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Analysing trade-offs in resource and labour allocation by smallholder farmers using inverse modelling techniques: A case-study from Kakamega district, western Kenya

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Abstract

Smallholder farms in sub-Saharan Africa face multiple trade-offs when deciding on the allocation of their financial, labour and nutrient resources. Day-to-day decisions have implications for the sustainability of their farming system, implying multiple trade-offs between short- and long-term objectives that have biophysical and socio-economic dimensions. We show that inverse modelling techniques can be used effectively for optimisation and trade-offs analysis of farming systems. By combining the multi-objective shuffled complex evolution metropolis algorithm and a crop/soil dynamic simulation model we were able to select farming strategies that resulted in the best possible trade-offs between different farming objectives. This integrated analytical tool allows optimisation of farmers' goals similar to linear programming, but an advantage over linear programming is that the proposed method takes into account a wider spectrum of biophysical processes including their interactions and feedbacks. Tradeoffs between resource productivity, use efficiency and conservation in relation to different patterns of resource allocation were analysed for a maize-based, simplified case study farm from western Kenya (2.2 ha – comprising fields of poor, medium and high soil fertility), under three scenarios of financial liquidity to invest in labour and inputs (2000, 5000 and 10,000 KSh ha^{-1}; 75 KSh = 1 US$). The maximum farm-scale maize production achieved was larger when financial resources increased. However, increasing maize yields above a certain threshold by applying mineral fertilisers was associated with larger N losses by leaching, runoff and soil erosion; such threshold was 2.7 t grain ha^{-1} for the scenario of no financial limitations (10,000 KSh ha^{-1}). N losses at farm scale fluctuated between 36 and 54 kg N ha^{-1} $season^{-1}$, while the maximum maize yields achieved were around 3.4 t grain ha^{-1}. Soil losses by erosion increased abruptly beyond a certain maize yield (e.g. 1.8 t grain ha^{-1} for the 2000 KSh ha^{-1} scenario), while the minimum rate of soil loss differed between financial scenarios. Investments in hiring labour were prioritised over fertiliser use to obtain the greatest yields and the allocation of available resources favoured the more fertile fields. This inverse modelling exercise allowed us to analyse trade-offs between different farmers' objectives and to compare potential resource allocation strategies to achieve them. The set of strategies to achieve different goals was more numerous and variable when the conditions were less conducive for farming. This questions the validity of the prevailing model of extension/communication, based on generalised recommendations for resource-poor farmers in Africa.

Keywords: DYNBAL model; MOSCEM; Soil erosion; N balance; Maize yield

1. Introduction

Smallholder farms in Sub-Saharan Africa face multiple trade-offs when deciding on the allocation of their available financial, labour and nutrient resources to competing

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production activities within their farms. Such trade-offs are reinforced by their limited access to production resources (Giller et al., 2006), poor development of factor markets (Ruben and Pender, 2004), and the fact that smallholder farms are spatially heterogeneous, due to the existence of gradients of decreasing soil fertility with increasing distance from the homestead (Tittonell et al., 2005). The operational, day-to-day decisions made by farmers in allocating resources have implications for the future fertility of their fields, and thence for the sustainability of the entire farm system. Studies across Africa indicate that smallholder farmers invest proportionally more (cash, nutrient and labour) resources in the relatively fertile fields near the homestead, particularly on mixed crop-livestock farms (e.g. Samaké et al., 2005; Zingore et al., 2007; Tittonell et al., 2007). This resource allocation pattern leads to the creation of zones of soil fertility within farms that do not necessarily result in efficient allocation of farm resources.

To increase productivity and ensure sustainability of smallholder farms in Sub-Saharan Africa (SSA) it is necessary to understand the trade-offs between immediate concerns such as generating food and cash, and reducing soil and nutrient losses or maintaining favourable soil physical properties, which have a cumulative impact on soil quality in the long-term. Nutrient losses through run-off and soil degradation by erosion are often indicated by farmers in the highlands of western Kenya as being underlying causes of poor productivity of their land (e.g. Tittonell et al., 2005), and formal assessments of soil losses in the area confirm this perception (e.g. De Bie, 2005). Nutrients are also lost through other processes that are normally less evident to farmers; e.g. leaching, which may take place at high rates for nutrients that are soluble in the soil. Such is the case for nitrogen (N), which is highly mobile in the soil solution, and one of the major limiting nutrients for crop production in SSA (Sanchez et al., 1997). Thus, a strategy of building up N capital in the soil would need to be coupled with the building up of soil organic matter (i.e. organic N), as mineral N is rapidly lost by leaching if not captured by crops (Giller et al., 1997). However, N inputs sufficient to increase biomass production and thereby soil organic matter are unlikely to be justified by immediate physical and/or financial returns, unless the efficiency of N 'capture' within the farm system is increased.

Analysing trade-offs of this nature implies also that multiple indicators need to be monitored simultaneously for the assessment of management strategies. Next to food production and changes in soil properties for a certain field within the farm, emphasis should be placed on labour productivity, since labour is often assumed to be the most limiting resource for the household (Barrett et al., 2002). Thus, the complexity of the interaction between multiple processes underlying agricultural production and farmers' decision making has to be embraced while designing research questions. For example, how best can farmers invest their labour and resources in the different fields (i.e. soil quality classes) within their farms in terms of achieving high overall physical (food) and economic returns to such resources at farm scale? Trade-offs in resource and labour allocation can be identified and analysed by means of integrated bio-economic models, which are able to simulate the biophysical processes that affect crop production and resource use (capture and conversion), the effect of management decisions, and their resulting impact on household income.

In search of methodologies to build up a truly integrated bio-economic model, Brown (2000) reviewed different modelling approaches and classified them along a continuum: at one extreme, the biophysical models to which an economic balance has been added, and at the other, the economic optimisation models that include biophysical components as 'activities' among the various choices for optimisation. The latter is the case of the multiple-goal linear programming models (MGLP), which have a strong economic focus and in which the biophysical processes are introduced as input/output combinations, represented by linear functions. MGLP models have been extensively applied to land use studies at different scales (e.g. Van Ittersum et al., 1998), and since linearity is not common among the functional relationships that describe biological processes relevant to agricultural production, piecewise linear functions have been used to approximate non-linear functions (e.g. Herrero et al., 1999). Despite some interesting applications to the multi-scale analysis of trade-offs related to land use in sub-Saharan African systems (e.g. López-Ridaura, 2005), their performance in assessing alternatives and innovations for natural resource management in smallholder farms has been critically revised (Van Paassen, 2004). Biophysically-biased, dynamic simulation models are suited to capturing farm heterogeneity in resource use efficiency, non-linear relationships (e.g. crop responses to applied nutrients) and feedbacks among different processes. However, optimisation of multiple objectives using dynamic models *per se* is virtually impossible, and often inverse modelling techniques are used to select combinations of values for a number of model parameters to optimise an objective function related to model performance (e.g. to minimise the difference between model output and measured variables). Dynamic models are also often used as technical coefficient generators for MGLP models, involving several operational instances and not achieving a true functional integration of the biophysical and economic aspects of the system (e.g. Castelán-Ortega et al., 2003).

Understanding the trade-offs faced by farmers when making operational (i.e. day to day) management decisions is a basic premise for addressing farm-scale questions related to: (i) the efficient use of their available resources; and (ii) the possibilities for technological interventions aimed at the sustainable intensification of the smallholder systems. We propose a new method for optimising farm-scale objectives and analysing trade-offs relevant to the sustainable intensification of farming systems, using inverse modelling techniques. Multi-Objective Shuffled Complex Evolution Metropolis (MOSCEM) (Vrugt et al., 2003) is

an algorithm that can be used to optimise several objective functions and map out Pareto-optimal sets of value combinations for a number of model input parameters. DYNamic simulation of Nutrient BALances (DYNBAL), a dynamic, process-based model that was tested and used in western Kenya (Tittonell et al., 2006), was linked to MOSCEM and used to simulate the underlying biophysical relationships that operate at field scale (crop growth, water balance, soil erosion, C and N dynamics, etc.), coupled with labour requirement relationships based on household data collection. This integrated analytical tool allows analysis of trade-offs while maintaining an appropriate degree of detail on the biophysical processes simulated and on their interactions and feedbacks.

We used this combined analytical tool to explore alternative management strategies for maize production in a case study farm from a densely-populated region in the highlands of western Kenya. This region has high agricultural potential, with soils that were originally fertile, mild temperatures and ample rainfall (Jaetzold and Schmidt, 1982). However, continuous cultivation without sufficient nutrient input has led to current maize yields ranging from 1 t ha^{-1} up to 2 t ha^{-1} in the more fertile fields (while on-station yields may be as high as 8 t ha^{-1} – Schnier et al., 1997), due mainly to poor soil availability of N and P (Shepherd et al., 1996). Nutrient resources such as mineral fertilisers and cattle manure represent important cash and labour investments for smallholder farmers, and the physical returns to such investments are highly affected by the spatial heterogeneity in soil quality characteristics of these systems (Vanlauwe et al., 2006). To reduce nutrient losses and thereby increase the efficiency of nutrient use (capture) within the system, parallel measures such as soil erosion control need to be employed. Our objective was to analyse trade-offs between N, cash and labour allocation strategies for ensuring food security, improving the efficiencies of nutrient capture and reducing soil losses in a simplified, case-study smallholder farm system from Kakamega district, western Kenya.

2. Materials and methods

2.1. A simplified case-study farm system in western Kenya

2.1.1. The farm system

The village selected (Mutsulio, Kakamega district, western Kenya) is located in an area characterised by major constraints related to access to and development of markets, high pressure on land due to high population density, and poor soil fertility status after continuous cultivation for decades with few or no nutrient inputs (Table 1A). Rainfall in the area has a bimodal pattern (i.e. the long and the short rains) and maize is the main grain crop cultivated for home consumption and the market. The analysis focused on a simplified farm system derived from data collected through qualitative and quantitative on-farm system analysis, using participatory rural appraisal techniques to assess resource flow and labour allocation patterns (Tittonell, 2003). The case study farm system selected for scenario analysis represented a relatively wealthy farm within its context, better-endowed than the village average for the total area of cropped land, area under cash crops, number of livestock, farm assets and general wealth indicators (e.g. type of house) (Table 1B). It was purposely selected to allow an ample range of assumptions to be made in relation to investments, resource availability and resource allocation decisions made by the farmer. This particular case farm household generated most of its income from farming, by growing tea and keeping dairy livestock, having surpluses of food crops that were also sold on the market. The farm had an area of 2.2 ha under maize, which was the dominant crop grown for home consumption with the surplus sold into the local market (Fig. 1).

