Rainfall or price variability: What determines rangeland management decisions? A simulation-optimization approach to South African savannas

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1 Introduction

Savannas, broadly defined as tropical ecosystems with a continuous grass layer and a discontinuous canopy of trees and shrubs, cover the greater part of the southern continents, namely 65% of Africa, 60% of Australia, and 45% of South America (Huntley and Walker 1982). Extensive livestock production is the most widespread land use of the more than 350 million people who live in savannas (Solbrig and Young 1993, Unesco 1979).

During the second half of the 20th century, population growth has increasingly lead to an intensification of land use. One of the major threats to livestock production in savannas is the decrease in grass productivity caused by increases in the biomass of woody plants.

Grossman and Gandar (1989) estimate that the encroachment of woody biomass (i.e. shrubs and trees) has degraded 2.6% and threatens 63% of South African Savannas. While Grossman and Gandar attribute these changes to overgrazing, proponents of the non-equilibrium theory of savanna dynamics argue that high rainfall variability essentially decouples plant and animal dynamics to such an extent that even high stocking rates can hardly influence vegetation dynamics, and hence, cause degradation (Ellis and Swift 1988). As a result, non-equilibrium theory recommends opportunistic behavior, i.e. farmers should adjust stocking rates in order to make maximum use of grass production (Westoby et al. 1989).

Empirical studies in South Africa have, however, shown that high stocking rates can indeed influence vegetation dynamics and animal production even when rainfall variability is high (Fynn and O'Connor 2000). A problem with empirical analysis of economic-ecological systems is that important bio-physical processes are variable in time and the impact of management decisions on ecological parameters has a strong inter-temporal character. Collecting bio-physical and economic data over extended periods of time is cost and time intensive and still represents only a single observation that does not account for the variety of alternative possible outcomes under stochastic rainfall regimes.

Consequently, the use of computer models to simulate stochastic processes inherent in savanna systems is an important instrument in savanna research. Nonetheless, integrating bio-physical processes and economic behavior in simulation models is a non-trivial task. For instance, Janssen et al. (2004) found that few studies provide an integrated view of both the non-linear and stochastic processes involved in savanna management. They proposed a "simulation-optimization" model that combines a notion of utility-driven management decisions with non-linear ecosystem dynamics driven by rainfall variability. Simulation-optimization refers to the application of optimization algorithms to find parameter combinations that optimize a performance measure of the simulation model (Paul and Chanev 1998, Fu 2004).

In this paper, we further analyze a simulation-optimization model for savanna rangelands under deterministic and stochastic rainfall regimes (Higgins et al. in press). Higgins et al. consider a case where price is constant, we expand this analysis to include stochastic and deterministic output price regimes. More specifically we ask, does explicitly accounting for prices in the management function lead to higher utility levels? This question is motivated by the notion that the ecological debate on rangeland management tends to attribute livestock dynamics almost solely to climate variability (Vetter 2003). If, however, price fluctuations had a significant impact on management decisions, new opportunities arise for policy makers to improve the sustainability of rangeland management via market based policy instruments. Our second aim is to explore whether optimal strategies under stochastic price and rainfall regimes differ qualitatively from those adopted under deterministic conditions. The paper is structured as follows. Section 2 describes how we model price movements based on South African price and rainfall data. Section 3 shows the results of a model baseline run and selected price scenarios. Finally, sections 4 and 5 discuss management strategies and policy implications arising from the analysis.

2 Model Structure

Simulation-optimization models differ from conventional optimal control models to simulate decisions on resource use. The dimension of the problem is reduced by restricting the range of possible values of the control variable. This is done by letting the control variable become a function (hereafter management function) of an observable system parameter, e.g. grass biomass in a grassland model. The underlying assumption is that the agent will adjust his behavior based on indicators of the system state and that the way he responds to changes in these indicators is constant over time. This makes it possible to more explicitly represent both inter-temporal bio-physical relationships and management decisions in a simulation model that can be optimized, e.g. with respect to an agent's utility.

The resulting time paths for state and control variables, however, cannot be considered optimal in the sense of optimal control theory as they can differ from the solution of the underlying control problem. Yet, given suitably flexible management functions, the result is an approximation of the theoretical optimum. Hence, when presenting the results of our analysis, we use the word 'optimal' to characterize the solutions found by the optimization algorithm, although they might only be quasi-optimal in the sense of optimal control theory.

