A Bayesian model of pasture curing

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Key Words
Modelling, pasture growth, curing

Introduction

Curing percentage (the percentage of dead material in the sward) is a necessary component of fire behaviour modelling and subsequent fire danger ratings in grasslands. Current methods of estimating curing have limitations. Curing is controlled by leaf turnover in grasses but individual leaf turnover rates of themselves do not give estimates of curing. Bayesian modelling provides the potential to incorporate leaf turnover rates representing the entire life cycle of each leaf into a standalone model of curing from which statistical summaries can be generated and used in field models. In this study, curing percentage was estimated over thermal time for four common C3 grasses, and tested against field data.

Methods

Leaf appearance rate, leaf elongation rate, leaf length, leaf life span, and leaf senescence rate were calculated from measurements conducted on wheat (*Triticum aestivum* L., cv. "Bob White"), annual ryegrass (*Lolium rigidum* Gaud., cv. "Wimmera"), phalaris *(Phalaris aquatica* L., cv. "Holdfast"), and brown-back wallaby grass (*Rytidosperma duttonianum* (Cashmore) Connor & Edgar) plants grown under optimal conditions (night/day temperature16°C/22°C; 15 hour photoperiod; adequate nutrition and water) in a glasshouse at the South Australian Research and Development Institute's Plant Research Centre at Waite Campus, Adelaide, South Australia.

The Bayesian model consisted of a series of linked non-linear sub-models that individually described leaf appearance rate, leaf elongation rate, leaf length, leaf life span, and leaf senescence rates as functions of degree-days. A Bayesian framework allowed all leaves and all plants of each species to be modelled simultaneously (Figure 1). The sub-models were used to form a single model that simultaneously described growth and senescence in individual leaves from 30 plants.

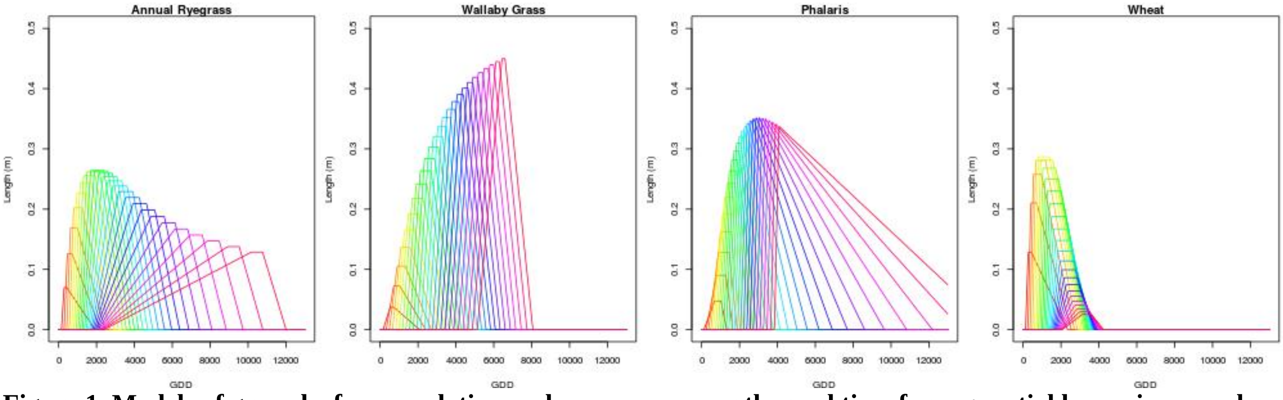

Figure 1. Models of green leaf accumulation and senescence over thermal time for sequential leaves in annual ryegrass, wallaby grass, phalaris and wheat, respectively.

Results

The graph of percentage dead matter derived from the mean of the posterior distributions of accumulation of predicted leaf biomass with thermal time for each species is shown in Figure 2.a.

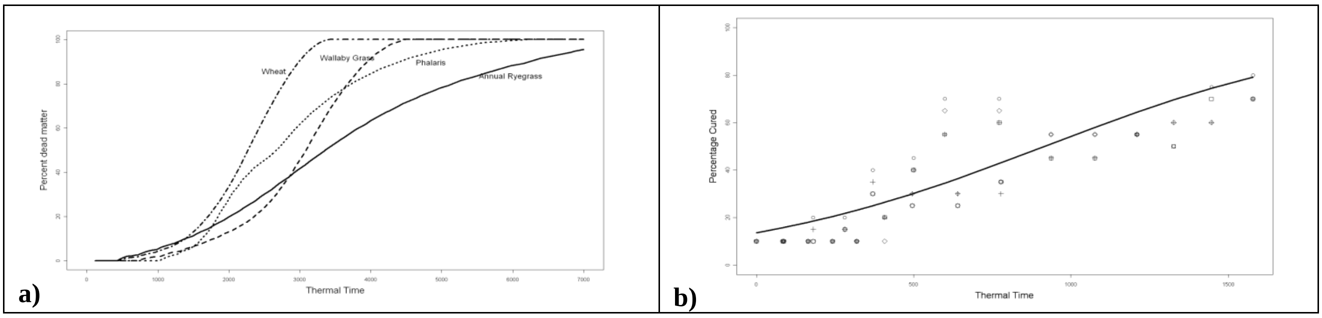

Figure 2. a) Percentage dead matter (calculated from posterior means) accumulated over thermal time for wheat, wallaby grass, phalaris and annual ryegrass; b) logistic curve based on the Bayesian model for phalaris (line) fitted against visual curing observations from four sub-districts of the Naracoorte Lucindale Council over thermal time (gdd (T_{base}=0□C) in the 2009-2010 and 2010-2011 fire seasons: ○) Frances; +) Avenue; □) Callendale; ◇) Wrattonbully.

The model was then used to generate predictions for the same species. A direct comparison against independent field curing observations was not possible because accounting for thermal time accumulation began later in plant growth and development in the field compared to the glasshouse plants used to generate the model. Logistic curves were fitted to the Bayesian model predictions and these logistic models were then compared to the field data. The suitability of the phalaris logistic curve to the field data from SE South Australia (Figure 2.b) reflects the characteristic fit of perennial species to the climatic and soil conditions of that region. The logistic curves from the other species may be better suited to other climatic areas, where grasses with other growth types dominate.

Conclusion

The Bayesian model detected differences between species in relation to the pattern of curing with thermal time (Figure 1) and while the shape was similar between wheat and wallaby grass, it differed in timing. The Bayesian models for both phalaris and annual ryegrass were similar to each other in shape, particularly after 60% curing had been reached (Figure 2.a).

Although visual assessment of curing is problematical (Cheney *et al.* 1998; Anderson *et al.* 2011; Newnham *et al.* 2011), it is still widely used by fire agencies. The logistic curve for phalaris matched the visually assessed curing records of the Naracoorte Lucindale Council in two fire seasons (Figure 2.b). The variation in curing between the two sources was well within the range reported between visual and destructive methods in the field (Anderson *et al.* 2011). The Bayesian curing model shows promise as a standalone model for estimating curing for fire management purposes.

References

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