Soil samples were taken from each individual field and analysed for particle size distribution, soil organic C, total N, available P, exchangeable bases and pH following standard methods for tropical soils (Anderson and Ingram, 1993). Soil bulk density was measured using standard sampling rings at intervals of 0.1 m up to 0.3 m depth. The slope of the field was measured using a clinometer. During one of the visits to the farm, the farmer was requested to classify his land according to his perception of soil quality into fertile (+), average (±) and poor (−) fields, and the area of all the fields belonging to each of these classes was summed up (Fig. 1). The slope of the fields (soil erosion) and the colour of the topsoil (organic matter content) were the main criteria used by the farmer to classify his fields, and there was in general good agreement between farmers' classification and the variation in the value of most soil fertility indicators that were measured (Tittonell et al., 2005). The simplified farm was divided into these three land quality units that were assumed to be homogeneous in terms of soil properties, and all the fields of the farm planted to maize were grouped in each of them (e.g. in Fig. 1, Maize 1 and Maize 3 were treated as one unit: (+) fertile). Thus, our simplified farm system consisted of three maize fields: one poor (0.4 ha), one average (1.3 ha) and one fertile (0.5 ha) (Table 2). To parameterise the model for these three different land qualities, the various indicators of soil properties were averaged for each land quality unit, using:

$$\mathrm{WASP}_{(X)j} = \sum_{i=1}^{n} \mathrm{SP}_{(X)ij}(FA_i/TALQ_j)$$

Where, $\mathrm{WASP}_{(X)j}$ = weighed average soil property X for land quality j (with $j = 1$–3: poor, average and fertile), $\mathrm{SP}_{(X)ij}$ = soil property X measured in field i (=1–n fields) within land quality j, FA_{ij} = area of each particular field i within land quality j [ha], TALQj = total area of the farm classified as land quality j [ha].

Table 1
(A) Biophysical and socioeconomic characteristics and main production activities of the study area in Kakamega district, western Kenya; (B) Comparison of key indicators between the average for 20 farms sampled in the village and the case-study farm household (values between brackets indicate standard deviation)

(A)

Biophysical and socioeconomic characteristics	Altitude 1800 m.a.s.l.; Total annual rainfall 2200 mm; Mean temperature 20.8 °C; Landscape: Very undulating topography (slopes up to 45%), heavily dissected fluvial landscape characterised by a continuum of ridges (uplands), breaking slopes, foot slopes and valley bottomlands; Soil types: Dominated by *humic Nitosols* and *dystro-mollic Nitosols* (FAO) in the uplands and slopes, locally known as *Ingusi* soils; Population density: 650 inhabitants km^{-2}, Ethnic group: Luhya
Main production activities	Food crops: maize/beans, secondarily sorghum, cassava and sweet potato; Cash crops: tea, coffee, sugarcane, fruits and vegetables; maize and beans also regarded as income-generating crops; Livestock: Local Zebu breeds and some graded dairy cows. Zero grazing, or grazing in communal land.

(B)

	Cropped area (ha)	Family size	Number of livestock*	% Area under tea	% Off-farm income	Months food self sufficiency
Village average ($n = 20$)	1.3 (1.5)	6.8 (1.7)	3.2 (2.4)	10.5 (22)	25 (16)	8.9 (1.7)
Case study farm	2.4	8.0	1.3	17.5	23	11.0

* No distinction made with regard to breeds; the value for the case study farm indicates 1 dairy cow +1 calf (1.0 + 0.3).

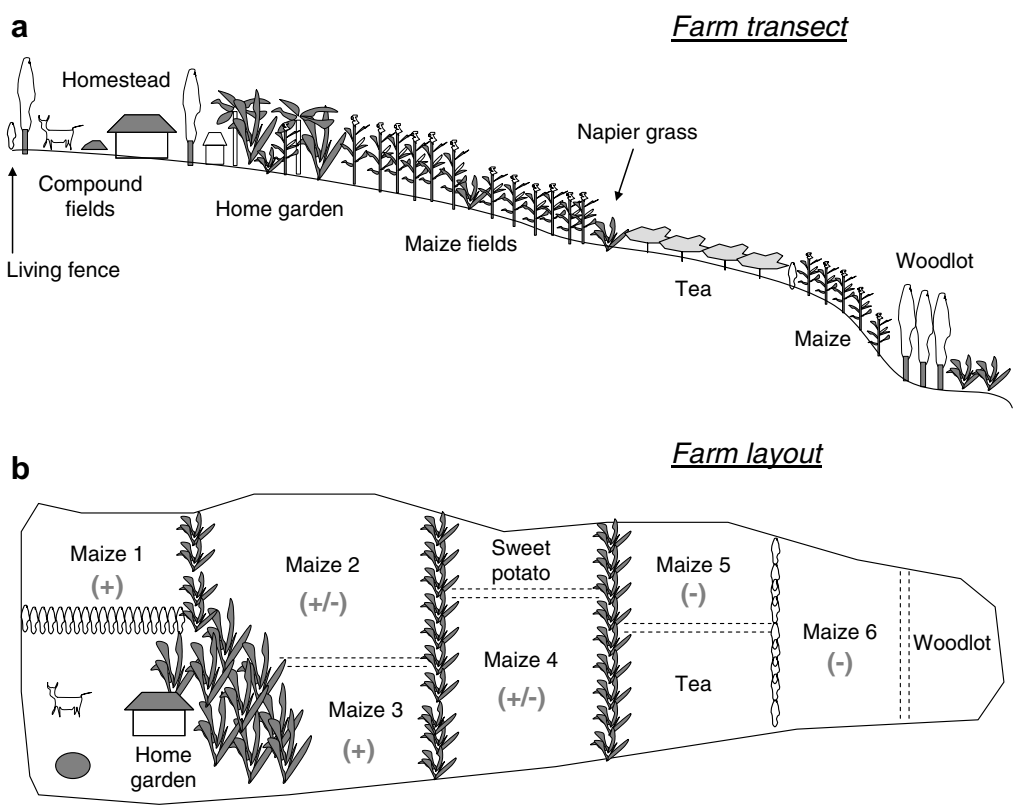


Fig. 1. A schematic representation of the case study farm: (a) Farm transect; (b) Farm layout. The 'quality' of each individual field or portion of the farm as classified by the farmer is indicated with signs: (−) poor, (±) average and (+) fertile land. In our simplification of the system, only maize was considered (ca. 80% of the cropped area), the farm was divided in three land quality units, the area of all fields planted to maize within each land quality unit was summed up, and weighed average soil indicators calculated for each unit and used to parameterise 3 instances of the model DYNBAL.

The main biophysical parameters used to characterise the land quality units for the simulation runs (weighed averages) are presented in Table 2, and current prices at farm gate collected during January/February 2005 in several villages across western Kenya in Table 3.

2.1.2. Assumptions

Several assumptions were necessary to simplify the system for the analysis at this early stage in the development of our methodology. It was assumed that maize was the only (sole) crop grown in all fields of the farm. Apart from

Table 2
Key biophysical parameters used to characterise the different land quality units for the simulation runs and range of measured maize yields

Land quality class	Area per land class (ha)	Clay content (%)	Silt content (%)	Soil organic C (g kg^{-1})	Total soil N (g kg^{-1})	Bulk density (Mg m^{-3})	Slope length (m)	Slope steepness (%)	Water content at field capacity (% v/v)*	Maize yields (t ha^{-1})
Fertile	0.5	39 ± 5.4	41 ± 3.0	21.6 ± 3.9	2.3 ± 0.4	1.26 ± 0.4	25 ± 8	2.1 ± 1.9	42	1.8–2.9
Average	1.3	33 ± 8.5	44 ± 5.6	17.9 ± 3.0	1.6 ± 0.5	1.24 ± 0.4	38 ± 18	9.6 ± 2.1	38	0.9–1.4
Poor	0.4	21 ± 7.2	50 ± 9.0	14.4 ± 3.2	1.7 ± 0.2	1.29 ± 0.3	39 ± 22	22.7 ± 11.0	35	0.5–1.2

* Calculated on the basis of particle size distribution, soil C content and bulk density (Van Keulen et al., 1995).

Table 3
Reference prices and calculated costs used for the simulation scenarios; data collected during January–February 2005 through interviews with key informants: farmers, extension agents, input suppliers and technicians of research institutes ($n = 9$–16)

Item [unit]	Price (KSh)	CV (%)	Use[a] (units ha^{-1})	Cost[b] (KSh ha^{-1})
Maize grain [Bag of 90 kg]				
January–June[c]	1620	7.3	–	–
July–December	860	10.4	–	–
Maize seed (hybrids 513, 614) [kg]	135	4.0	30	4050
Fertiliser prices [Bag of 50 kg][d]				
Di-ammonium phosphate (18:46:0)	2100	6.7	–	–
Calcium ammonium nitrate (46:0:0)	1870	16.4	–	–
Triple super phosphate (0:46:0)	2000	–	–	–
Manure [wheelbarrow ca. 30 kg FW]				
Good quality manure (e.g. 3% N)	50	26.7	–	–
Poor quality manure (e.g. 0.7% N)	32	49.6	–	–
Hired labour [person-day]				
First ploughing (hoe)	160	14.0	20.0	3200
Second ploughing, manure application and planting	87	26.6	24.4	2120
Weeding	380	50.6	11.1	4222
Harvesting (including chopping of crop residues)	97	13.5	26.6	2590
General farm husbandry (e.g. animal feeding, milking)	55	15.7	–	–
Soil movement (digging, trenching)	150	–	–	–
Ox ploughing [acre]	1350	15.7	2.2	3000

Exchange rate 75 KSh = 1 US$.
[a] Calculated for a typical maize crop, using input rates derived from participatory resource flow mapping. Labour needs for certain practices (e.g. manure application) depends on field characteristics such as distance from the homestead, accessibility, application rates, soil texture, crop yield, etc.
[b] In reality, casual labour costs are higher, as farmers are obliged to provide two meals per full working day to each employed person.
[c] Scarcity period: from the end of the short rains until harvest of the long rain season. Retail prices for that period are about 40 KSh per *goro–goro* (cf. 2 kg).
[d] Prices are highly variable and more expensive when fertilisers are sold in bags of 1–2 kg by local input suppliers.

the main operations considered in the model (cultivation, weeding and soil erosion control), timely management was assumed for all other operations and fields (e.g. date of fertilisation), which in reality does not occur, as farmers prioritise their best fields when allocating their labour (Tittonell et al., 2007). Labour was priced using local wages paid for hired labour, without discriminating between labour owned and hired, and in both cases man-days of 8 h per day were assumed. This assumption could be made on the basis that wealthier farmers normally use hired labour (permanent or temporary) for most farm activities. Other costs associated with hiring labour (e.g. offering meals to the casual workers) were not considered. Differences in soil fertility between land quality classes were assumed to be due to soil C and total N, while other nutrients were not limiting. This assumption, however, is quite unrealistic for P (Vanlauwe et al., 2006). Based on the latter study, it was simplistically assumed that fertiliser P was added to the soil when the rate of N fertilisation exceeded 60 kg N ha^{-1} at a rate of 0.1 kg ha^{-1} of P per kg ha^{-1} of applied N (a 10:1 N/P ratio), thereby increasing the costs of the nutrient inputs. Availability of fertilisers in local markets was assumed (i.e. low transaction costs for fertiliser acquisition assumed), which is not always the case in rural areas of western Kenya. Many of these simplifying assumptions may result in departures of optimal outcomes generated by the model from the actual situation. Thus results at farm scale should be interpreted with caution, particularly because other farm and non-farm activities that generate income (e.g. tea growing, dairy production, off-farm employment, cash remittances, etc.) were not considered when aggregating results at farm scale.