While the computational advantages of this approach outweigh the deviation from the theoretical optimum, this approach also mimics the management's decision process and can therefore be used to formulate management strategies.

2.1 Simulating Economic Behavior under risk

Here we describe only the modifications to the model described by Higgins et al. (in press). We use equations (1) and (2a/b) to represent the rangeland manager's profit and objective functions.

$$\Pi_{t+1} = p_t\sigma_t - \varphi p_t\upsilon_t - s(\sigma_t,\upsilon_t) - q\psi_t - c\delta_t - iB_{t+1};\quad \sigma,\upsilon,\psi,\delta \geq 0$$

$$B_{t+1} =: \begin{cases} 0\ for\quad B_t + \Pi_t \geq 0 \\ B_t + \Pi_t\ for\ B_t + \Pi_t < 0 \end{cases} \tag{1}$$

where t is a time subscript, p is the output price, σ and υ are animal sales and purchases, φ a price band factor, $s(\sigma,\upsilon)$ is a convex quadratic function representing decreasing returns to the scale of herd adjustments, q the unit technology investment cost, ψ the technology level, and c the unit cost of fire suppression δ. The last term represents the costs of borrowing cash with i being the interest rate and B the amount borrowed.

$$max \qquad NPV = \sum_{t=1}^{T} \frac{\Pi_t}{(r+1)^t} \tag{2a}$$

$$max \qquad U = E(NPV_j) - \frac{\varepsilon}{2} var(NPV_j);\quad j = 1,\ldots,n \tag{2b}$$

where NPV is the net present value of profits over planning horizon T using discount rate r. U is a risk sensitive utility index, where E(•) denotes expected value and *var(•)* the variance of the net present value of profits and ε is a measure of constant absolute risk aversion. In deterministic model runs, i.e. prices and rainfall are known, the manager maximizes NPV as in 2a and in stochastic model runs U in 2b is maximized for $j = 1,\ldots,n$ sequences of rainfall and price events. We assume that the decision maker adjusts σ, υ, ψ, and δ according to management functions that are specified using the function:

$$f(x;a,b) = \frac{x^b}{a^b + x^b} \tag{3}$$

such that

$$\sigma_t = Z_t(1 - f(GR_t; a_{GR}, b_{GR}) + f(p_t; a_p, b_p)); \qquad \sigma \leq Z_t \tag{4}$$

$$\upsilon_t = \hat{Z}_t(f(\hat{Z}_t; a_{\hat{Z}}, b_{\hat{Z}}) + (1 - f(p_t; a_{p'}, b_{p'}))); \qquad \upsilon \leq \hat{Z}_t \tag{5}$$

$$\delta_t = \delta_n + f(WR_t; a_{WR}, b_{WR})\delta_{\max} \tag{6}$$

$$K_t = \frac{GS_t}{\mu} f(\psi; a_\psi, b_\psi) \tag{7}$$

Equation (4) makes animal sales a function of available grass root biomass GR_t and farm gate price p in time t; animal sales can not be greater than the number of animals Z_t. Animal purchases (equation 5) are a function of the difference between available animals and potential carrying capacity $\hat{Z}_t$ (the maximum possible number of purchased animals). Hence, animal purchases increase with increasing potential for production and profit, while animal sales increase with price and/or if the potential for grass production decreases. Fire suppression beyond the grass biomass at which fires would naturally occur δ_n (equation 6) increases with tree root density WR_t. Fire suppression allows fuel to accumulate and therefore stimulates more intense fires which can repress woody plants and thereby prevent bush encroachment. Equation (7) defines carrying capacity K_t as a function of available grass biomass GS_t and the grass (intake) requirement per animal unit μ. Higher technology levels ψ increase the system's carrying capacity, but imply additional costs. The parameters a_x, b_x are (control) parameters in equations 4 to 7 and determine at what point and how fast action is taken with respect to the independent variable(s). Maximization of *NPV* or *U* takes place over the set of control (or management) parameters $a_{WR}, b_{WR}, a_{GR}, b_{GR}, a_p, b_p, a_{\hat{Z}}, b_{\hat{Z}}, a_{p'}, b_{p'}, \delta_{max}, and\ \ \psi$. To find the control set that maximizes the utility over a 50 year planning horizon we use the differential evolution algorithm DEoptim as implemented in the statistical software package R (Ardia 2006).

