing was r = 0.99 (based on 20 sire groups). For the real data the algorithm was able to separate producers with low/high boning room yield although the estimates were dependent on the number of animals supplied by each producer (the estimated boning room yield for the top supplier to the processor was 83 ± 0.6%). We found that producers outside the top 50 producers supplying the processing plant largely contributed noise to the estimation procedure, although information from multiple years and multiple processors could be used to refine the estimates of yield for individual producers (the top 50 producers supplied 50% of the lambs to the processor). The algorithm also demonstrated that it was feasible to estimate the lamb boning room yield for 20 hypothetical sire

groups (producers were randomly assigned to a single sire group because the direct link between producers and sire groups was unknown for this dataset).

On-farm productivity will increase directly as a result of this project through improved selection schemes for yield. There are no anticipated farm level costs associated with adopting the outputs of this project. Meat processors will initially directly benefit from the R&D (breeders/farmers will also indirectly benefit through accelerated breeding schemes for yield). Future research and development work will be required to develop a usable commercial product.

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1. Background

A mathematical method of determining the contribution of various individuals making up a time series of single bulk measurements has been developed. The method takes into account the variation and uncertainty typical of biological processes. The method has been extensively tested using simulations and a modification has already been applied to a problem in the dairy industry. The method has been shown to work in these contexts.

The goal of the proposal is to configure the algorithm to deal with the estimation of meat yields associated with individual producers from daily bulk measurements of meat yield made at the meat plant. Simulation studies will be used to demonstrate that:

- The algorithm can reliably recover differences in meat yield from individual producers from measurements of bulk daily yield (an average of yield from carcasses contributed by a number of producers).
- The errors associated with these estimates can be determined and that these errors are small enough to be useful to the lamb industry.

Carcass yield is an important trait for both farm and meat processor profitability. Yield is determined by genetics, environmental and management factors. Although heritability estimates of yield are well known selection gains are impeded by the phenotyping cost of measuring the yield of the progeny of an individual sire group. Similarly it is difficult for meat processors to associate yield with individual producers. This project aims to use available meat processer information to estimate the producer yield and the yield of the progeny of an individual sire group. This will allow for more rapid genetic selection of yield and improvement in producer management of animals for yield.

This project is a necessary first step in improving the flow of information from the meat processor up the supply chain to the producer and animal breeder. More effective transfer of information in the red meat industry supply chain will improve the productivity of the individual components of the supply chain as well as the entire supply chain. There is also an opportunity to extend this methodology to other traits of interest in the supply chain.

2. Project objectives

The primary objective of this project is to estimate the producer carcass yield based on daily measurements of yield at the meat processing plant, which are derived from multiple producers. That is, estimate the average yields of individual producers from the ensemble measured by the processor. The secondary objective of this project is to estimate the contribution of an individual sire group to carcass yield based on daily measurements of yield at the meat processing plant. This will allow for more rapid genetic selection of yield and improvement in producer management of animals for yield.

3. Methodology and results

In this section we outline the performance of the algorithm with simulated test data (Scenario 1) and real data from an Australian meat processor (Scenario 2). Simulated data is based on best available information on the variability in producer yield and number of producers processed per day. We outline simulations of the algorithm to estimate individual producer lean meat yield from daily average measurements of lean meat yield at the meat processor. The algorithm is also used to estimate sire group lean meat yield from daily average measurements of lean meat yield at the meat processor.

Scenario 1: Producer Yield

Lean meat yield (LMY, %) has a reported mean of 46.3%, a phenotypic variance of 6.26 and a heritability of 0.34 ± 0.05 in Australian sheep (Mortimer et al., 2010). We assume that the average yield is 46% with a standard deviation of 2.5% between producers. The standard deviation in yield between animals within producer is assumed to be 2.5%. In this simulation there are assumed to be 365 producers that supply the meat processor. Each producer supplies a total of 4000 animals to the processor each year. Each producer supplies 500 animals to the processor at a random time within successive 6.5 week intervals over the year. The meat processor processes 4000 lambs per day (i.e., 8 producers per day). The measurement accuracy of daily yield at the processor is assumed to have a coefficient of variation (CV) of 1% (i.e., 46% ± 0.46%).

The simulated measured daily yield (%) over 2 years at the meat processor is shown in Fig. 1. The relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor is shown in Fig. 2. In this example the correlation between algorithm-estimated producer yield and actual producer yield after 2 years is r = 0.91.