2.2. The analytical tool

2.2.1. The dynamic model: DYNBAL

Different crop and soil management situations within the farm were simulated using DYNBAL, a dynamic model that calculates N balances considering daily rates of inputs to and outputs from a certain field within a farm. The model includes four different sub-models or modules: crop growth, soil organic matter dynamics, water balance and soil erosion that provide the information for calculating the N balance, and simulate the interactions taking place during crop growth (e.g. effect of leaf area expansion on soil cover and erosion losses), using daily weather data inputs. The net rate of change of N in the system (field), or nitrogen balance, is the result of the N inputs and outputs to that particular soil/crop unit within the farm. N inputs include applications as mineral and organic fertiliser and as household wastes, N inputs from wet and dry deposition and from non-symbiotic N_2-fixation. N outputs include gaseous losses, leaching, soil erosion and N removal by harvest. The model considers a soil/crop system defined by the area of a certain field within a farm, so each field is simulated separately. The time span is the growing season, starting with soil preparation for planting and finishing after harvest (of grain and stover). The crop chosen for simulation is maize, as it is the main grain crop grown in the region and is highly responsive to soil fertility and management. The model parameterised for maize has been tested against on-farm data from western Kenya and yielded reasonably accurate predictions of on-farm yields and the response of the crop to applied fertilisers on different soil qualities (Fig. 2). A more detailed description of the model and its calibration and testing for the region is given in Tittonell et al. (2006).

2.2.2. Labour demand functions

Labour demands of different management activities were derived from data on labour calendars and participatory resource flow mapping exercises conducted on 60 farms from western Kenya (Tittonell, 2003), and functions relating labour allocation to different model parameters were built into DYNBAL (Fig. 3). Three types of labour directly affect processes simulated by the model: labour allocated to land preparation and planting (LABPLO and LABPLA), to weeding (LABWD) and to erosion control through ridge cropping and mulching (LABEC). Such a distinction was made because these activities may take place at different times during the growing season.

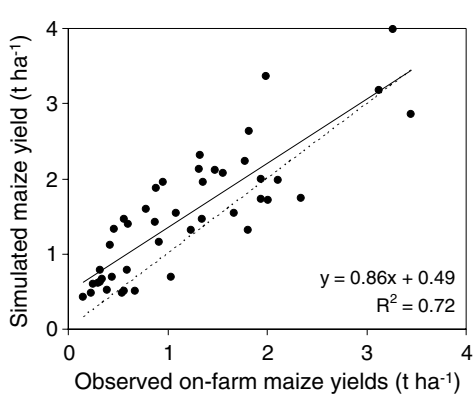


Fig. 2. Testing of the model DYNBAL against on-farm maize grain yields in western Kenya, including fertilised and non-fertilised fields, using mineral and organic fertilisers. Details on the process modelled and model performance for western Kenya are given by Tittonell et al. (2006).

The allocation of total available labour to cultivation and planting affects the planting date of the crop; cultivation is done manually by hand hoe (animal traction is not employed). When insufficient labour is allocated to these activities there is a delay in the start of crop growth which, depending on the length of this delay, will affect crop yield (Fig. 3a). The mathematical expression used to calculate this effect in the model was:

$$\mathrm{DELAY} = \mathrm{MIN}\left\{40, 40 - \frac{40}{20} \times (\mathrm{LABPLO} - 5)\right\}$$

Where, LABPLO is the amount of labour (man-days ha^{-1}) allocated to land preparation and DELAY is the delay in planting date (days) with respect to the optimum date for the area. The shape of these functions is explained by the fact that no delay in the planting date longer than 40 days was recorded; for labour allocated to second ploughing (including manure application) and planting (LABPLA), 3 man-days per ha was considered by farmers as a reasonable threshold.

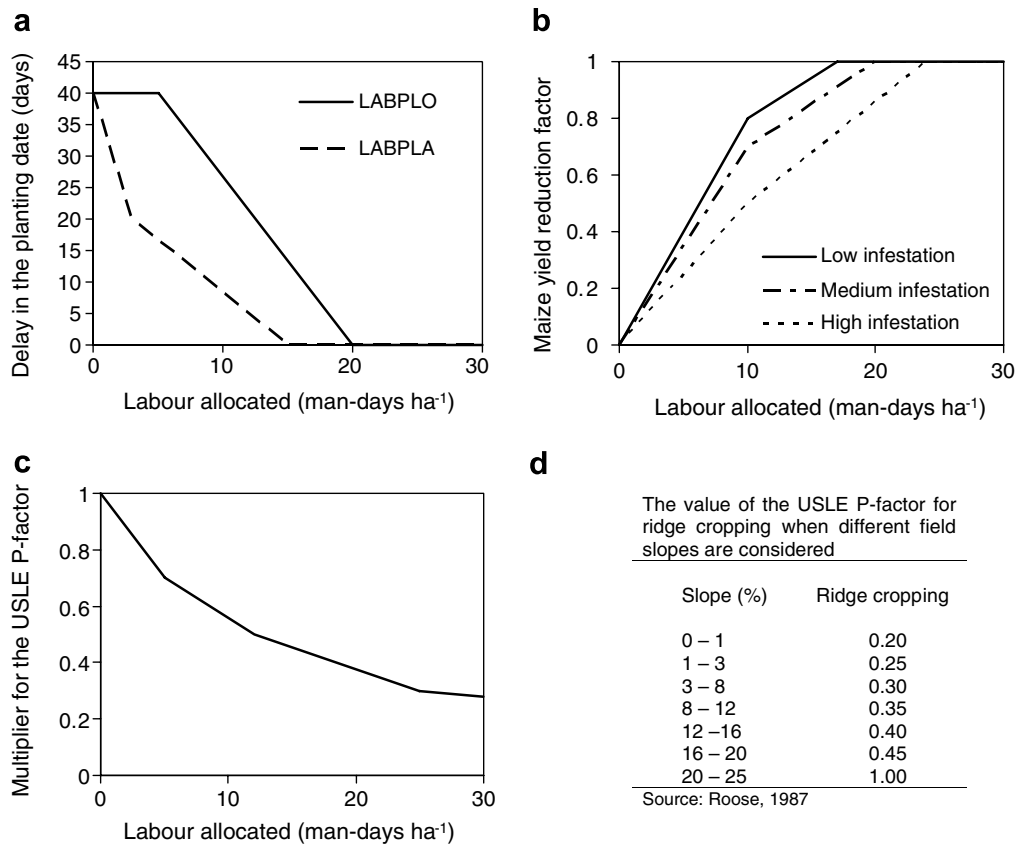
Restricting labour allocation to weeding reduces the value of a yield reduction factor due to weed competition (Fig. 3b). This simplistic approach was chosen because weed competition is not simulated dynamically in the current version of DYNBAL. A database consisting of on-farm maize yield measurements, management practices applied, soil fertility and weed infestation levels was used to derive these functions (Tittonell et al., 2007). It was assumed that when a certain amount of the available labour is allocated, weeding is done on time and there is no effect on crop yield. This threshold value varies for different intensities of weed infestation, regardless of the type of weed considered; three weed infestation intensities were recorded in the field and no *Striga* infestation was observed in any of the farms visited in Kakamega. The equation used in the model to calculate this effect was:

$$\mathrm{Yield}_{\mathrm{reduction}} = \mathrm{MAX}\left\{0, \mathrm{MIN}\left[1, \frac{0.8}{10} \times \mathrm{LAB}_{\mathrm{weed}}, 0.8 + \frac{0.2}{7.5} \times (\mathrm{LAB}_{\mathrm{weed}} - 10)\right]\right\}$$

Where, $\mathrm{LAB}_{\mathrm{weed}}$ represents the amount of labour allocated to weeding (man-days ha^{-1}), and $\mathrm{Yield}_{\mathrm{reduction}}$ is the multiplier (taking values between 0 and 1) used to calculate the reduction in yield due to weed competition.

Soil losses by erosion are calculated in DYNBAL using a version of the universal soil loss equation (USLE) adapted for tropical conditions (Roose, 1983):

$$\mathrm{Soil\ loss}\ (\mathrm{t\ ha^{-1}\ yr^{-1}}) = R \times K \times S \times L \times C \times P$$



The value of the USLE P-factor for ridge cropping when different field slopes are considered

Slope (%)	Ridge cropping
0 – 1	0.20
1 – 3	0.25
3 – 8	0.30
8 – 12	0.35
12 –16	0.40
16 – 20	0.45
20 – 25	1.00

Source: Roose, 1987

Fig. 3. Labour demand functions developed from participatory resource flow mapping and plenary discussion with farmers in western Kenya and built into the integrated analytical tool DYNBAL-MOSCEM. (a) Labour availability for land preparation and planting vs. delay in planting date; (b) Labour availability for weeding vs. maize yield reduction factor due to weed competition for fields with different weed infestation levels (scored by farmers); (c and d) the factor *P* of the universal soil loss equation (USLE), indicative values for ridge cropping and a multiplier to account for labour availability for ridging.

where, *R* represent the erosivity of rainfall, *K* the soil erodibility, *S* and *L* the steepness and length of the slope, *C* the type of crop covering the soil surface and *P* the effect of erosion control practices. In DYNBAL, *R* is calculated based on daily rainfall using the equation proposed by Roose (1983), *K* is estimated from soil texture and C content using the nomograph of Whitmore and Burnham (1969), and *C* is linked to leaf area development as simulated by the crop module and affected by a coefficient that represents the effect of mulching if present (Colvin et al., 1981). Values for the factor *P* for the practice of ridge cropping, as calculated by Roose (1987) when the slope of the field increases from 0% to 25%, are given in Fig. 3d.

Labour allocated to soil erosion control through 'non-permanent' methods such as soil ridging was related to the factor *P* of USLE through a multiplier ranging between 0 and 1, which increases the value of the factor *P* as less labour is available for erosion control (Fig. 3c). This empirical curve was derived from estimated values of *P* for different cropping systems from soil erosion plots in western Kenya (Rao et al., 1999), and by assuming that labour demands for soil movement to control erosion are similar to those for land preparation (first ploughing). Semi-permanent erosion control measures such as terracing were not considered, as they are not currently practised by farmers in the region (existing terraces were built when enforced by law during colonial times).

These functional relationships represent working assumptions that consider the interaction of various factors that may operate simultaneously within the farming systems analysed. For example, when ploughing of a certain field is delayed too late into the cropping season due to labour shortage, farmers may decide not to plant a crop at all and to leave the field fallow. Or, when certain fields within the farm were planted on time, labour demands for weeding the emerged crops start competing with labour demands for working on the other fields that remained unploughed. We recognise that linearity does not always hold for the relationship between labour availability and timing of management practices that are often affected by stochastic events (illness, social demands such as funerals, etc.), but we consider this a reasonable assumption for the aims of this analysis.

