From soil nutrient balances to regional policy analysis

A case study of integrated assessment in Machakos, Kenya

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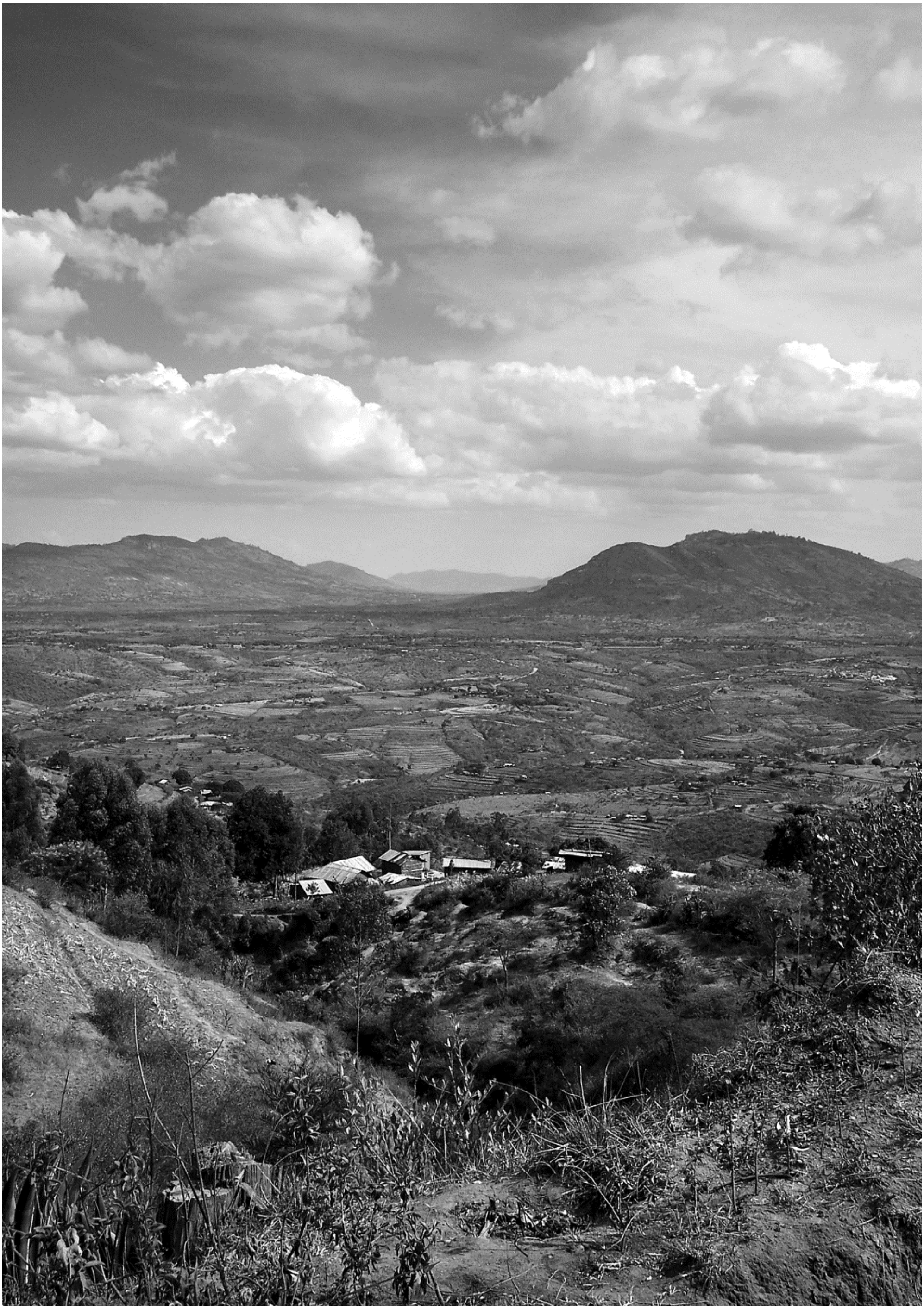
In loving memory of my dear friends
Felix Calderón, Marthijn Sonneveld and Ana María Meissner
who taught me the most beautiful lessons in life.



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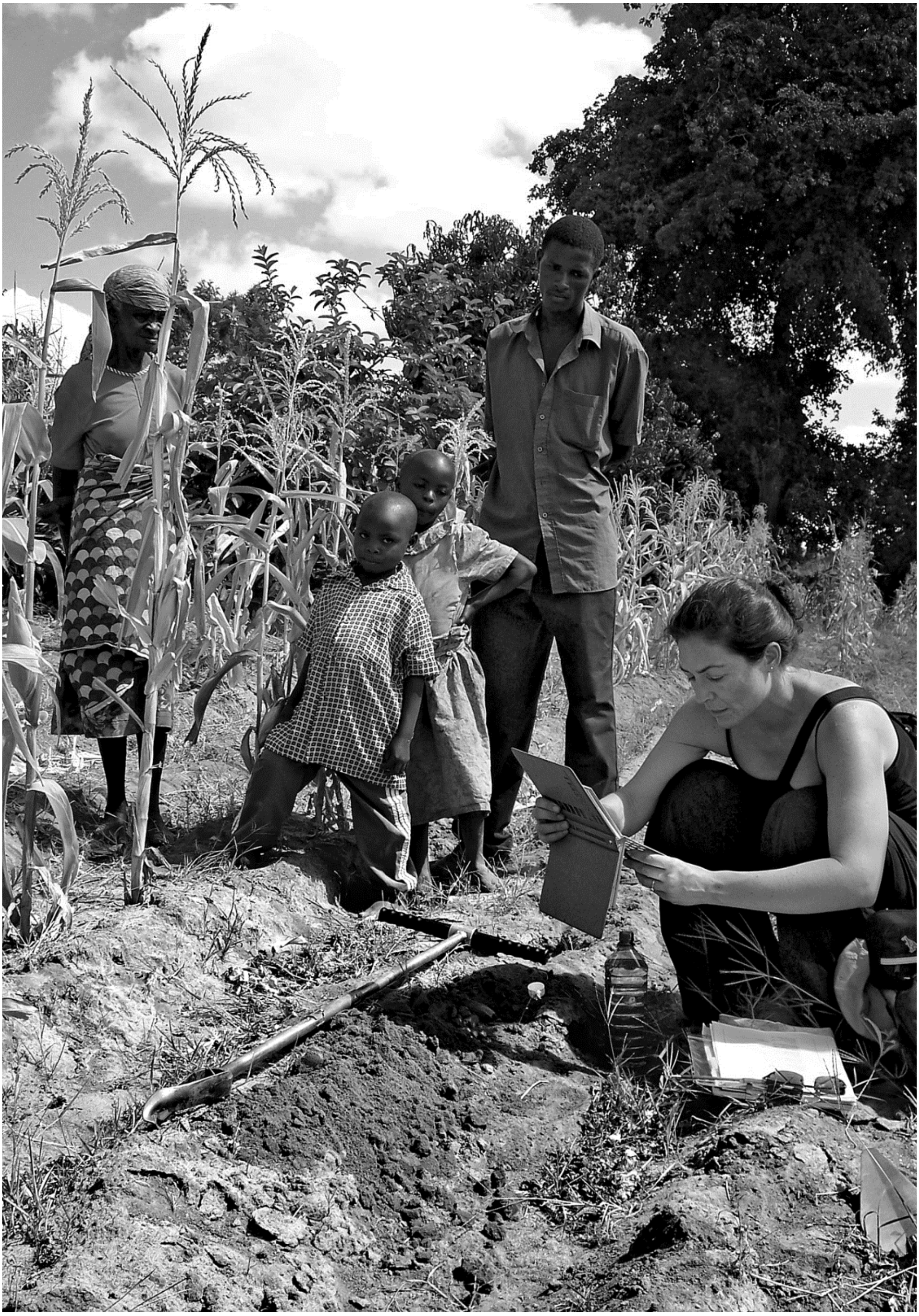

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Alejandra Mora Vallejo

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Chapter 1
Introduction

1.1 Overview

The world's population is rapidly growing and so is the combined need for more food, economic development and poverty reduction in a healthy environment. While achieving a proper balance among these components is already a difficult task, it will certainly be more challenging in the near future when the pressure over natural and economic resources increases.

