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REPORT 8

Maintaining Resilience in the ASALs of Kenya:
A Perspective on Stocking Rates in Extensive Livestock Systems

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Table of **contents**

1 **Introduction** 1

2 **Data** 2

3 **Methodology** 3

The pastoralist's dynamic stocking problem 4

Model results 6

The case with baseline climate 6

The case with a drier climate 7

4 **Conclusion** 10

5 **References** 11

Introduction

1

Overall, the dryland regions of Kenya face high and widespread vulnerability to hunger, caused by a number of proximate factors – including weakness of infrastructure, governance, and exposure to climatic variability. A significant portion of arable land is arid or semi-arid, and crop-based agriculture is difficult to maintain in those areas. The heavy dependence of the extensive livestock systems in that region on highly-variable availability of forage and herbaceous biomass is one of the key sources of vulnerability faced by livestock keepers.

In this analysis, we make use of household level data to illustrate some very basic characteristics of pastoral livestock keepers, so that we can represent their behavior and adjustment to environmental shocks. This approach enables us to highlight some critical dimensions of vulnerability, and point to potential avenues for strengthening their resilience.

The problem of the grazing commons

The extensive systems of northern Kenya are subject to the same dimensions of vulnerability as seen in others across the drylands of Eastern and Sahelian sub-Saharan Africa – namely the availability of feed and water for animals. The grazing lands that are used by the herders are typically un-restricted in access and are an 'open-access' resource to others who wish to graze their animals. This kind of situation is common to many common-pool resources that provide benefits for the users, but whose use is not restricted or regulated in any way. Other good examples are groundwater aquifers, which can be accessed by multiple water users and pumped in excess of their capacity to recharge. Similarly – grazing commons can be over-stocked with animals, beyond the biophysical capacity of the herbaceous grasslands to regenerate – thereby constituting a 'mining' of the resource beyond the level that would otherwise be able to provide a sustainable source of feed. The itinerant behavior of livestock herders – i.e. transhumance – is a response to this situation, and provides an important livelihood strategy for livestock keepers. Rather than solving the problem of the grazing commons, however – it merely spreads it out over space, and creates a complex web of resource exploitation patterns that have both a temporal and spatial dimension.

The behavioral tendency to over-graze is quite similar to other cases where non-cooperative behavior among users creates a sub-optimal pattern of resource extraction, and mainly comes from the inability of the individual user to consider the benefit of others, when deciding on the level of use that is best for himself. This results in a situation in which everyone is worse off than under the case where cooperation is undertaken, and the joint benefit of all users is considered. We will consider such a case in the next sections.

2 Data

[1] http://catalog.ihsn.org/index.php/catalog/1472

In order to come up with some realistic values for milk consumption and production at the household-level, for pastoralists, we made use of the data contained within the micro-level individual modules of the latest four Demographic and Health Surveys (DHS)[1] waves of survey data available for Kenya (1993, 1998, 2003, 2008). The DHS are nationally-representative household surveys that provide data on a wide range of indicators on population, health, and nutrition.

The key parameters that we defined from this data are described in the table below.

Table 1: Key information extracted from DHS data

large ruminants (head)	9
small ruminants (head)	26
dairy ruminants (head)	7
price of milk (Ksh per liter)	19
average TLU per hhold	18
share of animals producing milk	0.22
hhold costs per TLU (Ksh/TLU)	305
hhold expenditure on food	0.72
hhold Budget Share for dairy	0.10
hhold Budget Share for non-dairy foods	0.61
hhold Budget Share for non-foods	0.28
production of milk per TLU (liters/TLU)	15

Source: Own calculations based on DHS hhold data

These data were used to parameterize a dynamic programming model of animal stocking, which is described in the next section.

Methodology

3

Given that the problem of managing ruminants within an extensive production system relies largely upon the balancing of animal numbers with feed availability – we have chosen to characterize the pastoralists' problem in this simple way. As such, we leave all market factors as fixed and exogenous to the problem. Therefore, we do not consider the problem of long-range movement, trade or price adjustments in the market – since that would require a more aggregate-level of analysis. Assuming that the animals have a biophysical growth dynamic that determines the size of the herd over time, we have retained this as a key element of characterizing the dynamics in the model. In addition, we have assumed that the stocking rate (animals per unit area) has an effect upon the biophysical growth potential of herbaceous biomass illustrating an important feedback between user behavior and resource which we also use to characterize the producer's management problem.