2.2.3. The farm-scale aggregation and optimisation algorithm: MOSCEM

As stated in the introduction, farmers in Africa operate under severely resource-constrained conditions, and are

often confronted with multiple competing options for investment in hired labour and/or inputs. To help understand the trade-offs faced by such farmers, we propose the use of multi-objective evolutionary algorithms to examine the entire range of acceptable (Pareto optimal) management strategies. The multi-objective optimization problem can be stated as follows (here expressed as a minimisation problem):

$$\min_{\theta \in \Theta} F(\theta) = \begin{bmatrix} f_1(\theta) \\ \vdots \\ f_T(\theta) \end{bmatrix} \quad (1)$$

where $f_i(\theta)$ is the ith of T objective functions. The solution to this problem will, in general, not be a single "best" parameter set but will consist of a Pareto set of solutions corresponding to various trade-offs among the objectives. This Pareto set defines the parameters (or decision variables) along the best possible trade-off curve between a certain number objectives (f_i to f_T), without stating a subjective relative preference for minimizing one specific component of $F(\theta)$ at the expense of another. To further illustrate this concept, consider Fig. 4 which depicts the Pareto solution set for a simple problem where the aim is to simultaneously optimize two objectives (f_1, f_2) with respect to two parameters (θ_1, θ_2). In our case, the parameters will define the management strategy in the DYNBAL model, and will therefore from now on be termed decision variables. The points A and B indicate the solutions that optimize each of the individual criteria f_1 and f_2, whereas the solid black line joining A and B corresponds to the Pareto set of solutions. The black dots represent an initial set of parameter estimates, while the number in subscript denotes their corresponding Pareto rank. Moving along the line from A to B results in the improvement of f_2 while successively causing deterioration in f_1. The points falling on the line AB represent trade-offs between the objectives and are called non-dominated, non-inferior, or efficient solutions.

While it may be relatively simple to pose the optimization problem in a multi-objective framework, solving this problem to identify the Pareto set of solutions is not easy and has been the subject of much research. Ideally, the multi-objective optimization algorithm should find the set of all non-dominated solutions, which will constitute the global trade-off surface. However, because computational resources are finite, multi-objective solution algorithms typically approximate the Pareto set using a number of representative solutions. For linear models, multi-objective linear programming (MOP) methods can be used to analytically derive the set of efficient or non-dominated Pareto solutions (Cohon, 1978). However, for non-linear settings with a dynamic state variable model such as DYNBAL (in which the time dimension is included and in which the values of state variables can change over time), an alternative class of solution algorithms is needed.

An effective and efficient non-classical method for solving the multi-objective optimization problem in its original form has recently been developed (Vrugt et al., 2003). The method, entitled the Multi-Objective Shuffled Complex Evolution Metropolis (MOSCEM-UA) algorithm, is a general purpose global optimisation method that provides an efficient and effective estimate of the Pareto solution space within a single optimisation run and does not require subjective weighting of the various objectives. The MOSCEM-UA algorithm combines the strengths of complex shuffling (Duan et al., 1992), Metropolis annealing search (Metropolis et al., 1953), and multi-objective fitness assignment (Zitzler and Thiele, 1999). The specific strengths of this method are the global search in space and a relative fast

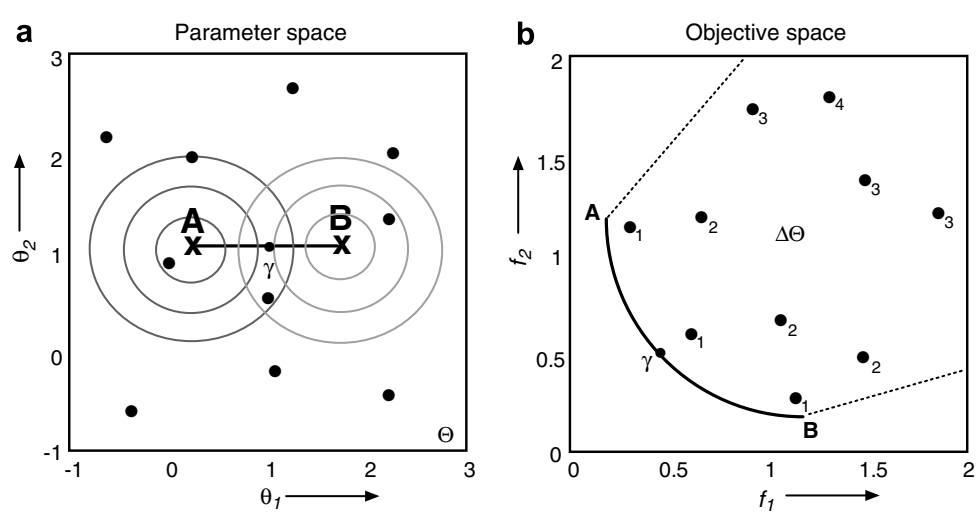


Fig. 4. Illustration of the concept of Pareto optimality for a problem having two parameters (θ_1, θ_2) and two criteria (f_1, f_2), in the parameter (a) and objective (b) space. The points A and B indicate the solutions that minimize each of the individual criteria f_1 and f_2. The thick line joining A and B corresponds to the Pareto set of solutions; γ is an element of the solution set, which is superior in the multi-criteria sense to any other point in Θ. (After Vrugt, 2004).

convergence to the parameter ranges of optimal solutions. Experiments conducted using standard synthetic multi-objective test problems have shown that the final population provides a fairly uniform approximation to the Pareto solution space (Vrugt et al., 2003).

Operationally, MOSCEM takes an initial population of points (i.e. combinations of management parameters for the DYNBAL model in our case), randomly spread out in the feasible parameter space. For each individual of the population the multi-objective vector $F(\theta)$ is computed, and the population is ranked and sorted using an improved version of the fitness assignment concept developed by Zitzler and Thiele (1999). The population is partitioned into several groups and, in each group k ($k = 1, 2, 3 \ldots q$), a parallel sub-group is launched starting from the point that exhibits the highest fitness. A new candidate point in each sub-group k_1 is generated using a multivariate normal distribution centred on the current draw of sub-group k_1 augmented with the covariance structure induced between the points in group k. A Metropolis-type of acceptance rule is used to test whether the offspring (candidate point) is accepted. If the offspring is accepted, it replaces the worst member of the current group k. After a number of iterations, the groups are replaced into the fixed population of points and new groups are formed through a process of shuffling (short sliding step or movement). Iterative application of the various algorithmic steps causes the population to converge toward the Pareto set of solutions.

2.2.4. The integrated tool

We used DYNBAL to construct a simplified representation of a smallholder farm in Western-Kenya with three zones of soil fertility. The criteria to simplify the system and the assumptions necessary were given in Section 2.1. Three instances of DYNBAL were parameterised, each representing a land quality unit, using the values given in Table 2 for parameterisation and initialisation of the model; no spatial interactions between land quality units were simulated. As each land quality unit comprises various fields and represent different areas within the farm, there might be a certain degree of variability within each unit that may lead to aggregation errors at farm scale.

A certain amount of cash was assumed to be available at the beginning of the season, which could be invested in fertilizer or in hiring extra labour. The assumption on investments in labour and fertilisers was based on calculations done from the results of the resource flow maps drawn by the farmer for the long rains season (i.e. amounts of fertiliser and labour allocated to each field times the price of these production factors – Table 3). An average investment in hired labour and fertilisers for maize production of cf. 3400 KSh ha^{-1} was calculated for this particular (relatively wealthy) case study farm. These externally-sourced resources together with the resources available internally within the farm were then allocated over the three fields. Using these inputs together with the other, standard inputs for DYNBAL (e.g. rainfall, radiation, temperature) each instance of the DYNBAL model was run for one growing season. Outputs of each of the DYNBAL instances, each representing one field type, were then aggregated to obtain results at the scale of our simplified farm system. For example, total farm maize yield was calculated by summing the maize yields of each of the land quality units. The objectives maximising farm yield, minimising farm erosion and minimising farm scale N losses – see later: Section 2.3.2 and Table 4, were optimised using MOSCEM by searching the best combination of values for the various decision variables with regard to cash investments and allocation of resources (i.e., labour for specific activities and mineral fertiliser) over the three land quality units.

The optimisation using MOSCEM leads to identification of the combinations of decision variable values that result in optimal two-dimension trade-off curves between these objectives. These trade-off curves (Pareto sets) can be used in aiding decision-making provided that weights (preferences) and threshold values are given to each of the objectives, for example, by defining which level of soil erosion is acceptable and what would be the maximum yield that could be achieve under those circumstances. This type of model outcome can also be used in discussions among stakeholders about different objectives, such as productivity vs. land degradation. In contrast with the type of results obtained using techniques such as MOP, which provide only the best, optimal solutions, the results generated by MOSCEM indicate combinations of decision variables that yield results close to the optimal trade-off curve, giving insight into a diversity of farming strategies that lead to similar values of the objective functions (i.e., management strategies that may lead to acceptable, although not optimal solutions).

2.3. Scenario analysis

2.3.1. The problem at stake

Nutrient use (fertilisers, manure) by farmers in the study area is limited due to their scarce availability (about 1 t manure cow^{-1} $season^{-1}$ can be recovered with good management, representing an application rate as low as <0.5 t ha^{-1} for our case-study farm), to their cost (in terms of cash and/or labour) and to the poor results obtained with their use; i.e. large nutrient losses, particularly for N. Soil erosion is a major problem for the sustainability of the farming systems on this heavily dissected landscape receiving 2000 mm of rain per year (cf. Table 1). During the field assessments, farmers often ascribed yield variability to differences in the slope of the fields (i.e. this was true for some 60% of the farmers who participated in the study in Shinyalu division, Kakamega). Areas of steep terrain within their farms were perceived as 'poor soils', prone to excessive run-off and 'washing out' of soil and fertilizers. Quantifiable indicators pertaining to both short- (food

Table 4
Objectives selected for the optimisation and trade-off analysis

Objective	Time scale relevance	Decision frame	Indicators	Optimisation criteria
I Primary				
1. Food production	Short-term	Operational	Maize grain production (t farm^{-1})	Maximise farm yield
2. Resource capture and use efficiency	Short and mid-term	Operational, tactical	N losses (kg N farm^{-1}) N balance (kg N ha^{-1}) Nitrogen productivity (kg grain kg^{-1} N applied) Gross N use efficiency (kg grain kg^{-1} N available) Rainfall use efficiency (kg grain mm^{-1})	Maximise N balance and minimise losses; N productivity larger than fertiliser:grain price ratio
3. Resource degradation	Mid and long-term	Tactical and strategic	Soil losses by erosion (t farm^{-1}) Changes in the N stock (%)	Minimise soil losses; positive changes in N stock
II Complementary				
4. Labour productivity	Short-term	Operational	Economic return to labour (KSh man-day^{-1})	Economic return above local labour wages
5. Economic viability	Short and long-term	Operational, tactical and strategic	Value of production (KSh) Gross benefit (KSh season^{-1}) Benefit/cost ratio	Maximise margin; minimise cost for potential production

The underlined indicators were those selected to define objective functions.

production) and long-term processes (soil erosion) were selected for the different objectives (Table 4). In the scenarios analysed, a certain amount of cash was available to the farmer at the beginning of the season, and decisions had to be made for its allocation to purchasing nutrient inputs and labour; these resources had to be allocated to different activities for the various field types (soil qualities) within his/her spatially heterogeneous farm.