Regarding agriculture, experts have raised the alarm of the need of unprecedented production growth in order to be able to feed the world by the year 2050 (FAO 2009a). At present agriculture is facing rapid changes in population and consumers' behaviour; thus attaining future's food security will require careful attention when agricultural production is progressively confronted with matters such as climate change, competing claims for land and water resources with urban areas, a decreasing number of farmers, increasing production costs (including energy), fluctuations in global markets, rising demand for bio-fuels, and growing environmental concern for preserving natural habits, endangered species and biodiversity (Trostle 2008, FAO 2009a, Tester and Langridge 2010). Because in some regions the chances of expanding the area under cultivations is not possible, the question that still remains is whether existing agricultural land can be used more productively and sustainably. To answer this question studies of yield gap analysis have become of great importance (van Ittersum *et al.* 2013, van Wart *et al,* 2013) . Yield gap is the evaluation of the difference between crop yield potential and actual farmers' yields (Lobell *et al*. 2009). This analysis provides a quantitative estimation of possible increases in food production capacity for a given location, and can also help to identify what is causing the yield gap and to target technologies that can improve actual productions systems (van Wart *et al,* 2013). Through these analyses it has been seen that while in the developed world arable land has no room for expansion (and will probably decrease), and yields are close to their potential, most of the expected agricultural growth is forecasted to take place in the developing world, where the potential yield gaps are higher and offer greater opportunities for improvement (Godfray *et al.* 2010).In addition, much of the suitable land for agricultural expansion is concentrated in a few countries in Latin America and sub-Saharan Africa (SSA) (FAO 2009b). Still, it is hard to foresee an exceptional increase of yields in some places of Africa, where on the contrary, in the last decades productivity growth has not been able to keep up with the growing population, and as a result the per capita food production has been steadily decreasing, resulting in more poverty and hunger (Tittonell and Giller, 2013). Evidently, raising the efficiency of agricultural production is one of the best options to tackle both problems (UN-MP 2005), but this is very difficult if we consider that the majority of the farming systems in SSA are predominantly based on subsistence agriculture, most people live under the poverty line, inhabit marginal areas and are strongly dependant

on their natural resources for survival. Moreover, their ways of coping with their constant limitations usually worsens the depletion of their resources, especially regarding to soils.
In these problematic regions increases in production will not happen all of a sudden, just driven by market forces, but they will probably require strong public interventions and investments (FAO 2003*)*. Therefore policies that direct these changes will be needed. Policy makers have acknowledged this situation and many strategies to address agricultural production and economic development have been suggested in several policy documents and initiatives such as the United Nations-Millenium Project (UN-MP 2005), the Kenyan Strategy for Revitalizing Agriculture (RoK 2004), the World Summit Food Declaration 2009 (FAO 2009b), and so on. However, most of these documents end up with a general "to do" list of recommendations but the actual effects of these technology or policy interventions are seldom fully evaluated for specific regions or cases.

Scientists have made available many approaches to evaluate the performance of agricultural systems (*e.g.,* Bouma *et al.* 2007). Normally these approaches look at biophysical and economic indicators independently such as pesticide leaching (Aylmore and Di 2000), soil nutrient balances (Stoorvogel *et al.* 1993), erosion (Foster *et al. 1996*), livelihoods and poverty (Kristjanson *et al.* 2005). Although it is important for policy makers to look at these indicators separately, it is very important to analyze the indicators in integrated manner. Only through the latter we can *ex-ante* evaluate policies and technologies for agricultural development properly.

In this thesis, an integrated assessment combining biophysical and economic research in order to provide proper information for policy makers is proposed. To do this the NUTMON and Tradeoff Analysis (TOA) methodologies are linked as a novel way to implement regional integrated analysis based on models of site-specific environmental and economic interactions. Because in regional land use analysis data issues are always challenging, aspects of new technologies for data gathering such as Digital Soil Mapping (DSM) are included and the effects of data resolution on model results are tested. The model linkage is illustrated with an application for the mixed farming systems in Machakos and Makueni districts (Eastern Province, Kenya), hereafter referred to as the Machakos study area. In this area, soil fertility decline has been found to be one of the major constraints to the development of agriculture.

1.2 Soil fertility in Africa

Hunger and poverty in SSA have been on the public agenda for a long time. Although at first attention was set on extensive droughts and major soil degradation processes which explained the stagnation of agricultural production (*e.g.* erosion, salinization), already in the early 90s' studies on regional nutrient balances determined that soil fertility decline was one of the key drivers behind low yields and that the existing land use systems were not sustainable. Researchers calculated annual nutrient losses of 22 kg for nitrogen; 2.5 kg for phosphorus and 15 kg for potassium per hectare on average (Stoorvogel and Smaling 1990, Stoorvogel *et al.* 1993). These findings were later confirmed by further research on soil nutrient balances in Africa (Pieri *et al.* 1995; Barbier 2000; Keeley and Scoones 2000; Gachimbi *et al.* 2002; UN-MP 2005). Even though in some cases nutrient depletion was less severe than what was initially predicted (e.g. Kenya in Lesschen 2003) and others studies presented a few positive cases where despite all limitations and a growing population, increases in production at the local level were actually achieved by means of indigenous techniques (Barbier 2000; Scoones and Toulmin 1998; Tiffen *et al.* 1994; Warren 2002; Zaal and Hoosterndorp 2002; Reij and Waters-Bayer 2001), at the regional scale the adoption rates of improved technologies have been generally low and the trend in soil fertility decline has not yet reverted (Tittonell and Giller, 2013). Thus the future productivity of agricultural systems in SSA is still seriously threatened by negative soil nutrient balances.

Soil fertility is a complex matter related to various land use drivers, such as socio-economic (e.g. income levels, infrastructure, demographic structure, population density), political (e.g. land tenure, subsidies and credits, nature protection, macro-economic policies like devaluation, liberalization of agricultural products) and biophysical (e.g. weather conditions, soil characteristics) factors (Turner *et al*. 1995 in Priess *et al.* 2001). For this reason, solutions to tackle soil fertility decline vary from innovative management alternatives to profound policy and market changes.

When selecting soil fertility interventions, plain blanket recommendations are normally not successful. The need for an integrated approach for soil fertility issues was complied with the development of the Integrated Nutrient Management (INM) technology (Smaling 1993, Deugd *et al* 1998, Gruhn,*et al.* 2000). INM addresses site-specific problems by incorporating the social and the economic aspects of the farm households in the analysis and increasing the stakeholder participation (De Jager 2005). With this integration, researchers, development organizations and farmers themselves are able to target a wide range of technologies that improve soil fertility, as displayed in Table 1.1 (Hilhorst and Muchena 2000). In this line, for example, Conservation Agriculture (CA) is being promoted to enhance soil health and sustain long term crop productivity based on 3 principles: minimum soil disturbance, permanent soil cover (mulch) and crop rotation (legumes). Recently, supporters of CA are suggesting this type of management over conventional agriculture in African small-scale farming systems. However, the use of crop residues for mulching has to compete with its use as livestock feed; therefore even if the adoption of new management practices could be beneficial, the process is not always simple and needs more research and guidance (Giller *et al.* 2011, Valbuena *et al*, 2012).

Table 1.1 Integrated Nutrient Management Practices to increase soil fertility

Adding Nutrients	Fallowing Application of mineral fertilizer Application of Rock Phosphate Inflow nutrients from grazing Cultivate N fixing plants
Minimize Nutrient Losses	Erosion control measures (runoff, leaching) Trees in the field Double digging
Managing Internal Flows	Application of manure, urine, slurry Recycle-composed organic matter Incorporated crop residues
Increase Efficiency of Nutrient Uptake	Select crops that match fertility level Concentrate nutrients in particular fields Managing nutrient application on crops

Source: Hilhorst and Muchena 2000

Table 1.2 Policy instruments that direct land use changes

Macro-economic policies	Price liberalization Removal of quantitative and administrative trade barriers Redefining the role of the government
Price policies	Subsidies on agricultural inputs and/ or products Price support that guaranties price for agricultural products
Regulatory instruments	Environmental regulation for pesticide and/or nutrient emissions Regulation on banning of certain agricultural inputs (pesticides) Land use regulations
Instruments focused on the farmer	Management support through an extension service Technological support that enables farms a better access to production technologies Economic support enabling farmers to obtain credits or crop insurance Land tenure regulation

Source: Stoorvogel *et al.* 2001, 2003

On the other hand, land use changes can be directed with policy instruments (Table 1.2). These vary from macro-economic policies, public investments, to commodity specific policies, price stabilization policies and public regulation (De Jager 2005).