We first begin by characterizing the optimal stocking rate decisions of an idealized livestock keeper who is considering all of the feedbacks between stocking and biomass growth, and is also far-sighted in his perspective of long-run sustainability of the livestock enterprise. This provides us with a benchmark of efficiency that we can contrast with the usual short-sighted behavior of the livestock keeper who only considers short-term benefits without looking at the long-term implications of over-stocking the grazing commons.

The basic approach that we use to characterize the optimal behavior of the far-sighted pastoralist is that of dynamic programming – in which the decision maker makes an explicit tradeoff between the benefits that occur in the present period and those that will accrue in the future.

Bellman (1957) developed the fundamental principle of dynamic programming, referred to as the "principle of optimality." The principle states that an optimal sequence of actions has the property that, whatever the initial state and decisions are, the remaining decisions constitute an optimal sequence of actions resulting from the first decision. In other words, whatever the decision maker does tomorrow must be optimal going forward, conditional on the state and decision today. There are a number of solution techniques built around this principle. The most popular include backward recursion, value function iteration, and policy function iteration.

The critical insight by Bellman (1957) allows us to reformulate the dynamic problem using the Bellman equation, and solve using dynamic programming techniques. The Bellman equation for a generically-posed problem – where x_t and c_t are the state and control variables, respectively, in period t – can be written as:

$$(1) \quad V(x_t) = \max_{c_t} \left\{ f\left(c_t, x_t\right) + \beta V\left(x_{t+1}\right) \middle| \; x_{t+1} = g\left(x_t, c_t\right) \right\}$$

Where the objective of the decision maker combines the immediate benefit, given by the function $f(c_t,x_t)$, and the discounted optimized value of the problem in the next period $\beta V(x_{t+1})$ – where β is the discount factor, and $V(x_{t+1})$ is the value function based on next period's stock value (x_{t+1})[2]. The process by which the decision-maker's control in period t determines the value of the state variable in period $t+1$ is given by the transition equation $x_{t+1}= g(x_t,c_t)$.

In a very simple problem, the control variable could be the level of consumption of a finite resource, whereas the state variable is the stock of that resource in any particular period. The immediate benefit of consumption could be a simple 'felicity' function $[f(c)=c^a, \alpha<1]$ and the transition equation a simple subtractive process, such that $x_{t+1} =g(x_t,c_t)=x_t-c_t$. If we allow for an infinite time horizon and let denote the subsequent period state (dropping all time sub-scripts), we can write the Bellman equation of this very simple problem in a more compact form as

$$(2)\quad V(x) = \max_c\left\{c^\alpha + \beta V\left(x^+\right) \middle| \; x^+ = x - c\right\} = \max_c\left\{c^\alpha + \beta V\left(x-c\right)\right\}$$

This "cake-eating" problem captures the behavior of a forward-looking decision-maker who's trying to 'eat' a finite resource over an indeterminate horizon, starting with an initial stock (x) of the resource, and who will draw it down in an optimal way, over time. This framework can be extended to situations with stochastic state variables, as well – but we will remain within a deterministic framework, for now.

[2] The value function $(V(x_t))$ represents the maximized (i.e. optimal) value of the decision problem written in equation 1, above, given the current value of the state variable in period t (x_t). The function $V(\bullet)$ appears on both sides of the equation, which implies that the decision maker's decision in period t will result in a new value of the state variable x_{t+1} in the next period, that will also be managed optimally.

The pastoralist's dynamic stocking problem

In this paper, we're interested in the pastoralist's forward-looking problem, in which the decision-maker would be trying to maximize the benefit derived from a herd of animals. In this case, the number of livestock is the state variable that changes over time, and the benefit comes from the milk produced by the animals, as well as the revenue that come from animal sales (minus the cost of maintaining the herd).

In order to address this problem, we modified a model that was applied to the case of northern Senegal (the "Ferlo" region) by Hein (2010), which focused on the problem of stocking animals in the semi-arid rangeland in northern Senegal. The decision (control) variable in the model is the long-term stocking density. The model accounts for stochastic states in the form of rainfall and the feedback effect of grazing on vegetation. The model abstracts away from common property problems endemic to grazing and should consequently be viewed from the point of the optimal rangeland manager.