A requirement for better performance of the algorithm is that the number of days that yield is measured (2 years) is greater than the number of producers (365 days). This ensures that there is a greater number of measurements (daily processor yield) than unknown parameters (producer yields). However, the algorithm will still perform if the number of days that yield is measured is less than the number of producers. The relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor with 1.5 years of processor data is shown in Fig. 3. The correlation between algorithm-estimated producer yield and actual producer yield after 1.5 years is r = 0.79.

The measurement accuracy of daily yield at the processor has a key role on the performance of the algorithm. The relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 2% yield sensor is shown in Fig. 4. In this example the correlation between algorithm-estimated producer yield and actual producer yield after 2 years is r = 0.70.

It is more difficult for the algorithm to detect differences between producers if the variance between producers is low. If the average yield is assumed to be 46% with a standard deviation of 1.25% between producers (the standard deviation in yield between animals within producer is assumed to be 2.5%) then the relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor with 2 years of processor data is shown in Fig. 5. The correlation between algorithm-estimated producer yield and actual producer yield after 2 years is r = 0.75.

It is more difficult for the algorithm to detect differences between producers if the producers supply a smaller number of animals on a more frequent basis. If each producer supplies 250 animals to the processor at a random time within successive 3.25 week intervals over the year (i.e., 16 producers per day) then the relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor is shown in Fig. 6. In this example the correlation between algorithm-estimated producer yield and actual producer yield after 2 years is r = 0.82.

Scenario 1: Sire Group Yield

The algorithm can also be used to estimate the yield for different sire groups. We assume that the 365 producers each belong to one of 20 sire groups (assuming for simplicity that producers source sires from a single sire group). We assume that the standard deviation in yield between sire groups is 2.5% (the standard deviation in yield between animals within producer is assumed to be 2.5%). The relationship between the algorithm predicted sire group yield (%) and actual sire group yield (%) for a 1% yield sensor is shown in Fig. 7. In this example the correlation between algorithm-estimated sire group yield and actual sire group yield after 2 years is r = 0.99.

The algorithm also performs well if the standard deviation in yield between sire groups is reduced to 1.25% (the standard deviation in yield between animals within producer is assumed to be 2.5%). For this example the relationship between the algorithm predicted sire group yield (%) and actual sire group yield (%) for a 1% yield sensor is shown in Fig. 8. In this example the correlation between algorithm-estimated sire group yield and actual sire group yield after 2 years is r = 0.98.

The algorithm also performs well if we assume that the 365 producers belong to 60 sire groups. We assume that the standard deviation in yield between sire groups is 2.5% (the standard deviation in yield between animals within producer is assumed to be 2.5%). The relationship between the algorithm predicted sire group yield (%) and actual sire group yield (%) for a 1% yield sensor is shown in Fig. 9. In this example the correlation between algorithm-estimated sire group yield and actual sire group yield after 2 years is r = 0.98.

Scenario 2: Algorithm testing with real meat processor lamb data

Daily boning room yield for lamb and lamb supply records were obtained from an Australian meat processor for 2014. The algorithm predicted boning room lamb yield (%) for the top 50 producers to the processing plant (229 working days in 2014) is shown in Fig. 10. The mean boning room yield for producers was 84.2%. The top 50 producers supply 50% of the lambs to the processor, the top 25 producers supply 41% of the lambs to the processor and the top 10 producers supply 33% of the lambs to the processor. There were 635 unique producers supplying the processor in 2014. The calculation assumes that the variance in boning room yield between producers (σ_p^2) and the measurement error variance in boning room yield (σ_e^2) are known (σ_p = 4% (based on Mortimer et al., 2010), σ_e = 1.5% (based on typical weighing accuracy/repeatability)). The algorithm is able to separate producers with low/high boning room yield although the estimates are dependent on the number of animals supplied by each producer. The estimated boning room yield for the top supplier to the processor was 83 ± 0.6%. Producers outside the top 50 producers supplying the processing plant largely contribute noise to the estimation procedure, although information from multiple years and multiple processors could be used to refine the estimates of yield for individual producers.

