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Using seasonal stochastic dynamic programming to identify optimal management decisions that achieve maximum economic sustainable yields from grasslands under climate risk

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ABSTRACT

There are significant challenges in managing the trade-offs between the production of pastures and grazing livestock for profit in the short term, and the persistence of the pasture resource in the longer term under stochastic climatic conditions. The profitability of using technologies such as grazing management, fertiliser inputs and the renovation of pastures are all influenced by complex inter-temporal relations that need to be considered to provide suitable information for managers to enhance tactical and strategic decision making.

In this study pasture is viewed as an exploitable renewable resource with its state defined by total pasture quantity and the proportion of desirable species in the sward. The decision problem was formulated as a stochastic dynamic programming (SDP) model where the decision variables are seasonal stocking rate and pasture re-sowing and the objective is to maximise the present value of future economic returns. The solution defines the optimal seasonal decisions for all intervening states of the system as uncertainty unfolds.

The model was applied to a representative farm in the high rainfall temperate pasture zone of Australia and the pasture states under which tactical grazing rest, low stocking rates and pasture re-sowing are optimal were identified. Results provide useful general insights as well as specific prescriptions for the case study farm. The framework developed in this paper provides a means of identifying optimal tactical and strategic decisions that achieve maximum sustainable economic yields from grazing systems.

1. Introduction

Managing any grazing system effectively requires an understanding of the complex dynamic interactions between the state of the pasture resource and the application of different technologies while also considering the influences of a stochastic climate on decision making. Relevant technologies include grazing management, fertiliser application and the renovation of pastures through the introduction of new species. The decision maker needs to account for multiple and conflicting objectives of pasture resource production, persistence of desirable pasture species, livestock productivity and profit (Behrendt et al., 2013a).

The decisions for developing and managing a pasture resource occur at different stages over the planning horizon. For example, in most grazing enterprises, the renovation of a pasture with sown species is a long-term strategic decision, whereas the application of fertiliser tends to operate at a more tactical level within production years. Grazing management includes both stocking rate and time livestock spend grazing a paddock (and the corresponding rest periods from grazing) as decision variables. This means that grazing management operates at a tactical level, over periods ranging from a year in so-called 'set stocking' systems to days in intensive rotational grazing systems, but it also operates at a strategic level in the context of herd management maintaining a targeted stocking rate.

The benefits of each technology cannot be considered in isolation because of the presence of interactions between the technologies and sources of exogenous risk to the grazing system, such as climate and price variability (Antle, 1983; Hutchinson, 1992). These interactions occur over the short term through the production of pasture, and over the longer term through changes in the botanical composition of the pasture, which include both desirable and undesirable species groups (Dowling et al., 2005; Hutchinson, 1992). Botanical composition change has frequently been considered in rangeland studies (Stafford Smith et al., 1995; Torell et al., 1991), but has largely been neglected in temperate grasslands. Solutions to the complex problem of defining inter-temporal trade-offs between the productivity of a grazing system and

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the persistence of both desirable and undesirable species within pastures, can be obtained by modelling grasslands as exploitable renewable resources (Clark, 1990) using a bioeconomic approach.

In summary, the farm manager faces a complex, dynamic decision problem that involves multiple and conflicting objectives of pasture resource production and persistence, livestock productivity, and profit. The decision problem sits within a dynamic and risky environment, with investments in sowing pastures, building (and depleting) soil fertility and grazing management being made whilst considering the state of the pasture resource as it responds to uncertain climatic conditions. In essence, this is a sequential decision problem (Behrendt et al., 2013a), where producers manage the grazing system by making both tactical and strategic decisions at intervening states of the system as uncertainty unfolds (Trebeck and Hardaker, 1972). Climate risk is embedded within the sequential decision problem (Behrendt et al., 2013a; Hardaker et al., 1991), influencing the state of the system after decisions are made and before income is received.

The state of the grassland resource at any time can be represented as a set of three state variables: herbage mass, botanical composition, and soil fertility. The pasture state can be influenced by the strategic decisions available to the producer, such as re-sowing of a pasture with desirable species and choosing the most appropriate stocking rate, as well as tactical decisions, such as fertiliser application and grazing management. In a multi-area grazing system, such as a farm with multiple paddocks, a mosaic of pasture states and soil fertility conditions exist and the decision problem becomes more complex.

The exclusion of seasonal variability and tactical responses embedded in a sequential decision process has been shown to provide incorrect estimates of the economic benefits of a technology involved in complex biological and dynamic systems (Marshall et al., 1997). Finding optimal development paths in the pasture resource problem requires embedded risk to be considered. That is, any development plan needs to be adjusted over time depending on uncertain events and states that influence economic returns and occur as the farm plan evolves. This situation defines conditions whereby the pasture resource problem may be formulated as a stochastic dynamic programming problem (Kennedy, 1986).

In this paper, we develop a bioeconomic framework to optimise pasture development and management where both pasture quantity and quality are considered within a stochastic environment. The model is used to derive optimal tactical and strategic decision rules that will result in maximum economic sustainable yields from the pasture resource.