2.2 South African beef prices

The real average South African annual beef price shows regular cycles and a long term decreasing trend. To see how much of the cyclical beef price behavior is attributable to rainfall and how much is due to other market phenomena we set up a non-linear regression model of the form:

$$p_a = cos(\beta_1 t)\beta_2 + \beta_3 t + \beta_4 + \beta_5 mar + \varepsilon \tag{8}$$

where p_a= annual average beef price, t = year, *mar* = the two year moving average of mean annual rainfall lagged by five years, and ε a normally distributed random term. The model is based on average monthly and annual rainfall and beef price data for South Africa from 1981 to 2002 (SAWS 2005, SAMIC 2005). Since monthly rainfall data is only available starting in 1991, we estimate annual and monthly prices separately. Regression results are presented in Table 1 and confirm that both cyclical factors and rainfall influence the annual average beef price. Comparing the number of slaughtered animals with the average herd size over time (not shown) suggests that a lagged price response to average rainfall is a reasonable assumption, given that herd building processes after consecutive dry years may take several years.

Using $p_{a,m} = p_t$, $a = 1,...,11$, $m = 1,...,12$ and $p_{a,m} - p_{monthly} = p_m$ we expand the predicted average annual price to correct average monthly price data from 1987 to 2002 and obtain p_m, the average monthly price without annual variation. Here $p_{monthly}$ is the empirical monthly price. Autocorrelation analysis showed that p_m follows an autoregressive process of order 1. The noise in p_m was not normally distributed, and a Kolgomorov-Smirnov test revealed that it follows a log-logistic distribution (Table 1). We, therefore, model monthly price movements as:

$$p_m - \delta = \alpha(lag_1(p_m) - \delta) + \upsilon \tag{9}$$

where p_m = monthly average price (lag_1 = a one month lag), α = the autoregression coefficient, δ = the average of the time series, and υ is log-logistic random noise. We simulate monthly rainfall using a gamma distributed random number with mean and variance defined by empirical rainfall data from South African savannas (Higgins et al. in press).

3 Analysis

In order to demonstrate the benefit of including prices in the management function (equations 4 and 5), we first examine hypothetical price and rainfall scenarios (section 3.1). Here and in the subsequent sections, the term ‘with price rule’ refers to applying equations 4 and 5 as defined above, whereas ‘without price rule’ implies neglecting the second term on the right-hand-side of equations 4 and 5. In section 3.2 we examine more realistic price and rainfall scenarios. We first examine scenarios where price and rainfall known over the planning horizon (we call these deterministic scenarios). We then examine how stochastic prices and rainfall change the conclusions drawn from deterministic model runs (we call these stochastic scenarios). Finally, section 3.3 demonstrates the sensitivity of the grass/tree ratio to the costs of fire suppression. The parameter values used for the simulations are documented in Table 2.

3.1 Using hypothetical rainfall and price data

This hypothetical price and rainfall scenario assumes that price is positively correlated with rainfall, and hence, goes down during dry seasons. The optimal solutions for this case show that animal sales peak during the dry season when prices are lowest (Figure 1a). Purchases similarly exhibit anti-cyclic fluctuations. Without the price rule (Figure 1a) animal sales and purchases are motivated by the abundance of grass biomass that drops off quickly during the dry season. During the rainy season the animal stock is built up to benefit from grass biomass availability, while animals are sold during dry seasons to avoid mortality due to grass biomass shortages. However, including the price rule (Figure 1b) shows that the sales are not optimally timed with respect to the price. Figure 1b shows a strong relationship between price and animal sales. As a consequence of the improved timing of sales and purchases the economic utility is considerably higher with the price rule (see figure 5). Figure 2 shows that, in the hypothetical price and rainfall scenario, the effects of the price rule on the grass/tree ratio are negligible. Yet, including the price rule allows a more rapid build-up of the animal stock during the first ten years of the planning horizon.