The algorithm predicted lamb boning room yield (%) for a hypothetical grouping of producers into 20 sire groups (producers randomly assigned to a single sire group) is shown in Fig. 11. This demonstrates that it is feasible to estimate the lamb boning room yield (%) for individual sire groups (although the direct link between producers and sire groups is unknown for this dataset).

4. Discussion/conclusion

The algorithms applied in this project are based on bulk measurements of phenotype (yield from multiple carcasses as opposed to individual carcasses) in the processing plant. Such algorithms will therefore allow for more rapid introduction of new sensor technology into meat processing plants (bulk measurements from multiple carcasses are generally easier and cheaper than from individual carcasses).

The algorithm applied during this project is a proof of concept only and benchmarking the performance of the algorithm is beyond the scope of this research project. It would thus not be recommended for any commercial use without further validation work being undertaken.

5. Figures

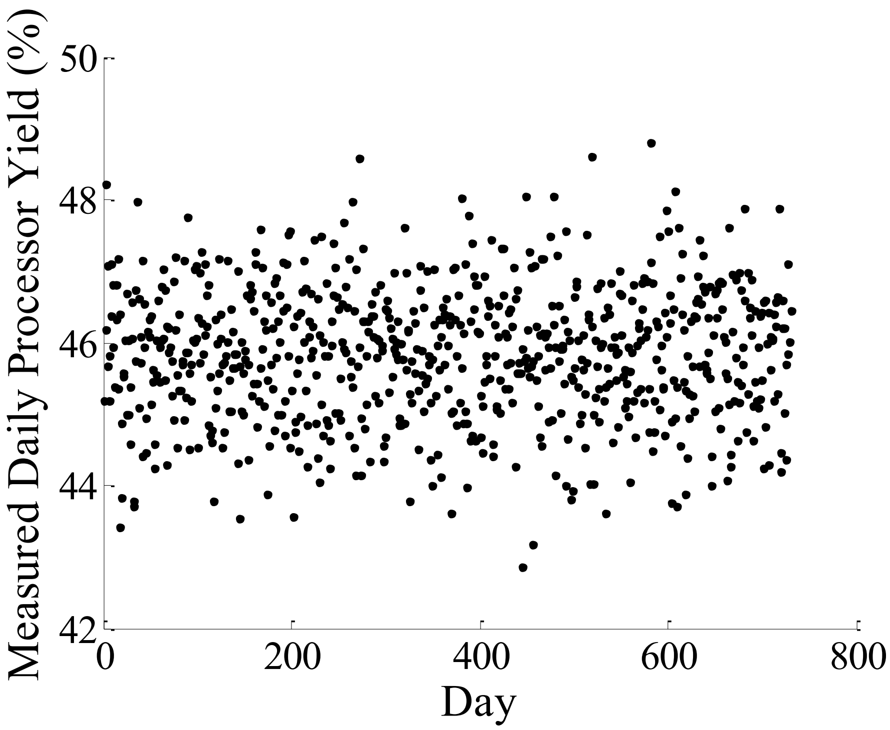

Figure 1: The simulated measured daily average yield (%) over two years at the meat processor (Scenario 1).