Finally, it is also important to mention that when working on soil fertility issues, several myths exists regarding soil fertility management (Table 1.3). As a consequence, many development agencies have based their interventions on incorrect assumptions, supporting strategies that will unlikely address the problem of soil fertility and, what is worse, they may waste precious development resources away from effective intervention strategies (Vanlauwe and Giller 2006).

Table 1.3 Popular myths around soil fertility management in sub-Saharan Africa

Myths surrounding nutrient balances	Nutrient balances are always negative	Fact: Diversity of plot management within farms produces gradients of soil fertility. Normally most organic and mineral fertilizers are used close to the homestead to ensure good crop yields and save labor. Therefore some fields have very positive nutrient balances through concentration of nutrients from other parts of the farm and those that are far from the homestead have negative nutrient balances.
	Nutrient balances can be used to derive crop fertilizer requirements	Fact: This assertion does not consider soil nutrient stocks. If no crop response is visible when applying fertilizer, farmers will hardly invest in them. Moreover, a negative nutrient balance will not be solved by simply supplying the same amount of nutrients in the form of mineral fertilizers because losses (leaching, mineralization, etc.) and other soil processes have to be considered as well.
Myths surrounding fertilizers	Fertilizers damage the soil	Fact: Fertilizer use generally increases crop yields and thus increases the amount of organic matter returned to the soil through roots and crop residues, improving soil fertility. The most common case where the use of fertilizer can cause a problem is the potential acidification with ammonium-based N fertilizers in soils with poor buffering capacity, in which case liming is recommended.
	Fertilizers are not used in Africa as they are too expensive	Fact: In most places cash is scarce, so even if prices are lowered it might still be a problem to buy fertilizer. Other problems are fertilizer packing, market prices of staple food, inadequate agricultural policies, lack of competitive and transparent private markets, and so on.
	Fertilizer recommendations are a useful tool in disseminating information regarding fertilizer use to small-scale farmers	Fact: Standard or 'blanket' recommendations do not consider the soil fertility status of the individual production units, organic matter pool, weather conditions, potential crop production and so on. Guidelines for fertilizer use need to be flexible.
	Fertilizers cause eutrophication in Africa	Fact: The most likely cause of eutrophication is not excess of mineral fertilizer use but the loading of nutrients in erosion deposits and organic matter draining as untreated sewage waste from the major cities.
Myths surrounding rock phosphates	Adding RP to compost increases it short term P availability	Fact: pH of compost (neutral to higher) does not favor the dissolution of RP. Other problems of RP are bulkiness, low availability and presence of heavy metals.
Myths surrounding organic inputs	Organic inputs can sustain crop production	Fact: A combination of organic and mineral soil nutrients is strongly recommended. While organic matter improves CEC, soil structure, etc. it is often not widely available and affordable in the quantity that is needed. Organic inputs are not substitutes for mineral fertilizers as both inputs fulfill different functions.
	Organic inputs decrease pest and disease attack	Fact: Effects are not always positive. While increasing organic matter may often have beneficial effects on biological activity and lead to less pest and disease attack, some cases have been reported in which all crop is lost due to pest infection.

Myths surrounding legumes	All legumes fix nitrogen	Fact: The Leguminosae family is comprised of three subfamilies: the Caesalpiniodeae, the Mimosoideae and the Papilionoideae, being the Caesalpiniodeae the oldest and ancestral subfamily from which the other sub-families diverged. All legumes have tissues that are rich in N compared with other plant families, but only a quarter of the caesalpiniod legume species are able to nodulate
	All legumes have a specific need for inoculation	Fact: Considering the huge diversity of legumes in the tropics the norm is that legumes are "promiscuous" in nodulation with indigenous strains in the soil. Inoculation is needed when (1) compatible rhizobia are absent; (2) the population of compatible rhizobia is small; (3) the indigenous rhizobia are ineffective or less effective in N2-fixation with the legume than selected inoculant strains.
	Legumes are a source of free nitrogen	Fact: All soil-improving technologies have a cost in terms of labour and land.
	Growing legumes always leads to improvement in soil fertility	Fact: Apart from the fact that not all legumes can nodulate and fix N2, many legumes do not contribute substantially to improving soil fertility. Where constraints such as deficiencies in P or K, or drought, limit legume growth, inputs of N from N2-fixation will also be restricted. Even when legumes grow well, the contribution to soil fertility depends on the amount of N2-fixed in relation to the amount removed from the system in the crop harvest, reflected in the N-harvest index.

The development of methods for the interdisciplinary evaluation (agronomic, economic, social) of soil fertility interventions is vital for the improvement of the communication among researchers, farmers and other stake holders which together will more likely make a difference in the sustainability of African farming systems.

1.3. NUTMON methodology

NUTMON is a participatory, integrated, multi-disciplinary methodology which works at the farm level, targeting different actors in the process of managing natural resources, particularly those related to soil fertility (De Jager *et al.* 1998[a], Van Den Bosch *et al.* 1998[a]). This methodology quantifies periodic input and output flows at the plot and farm level, generating a detailed dynamic farm inventory. This information is later used to calculate nutrient (N, P and K) flows, cash flows (*e.g.* gross margins, farm income), stocks and balances of individual farms (De Jager *et al.* 2001). NUTMON includes a selection of well described standardize techniques to characterize and monitor farming systems and their agro-ecological conditions, focusing at the plot and the farm level where most of the decisions regarding farm management are taken. Because the methodology is intended to monitor nutrient balances, it also includes records of specific characteristics of the farming systems, such as crop-livestock interactions, that are not registered in traditional farm surveys. In addition, NUTMON has software that provides a systematic way to manage the acquired data, resulting in standard descriptions and analyses of the farming systems. NUTMON allows farmers and researchers to jointly analyze the environmental and financial sustainability of the farming systems (De Jager *et al.* 1998a; De Jager *et al.* 1998b;

Van den Bosch *et al.* 1998a; Van den Bosch *et al.* 1998b). Finally, NUTMON facilitates the analysis of the contributions of independent fluxes in the farm under the current land use practices and discuss with the farmers different ways to increase soil fertility in their own systems, allowing networking and participatory learning. (De Jager *et al.* 2001).

A standard conceptual model of the farming system in NUTMON describes the farm resources through an inventory of nutrient stocks and flows (Figure 1.1). The conceptual model sub-divides the farm in various units and identifies different nutrient flows. The units represent nutrient pools while different flows describe the processes that relocate them. The units are grouped into a number of basic components: Household (HH), Farm Section Units (FSU), Primary Production Units (PPU), Secondary Production Units (SPU), Redistribution Units (RU), Stock (STOCK) and the external world (EXT). HH is characterized by consumer and labor units including their gender, age distribution, and education, as well as capital stocks. Land resources are described by FSUs which are land units that are considered homogeneous with well described characteristics. PPUs are the basic units of analysis and are defined as cropping activities of one or more crops in well-defined fields over a specific period. A single FSU can contain one or more PPUs. The animals present in the farm are described as SPUs which are groups of animals of the same species under similar management conditions in relation to feeding, confinement, grazing, etc. The places within the farm where nutrients are accumulated and frequently reallocated (such as stables, corrals, dung hills, garbage heaps, compost pits, and latrines) are called the RUs. The STOCK is the temporary storage of crop products and residues, as well as inputs. Finally, EXT comprises everything outside the farm limits including *e.g.,* markets and neighbors.