2.3.2. Optimisation

Three scenarios of financial liquidity were analysed, in which initial cash reserves of KSh 2000, 5000 and 10,000 (1 US$ = 75 KSh) per hectare were available to the farmer at the beginning of the season to invest solely in cropping practices (i.e. other household expenditures or investments in other activities such as livestock feeding were not considered). Investments in cropping practices included: buying mineral N fertiliser (Calcium Ammonium Nitrate), and hiring labour for land preparation and planting, for weeding and for soil erosion control. Since most labour was hired in by this particular household, a conservatively small value of 20 man-day season^{-1} was assumed to be the total amount of family labour allocated to maize production (based on labour calendars – Tittonell, 2003), for all of the activities considered in this analysis, and all labour needed above that threshold must be hired. Another set of decision variables described the allocation of available resources at farm level (total N fertiliser bought by the farmer and the total labour hired in for land preparation and erosion control, planting and weeding) to each land quality unit within the farm. Parameters of the type 'fraction of the resource x allocated to the land quality j' were defined for the land quality units fertile and average (Fields 1 and 2, respectively), while the fraction allocated to the poor land quality unit (Field 3) was computed as 1 minus the sum of the fractions allocated to fertile and average.

The combination of possible investments in cropping practices and spatial allocation of the available resources led to a set of 12 decision variables to be analysed:

1. Fraction of the total cash reserves invested in mineral fertiliser.
2. Fraction of the total cash reserves invested in hiring labour for ploughing and planting.
3. Fraction of the total cash reserves invested in hiring extra labour for erosion control.
4. Fraction of the total cash reserves invested in hiring labour for weeding.
5. Fraction of mineral fertiliser bought allocated to fertile fields.
6. Fraction of mineral fertiliser bought allocated to average fields.
7. Fraction of labour hired for ploughing and planting allocated to fertile fields.
8. Fraction of labour hired for ploughing and planting allocated to average fields.
9. Fraction of extra labour hired for erosion control allocated to fertile fields.
10. Fraction of extra labour hired for erosion control allocated to average fields.
11. Fraction of labour hired for weeding allocated to fertile fields.
12. Fraction of labour hired for weeding allocated to average fields.

Different combinations of these 12 decision variables were used, together with the standard model parameterisation for the three land quality units of this particular farm (cf. Table 2), to run the dynamic model. Indicators corresponding to those defined as primary objectives were selected for optimisation (i.e. defined as objective functions), while others were calculated from the model outputs for each scenario analysed (Table 4). Primary objectives included maize yield, N losses by leaching and erosion, and soil losses by erosion, all of them on a seasonal basis and aggregated at the farm scale, which were used to construct trade-off curves. For simplicity, and because the model runs were set for a single season (the long rains), it was assumed that soil lost from one field does not end up in the other fields as a sediment; i.e., fields were not spatially connected. We consider this to be a realistic assumption given the steepness of the most of the fields. From the model outputs, complementary indicators such as returns to labour, N use efficiency or gross economic margin were derived.

3. Results

3.1. Trade-offs between productivity, efficiency and resource conservation objectives

3.1.1. Maize production and nitrogen losses

Increasing maize yields by applying mineral fertilisers was necessarily associated with larger N losses by leaching, runoff and soil erosion, as shown for the scenario of highest financial liquidity (KSh 10,000) in Fig. 5. Each point in the graph represents the model output for a certain combination of parameters (i.e. parameter set), when the objective functions were farm scale N losses and maize grain yields. The optimisation routine in MOSCEM starts with a randomly drawn initial population of parameter combinations (i.e. 'farm strategies') represented by the dots within the circle. During the optimisation, the population of solutions evolves towards the best possible trade-off curve between the two objectives. Such evolution is represented by the arrows in Fig. 5 and all points on the outer curve represent Pareto efficient solutions. This trade-off curve is an outcome of the optimisation as it indicates either the maximum yields that can be achieved accepting a certain rate of N losses, or the minimum N losses that may be achieved sacrificing maize yields. On the Pareto efficient frontier, N losses at farm scale fluctuated between ca. 80 and 120 kg farm^{-1}, corresponding to rates of 36–54 kg N ha^{-1} season^{-1}, while the maximum maize yields achieved were around 3.4 t grain ha^{-1} season^{-1} (a farm scale production level of c. 7.4 t).

When the results of the different scenarios of financial liquidity are contrasted (KSh 2000, 5000 or 10,000 available to the farmer; Fig. 6), it is clear that the lower boundary of N losses at farm scale was similar in all three cases. This represents a baseline N loss rate (36 kg N ha^{-1} season^{-1}) calculated by the model that may be expected on this farm system under any of the resource allocation strategies. The major difference between the analysed scenarios was the attainable maize yield; it increased when more cash was available, but this led also to larger N losses. A rapid,

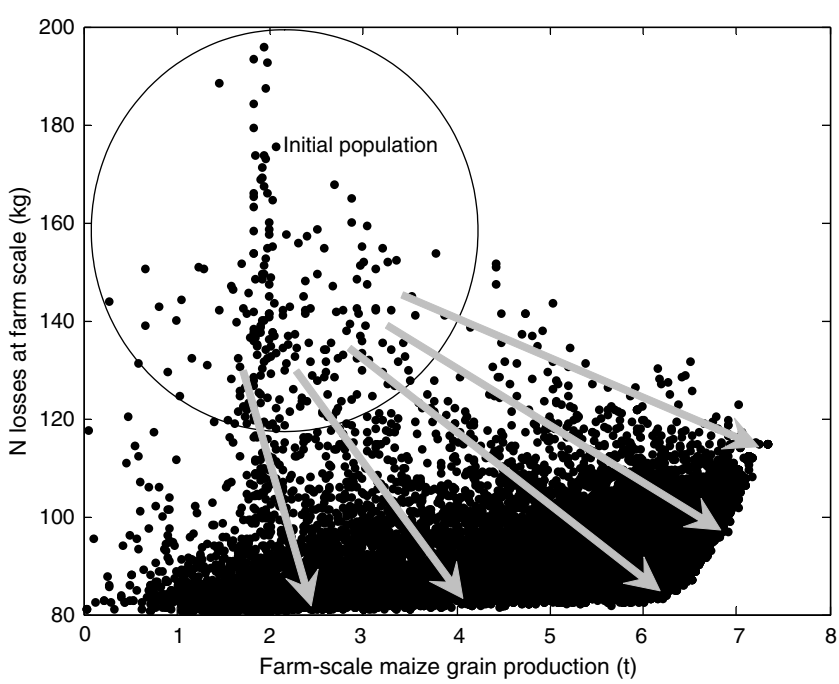


Fig. 5. Results of the optimisation of the objectives 'maximising maize production at farm scale' and 'minimising N losses at farm scale' for the scenario of high investment capacity (10,000 KSh ha^{-1}). The circle indicates the initial random population of feasible solutions (sets of DYNBAL parameter combinations) and the arrows indicate their evolution towards the Pareto efficient frontier (trade-off curve) after several iterations.

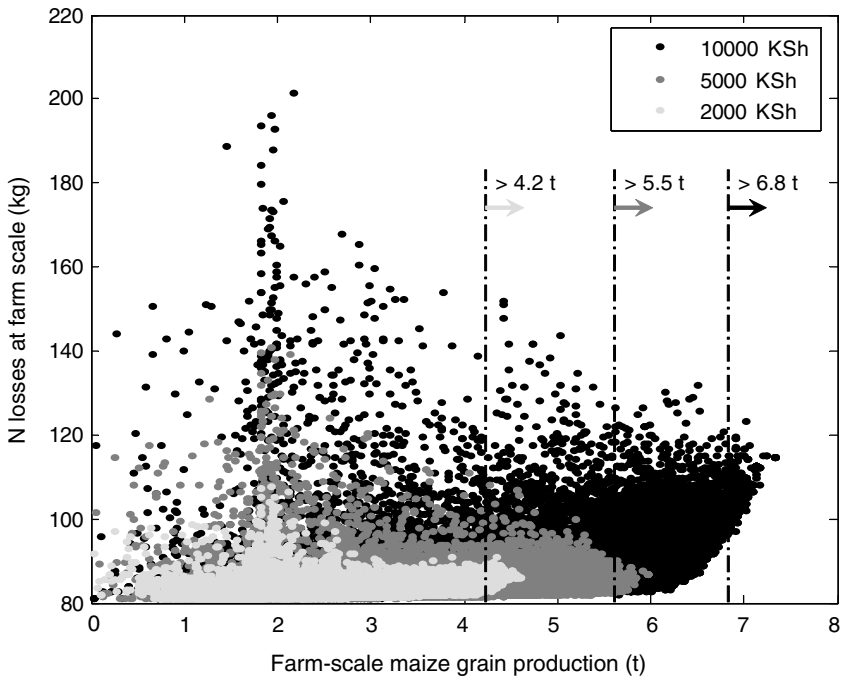


Fig. 6. Results of the optimisation of the objectives 'maximising maize production at farm scale' and 'minimising N losses at farm scale' for the three scenarios of investment capacity (2000, 5000 and 10,000 KSh ha^{-1}). The vertical lines indicate the yield thresholds for selection of the best sets of solutions in terms of maize production for each of the scenarios.

more than proportional increase in the rate of N losses was obtained when maize production at farm scale increased above 6 t $farm^{-1}$ (i.e. an average yield of 2.7 t ha^{-1}) in the highest cash availability scenario. Several allocation strategies within the poorest financial scenario led to the production of 4 t $farm^{-1}$ of maize (average yield 1.8 t ha^{-1}), with farm scale N losses ranging around the baseline of 80 kg $farm^{-1}$. Yield levels as high as 1.8 t ha^{-1} are normally achieved in the most fertile fields of smallholder farms in western Kenya (cf. Table 2). N losses by leaching reported by previous studies on African systems were highly variable: 8–15 kg N ha^{-1} $year^{-1}$ (Grimme and Juo, 1985), 10 kg N ha^{-1} $year^{-1}$ (Akonde et al., 1997), or 36–153 kg N ha^{-1} $year^{-1}$ (Poss and Saragoni, 1992), while N losses by erosion measured in western Kenya for different cropping systems ranged between 41 and 159 kg N ha^{-1} $year^{-1}$ (Rao et al., 1999).