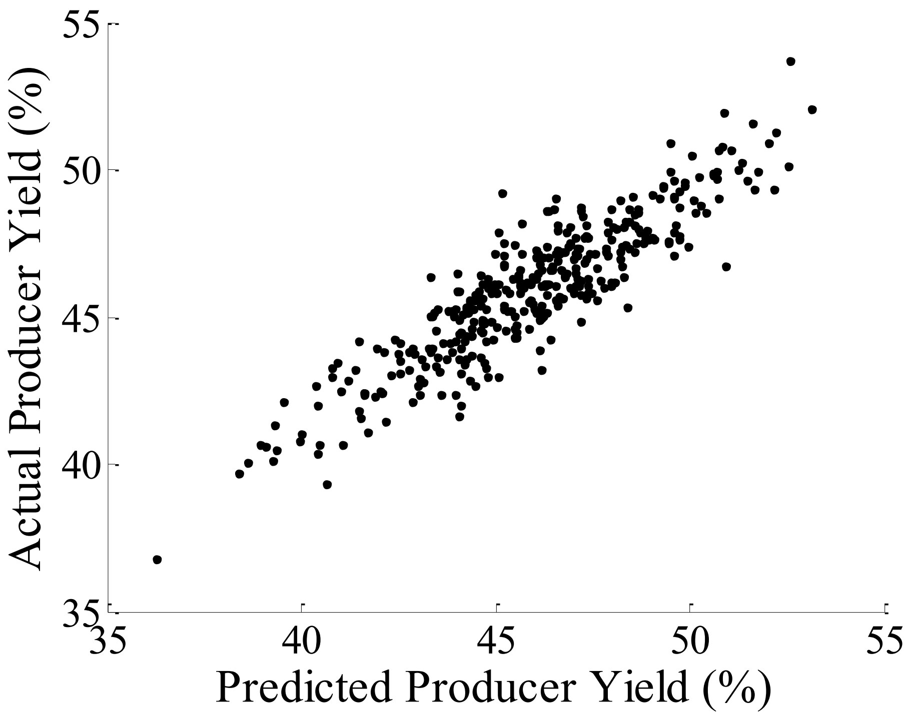

Figure 2: Relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor (Scenario 1, 2 years processor data, standard deviation in LMY between producers is 2.5%, 8 producers per day). R^2=0.82.

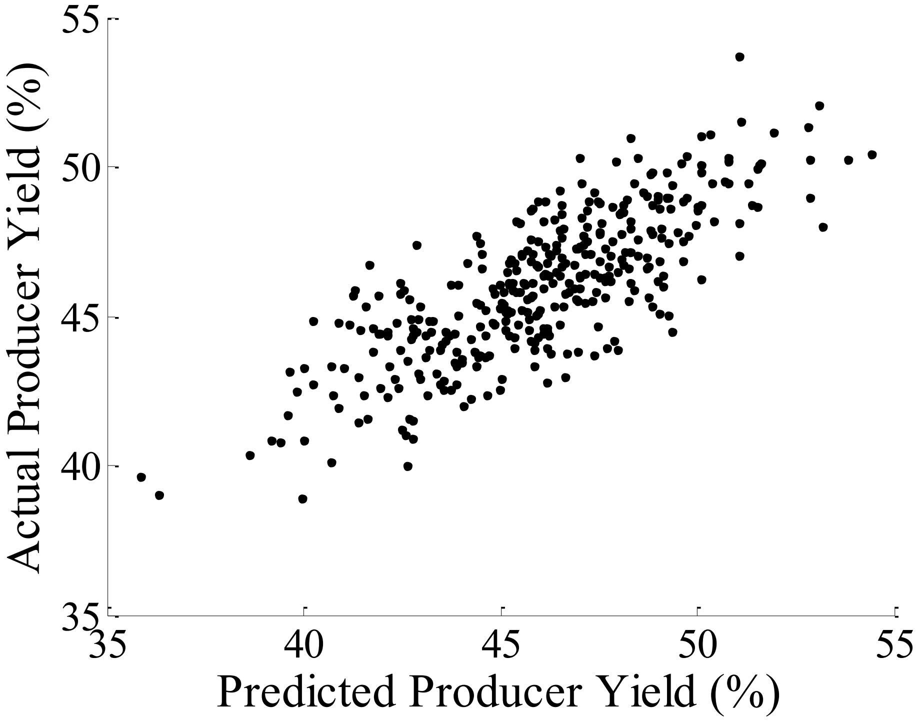

Figure 3: Relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor (Scenario 1, **1.5** years processor data, standard deviation in LMY between producers is 2.5%, 8 producers per day). R^2=0.63.