The farm inventory starts with the drawing of farm sketches along with the farmers, to show the spatial location and configuration of the different units within the farm. During data collection, the various flows within the units and outside the farm boundaries are visualized and registered in close collaboration with the household members. Transect walks and local soil classification results in a description of the basic FSUs at the farm. The participatory approach guarantees that the FSUs are also recognized by the farmer which is crucial for the future development and implementation of potential interventions.

A standard structured questionnaire is used for monitoring soil nutrient flows on the farms. Typically, farm management is monitored during one or two growing seasons through frequent (*e.g.*, bi-weekly or monthly) visits to the farm. Table 1.4 provides an overview of the key information that is collected during the survey. The NUTMON software facilitates the entry, checking and handling of the survey data. The soil nutrient balance is estimated on the basis of five nutrient inputs and five nutrient outputs (Figure 1.1).

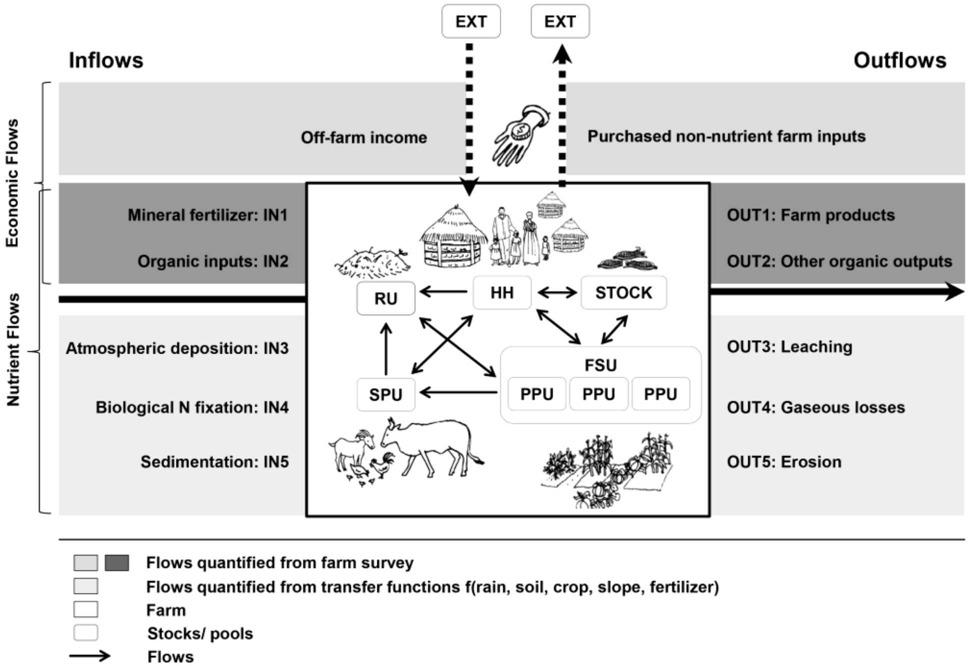

Figure 1.1 NUTMON conceptual model of the farming system

Some of these flows (including mineral and organic fertilizer application, harvest of farm products and residues) are quantified during monitoring based on information provided by the household members during the farm survey. Other flows, such as atmospheric deposition, biological fixation, leaching, and gaseous losses, are more difficult to quantify and are derived from transfer functions (Stoorvogel and Smaling 1990; Smaling *et al.* 1993, Van Den Bosch *et al.* 1998[a]). Based on the nutrient flows entering and leaving PPUs and the farm, the NUTMON software calculates nutrient balances for the PPUs and the farm for a determined period as the net difference of inputs and outputs. The balances indicate whether soil fertility is declining or whether nutrient stocks are building up. The estimation of total nutrient stocks is based on soil samples and allows flows to be related to available stocks. Together with the information of the individual flows, the analysis shows where nutrient use efficiencies are low and how the system can be improved (De Jager *et al.* 1998[a]; Gachimbi *et al.* 2005; Van Den Bosch *et al.* 1998[a]; Van Den Bosch *et al.* 2001). Through the registration of cash flows and prices, NUTMON can also evaluate the economic performance of the farms and the individual activities.

Table 1.4 Main information categories included in the NUTMON questionnaire (Van den Bosch et al. 1998)

	Information group	Type of information
Farm Inventory	General farm data	Geographical situation, land ownership etc
	Demographic structure of the household	Identification of all persons at the farm, sex, age and occupation
	PPUs	Identification of parcels and parcel sizes
	SPUs	Identification of animal groups
	Sketch of the farm	Sketch of farm infrastructure with FSUs and PPUs
	Other compartments	Identification of RUs
	Implements and machinery	Identification of implements, number and age
Input-output monitoring	PPUs	Identification of the fields and crops present at the time of monitoring
	Input PPUs	Quantity and source of fertilizers, seeds, manure, crop residues, feeds, pesticides, labor, traction etc.
	Output PPUs	Quantity and destination of harvested products and crop residues
	SPUs	Number of animals born, purchased, gifts, consumed, died
	Inputs in SPUs	Quantity and source of fodder, concentrates, veterinary services, labor, etc
	Output SPUs	Quantity and destination of milk, eggs, hides, skins, hiring out of animals, traction
	Average confinement of the animals	Confinement to fields, pastures, fallows, farm yards, kraals and outside the farm
	Redistribution of manure	Quantity and destination of manure
	Inputs and outputs food stock	Book keeping of staple food in stock
	Family labor	For each person: days spent on crops, livestock, general farm, household, off-farm activities
Input-output cash flows	Off-farm income	Estimated off-farm income and amount invested in farm activities
	Output of cash-flows	Hired labor, purchase of mineral and organic fertilizer, feeds and amendments, Purchase of staple food
	Price data base	Collection of price distribution of all products to be used as a reference

NUTMON provides insight into the nutrient dynamics of farming systems (Van Den Bosch *et al.* 2001). As such, NUTMON contributes to the development of different integrated nutrient management technologies that can be tested in subsequent farm experimentation (Gachimbi *et al.* 2005). The results are discussed with farmers to illustrate the effects of management practices on soil fertility and to identify some possible solutions such as improving manure use, applying erosion control methods, cultivating N-fixing crops, composting, and fallowing. It should be noted that the development of potential interventions requires expert judgment of both scientists and farmers, but that they also need further testing in the field. NUTMON was developed to evaluate existing systems *ex post* and does not include essential feedbacks (between *e.g.,* agricultural inputs and production) to evaluate alternative systems. To use these results at the regional level, farmers' field schools can be implemented or stakeholder meetings can be organized, in which researchers and farmers are able to share their findings and start experimentation under different agro-ecological conditions. Although nutrient balances are useful in targeting potential interventions that may resolve the major constraints of the farming systems, the methodology does not allow for the evaluation of these interventions, which is fundamental for the development of better policies. However, the information generated in the soil nutrient balances studies is a solid base for further research.

1.4 Tradeoff Analysis (TOA)

TOA (Antle and Capalbo 2001; Stoorvogel *et al.* 2001 and 2004) is a participatory approach developed to perform integrated assessment of agricultural systems and to provide a decision support tool for agricultural and environmental policy analysis.

In this type of assessment, the farming systems are characterized in both bio-physical and economic terms by means of quantitative (sustainability) indicators. The relationship between these indicators is established in the form of tradeoffs curves and the analysis is done by looking at how these tradeoffs are affected by alternative technology and policy scenarios. Because the indicators are in different axes they do not need to be expressed in similar units. TOA combines biophysical models (normally crop production and environmental) with econometric production models (*e.g.,* Salasya 2005; Marenya and Barrett 2009). The econometric production models include input demand and output supply functions that are estimated using actual farm survey data. The model specification is similar to conventional econometric production models, except that in the case of TOA the site-specific effects of soils, climate and input use on production are represented in the input demand and output supply functions by crop inherent productivities, hereafter called *inprods*. These *inprods* are yield predictions obtained from crop growth simulation models with average management and site-specific soil and climate data. In the econometric models, *inprods* are interpreted as an indicator for the site-specific productivity potential expected by farmers. Once the econometric production models are estimated, they are later used to parameterize a simulation model of farm land use and management decisions on a site-specific basis. TOA includes software to model the system and to simulate tradeoffs under alternative scenarios (Stoorvogel *et al.* 2004). The results of the analysis can be presented as two-dimensional tradeoff graphs, tables and maps, which are all forms that can be easily communicated to stakeholders and policy makers.