The model simulations indicate that more than c. 6.2 t $farm^{-1}$ of maize can only be obtained by increasing the use of N fertiliser, directly resulting in larger N losses by leaching and poorer N capture efficiencies. To analyse what these trade-off curves imply in terms of investment and resource allocation strategies, the points (i.e. 'strategies', parameter sets) corresponding to farm-scale maize yields above 4.2, 5.5 and 6.8 t ha^{-1} (i.e. the points on the Pareto frontier to the right of each vertical line drawn in Fig. 6) for the scenarios of KSh 2000, 5000 and 10,000 initial cash reserves, respectively, were isolated. The combination of key model parameters leading to these points, which represent the fulfilment of the food production goal, are analysed in the following section.

3.1.2. Investment and allocation strategies

Different investment strategies, in terms of hiring labour for the various management practices and buying mineral N fertilisers, which led to the highest maize production for each scenario are depicted in Fig. 7. The investment strategies are expressed as fractions of the total cash available invested. Plotting the relative investment in buying N fertiliser against the relative investment in hiring labour for weeding (Fig. 7a), shows that hiring labour is a priority in all scenarios to obtain the greatest yields. Large yields were also obtained for the three scenarios when investments in hiring labour for land preparation were prioritised over labour for soil erosion control (Fig. 7b). These prioritisation patterns were stronger for the scenario with the least investment capacity, and the set of solutions leading to the greatest yields in this case was the most variable.

For the scenarios of poor and intermediate levels of investment capacity (KSh 2000 and 5000), prioritising weeding over mineral N fertiliser use was a more explicit decision pattern than when KSh 10,000 were available to the farmer (Fig. 7a). Under the situation of low initial cash reserves, high maize production (>4.2 t $farm^{-1}$) was achieved with a wider range of relative investments in weed control (0–50%) and N fertiliser (0–25%), compared with the other scenarios (i.e. the 'cloud' of solutions was more dispersed). When cash availability was KSh 5000, the strategies leading to the most production (>5.5 t $farm^{-1}$) where those in which between 50% and 70% of the available cash was invested in weeding, while little was invested in N (0–10%). When KSh 10,000 were available the relative investment in mineral N fertilisers increased up to 30–40% of the

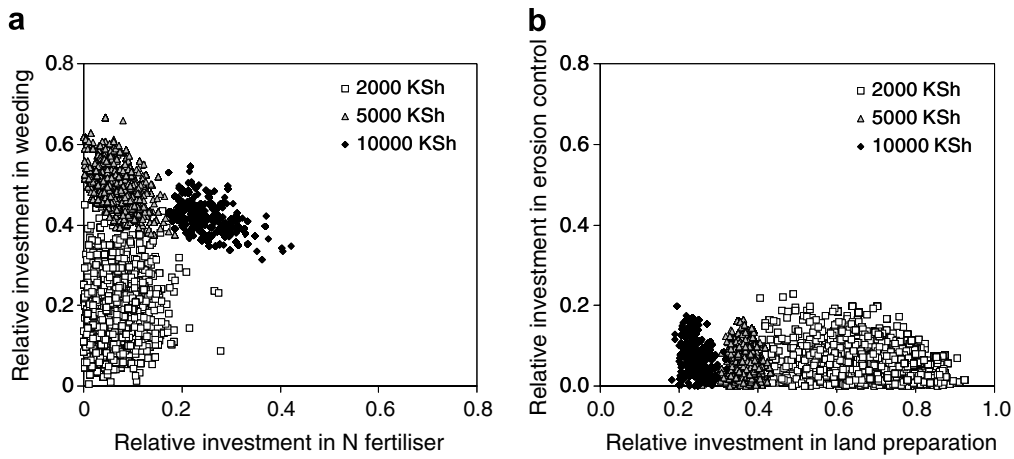


Fig. 7. Relative investment of the available cash for the selected subsets of solutions (cf. Fig. 5): maize production above 4.2, 5.5 and 6.8 t ha^{-1} for the scenarios of 2000, 5000 and 10,000 KSh ha^{-1}, respectively. (a) Relative investment in labour for weeding vs. purchasing N fertiliser; (b) relative investment in labour for early land preparation vs. labour for erosion control (ridging of sloped fields).

total cash available. The yield obtained using more N fertiliser in the high investment scenario (>6.8 t farm^{-1}) allowed relatively less investment in labour for weeding (compensation), ranging roughly between 30% and 50%.

Model results also indicated that in the case of low initial cash reserves, KSh 2000, most of that cash (45–85%) has to be invested in preparing the land for timely planting to fulfil the joint objectives of maximising yields and minimising N losses. In absolute terms, the investment in land preparation did not differ much between the scenarios of KSh 2000 and KSh 5000, while availability of KSh 10,000 allowed earlier land preparation and therefore timelier planting of the crop. The strategy of prioritising labour for land preparation allowing early planting over using labour for ridge cropping is in line with previous model- and data-based studies that indicated planting date as one of the main factors affecting maize yield and nutrient use efficiency (Tittonell et al., 2007). Again, the cloud of solutions leading to the highest yields for the scenario of low initial cash reserves was more dispersed (i.e. less sensitive) than those when more cash was available. It is important to note that early planting allows a faster canopy closure and proper soil cover that protects the soil surface from the effect of rainfall, also reducing soil erosion. The smaller investments in soil erosion control at the farm scale are also the result of differential resource allocation to the various fields of the farm. Ridging will substantially reduce soil erosion only in the fields of the farm where the slope is pronounced (cf. Table 2).

Thus, the relative spatial allocation of the acquired resources (fertiliser and labour) within the farm also had an impact on the strategies leading to the greatest yields for each scenario. This is illustrated for the allocation of labour to weeding within the farm for the lowest and highest investment capacity scenarios (Fig. 8). When KSh 2000 were available to the farmer, the relative investment in (and the absolute amount of) labour available for weeding was small (cf. Fig. 7a). The best strategy to allocate this labour,

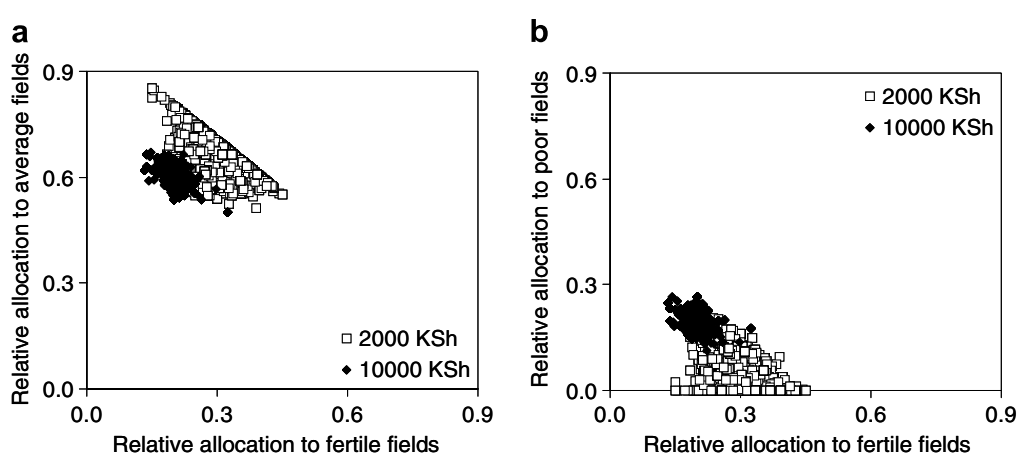


Fig. 8. Relative allocation of labour available during weeding time to fields of different soil quality (fertile, average and poor) for the selected subsets of solutions (cf. Fig. 5): maize production above 4.2 and 6.8 t ha^{-1} for the scenarios of 2000 and 10,000 KSh ha^{-1}, respectively. (a) Relative labour allocation to fertile and average fields and (b) relative labour allocation to fertile and poor fields.

according to the model results, is to focus it on the fields of better soil quality; 15–45% to the fertile fields and 50–80% to the average fields, which leaves little labour for the poor-fertility fields. The larger relative allocation to the fields of average soil quality is partly explained by its larger area, but also consistent with the economic theory suggesting that scarce resources are preferably allocated to activities that yield higher marginal returns. When KSh 10,000 are available, allocation of around 20% of the hired labour for weeding to the poorest field becomes an option (note also that this field has a slope of >20% and weeds may cover the soil and reduce erosion).

3.1.3. Maize production and soil erosion

For each of the three scenarios of initial cash reserves there was a range of increasing maize yield values that did not result in an increase in soil erosion (Fig. 9). As in the previous analysis, better investment capacities allowed greater maize production to be achieved at farm scale. Above a certain threshold that varied for each scenario, there was a clear trade-off between increased yields and larger soil losses, but the nature of the trade-offs (i.e., the slope of the curve) differed markedly between the scenario of KSh 2000 and the other two. For the scenario of low initial cash reserves, soil losses by erosion increased abruptly beyond a certain maize production (cf. 4 t farm^{-1}) due to less capacity to invest in erosion control. In the trade-off curves between N losses and maize production (cf. Fig. 6), there were practically no differences between the minimum rates of N losses achievable for the different scenarios. In this case, however, the minimum achievable rates of soil loss by erosion varied among scenarios (Fig. 9). For a certain maize production level, the rate of soil erosion was less when the availability of cash was higher, due to an increased capacity to invest in erosion control. These differences in soil loss rates, however, that were in the order of 1–2 t ha^{-1} yr^{-1} may not result in significant differences in reality, given the uncertainties in other parameters. In the zone of the curves corresponding to the greatest maize production, soil losses tended to increase, though at a clearly different incremental rate for the three scenarios.