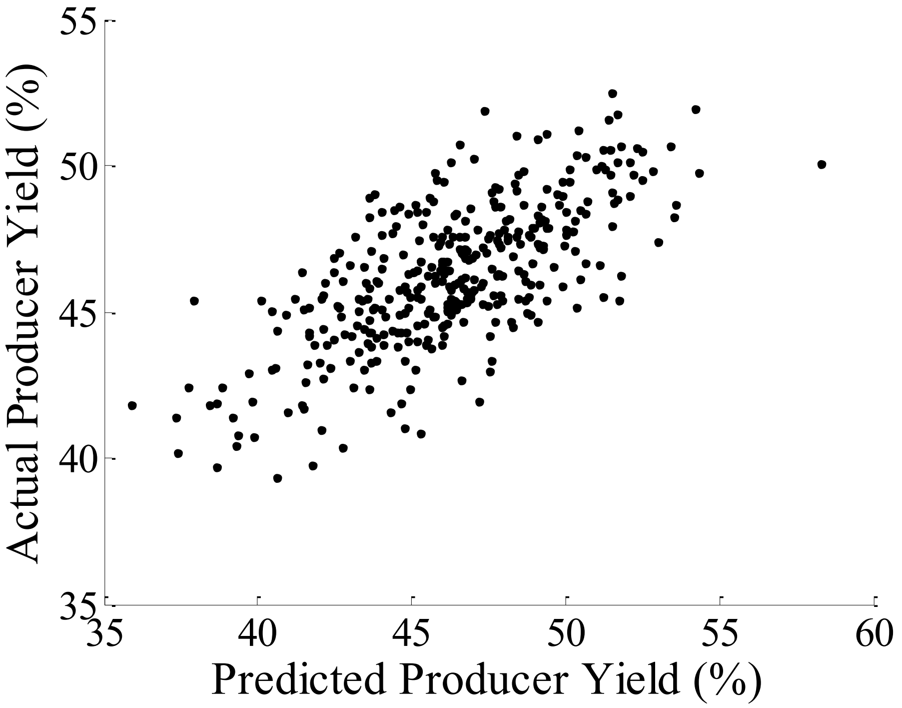

Figure 4: Relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a **2%** yield sensor (Scenario 1, 2 years processor data, standard deviation in LMY between producers is 2.5%, 8 producers per day). R^2=0.49.

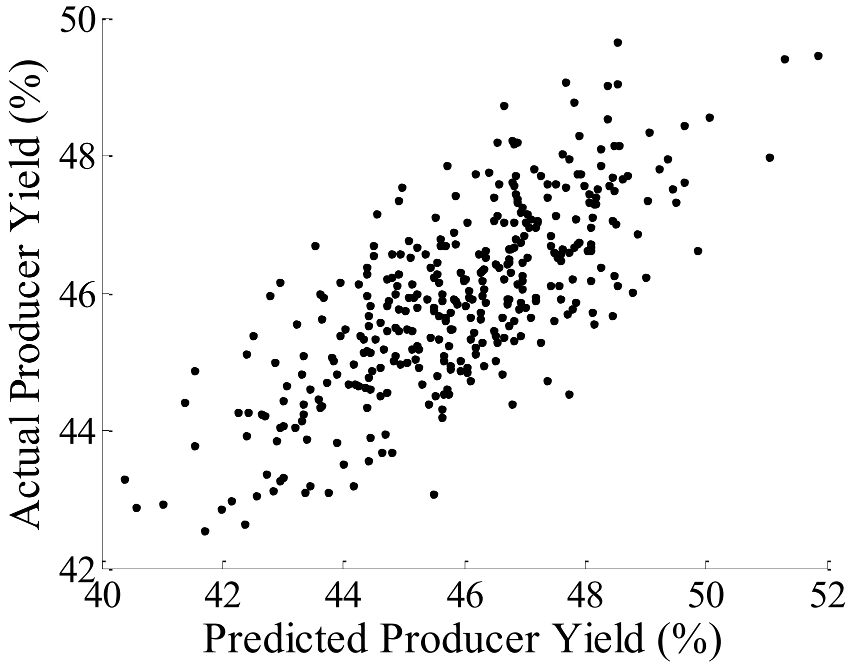

Figure 5: Relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor (Scenario 1, 2 years processor data, standard deviation in LMY between producers is **1.25%**, 8 producers per day). R^2=0.56.