3.2 Using simulated rainfall and price data

Optimal solutions using the deterministic and stochastic rainfall and prices scenarios suggest that bush encroachment is an inevitable consequence of economically optimal management of our model farm (Figure 3). In the deterministic scenario (Figure 3a), tree root biomass exceeds grass root biomass after approximately 15 years without the price rule, whereas with the price rule, trees start to dominate grasses only after 25 years.

In line with the deterministic model run, bush encroachment occurs earlier without the price rule when rainfall and prices are stochastic (Figure 3b). However, in the stochastic case, early bush encroachment means that livestock holding is abandoned earlier (Figure 4b). Moreover, higher stocking rates can be achieved by adjusting management strategies according to price variation (Figure 4a, 4b), this is also reflected in higher utility levels achieved with the price rule (Figure 5). Although economic utility is lower in stochastic scenarios, accounting for prices in the management function always improves the utility of the optimal model solution (Figure 5).

Irrespective of the price rule, both deterministic and stochastic scenarios tend towards a bush encroached state, i.e. including prices in the management functions does not prevent bush encroachment as in the hypothetical scenario in section 3.1. The reason is that rainfall, and hence, grass biomass availability remains the major limiting factor of production. In the next section we examine how tree dominance is influenced by management costs.

3.3 Bush encroachment and the cost of fire suppression

One of the most effective instruments to control bush encroachment is fire suppression (δ_t in equation 1 and 6). Reducing the costs of fire suppression c (in the stochastic case) enables the model farmer to keep the farm from degrading into a tree dominated state and livestock holding remains profitable throughout the planning horizon (Figure 6).

It could be argued that higher technology levels (ψ in equation 1) might also contribute to alleviate the effect of grazing on bush encroachment. Yet, Higgins et al. (in press) have demonstrated that technology levels are likely to be kept low even at zero costs. This is because technological measures that increase stocking rates increase the risk of livestock population crashes in droughts. Conservative use of technologies to increase stocking rates is therefore economically optimal.

4 Discussion

This paper contributes to the debate on sustainable rangeland management in two important ways. Firstly, we use a methodology that enables us to explicitly account for non-linearity and stochasticity in both economic and ecological factors that influence rangeland management. And secondly, we show that accounting for these system characteristics leads to qualitatively different interpretations than those derived from studies that ignore one or more of these features.

Our analyses suggest that both equilibrium and non-equilibrium processes are important in savanna rangelands, and consequently that the polarization of the debate into non-equilibrium versus equilibrium is counterproductive. We found that optimal strategies involve both opportunistic and conservative behavior depending on whether exogenous factors, such as rainfall and prices, are favorable or not for production.

For the specific case of South Africa, we show that economically optimal management strategies may lead to ecological degradation (bush encroachment) if the costs of fire management are high. Janssen et al. (2004) also acknowledge the role of fire suppression in keeping savanna systems away from a tree dominated state. In addition, we find that bush encroachment can be influenced by the interplay between stochastic rainfall and prices, which confirms that it is necessary to account for both rainfall and price fluctuations in empirical studies on the degradation of managed savanna systems.

5 Conclusions

As expected, our results confirm that higher utility levels can be achieved as a consequence of increased flexibility to prices in the management functions of the simulation-optimization model. Yet, they suggest that price policy instruments are unlikely to be successful in reducing bush encroachment in commercially managed South African Savannas. One of the reasons is that the quantitative dimension of animal sales and purchases is insensitive to changes in price variability. Instead higher utility levels are achieved by a more efficient timing of sales and purchases and this does not necessarily reduce the risk of bush encroachment. Alternatively we identify fire management as an effective instrument at the farm level to avoid bush encroachment. The results suggest that more effective technologies to control fires or transfers to reduce the costs of fire control are promising measures to encourage the use of sustainable rangeland management strategies.