TOA is a participatory methodology and requires collaborative work among stakeholders, policy makers and scientists to formulate the research priority settings. Together they must identify a limited number of key quantifiable indicators for the region under study, what kind of tradeoffs can occur, what are possible technology and policy scenarios to be evaluated, and so on. The indicators, trade-offs and scenarios need to be defined in an early stage of the process as they may require specific research activities to be included in the analysis.

The choice of relevant indicators depends basically on the local agro-ecological conditions, the particular interest of the stakeholders and the type of scenarios to be evaluated. These indicators include economic performance (*e.g.* annual net returns, poverty index, food security, and risk) and environmental performance (*e.g.* soil organic matter content and other indicators of soil quality, soil erosion, chemical leaching, and human health.). Subsequently, the tradeoff curves are constructed by varying a particular variable of interest like grain price and see how the relationship between key indicators (*e.g.* income *vs.* pesticide leaching) is affected. In this way, the tradeoff curves represent the principle of opportunity cost among scarce resources. Finally, the effects of technology scenarios, such as the introduction of a new crop variety, or a change in policy, are evaluated in terms of their effect on the tradeoff curve compared to a so called "base scenario". The alternative scenarios are constructed by varying certain model parameters in model simulation.

A considerable amount of site-specific data is needed to implement TOA. Firstly, TOA requires experimental data to calibrate the biophysical simulation models to assess *inprods* and environmental impacts. Secondly, detailed information on soil and climate conditions is required to run the calibrated biophysical models. Thirdly, the economic simulation model needs to be calibrated for which farm survey data are required to describe the current agricultural practices and decision making. Finally, additional information may be needed for the formulation of alternative scenarios. TOA is a spatially explicit methodology and soil and climate information is included in the analysis. As mention in the previous section, soil and climate data are used as inputs of the biophysical models of crop (and livestock) production as well as in the environmental models. In addition, site-specific farm data are required to estimate the behavioral parameters of the econometric-process models including data on variable inputs and outputs (*e.g.* seed quantity, fertilizer use, production of crops and residues), and fixed factors (*e.g.* land size, equipment, household characteristics). In some cases, depending on the indicators, tradeoffs and scenarios of interest to stakeholders, additional experimental data may be needed to calibrate simulation models to assess crop growth, land degradation, or alternative technologies. Probably, data collection is the most limiting factor for this type of analysis. The rapid turnover of policy analysis leaves little room for extensive data collection.

A strong point of TOA is the use of different disciplinary models in the analysis that are linked. These models can be sub-divided in three main groups: (i) production models to estimate the inherent productivity of specific fields, (ii) econometric production models to understand farmers' behavior, and iii) environmental process models to estimate the environmental impact of farmers activities. Although it is extremely difficult to calibrate a regional integrated assessment model, the individual models can be calibrated. The calibration of the models for the local conditions of the study area takes place in the model estimation phase (Stoorvogel *et al*. 2004).

The crop production models (and potentially livestock models) are used in TOA to capture the spatial and temporal variation of the land (soil and climate) through the *inprods*. The TOA software calculates *inprods* using calibrated crop growth simulation models from the DSSAT suite of models (Jones *et al.* 2003). In these calculations the soil and weather conditions on the farms can either be measured or derived from a GIS database. The *inprods* are used as indicators for the productivity of farmers' fields in the economic models as a manner to explain the variation in management decisions made by the farmers. The calibration therefore focuses on the relative differences in productivity and not on the absolute level of the estimates. The calibration of the crop growth simulation models can either be through field experiments or through a selection of crop varieties in the crop growth simulation model that explain most of the variation observed in the field.

Subsequently, the estimation of the econometric production models is carried out using the farm survey data and the *inprod* indexes of the surveyed farms. Parameters for price distributions and other exogenous variables of the production models are also estimated using the survey data (Antle and Capalbo 2001). The econometric production models are then composed by a series of input demand and output supply equations representing farmers' crop choice and input use as functions of economic variables (input and output prices, farm characteristics) and the biophysical variables (*inprods*). The environmental impact models need to be calibrated following their own specific procedures depending on the process or indicator.

Crop and econometric production models described above are finally used to parameterize an econometric simulation model that predicts crop choice, input demand and output supply on a site-specific basis (Stoorvogel *et al.* 2001 and 2004). Although with TOA it is possible to run the simulation for the original survey fields at their exact locations, the model also has the option to draw fields randomly from the area, thus creating a new sample of fields which allows the extrapolation and stratification of the area. In order to do this, the TOA samples a set of fields from the area by creating a random set of coordinates and verifying the selected coordinates against a set of user-defined spatial conditions (e.g. soil type, altitude). If the location is accepted, a field size is drawn from a given distribution of field size and the *inprod* of that particular field is assessed using the crop growth simulation model (Stoorvogel *et al.* 2004). Next, the actual simulation of land use and input use begins. Each individual simulation run starts with drawing input and output prices from the distributions after which land use and input use decisions are simulated.

The output of the econometric simulation model includes land use and land management for each of the fields, under different conditions (the tradeoff points) and for several repetitions. This output can subsequently be the input for the environmental process model that estimates the impact of specific decisions on that location in terms of, e.g. erosion or any other environmental process. This process is repeated for each scenario. Outcomes can be displayed spatially as maps or they can also be aggregated to construct regional tradeoff curves.

1.5 Machakos

The Machakos study area (Figure 1.2) is a hilly drought-prone farming area of nearly 13,500 km^2 located 50 km south of the capitol of Kenya, Nairobi. It includes both Machakos and Makueni districts, Makueni being formerly part of Machakos district but separated in 1992 for administrative purposes. Machakos became quite famous after the publication of the book “More people, less erosion” by Tiffen *et al.* (1994). In this book, the authors take the Machakos case to illustrate how population pressure not always has a negative impact on land resources, but it can also stimulate farmers to adopt innovative land management techniques that reverse the process of acute land degradation, while increasing agricultural productivity and per capita income. Many studies have been carried out in the area since (Babier 2000; Warren 2002, Zaal and Oostendorp 2002; Mortimore and Tiffen 2004) and question the “benefits” of population pressure over land (Siedenburg 2006; Tiffen and Mortimore 2006; Malakoff 2011).

Land degradation started in Machakos during colonial times, when the existing high potential agricultural areas were reserved for the white settlements and the local population was forced to migrate to the fragile environment of the semi-arid lands. In the late 1930s authorities recognized signs of massive erosion and degradation that resulted in poverty. From then until independence, the environmental concern of the authorities led to enforced interventions to stop land degradation in the region. Initially, drastic measures were implemented such as mandatory destocking through cattle sales and compulsory communal work involving terracing and grass-planting.

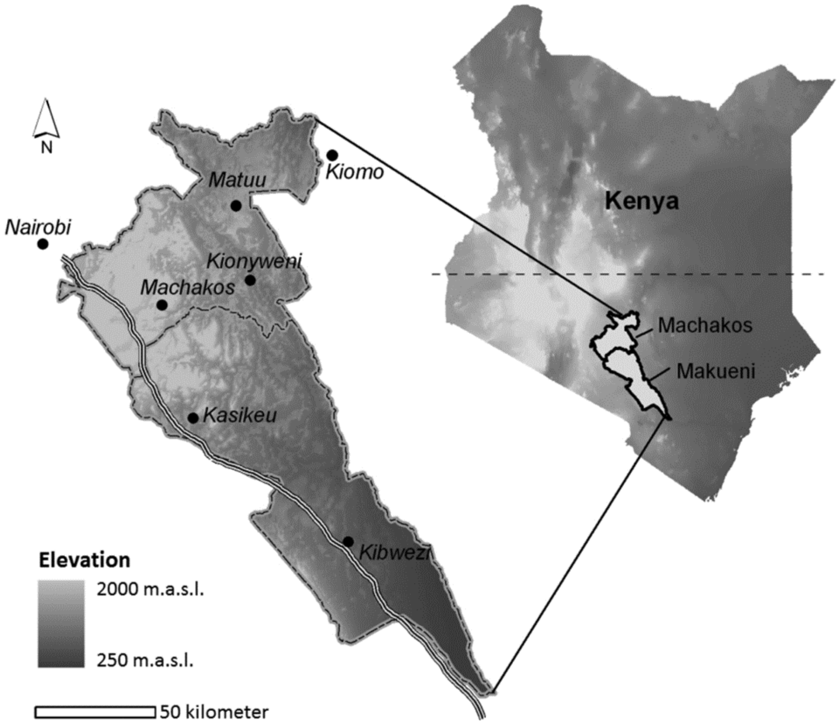

Figure 1.2 Location of the Machakos study area

Gradually, voluntary terracing and other soil conservation practices were adopted by the local farmers and maintained after they reclaimed their disputed land in the late 60s (Tiffen *et al.* 1994). As a result, within a few decades the farming systems shifted from unsustainable to a more sustainable agriculture, a process that has also been described as "the Machakos Miracle" (Zaal and Oostendorp 2002).