Larger yields associated with increased rates of soil erosion appear to be counter-intuitive, as larger biomass production would offer a better cover of the soil surface. This happened in the scenario of low initial cash reserves due to two main reasons: (i) the scarce labour available was mostly allocated to land preparation and weed control and almost nothing to erosion control; and (ii) given the poor yields, all fields had to be cultivated to achieve more than 4 t farm^{-1} of grain, leading to late planting of the poor-fertility field (>20% slope) without ridging. Larger initial cash reserves allowed more investment in labour to control erosion and therefore larger yields could be obtained reducing the cost of soil losses. Thus, the effect of cash availability was characterised by a shift from one trade-off curve to another; increasing cash investments were necessary for the system to 'jump' from trade-off situations of greater soil losses and smaller yields to more

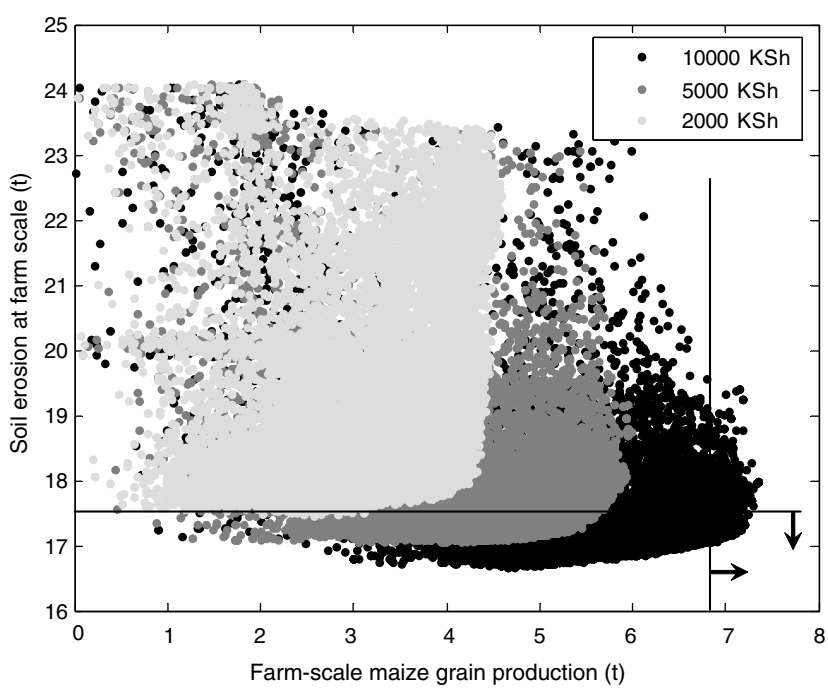


Fig. 9. Results of the optimisation of the objectives 'maximising maize production at farm scale' and 'minimising soil losses by erosion at farm scale' for the three scenarios of investment capacity (2000, 5000 and 10,000 KSh ha^{-1}). The vertical and horizontal lines indicate, for the high investment scenario (10,000 KSh ha^{-1}), the subset of solutions that satisfy both objectives. The selected subsets were those with maize production larger than 6.8, 5.6 and 4.2 t farm^{-1} and soil erosion losses smaller than 17.5, 18.0 and 18.5 t farm^{-1}, respectively.

favourable ones. Thus larger maize yields were associated with smaller soil losses, but not through a direct relationship.

3.2. Compromise between food production and resource conservation

Further, we analysed compromise cases in terms of attaining food production and resource conservation objectives by isolating for each scenario the subset of solutions leading to the maximum maize yields with the minimum soil losses by erosion. The subsets of solutions selected comprised those with maize production larger than 6.8, 5.6 and 4.2 t farm^{-1} and soil erosion losses smaller than 17.5, 18.0 and 18.5 t farm^{-1} (equivalent to average soil losses of 8.0, 8.2 and 8.4 t ha^{-1}) for the scenarios of KSh 2000, 5000 and 10,000 of initial cash reserves, respectively. Such a subset is indicated in Fig. 9 for the KSh 10,000 scenario; i.e. the subset of points along the Pareto set comprised in between the vertical and horizontal lines drawn in the graph (lower-right corner). The average rate of soil losses by erosion that can be expected under forest vegetation in this type of environment may be as high as 5 t ha^{-1} yr^{-1} (M. van Noordwijk, pers. comm.), suggesting that the selected thresholds may be considered conservative for arable land. For each of these subsets of optimal solutions, the average value and standard deviation of the primary objective indicators, model parameters and complementary indicators achieved at farm scale were calculated (Table 5). For the same subsets of solutions, average indicators and allocation parameters and their standard deviation were calculated for each land quality unit within the farm system (Table 6; note that these values are expressed as per land quality unit and that the area of each of them within the farm varies, cf. Table 2).

For the scenario of high initial cash reserves, increased N leaching as a consequence of larger rates of N application (1.0, 3.8 and 26.8 kg N ha^{-1}) leads to a lower productivity of the applied N (Table 5). However, the productivity of the applied N was larger but also highly variable for the scenario of the lowest initial cash reserves, indicating that crop yields in this case varied from high apparent responses to applied N to virtual crop failure. When the availability of N in the soil was calculated from the values in Table 2 and included in the calculation of the gross N use efficiency [=grain yield/(soil N + fertiliser N)], the average figures at farm scale indicated a more efficient use of the natural resource base with increasing investments. However, the gross N use efficiency varied widely across soils of different quality (Table 6). With increasing investments, more

Table 5
Average values and standard deviation of farm-scale indicators and model parameters when harmonising food production and resource conservation objectives (cf. Fig. 9)

Indicator/parameter	Scenario		
	2000 KSh	5000 KSh	10,000 KSh
Objective indicators			
Maize production (t farm^{-1} season^{-1})	4.3 (0.0)	5.7 (0.1)	7.1 (0.1)
N losses (kg N farm^{-1} season^{-1})	84 (1)	87 (2)	109 (3)
Soil erosion (t farm^{-1} season^{-1})	18 (1)	18 (0)	17 (0)
Summary of model parameters			
Total N fertiliser used (kg farm^{-1})	5 (3)	18 (8)	128 (16)
Labour used (man-days farm^{-1})			
Ploughing and planting	49 (1)	53 (1)	63 (4)
Weeding	21 (1)	34 (1)	43 (2)
Ridge cropping and mulching	21 (1)	26 (2)	38 (4)
Total	91 (1)	113 (2)	145 (3)
Investment in N fertiliser (KSh season^{-1})	187 (94)	673 (321)	4787 (624)
Total investment in labour (KSh season^{-1})	4151 (122)	10,250 (333)	16,872 (668)
Complementary indicators			
Rainfall use efficiency (kg grain mm^{-1})	12.6 (0.3)	16.6 (0.2)	20.6 (0.2)
N productivity (kg grain kg N applied^{-1})	1913 (6411)	531 (957)	75 (7)
Gross N use efficiency (kg grain kg N available^{-1})	18 (70)	23 (86)	24 (3)
Value of production (KSh season^{-1})[a]	59,340	78,660	97,980
Gross benefit (KSh season^{-1})[a,b]	55,040	67,730	76,230
Return to labour (KSh man-day^{-1})[a,b]	618	605	548
Benefit/cost ratio[a,b]	12.8	6.2	3.5
Daily gross benefit (KSh family^{-1} day^{-1})[a,b]	151	186	209
Gross benefit per capita (KSh person^{-1} day^{-1})[a,b,c]	22	27	31

[a] Calculations done considering the average values for the objective indicators and model parameters.
[b] Calculations done considering only the direct costs of N fertiliser use and labour hired in; fixed costs and/or other variable costs such as buying seeds were not considered.
[c] Calculated assuming the local average family size of 6.8 members per household.

Table 6
Selected field-scale indicators and allocation strategies when harmonising food production and resource conservation objectives for the three scenarios of financial liquidity: 2000, 5000 or 10,000 KSh available for investment during the long-rains season on one farm (cf. Fig. 9)

Scenario/ land quality uint	Area (ha)	Maize production (t field^{-1})	Maize yield (t ha^{-1})	N balance (kg field^{-1})	Change in soil N stock (%)	Soil loss rate (t field^{-1})	Fertiliser use (kg field^{-1})	Gross N use efficiency*	Fraction of total labour allocated	Fraction of total cash allocated
2000 KSh										
Fertile	0.5	1.4 (0.1)	2.8 (0.2)	+4 (0.5)	+10 (3)	0.1 (0.0)	2 (0.5)	17.3	0.2 (0.0)	0.2 (0.0)
Average	1.3	2.7 (0.1)	2.1 (0.1)	−38 (0.5)	−42 (9)	2.7 (0.1)	1.5 (1.0)	34.0	0.7 (0.1)	0.6 (0.1)
Poor	0.4	0.2 (0.1)	0.5 (0.3)	−22 (0.2)	−85 (21)	15.4 (0.1)	1.5 (1.1)	2.4	0.1 (0.0)	0.2 (0.1)
5000 KSh										
Fertile	0.5	1.5 (0.1)	3.0 (0.2)	+5 (1.0)	+12 (4)	0.1 (0.0)	5.4 (3.6)	18.2	0.2 (0.0)	0.2 (0.1)
Average	1.3	3.6 (0.1)	2.8 (0.1)	−38 (0.7)	−42 (9)	2.5 (0.1)	3.6 (1.8)	44.8	0.7 (0.1)	0.6 (0.1)
Poor	0.4	0.6 (0.1)	0.6 (0.4)	−21 (0.6)	−81 (20)	15.3 (0.0)	9.0 (3.5)	6.9	0.1 (0.0)	0.2 (0.1)
10,000 KSh										
Fertile	0.5	1.8 (0.0)	3.6 (0.1)	+8 (1.8)	+17 (5)	0.1 (0.0)	25.6 (12.8)	19.6	0.2 (0.0)	0.2 (0.0)
Average	1.3	4.2 (0.1)	3.2 (0.2)	−29 (3.3)	−32 (9)	2.1 (0.1)	51.2 (13.0)	41.1	0.6 (0.1)	0.6 (0.1)
Poor	0.4	1.1 (0.1)	2.8 (0.6)	−16 (1.9)	−61 (18)	15.2 (0.0)	53.1 (52.0)	10.3	0.2 (0.0)	0.2 (0.1)

Average values for the subset of selected solutions are presented followed by their standard deviation between brackets.
* In kg grain per kg of N available (soil + fertiliser); calculations done using the mean values of maize production and fertiliser use.

fertiliser was used in the poor-fertility fields, and the applied N was less efficiently used, leading to larger N losses. The most efficient use of N was achieved in the average fields, as determined by the greater response to N applications in those fields. Under the scenario of the highest initial cash reserves, the allocation of fertiliser to the best fields was less favoured due to the better yields that can be achieved in those fields without N application. Under the same scenario, the optimum rate of fertiliser use in the poor-fertility fields varied widely.

Most of the total labour available on the farm for each scenario was used for land preparation and planting, particularly in the scenario of low initial cash reserves (Table 5), and the largest fractions of the total labour and cash resources were allocated to the average-fertility fields (Table 6), as influenced also by their larger area within the farm. The returns to labour calculated from the gross monetary benefit (=value of production − investments in N and labour) did not differ much between scenarios because of the larger investment in labour when the initial cash reserves were larger. The benefit:cost ratio was larger when less cash was invested on a seasonal basis. The gross benefits obtained from these modelling results, simplistically assuming that all the maize produced was sold, represent US$ 2–2.8 a day for the household (1 US$ = 75 KSh), barely US$ 0.3–0.4 per capita (for the local average of 6.8 family members – cf. Table 1). According to the modelling results for this simplified farm system, improving the gross benefit potentially achieved by the family by growing maize would require boosting the yields in the poor outfields of the farm from about 0.5 t ha^{-1} to almost 3 t ha^{-1}. However, the improved management associated with larger investments also led to more favourable values for some of the indicators related to long term sustainability. For example, the N capital of the system was reduced more drastically when less cash was invested, as reflected by the changes in the soil N stocks (Table 6). Grain production per unit of N lost varied from 60–80 kg grain kg N lost^{-1} in the average and fertile fields to 10–30 kg grain kg N lost^{-1} in the poor fields. The average values at farm scale were 46, 59 and 62 kg grain kg N lost^{-1} for the investment scenarios of KSh 2000, 5000 and 10,000, reflecting different environmental and sustainability costs.