6 References

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Tables and Figures

Table 1: Parameter estimates for annual average and monthly price models (equations 8 and 9) and Kolgomorov-Smirnov test results for the distribution of υ

Parameter	Estimate	Std. Error	t-value	Pr(>|t|)
Annual average price model (R^2=0.8)				
β_1	1.04	0.03	30.07	<0.001
β_2	-111.96	36.23	-3.09	0.01
β_3^a	-26.84	5.61	-4.79	0
β_4	1928.22	252.76	7.63	<0.001
β_5	-1.09	0.43	-2.57	0.03
Monthly price model AR1				
α	0.8673			
δ	0.81			
Log-logistic distribution parameters		*Kolgomorov-Smirnov test*		
location (μ)	5.69	D		0.0505
scale (σ)	0.88	p-value		0.7151

[a] β_3 is assumed 0 in all simulations

Table 2: Parameter values of the parameters in equations 1-7 used in simulations

Parameter	Value	Parameter	Value
t	1-600[a]	$s(\sigma,\upsilon)_a$	1
p	1324.5 (324)[b]	$s(\sigma,\upsilon)_b$	5000
φ	1.1		
q	1.6		
c	0.8 (0.4)[c]		
i	0.01		
ε	0.05		
r	0.05 per year		
n	40		
δ_n	0.3		
a_ψ	0.5		
b_ψ	1		

[a] Planning horizon (50 years in monthly steps)

[b] Average and standard deviation of simulated price series

[c] Value in parenthesis used for simulation in section 3.3

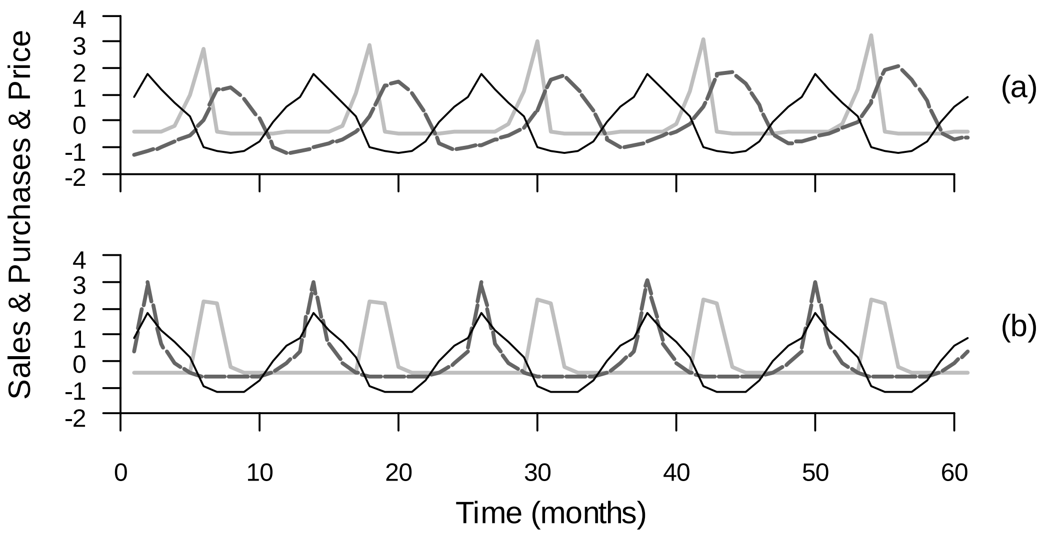

Figure 1: Optimal monthly patterns of standardized animal sales (dashed grey), purchases (solid grey) and producer prices (black) without price rule (a) and with price rule (b) using periodic price and rainfall scenarios.