Despite these optimistic views about Machakos, at present many farmers in the area still face enormous difficulties to sustain their livelihoods with poverty rates ranging from 40 to 90 percent (Thornton *et al.* 2002) with an average of 66% (RoK 2005). In addition, although some forms of land degradation have been prevented, the effects of the population pressure on the fragile environment are still being felt, including pollution from the industries, destruction of forests, soil erosion and desertification. Although less visible, recent studies of soil nutrient balances in Machakos established that yields are low, nutrient balances are generally negative, and agricultural production is still threatened by soil fertility decline (De Jager *et al.* 2006).

The Machakos study area presents a large variation in biophysical and socio-economic conditions. Altitude ranges from 400 to 2,100 meters above sea level, climate is semi-arid with low and highly variable rainfall distributed in two rainy seasons. The short rains occur from November to January and are usually more reliable than the long rain season, which takes place from March to June. Mean annual rainfall varies in from 500 mm in the lower parts to 1,300 mm in the higher parts with significant annual variation (Tiffen *et al.* 1994). Mean annual temperature ranges from 15ºC to 25ºC resulting in a wide range of agro-ecological conditions (MoA 1987). Drought events occur in cycles of four or five years, normally in runs of two or more seasons, having great impact on food security (Tiffen *et al.* 1994). Soils are generally deep to very deep, with soil texture classes ranging from sandy clay loam to sandy clay. The inherent soil fertility is very poor with common deficiencies in nitrogen and phosphorus. Soil organic carbon content is very low (<2%). According to USDA Soil Taxonomy (Soil Survey Staff 1975), soils are classified as typic Eutrustox, ultic Haplustalfs, oxic Paleustults and rhodic Paleustalfs (MoA 1987). A low resolution soil map combining the soil units of the 1:1,000,000 Exploratory Soil Map of Kenya (Sombroek *et al.* 1980) with the representative soil profile descriptions (Table 1.5) of the Fertilizer Use Recommendation Program (MoA 1987) can be seen in Figure 1.3.

Approximately 50% of the area is dedicated to agriculture, which is the main economic sector in this region. Farmers also obtain a considerable part of their income from non-farming activities inside and outside the district as well (Tiffen *et al.* 1994; De Jager *et al.* 1998[b]; Oale 2011). The mountainous areas offer better conditions for agricultural development in terms of rainfall and market opportunities and for that reason they are more densely populated than the plains to the south. Agriculture is represented by semi-subsistence farming systems that include both crop and livestock production. These type of systems have typical characteristics like a low degree of specialization and a high degree of diversification; mixed crop-livestock systems; inter-cropping; high rates of crop failure; small field size and seasonal reconfiguration of sub-parcels within fields; limited or zero use of purchased inputs; high transportation and other transaction costs; and lack of formal markets. Maize is the most important staple crop but a wide variety of other food (*e.g.,* beans, tomatoes, kales, orange and cassava) and cash crops (*e.g.,* coffee and tea) are grown.

Farmers practice soil nutrient management through the application of manure and chemical fertilizer. Whereas fertilizer use is constrained to better endowed plots with lower risk of crop failure, manure is more often applied on plots that do have some kind of land problem (De Jager *et al.* 2004). Soil conservation practices have been implemented in the area since colonial times and the area is well known for the widespread use of terracing. Other soil and water conservation measures commonly used are strips, contour farming and ridging (De Jager *et al.* 2004; Tiffen *et al.* 1994).

Table 1.5. Soil profile descriptions of the soil units of the low resolution soil map.

Map Unit	Soil FURP	Soil type	Horizon	Depth	WVC (lower)	WVC (upper)	WVC (sat)	Rooting factor	Bulk Density	SOC %	Clay %	Silt %	pH water	pH buffer	CEC
1	26.1	Rhodic ferralsol	Ap	14	0.149	0.214	0.404	1	1.31	1.37	34	6	6.9	5.7	11.9
			AB	30	0.151	0.218	0.413	1	1.32	0.95	36	6	6.8	6.2	10.2
			Ah	60	0.180	0.256	0.456	1	1.32	1.01	34	6	6.8	5.6	10.0
			BU1	90	0.180	0.269	0.469	1	1.34	0.69	40	4	6.6	5.6	7.4
			BU2	114	0.180	0.276	0.476	1	1.36	0.49	42	4	6.3	5.8	7.7
			BU3	136	0.180	0.278	0.478	1	1.35	0.46	44	2	6.3	5.8	7.9
2	26.2	Orthic Acrisol	Ah	18	0.095	0.160	0.325	1	1.51	0.64	10	8	6.1	5.7	3.8
			BA	33	0.182	0.269	0.404	1	1.36	0.42	24	4	6.3	5.3	6.8
			Bt1	58	0.180	0.273	0.473	1	1.41	0.32	34	6	5.8	4.8	10.4
			Bt2	92	0.180	0.281	0.481	1	1.37	0.34	44	6	6.1	5.0	11.9
			BC	124	0.180	0.276	0.476	1	1.39	0.33	38	6	6.4	5.1	10.0
3	26.3	Ferralo-orthic acrisol	Ah	20	0.174	0.259	0.464	1	1.25	1.05	42	10	6.4	6.0	11.6
			BA	35	0.181	0.298	0.483	1	1.25	0.68	50	8	6.5	5.8	10.8
			BU1	68	0.180	0.287	0.487	1	1.32	0.43	54	6	6.0	5.1	10.0
			Bt1	104	0.180	0.290	0.490	1	1.32	0.37	56	6	5.3	4.8	9.7
			Bt2	153	0.180	0.294	0.494	1	1.31	0.35	60	6	5.0	4.7	11.2
4	26.4	Chromic luvisol	Ap	16	0.220	0.309	0.502	1	1.32	0.57	48	12	6.3	5.4	14.2
			Bt1	40	0.217	0.322	0.491	1	1.40	0.31	58	6	6.5	5.6	15.0
			Bt2	75	0.180	0.291	0.491	1	1.33	0.31	56	8	6.3	5.7	14.6
			Bt3	125	0.180	0.291	0.491	1	1.35	0.24	54	8	7.2	6.0	14.0
5	(16)	Pellic vertisol	A	12	0.180	0.284	0.484	1	1.32	0.49	53	5	7.3	6.4	32.7
			Ak1	70	0.180	0.288	0.488	1	1.35	0.30	51	5	8.5	6.9	32.1
			ACK2	94	0.180	0.290	0.490	1	1.33	0.34	55	8	8.4	6.9	32.7
6	24.2	Rhodic ferralsol	Ap	15	0.247	0.321	0.541	1	1.07	1.65	56	24	5.7	5.1	23.5
			Bu1	40	0.234	0.322	0.457	1	1.00	0.94	74	10	5.7	4.6	18.9
			Bu2	54	0.181	0.293	0.493	1	1.20	0.81	74	12	5.6	4.7	18.8
			Bu3	104	0.180	0.297	0.497	1	1.20	0.73	76	14	5.3	4.6	18.9
			Bu4	135	0.180	0.299	0.499	1	1.22	0.64	76	12	5.4	4.6	15.6
7	21.2	Eutric nitisol	Ah	12	0.270	0.359	0.570	1	1.07	1.46	76	13	5.3	4.0	22.3
			BA	40	0.275	0.420	0.605	1	1.00	1.02	80	11	5.7	4.0	19.5
			Bt1	77	0.181	0.303	0.503	1	1.17	0.75	84	11	5.6	4.2	18.8
			Bt2	106	0.180	0.302	0.502	1	1.20	0.65	80	9	5.2	4.7	16.2
			Bt3	125	0.180	0.307	0.507	1	1.23	0.45	80	11	5.1	5.0	18.0

The majority of farms has no access to irrigation. Only in a few locations neighboring the Athi river irrigation occurs. In these areas, access to simple small-scale irrigation allows the cultivation of vegetables such as chili peppers, tomatoes, onions and eggplant for commercial production. In cases where water and marketing constraints are alleviated farmers directly respond by applying higher doses of mineral and organic fertilizer. This change in farm management results in higher and more stable yields and higher financial returns (De Jager *et al.* 2004). In De Jager *et al.* (2001) a full description of the study area and its farming systems is given. Livestock is managed mostly as free grazing, although intensive zero-grazing units are proliferating in the region.