The control variable is livestock sold at time t,SL_t. The state is the size of the livestock herd measured in Tropical Livestock Units (TLU), TLU. Livestock feed on fodder F_t which is produced on the land depending on rain r_t and Rainfall Use Efficiency (RUE) RUE_t.
Current period benefits from the revenue generated by animal sales, defined as

$$(3)\quad \mathrm{Revenue}_t = SL_t\left(\alpha_0 - \alpha_1 SL_t\right)$$

Where α_0 and α_1 are the intercept and slope of the live animal market demand function, respectively. Together with sales revenue, the decision maker also considers the benefits from consumption given by a 'utility function'

$$(4)\quad Utility(c) = k_0\left(c_t\right)^{\varepsilon}$$

where κ_0 is a constant that defines the intercept of the utility function, and ε represents the budget share of consumption of dairy products consumed by the average pastoralist household. The milk that is available for consumption depends on the milk productivity of a cow ($milk_{TLU}$) as well as the number of dairy animals (TLU^{diary}). Combining the consumption benefits with the revenue from sales (minus herd maintenance costs), gives us the objective of the decision-maker's problem

$$Benefit = Utility\ (c_t) + Revenue_t - cost_t = k_0(c_t)^{\varepsilon} + SL_t(\alpha_0 - \alpha_1 SL_t) - cost_{TLU} \bullet TLU_t,$$

where the cost per tropical livestock unit (TLU) is multiplied by the herd size (in TLU). In our problem, livestock production is governed by grass-based feed, thus the pastoralist must consider the availability of the feed resource and manage its productivity through controlling the stocking density (TLU per hectare). Over-stocking will compromise the productivity of the herbaceous biomass, by reducing its biological rainfall use efficiency (RUE). RUE defines the efficiency of rainfall expressed in biomass/ha per year per mm effective rainfall. This indicates the effectiveness to transfer rain to biomass, and can be written as

$$(5)\quad RUE_t = \left(\alpha_2 r_t^2 + 2\alpha_3 r_t - \alpha_4\right) - \left(\left(SR_t\right)^2\left(\mu r_t^2 - 2\mu r_{\min} r_t + v\right)\right)$$

where the first part represents the biophysical growth that would happen if we did not consider any feedback from stocking rates – but which is subtracted by the interaction effect with animals that are trampling herbaceous biomass underfoot. Parameters *α,μ,*v are scaling parameters. The parameter r_{min} is the minimum rainfall needed for biomass growth, whereas SR_t is the long term stocking density calculated as,

$$(6)\quad SR_t = \frac{TLU_t}{H}$$

where H is the land area being grazed. The stocking density represents the intensiveness of grazing but does not capture the important variation in spatial distribution of grazing.

Fodder production is governed by the product of RUE and rainfall (*r*). In this model RUE captures all the essential productivity features of the land, and makes feed availability dependent upon a 3rd-order polynomial in rainfall amounts.

$$(7)\quad F_t = RUE_t \cdot r_t$$

There is a limit to the stocking rate of the rangeland which depends on the feeding requirements of a TLU, the fraction of the forage that is accessible and digestible, and other factors which are captured in the parameter Φ below

$$(8)\quad SR_t^{MAX} = \frac{F_t}{\phi}$$

Finally, the stocking rate of animals changes according to the level of offtake (SL) as well as the biophysical growth potential of livestock, which takes the form of a logistic growth function. The growth function contains a scaling parameter λ, as well as an explicit linkage to feed availability through the maximum stocking rate given by equation (*8*).

Taken together – we obtain an equation which describes the change in the stocking rate of animals over time,

$$(9) \qquad SR_{t+1} - SR_t = \lambda\left(1 - \frac{SR_t}{SR_t^{MAX}}\right)SR_t - SL_t$$

We could convert this to the actual numbers of TLU, by multiplying by grazing area, so that we obtain

$$(10) \qquad TLU_{t+1} - TLU_t = \lambda\left(1 - \frac{SR_t}{SR_t^{MAX}}\right)TLU_t - SL_t \cdot area$$

Therefore – taking all these relationships (equations 3 to 10) together, we can formulate a model in which the forward-looking pastoralist decides upon the optimal stocking rates that maximize the long-term benefits from livestock-keeping, which are balanced with the sustainability of the biomass-based feed resource. This can be summarized in the following Bellman equation:

$$V(TLU) = \max_{c,SL} c \begin{Bmatrix} k_0(c)^{\varepsilon} + SL_t(\alpha_0 - \alpha_1 SL) - \cos t_{TLU} \cdot TLU + \beta \cdot V(TLU^+) \\ \text{s.t.} \\ TLU^+ = TLU + \lambda\left(1 - \frac{SR}{SR^{MAX}}\right)TLU - SL \cdot area, \quad SR = \frac{TLU}{area}, \quad SR^{MAX} = \frac{RUE \cdot r}{\phi} \\ RUE = \left(\alpha_2 r^2 + 2\alpha_3 r - \alpha_4\right) - \left((SR)^2\left(\mu r^2 - 2\mu r_{\min} r + v\right)\right), \quad c \le milk_{TLU} \cdot TLU^{dairy} \end{Bmatrix}$$