4. Discussion

This inverse modelling exercise allowed us to analyse trade-offs between different farmers' objectives and to compare potential resource allocation strategies to achieve them. The underlying soil quality of the different fields of the farm affected the efficiency of resource capture and use, and hence the results of the optimisation in terms of investment and allocation strategies (cf. Table 6). The allocation of N fertiliser favoured the more fertile fields located closer to the homestead, where the efficiency of N capture was greater. Threshold yields were identified for the various fields and at the farm scale, above which N losses and soil erosion increased abruptly (Figs. 6 and 9); these thresholds were largely affected by the capacity to invest in erosion control or in applying fertiliser to the crops in the fertile fields (where the N capture efficiency was larger, as illustrated by the positive N balances in Table 6). A certain degree of substitution between labour and nutrient use was possible due to the relatively good fertility of these soils (cf. Table 2). However, soils in the area of Kakamega in western Kenya are normally regarded as resilient and of high potential for agricultural production (Shepherd et al., 1996). Our results, which suggest that investment should favour labour for crop management over nutrient use or soil erosion control, are not likely to be equally relevant for regions with poorer soils, with more fragile physical attributes or situations with different price-cost ratios, pre-

sumably. Irrespective of the amount of labour used, crops are likely to yield little on poor soils when no nutrient inputs are used.

As pointed out by Thornton and Herrero (2001), the assessment of the feasibility of proposed management alternatives for smallholder farmers requires a clear understanding of the management aspects of the household in relation to the biophysical aspects of the production system. The inverse modelling approach used here for analysing conflicting objectives at farm scale combined good detail on the underlying crop and soil biophysical processes, and their feedbacks, with the possibility of accounting for a number of likely farmers' goals (i.e. increasing food production, reducing erosion) through optimisation. In this respect, our approach has an advantage over linear programming approaches (e.g. MGLP), which do not account for biophysical feedbacks (Brown, 2000). However, the biophysical, dynamic component of the optimisation tool should be kept as simple as possible, since the performance of inverse modelling decreases when the number of parameters to calibrate is large (i.e., the number of parameters should not exceed c. 40 – Vrugt, 2004). On the other hand, when several processes of different nature (decisions, biophysical parameters) are considered simultaneously, the system under analysis becomes complex and then linearity is more often the exception than the rule. Thus, while MGLP approaches coupled with dynamic technical coefficient generators are useful at the scale of analysis necessary for land use studies (i.e. village, water catchments, regions) (e.g. Hengsdijk et al., 1999; Baijukya et al., 2006), the analysis of decision making at farm scale could be better accomplished by using inverse modelling, embracing the complexity, heterogeneity and feedbacks within the system.

One of the weakest points of the approach used here probably was the definition of labour demand functions on the basis of field exercises involving farmers, which involved a substantial degree of linearity. This was a necessary assumption in view of the limited knowledge available on the relationship between labour use for different practices and crop performance for these smallholder systems (Giller et al., 2006). Currently, such relationships are being analysed in the framework of a coordinated project in eight African countries (AfricaNUANCES, 2004) by establishing field experiments designed to quantify the relationship between weed pressure, labour applied to control weeds, and the effect on crop production. The build-up of weed populations, depending on the types of weeds considered, may also be seen as an indicator of the sustainability of the system in the long term. When strategic management decisions are considered, instead of operational decisions as analysed here, the processes affecting this indicator should be modelled in more detail.

In real-life applications of this approach, such as in aiding decision-making on resource allocation, more complex formulations than the simplified case analysed here would be necessary, including other on- and off-farm activities and/or income sources in the model, and considering longer time spans of the simulations. Since our optimisation exercise was conducted for a single enterprise within a simplified, relatively wealthy farm and considering a limited number of objectives over one season, these results cannot be regarded as 'optimal' in a practical sense (e.g. long-term farmers' objectives such as education of their children, or returns from other activities on the farm, were not considered).

The results from this exercise on a simplified farm system suggested that cropping with few external nutrient inputs on soils of heterogeneous quality as observed in these systems requires large investments in labour and proper management skills. Comparing the investment strategies (Fig. 7) with the trade-off curves (Fig. 6) reveals that up to almost 6 t farm^{-1} of maize (average yield 2.7 t ha^{-1}) could be produced on the farm investing barely (0.1×5000=) 500 KSh ha^{-1} in mineral N fertilisers (equivalent to about 10 kg of N fertiliser), when timely planting and weeding are ensured by hiring sufficient labour (assuming that N is the only limiting nutrient). The average N fertiliser use intensity in the area was 24 kg per farm (Tittonell et al., 2005), representing an investment of KSh 890 at current (2005) prices. Maize production levels higher than 6 t for this case-study, relatively wealthy farm were only obtained under the financial scenario of KSh 10,000 initial cash reserves, with cash investments in N fertiliser ranging from 1800 to 3500 KSh ha^{-1}, representing between 50 and 100 kg of N fertiliser (equivalent to application rates of barely 23 and 46 kg N ha^{-1}). These small application rates suggest that intensification of the system to more than double the current local average maize yields of 1–1.5 t ha^{-1} could be achieved with relatively small investments in nutrient inputs, provided that labour is available to ensure that nutrient capture is efficient (e.g. reduce erosion losses) and that the nutrients are converted (through a reduction in weed competition, for example) into crop yield. However, other constraints not considered here, such as access to fertiliser, the opportunity costs of labour and/or farmers knowledge and experience in their use, are important in explaining the gap between average yields observed and those predicted by the model for this case study farm.

Although these fertiliser application rates are small, they represent substantial investments for poor farmers; for example, the average labour wage paid in the study area ranges around KSh 150 a day, whereas in nearby areas of even higher population densities (e.g. Vihiga district) the daily wage can be as low as KSh 50 a day. Simplistically, considering an annual food requirement in grain equivalents of 170 kg person^{-1} and the average household size for the area (6.8 family members), around 1.2 t of maize grain is necessary to achieve a baseline of food security. Assuming that an investment of 500 KSh ha^{-1} coupled with proper management would lead to producing 6 t of maize in one season on our case study farm, a surplus of 4.8 t of maize would be available for sale to the market (i.e. about 50 bags). Depending on the time of the year this

surplus maize production represents income of between KSh 40,000 and 80,000. In spite of these figures pointing to a presumably high profitability of farming with few external inputs, the use of mineral fertilisers by smallholder farmers is limited in most of sub-Saharan Africa (Bationo et al., 2004). The lack of investment in fertilisers may be ascribed to several reasons, including their cost, their availability in local markets and the lack of knowledge on their types and uses. However, this also points to questioning whether our current understanding of smallholder systems allows us to capture farmers' *real* objectives.

Even for farmers who are experienced in using fertilisers, the decision whether or not to buy fertiliser at the beginning of the season is more strongly affected by financial liquidity at that specific time (e.g. in March – cf. Table 3), rather than by the cost of the fertiliser *per se*. The results of the optimisation indicate that as the availability of cash at the beginning of the season increased, the absolute amount, and also the fraction of the available cash invested in N fertiliser increased (i.e. 4%, 6% and 22% of the total) (Table 5). The use of mineral N fertiliser may improve land and labour productivity at farm-scale provided that simultaneous measures are taken to improve N capture within the system, although these may represent trade-offs between short- and long-term farmers' objectives. Larger investments in labour and N fertiliser in our analysis led to more efficient use of the environmental resources (i.e. rainfall) as well as of some of the production factors (i.e. land, assets, management). For other production factors the selected indicators suggested somewhat better results for the scenario of poor investment capacity, e.g., labour productivity, returns to capital invested in N fertiliser. This suggests that caution should be exercised when selecting indicators to use in trade-off analysis. For example, in these low-input systems the sensitivity of the benefit:cost ratio to the variable costs is often large. This may lead to improper conclusions when investments in input-based technologies are compared with respect to current practices (characterised by no or little input use). In reality, farmers are normally more interested in obtaining large maize yields and less in rates of N loss or benefit:cost ratios.

On the other hand, different indicators pertaining to the sustainability of the system as a whole should be considered simultaneously, provided that relevant thresholds for each indicator can be identified. The identification of such thresholds can be done through participatory exercises including several stakeholders with their respective objectives (e.g. Solano et al., 2001), and defining the proper scale of analysis in each case. An interesting, emerging indicator that may be used for comparison across farming systems and/or environments is the dispersion of the 'cloud' of feasible strategies obtained after optimisation; this is illustrated by our results in Figs. 7 and 8. Under the scenario of high investment capacity, the spread in acceptable parameter combinations was smaller, the model output was more sensitive to the strategy chosen, and therefore more clearly delimited farming strategies could be derived from the analysis. Conversely, when less cash was available to invest in labour and nutrients, the set of parameter combinations (i.e. possible strategies) was larger, indicating a higher rate of substitution between alternative allocation strategies leading to the same result (less sensitivity).

This provides an important insight into the highly variable investments and management strategies of smallholder farmers that is often observed. If conditions for investment are unfavourable, many different management strategies (but not necessarily many different decisions) lead to the same or similar results in terms of productivity and sustainability of the farm system. This relates also to the concept that variation in optimal solutions may not explain variation in non-optimal solutions – i.e., those observed in reality. In our study, the comparison was done between different financial scenarios. The same type of analysis could be done across agroecological zones, climatic situations, varying socio-economic conditions, market opportunities and/or policy environments. At least two preliminary hypotheses can be derived from this. The first hypothesis is related to the idea that the spread of feasible solutions at farm scale is affected by farm characteristics, which in turn varies across farms of different social status and is affected by location-specific factors (e.g. landscape, markets). The second challenges the concept of 'blanket' management recommendations, as the set of resource allocation strategies leading to Pareto-efficient results is much wider when farming conditions are less favourable. By contrast, the concept of technical recommendations works better in subsidised farming systems relying on high external input use and/or price control policies – i.e. more stable conditions, as demonstrated by the fact that most farmers in such systems use the same crop varieties, plant at the same time, apply the same type and amount of fertilisers and biocides, use the same commercialisation channels, etc. Therefore, technological interventions to target smallholder farming systems such as those in western Kenya should be designed by considering farm heterogeneity and its drivers, and by building farmers' decision-making capacities through deeper knowledge and understanding of the systems they manage, instead of simply recommending specific management practices.

5. Notes

The terms 'resource' and 'efficiency' have a very specific meaning in disciplines such as economics. Here we use these terms broadly, defining resources as labour, cash, nutrients and other biophysical factors (e.g. solar radiation) used for farm production, and efficiency as the ratio between the amount of output obtained from per unit of input added to a process taking place within a well delimited (sub-)system and over a certain time span (the season in our case); with inputs and outputs expressed in their different units (e.g. labour productivity in kg of grain produced per man-day of labour invested in cropping, or N

productivity in kg of grain per kg of fertilizer N applied to the soil).

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