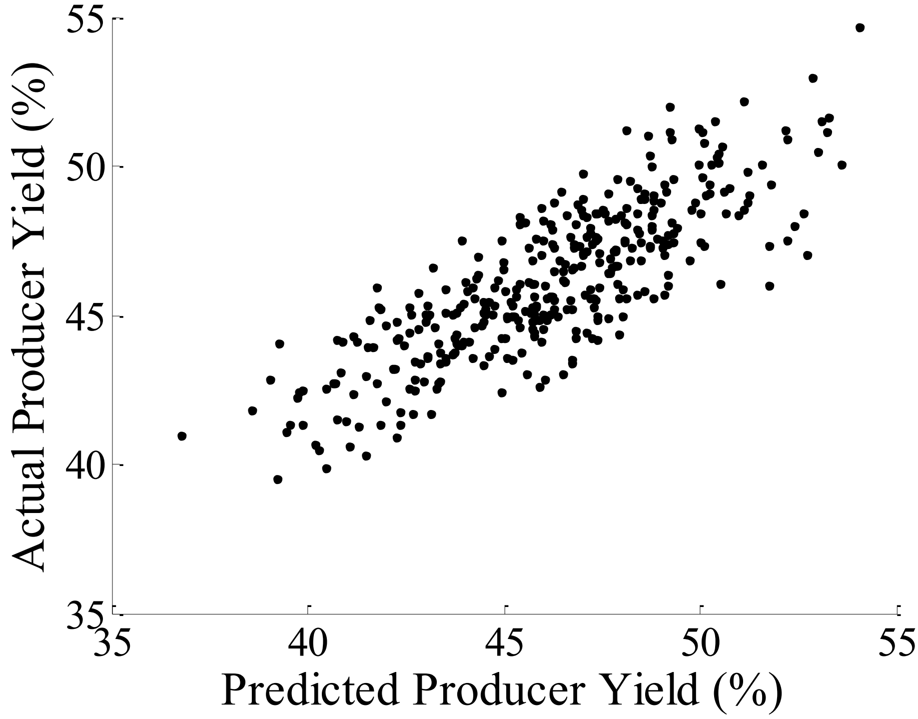

Figure 6: Relationship between the algorithm predicted producer yield (%) and actual producer yield (%) for a 1% yield sensor (Scenario 1, 2 years processor data, standard deviation in LMY between producers is 2.5%, **16** producers per day). R^2=0.65.

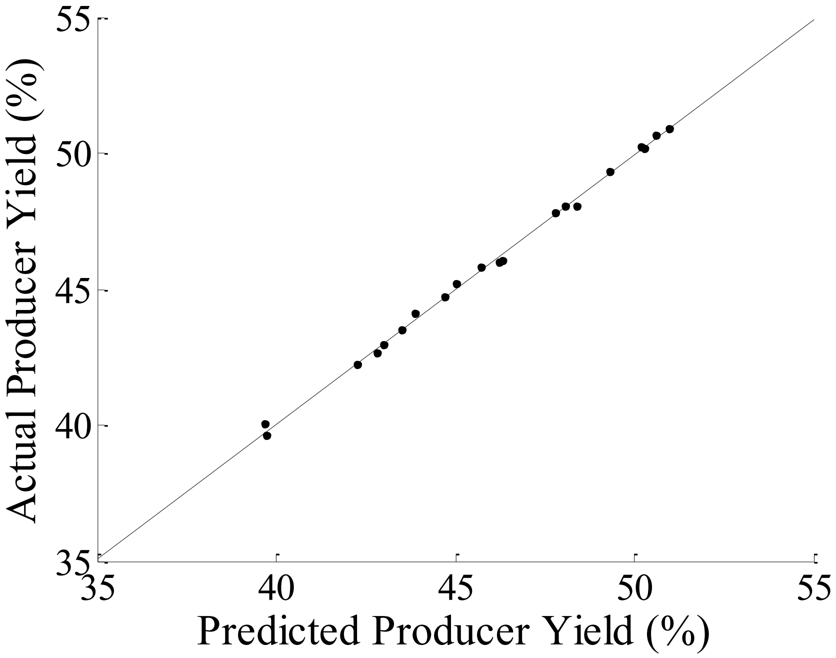

Figure 7: Relationship between the algorithm predicted sire group yield (%) and actual sire group yield (%) for a 1% yield sensor (Scenario 1, 2 years data, standard deviation in LMY between sire groups is 2.5%, 20 sire groups). R^2=0.99.