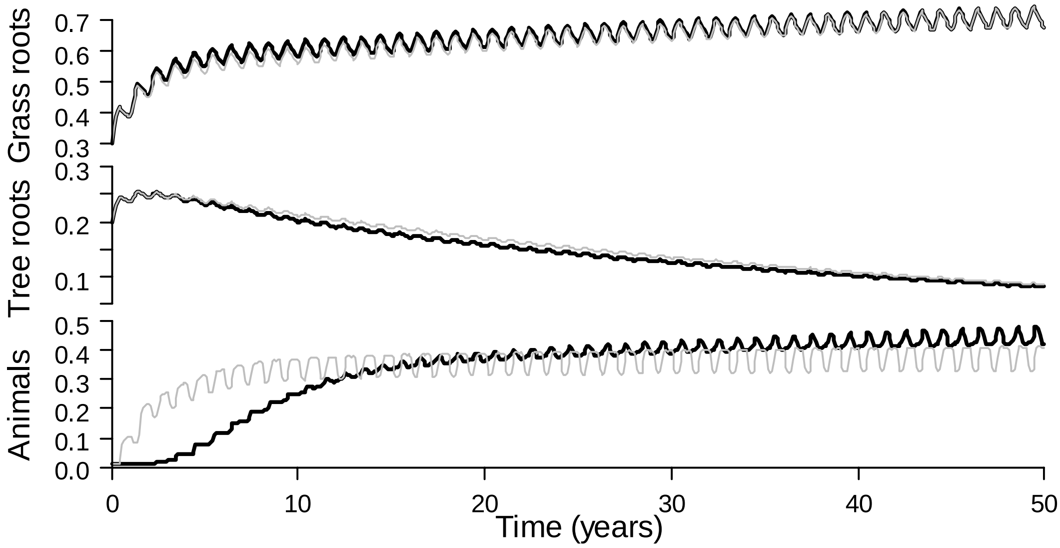

Figure 2: Grass and tree root biomass and animal numbers under the optimal management strategy over the planning horizon with price rule)grey) and without the price rule (black) using hypothetical price and rainfall scenarios.

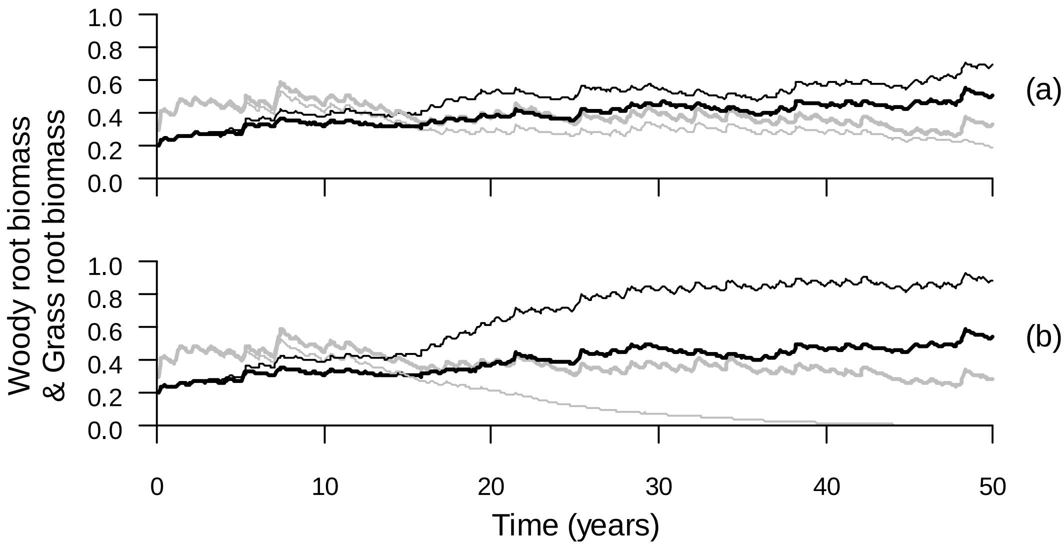

Figure 3: Grass root (grey) and tree root (black) biomass under the optimal management strategy with (bold) and without (thin) price rule using deterministic (a) and stochastic (b) scenarios.