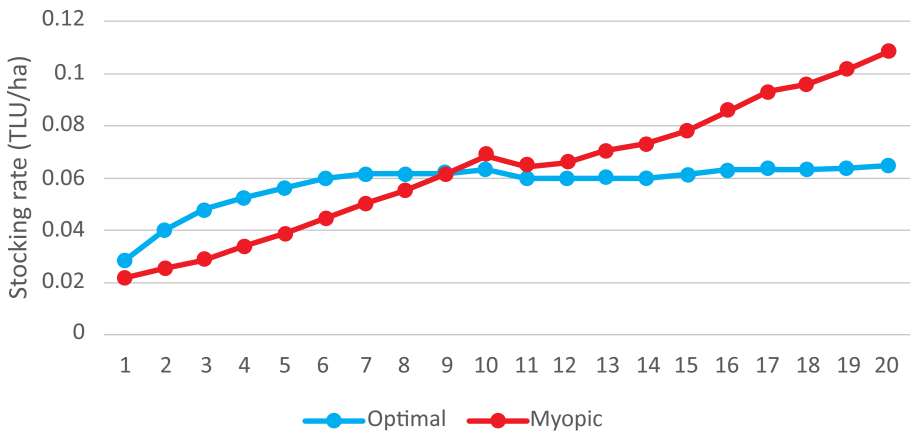
In the following section, we describe the results from our model.

Model results

a. The case with baseline climate

In this case, we describe how the stocking rate of animals would evolve under a baseline pattern of rainfall, under both optimal and sub-optimal (i.e. myopic) management. This becomes clear when we look at the projection of stocking rates over time, as shown in Figure 1 below.

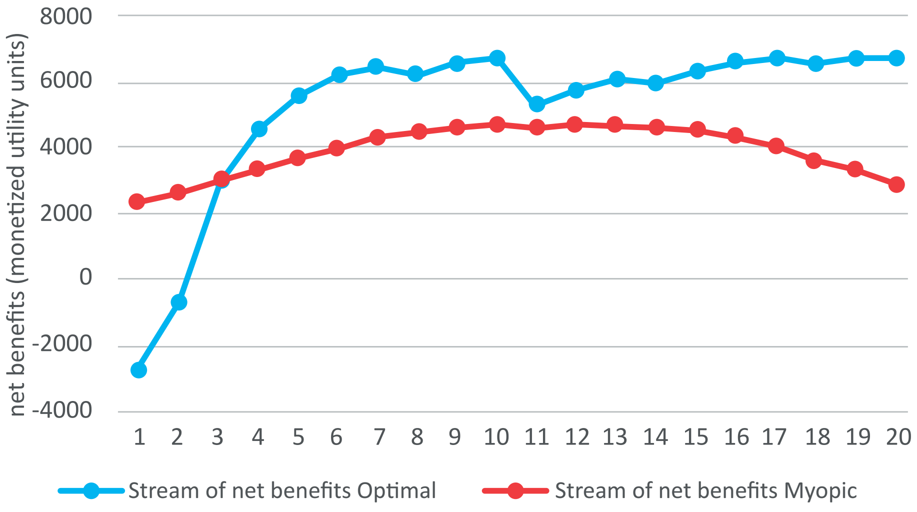
Figure 1: Comparison of stocking rates under optimal and myopic (sub-optimal) management



This corresponds with what we would expect from the myopic case – which ignores longer-term benefits, and results in a much higher stocking rate in the longer term.

The resulting welfare implications are shown in Figure 2, below, in which we see that the myopic user ends up with higher benefits in the earlier periods, but is over-taken by the more forward-looking producer who is able to maximize benefits to a much higher level, in the longer term.

Figure 2: Comparison of net benefits under optimal and myopic (sub-optimal) management



This shows that the forward-looking livestock keeper who is able to forgo some short-term benefit for longer-term gain, can actually do better in terms of welfare outcomes in the long-run, even though the overall stocking levels end up being lower.