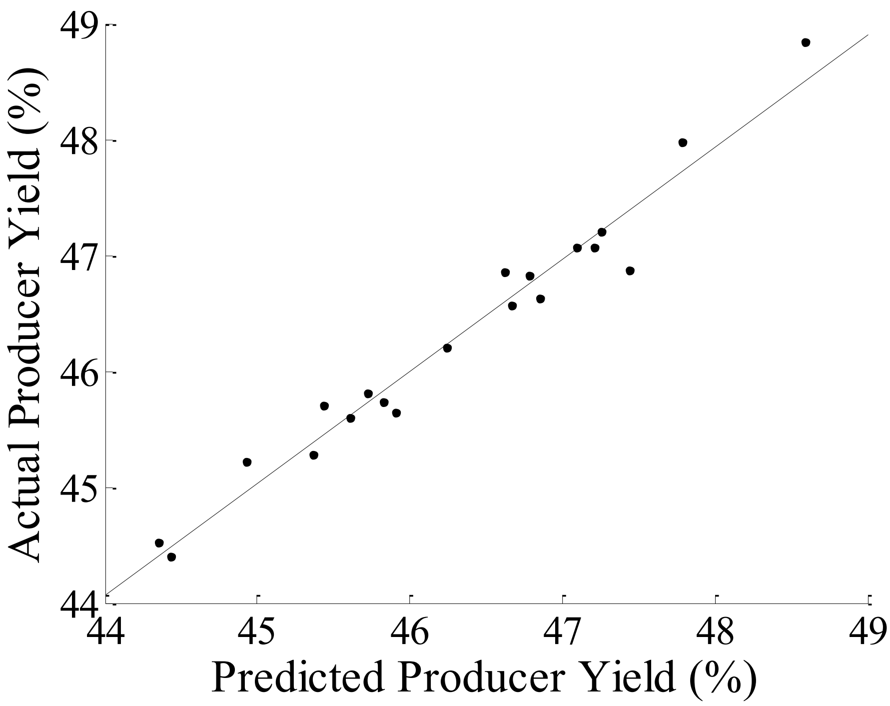

Figure 8: Relationship between the algorithm predicted sire group yield (%) and actual sire group yield (%) for a 1% yield sensor (Scenario 1, 2 years data, standard deviation in LMY between sire groups is **1.25%**, 20 sire groups). R^2=0.97.

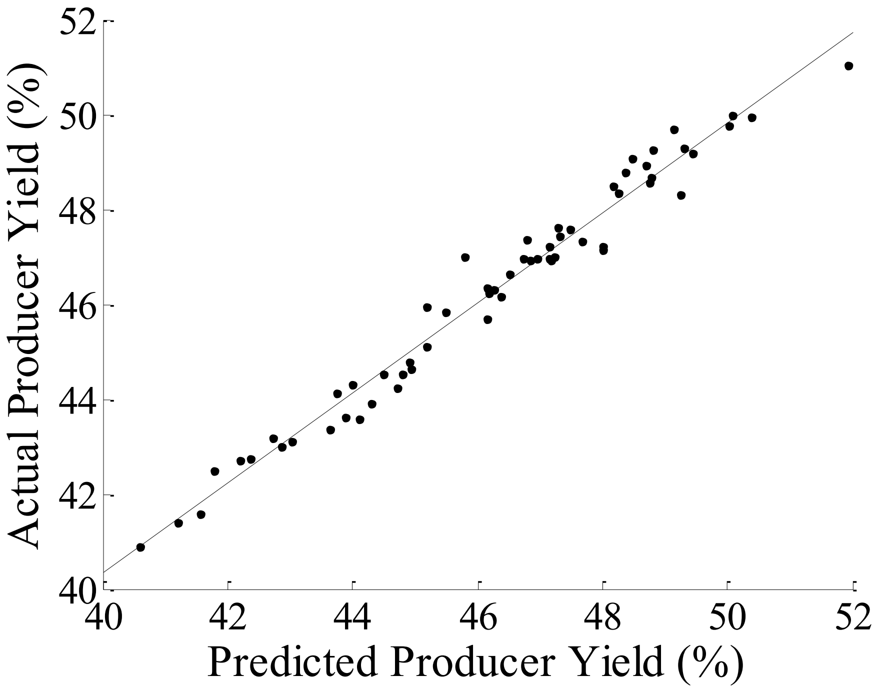

Figure 9: Relationship between the algorithm predicted sire group yield (%) and actual sire group yield (%) for a 1% yield sensor (Scenario 1, 2 years data, standard deviation in LMY between sire groups is 2.5%, **60** sire groups). R^2=0.97.