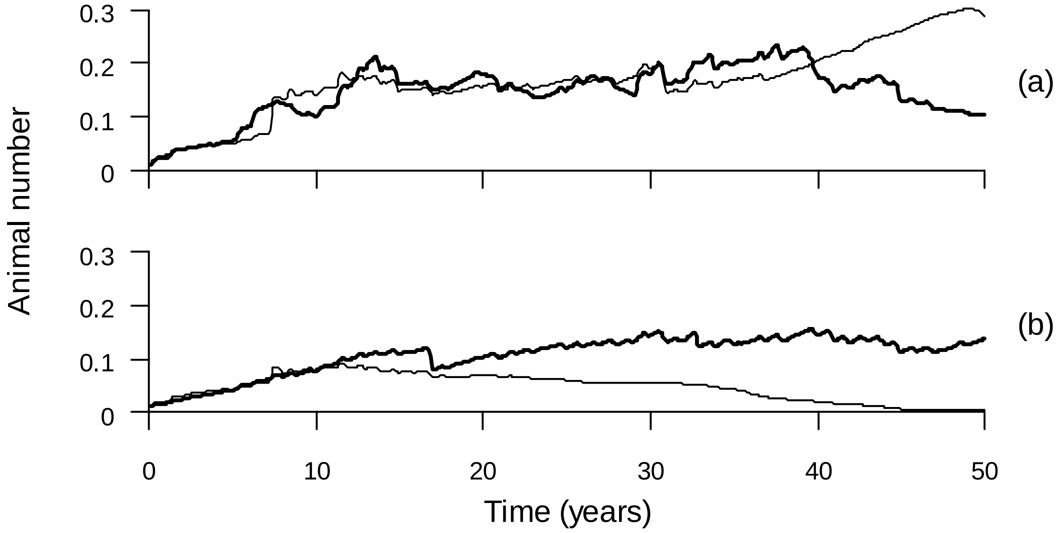

Figure 4: Animal numbers under the optimal management strategy with (bold) and without (thin) price rule using deterministic (a) and stochastic (b) scenarios.

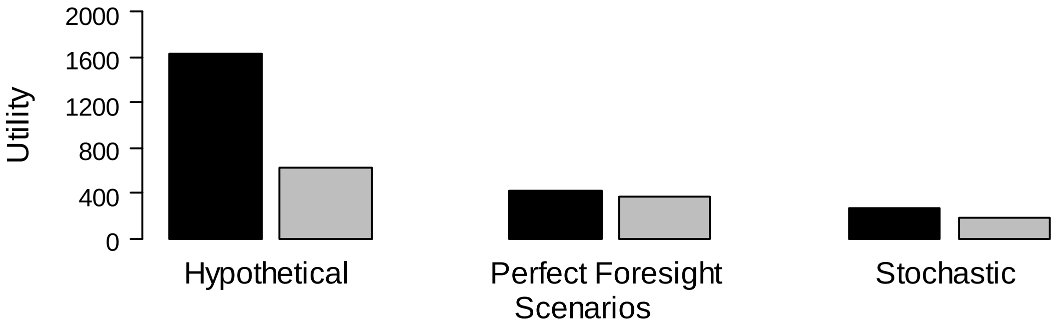

Figure 5: Optimal objective function values with and without price rule for hypothetical, deterministic and stochastic rainfall and prices

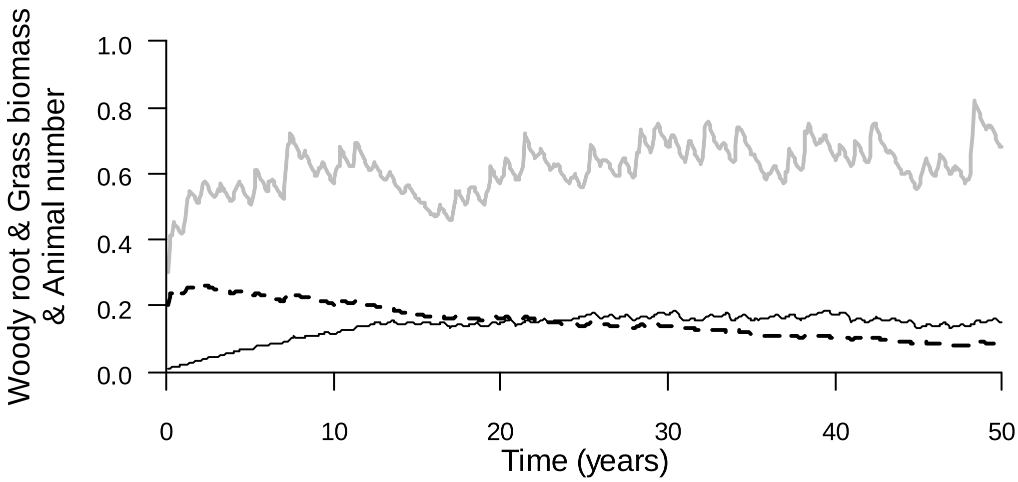

Figure 6: Grass and tree root biomass and animal numbers under the optimal management strategy selected given reduced fire control costs.