2. Methods

The framework developed takes into account the impact of embedded climate risk, technology application and management on the botanical composition of the pasture resource over time which, in turn, impacts on optimal management strategies. This is achieved through the use of two simulation models, *AusFarm* (CSIRO, 2007) and the dynamic pasture resource development (DPRD) simulation model, described in Behrendt (2008); Behrendt et al. (2013a) and Behrendt et al. (2013b). The *AusFarm* model, a complex biophysical simulation model, was calibrated to data from the Cicerone Project farmlet experiment (Scott et al., 2013), and it was used to derive pasture production parameters for the DPRD model. The DPRD model was then used to solve the decision problem using a seasonal stochastic dynamic programming (SDP) framework.

2.1. Seasonal stochastic dynamic programming model

The SDP solution process uses four seasonal transition probability matrices that are applied sequentially to solve a recursive equation with the objective of maximising the expected net present value of returns from sheep production systems over the long run. The SDP model finds seasonally optimal tactical and strategic decision rules in terms of stocking rates and pasture sowing, as functions of pasture mass and composition (proportion of desirables).

Two SDP recursive equations represent the four seasons. The SDP recursive equation for the first three seasons starting with autumn is as follows:

$$V_t^s(\mathbf{z}_t^s) = \max_{\mathbf{u}_t^s}\left[E\left[\pi(\mathbf{z}_t^s,\mathbf{u}_t^s)\right] + \delta_s E\left[V_t^{s+1}\left(\theta^s(\mathbf{z}_t^s,\mathbf{u}_t^s)\right)\right]\right];\text{for } s = 1,2,3. \quad (1)$$

The SDP recursive equation for the final season, summer, in a year is as follows:

$$V_t^s(\mathbf{z}_t^s) = \max_{\mathbf{u}_t^s}\left[E\left[\pi(\mathbf{z}_t^s,\mathbf{u}_t^s)\right] + \delta_s E\left[V_{t+1}^{1}\left(\theta^s(\mathbf{z}_t^s,\mathbf{u}_t^s)\right)\right]\right];\text{for } s = 4 \quad (2)$$

where s denotes the season ($s = 1,\ldots,4$); t denotes the year; V_t^s is the optimal value function for the given season and year; E is the expectation operator; π is the stage return function for a given season; $\mathbf{z}_t^s$ is a state vector consisting of three state variables (defined below) for the given season and year; $\mathbf{u}_t^s$ is a decision vector consisting of two decision variables (defined below) for the given season and year; θ^s is the transformation function for the given season; and δ_s is the discount factor ($\delta_s = 1 / (1 + \rho_s)$).The seasonal discount rate, ρ_s, is pro-rated from the annual discount rate, ρ, based on the length of the season in days ($\rho_s = \rho \cdot D_s / 365$). The difference between Eqs. (1) and (2) is in the season and year indexes of the future value of the system, V_t^{s+1}, which refers to the next season in the current year, and V_{t+1}^1 refers to the first season in the next year.

The state vector $\mathbf{z}_t^s$ contains three state variables:

$$\mathbf{z}_t^s = \left(x_t^s, yd_t^s, yud_t^s\right) \quad (3)$$

where x is the proportion of desirable species in the sward and represents their basal area within the paddock; yd is the herbage mass of desirable species in the sward (kg Dry Matter/ha) and yud is the herbage mass of undesirable species (kg DM/ha). All state variables are measured at the start of season s in year t.

The decision vector $\mathbf{u}_t^s$contains two decision variables:

$$\mathbf{u}_t^s = \left(sr_t^s, rs_t^s\right) \quad (4)$$

where sr is the stocking rate (hd/ha) and rs is the decision to re-sow the pasture, with both decisions taken at the start of season s in year t.

The transformation functions, θ^s, are represented by transition probability matrices derived through Monte Carlo simulation with the biological model described in Behrendt et al. (2013a) and Behrendt et al. (2013b) as described below, and using stochastic multipliers derived from climatic data as explained in Behrendt (2008). The biological model defines the expected levels of production and the impact of disturbance as determined by stocking rate and re-sowing decisions.

To solve the problem we define the Markovian transition probability matrices $\mathbf{P}^s$ and rewrite the expectation operators in discrete terms. The elements P_{ij}^s of matrix $\mathbf{P}^s$ represent the probability of moving from state i in season s to state j in season $s + 1$. The elements of the transition matrices given the decision $\mathbf{u}^s$ are as follows:

$$P_{ij}^s(\mathbf{u}^s) = P\left(\mathbf{z}_j^{s+1} | \mathbf{z}_i^s, \mathbf{u}^s, r^s\right) \quad (5)$$

where r^s is an index of rainfall and other climatic variables that affect pasture growth. We can now write the expectations for the recursive equations as follows:

$$E\pi(\mathbf{z}_i^s,\mathbf{u}^s) = \sum_j P(r_j)\pi(\mathbf{z}_i^s,\mathbf{u}^s,r_j) \quad (6)$$

$$EV\left(\theta^s(\mathbf{z}_i^s,\mathbf{u}^s)\right) = \sum_j P_{ij}^s(\mathbf{u}^s)V\left(\mathbf{z}_j^{s+1}\right) \quad (7)$$