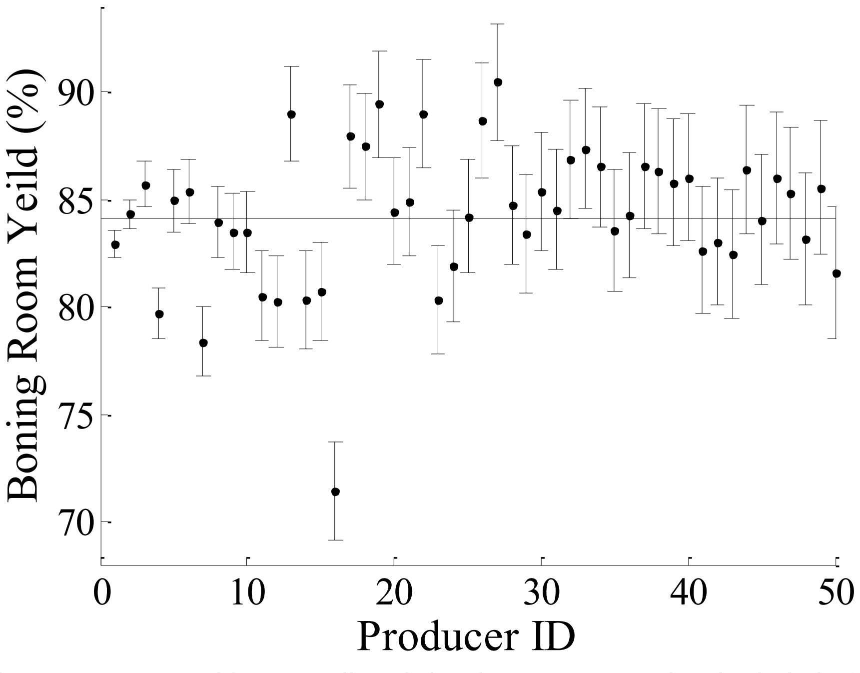

Figure 10: Algorithm predicted boning room lamb yield (%) for the top 50 producers to the processing plant (229 working days in 2014). The top 50 producers supply 50% of the lambs to the processor. Error bars denote standard errors and the horizontal line denotes the mean boning room yield for 2014. Producers are listed in decreasing order of standard error.

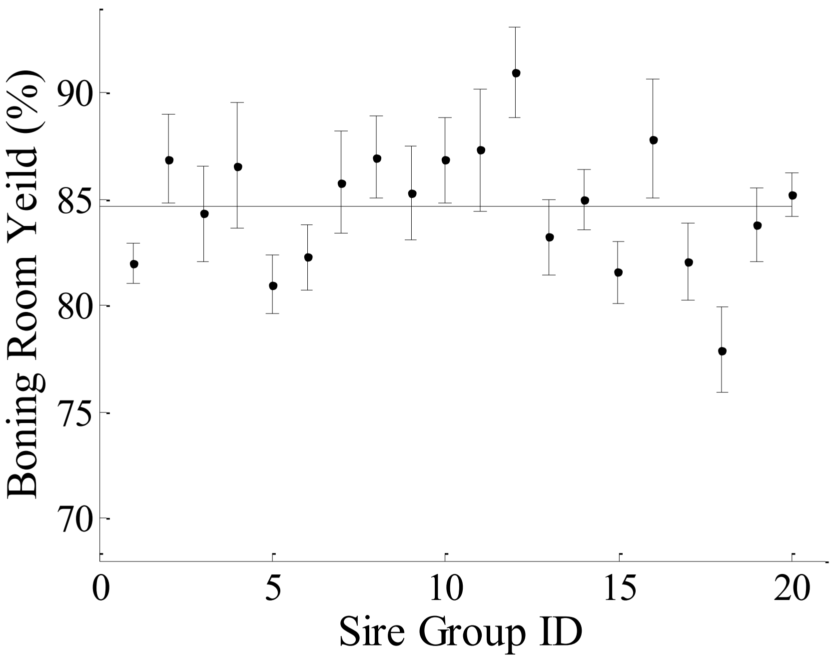

Figure 11: The algorithm predicted boning room lamb yield (%) for a hypothetical grouping of producers into 20 sire groups (635 producers randomly assigned to a single sire group). Error bars denote standard errors and the horizontal line denotes the mean boning room yield.

6. References

S. I. Mortimer, J. H. J. van der Werf, R. H. Jacob, D.W. Pethick, K. L. Pearce, R. D. Warner, G. H. Geesink, J. E. Hocking Edwards, G. E. Gardner, E. N. Ponnampalam, S. M. Kitessa, A. J. Ball and D. L. Hopkins 2010. Preliminary estimates of genetic parameters for carcass and meat quality traits in Australian sheep. Animal Production Science, 2010, 50:1135–1144.