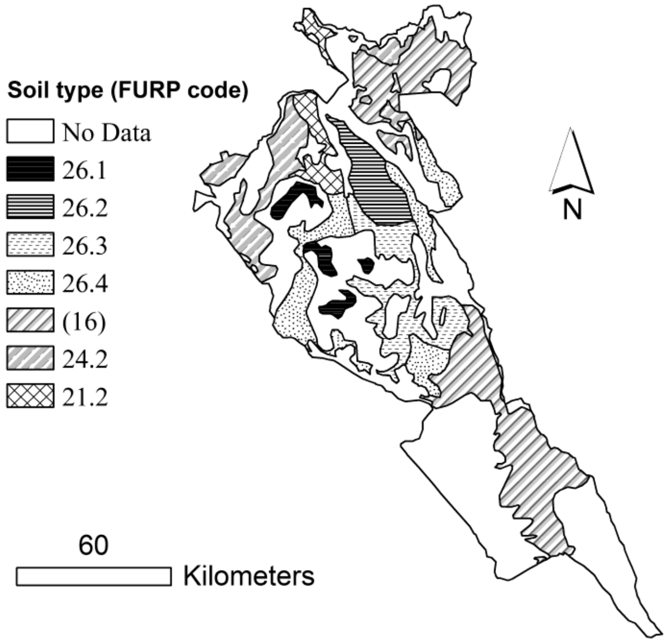

Figure 1.3 **Low resolution soil map of the Machakos Study Area (Kenya)**

1.6 This thesis

While in the 60s, agricultural research focused on developing technology to essentially increase production, today achieving higher yields is just one piece of the puzzle and scientists have to deal with complex systems where agricultural policies, local and international markets, capacity building and environment also play a role. Hence, key to future agricultural production is sustainability, equally social, environmental and economic. For this reason, research nowadays should be directed towards the integrated analysis of agricultural systems, and tools and methods to deal comprehensively with all the emerging agricultural concerns have to be improved and promoted.

The main objective of this thesis is to combine biophysical and economic research into integrated assessment to develop a proper method for regional policy analysis. This integration is proposed as a suitable way to perform ex-ante evaluation of alternative agricultural policies and technologies. Results of this type of assessment provide policy makers with reliable information so they can target effective policy and technology interventions. Policy makers need a clear overview of the possible consequences of their decisions and this can only be achieved if economic, biophysical and environmental indicators are connected. Because the assessment of regional policy analysis often requires a large amount of specific data and great efforts in model development, this thesis proposes to use previous research and existing models as a solid base to a new integrated approach. In the same line, existing data and modern techniques of data collection are used to acquire sufficient and adequate data for this type of regional land use analysis. This leads to the following research questions:

- Are digital soil mapping techniques suitable for developing high resolution input data for land use models?
- Can biophysical and economic models be combined for the integrated assessment of policy and technology interventions?
- Is integrated assessment able to site-specifically evaluate the economic and environmental consequences of agricultural interventions proposed in policy documents?
- Does the resolution of the input data influences the outcome of the land use models? To what extent higher resolution data are required to come to a similar or 'good enough' result for policy advice? When policy makers are interested in general trends or aggregated results only, do we really need detailed high resolution data for the analysis?

This thesis consists of six chapters, including this introduction and the synthesis. The case study of this thesis is carried out in Machakos, Kenya. Integrated assessment uses different type of models (bio-physical, econometric and environmental) which all need sufficient data in the set-up phase. Specifically crop production and environmental models require adequate soil and climate data. In this case, soil information available was scarce and of low resolution. Chapter 2 describes the use of Digital Soil Mapping (DSM) techniques to create a reconnaissance survey in Kenya, specific for this case study. In this chapter DSM techniques are evaluated whether they are a powerful spatial prediction tool for small scale applications up to catchment or regional extent, and if the accuracy of a soil map achieved with standard soil surveying techniques can be improved using DSM. The soil properties targeted for this evaluation are soil organic carbon (SOC) and clay content, which are used as driving factors of crop growth simulation models.

Subsequently, the linkage of two existing complementary methodologies, namely NUTMON and TOA, is a great opportunity for integrated assessment. This linkage is fully described in Chapter 3. NUTMON surveys had previously been applied in Kenya to address the problem of soil fertility decline through the calculation of farm nutrient balances, and TOA analysis had been carried out in the potato-pasture systems of the Andes to measure pesticide leaching effects. In order to draw conclusions from nutrient balances in Africa and move the discussion forwards, local diagnosis has to be translated into regional interventions. The linkage of NUTMON and TOA methodologies provides an approach to evaluate possible effects of technology and policy interventions in a comprehensive ex-ante manner and this information is crucial for informed policy making. The complementary aspects of both methodologies are explained in this chapter, together with details on why they benefit from each other. The case of Machakos study area was used for setting up the model and in this chapter two alternative scenarios were analyzed. To go into more detail, in Chapter 4 a set of agricultural policy and technology interventions that are commonly suggested in several development strategies and documents are discussed, and the NUTMON-TOA approach is used to evaluate the economic and environmental consequences of these strategies in the farming systems of Machakos. In this chapter, robust scenarios to model different agricultural interventions proposed in real policy documents are evaluated and it is assessed whether the soil fertility interventions suggested are effective measures in the semi-subsistence farming systems in Kenya.

Next, Chapter 5 refers to the effects of biophysical data resolution on the model results for integrated assessment. To examine how the resolution of the input data influences the outcome of land use models, in this chapter the results of two different (low and high resolution) datasets of soil and climate are evaluated by quantifying their effect over i) the calculation of model variables; ii) over model estimation; iii) over the calculation of the sustainability indicators and iv) over tradeoffs and scenario assessment. We look at these variables at the farm, village and regional level. This inquires to what extent higher resolution data are required to obtain a 'good enough' result for policy advice and if detailed high resolution data for the analysis is really needed when policy makers are interested in general trends or aggregated results only. Finally, Chapter 6 concludes this thesis and discusses the main findings of this research.

Chapter 2

Small Scale Digital Soil Mapping in Southeastern Kenya

Published as:

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2.1 Introduction

Increasing environmental concern has augmented the demand for regional land use analysis. While in the past regional land use analysis was often based on qualitative procedures (FAO, 1976), currently more quantitative methods are required and become available (Stoorvogel *et al.,* 2001; Bouma *et al.,* 2007). Soil information is important for many regional land use analysis models. This is especially true in models that deal with processes of land productivity and degradation. However, traditional soil surveys do not provide quantitative data at the detailed scale level that is required (Kravchenko *et al*., 2006[a]; McBratney *et al*., 2000; Ziadat, 2005) and new methods of soil mapping are needed.