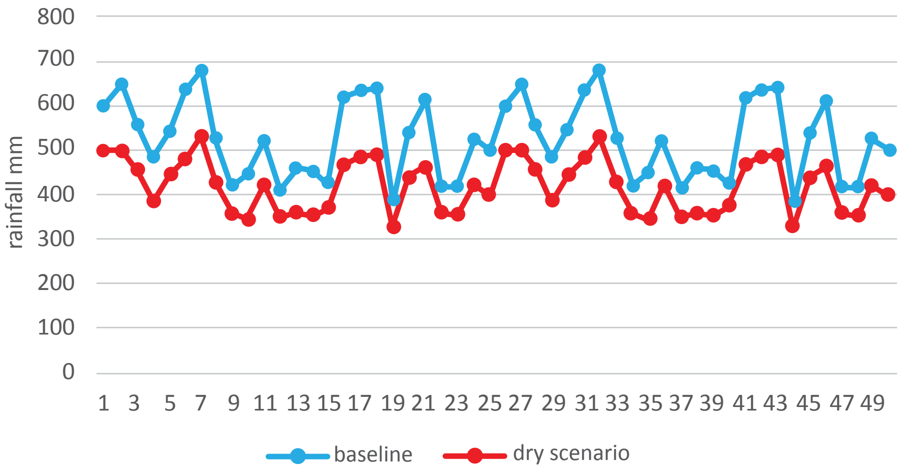
We now contrast this with a change in climate, towards a drier regime of rainfall, as is done in the next sub-section.

b. The case with a drier climate

Now we contrast optimal and sub-optimal (i.e. myopic) management under conditions of a drier climate to see what the results outcome is for the livestock keepers.

By taking a typical series of rainfall for Kenya, we can impose a 'dry' climate by shifting the pattern downwards, with stronger effect for wet and average years, compared to the drier. Years. Figure 3, below, gives us a picture of what this looks like.

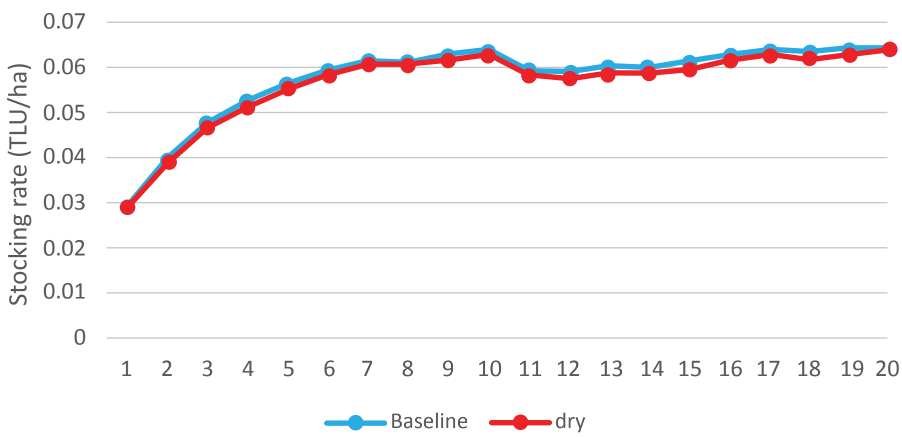
Figure 3: Comparison of 'average' (baseline) and 'dry' rainfall patterns.



In this case we preserve the frequency of rainfall events, but simply change their magnitude so that the overall realized levels are lower.

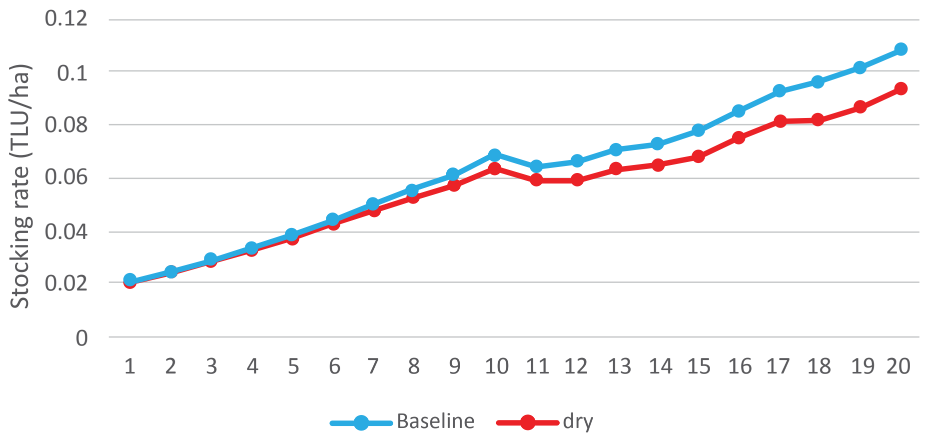
We then use this series within the model, to see how the pastoralist changes behavior, as is seen in the case of the forward-looking pastoralist who behaves optimally (Figure 4, below).

Figure 4: Comparison of optimal stocking behavior under 'average' and 'dry' rainfall regimes



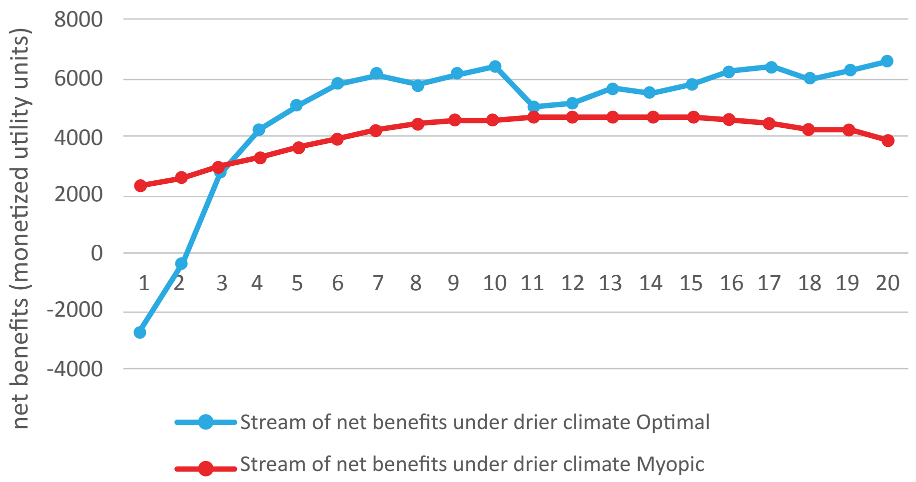
In this case, the difference is very small – for the case of optimal behavior. In the case of sub-optimal, myopic behavior – the difference in stocking rate is more pronounced (Figure 5, below), especially in the later periods of the simulation.

Figure 5: Comparison of myopic stocking behavior under 'average' and 'dry' rainfall regimes



The contrast between net benefits realized over time, as we see in Figure 6 below, is still obvious – even though the overall distance between the two lines is closer (compared to Figure 2)

Figure 6: Comparison of net benefits from optimal and myopic management under drier climate



If we compare the difference between the stream of benefits shown in Figures 2 and 6 in terms of a total (un-discounted)[3] sum over the time periods – we'd see that the gains to optimal management are 33% under a baseline climate case, whereas this gain drops to 20% under the drier climate. This reflect the fact that the forward-looking livestock keeper is more constrained under a drier climate and is not able to realize as big an improvement as under the myopic case. The difference between the optimal and sub-optimal gains, however, still remains significant, and illustrates the fact that additional forage scarcity, caused by climatic changes, might make the improved management of livestock numbers just as important, as a strategy to enhancing resilience.

[3] We could discount the net benefits more heavily in each successive period – as is commonly done in economic analysis. This would leave the overall difference between them the same, however.

4 Conclusions

In this analysis, we have illustrated the benefits that can be realized from better management of livestock in extensive systems. We have used a fairly simplified approach to illustrate this, and have restricted ourselves to focusing on stocking rate decisions, rather than that of transhumance – which would provide an even wider range of response. We have done this for reasons of simplicity, and can expand on this in future.

Other necessary simplifications left out the market perspective, and the role that trade in livestock as well as (potentially) feed could have on livestock populations. In this analysis, we considered the 'average' pastoralist, and do not consider the range of responses possible from different pastoralist household types across the ASAL region. This can be taken up in further work.

The basic point of this analysis is to illustrate that the long-run benefits of limiting stocking rates to better match feed availability are clear and significant – under a range of climatic conditions. Looking at the effect that increased frequency of dry years in succession will be another extension of this work – among many other possible extensions – and is a key aspect of coping with shocks and increasing resilience that is of relevance in the drylands of Africa where the majority of pastoralists reside.

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5

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