Standard soil surveying techniques (USDA, 1984; USDA, 2007; Soil Survey Staff, 1993) have had great importance in pedology. However, conventional soil surveys provide qualitative data in the form of chloropleth maps which are a simplification of the existing soil resources (Zhu *et al*., 2001). Moreover, the traditional methods are expensive and time consuming due to the large number of observations and the limited use of auxiliary information. Recently, with the rapid development of computers and information technology, together with the availability of new types of remote sensors, a more quantitative approach has been developed that may replace the traditional inventory techniques. These new techniques include the modeling of continuous surfaces based on the factors of soil formation, as well as the assessment of accuracy and uncertainty of the predictions (McBratney *et al*., 2000). This approach is commonly referred to as digital soil mapping (McBratney *et al*., 2003). In digital soil mapping a limited number of soil observations can be used. These observations are then related to auxiliary information representing important soil forming factors: digital elevation models representing topography, satellite images representing land cover and climate, and geological maps representing parent material and possibly age. These relationships can now be used to predict soil properties for the entire area for which auxiliary information is available. In early applications, soil observations were related only to terrain attribute maps using simple regression models, but later the predictors were broadened to an array of environmental variables giving origin to the terms "environmental correlation" (McKenzie and Ryan, 1999) or the "CLORPT techniques" (McBratney *et al*., 2000). Alternatively, hybrid methods have been developed from the combination of geostatistics and environmental correlation, where the observations or the residuals of the regression are interpolated using co-kriging or regression kriging (Hengl *et al.,* 2004).

Literature provides a large number of examples where digital soil mapping is presented as an efficient surveying technique. However, in many of these cases the techniques are applied in small areas (less than 100 ha) with at least 200 observations per square kilometer (Bhatti *et al*., 1991; Florinsky *et al*., 2002; Kravchenko *et al*., 2006b; McBratney *et al*., 2000), or for (semi-) detailed soil surveys in areas of less than 150 km^2, in which the number of observations per square kilometer ranges from one to 20 (Gessler *et al*., 2000; Ryan *et al*., 2000). In addition we see that in many of these successful stories soil variation is induced by a limited number of soil forming factors. For example, by correlating soil reflectance with Landsat Thematic Mapper images, Bhatti *et al*. (1991) effectively estimated soil properties; Gessler *et al*. (2000) built a model for soil organic carbon (SOC) that accounted for 78% of the variation using topography and terrain attributes only; and McKenzie and Austin (1993) attained a good prediction of soil clay content with parent material and relief as explanatory variables, using just about 200 soil samples for an area of 500 km^2. Furthermore, small scale applications of digital soil mapping (Frazier and Cheng, 1989; Hengl *et al*., 2004; McBratney *et al*., 2000) indicate that hybrid methods represent a powerful spatial prediction tool, especially up to catchment or regional extent. Many of the examples of digital soil mapping applications come from Western Europe, the United States and Canada where good explorative soil surveys are already available. However, there is a call for explorative soil surveys in many tropical countries where the national surveys have not progressed as much as in many developed countries. In these cases, it is urgent to find methodologies that enable to rapidly and effectively capture information about the spatial variability of the soils and reduce the need for intensive and expensive sampling. Hence, the question that remains is whether the digital soil mapping techniques are suitable for explorative or reconnaissance surveys, where we have to look at larger areas, with limited data availability and considerable inherent soil variation caused by the interaction of different soil forming factors.

In this research we tested the digital soil mapping techniques for a reconnaissance survey in Kenya. The final soil map of this study was intended for the analysis of agricultural productivity focusing on terraced maize fields. We, therefore, focused on SOC and clay content because these properties are important driving factors behind crop production and can be used in crop growth simulation models as indicators of soil fertility and water holding capacity. SOC is expected to be highly variable as it is influenced by land use. In contrary, we expect the clay content to be less variable and more dependent on parent material and soil development. In previous studies (Gessler *et al*., 2000; Kravchenko *et al*., 2006[b]) both properties have shown strong spatial structure, suggesting the potential of using terrain attributes and other auxiliary information in order to model their variability. We will examine if this assumption is still valid when samples are taken one to several kilometers apart in areas that are so large that the spatial prediction is performed with much less than one observation per square kilometer.

2.2 Materials and methods

2.2.1 Study area

The 13,500 km^2 study area (Figure 2.1) is located in the Eastern Province of Kenya (Machakos and Makueni districts) with an elevation ranging from 400 to 2,100 meters above sea level.

The area presents significant environmental variation. In terms of geology, the Basement System, generally considered to be from the Precambian, covers most of the area. Originally, this system consisted of sedimentary rocks, but in a later stage some intrusions with igneous rocks took place. These rocks were later considerably metamorphosed or granitized, as a result of an east-west compression which folded the original sediments and depressed them into the lower parts of the Earth's crust. As a result of these processes, a wide variety of gneisses and schists are now found in the district, including amphibolites, quartzites and biotite granitoid gneisses. In the early Miocene, the formation of the Rift Valley produced crustal disturbance in the whole region and large flows of phonolite lava covered the Basement System rocks, such as the Kapiti phonolite in the northwest. All along the eastern border of the district, the Yatta Plateau is a resistant cap of coarsely porphyritic phonolite from the Tertiary. During the upper Pleistocene epoch, another volcanic episode took place in the southern part of the area, where some olivine basalt vents with associated lavas and ashes formed the Chyulu range (Baker, 1952; USDA, 1978).

Most of the soils in the area are deep to very deep, friable, with textures ranging from sandy clay loam to sandy clay. They generally present a porous massive structure with moderate to high water holding capacity and good drainage. Superficial runoff does not normally occur, though erosion can take place since most of the heavy rains occur at the beginning of the planting season when the land is still bare. Limitations such as salinity, sodicity, stoniness and rockiness are rare. However, inherent soil fertility is very poor with low SOC (<1%) and soils are generally deficient in nitrogen and phosphorus (MoA, 1987; Onduru *et al*., 2001). Average soil properties for the upper 30 cm of the main soil types are shown in Table 2.1. According to the Soil Taxonomy (Soil Survey Staff, 1975), soils are classified as typic Eutrustox, ultic Haplustalfs, oxic Paleustults and rhodic Paleustalfs. Typic Eutrustox soils are dark reddish brown to dark red in color and can be found in the uplands of the hilly part of the district, which represent the remnants of the oldest land surface in the area. The parent rock is mainly quartzite. This type of soil exists in the densely populated areas where most of the fields have been terraced. In the lowlands and to the west border of the study area the rhodic Paleustalfs are found. These soils are dusky red to dark reddish brown in color, generated mainly from biotite gneisses.

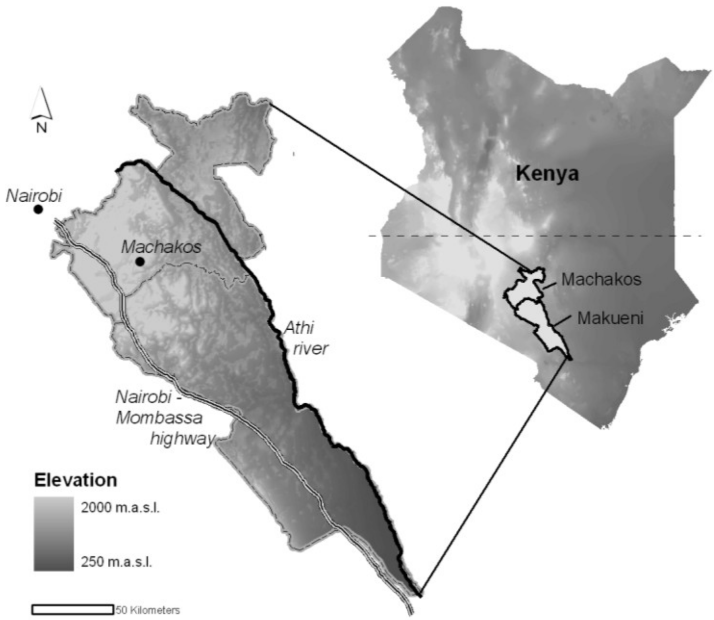

Figure 2.1. Location of the study area

The southern part of the area and the east are dominated by a combination of ultic Haplustalfs and oxic Paleustults, which are dark brown to yellowish brown in color. The parent material consists of undifferentiated basement system rocks for the first and biotite gneisses for the last (MoA, 1987). The semi-arid climate in the study area has a low, highly variable rainfall distributed in two rainy seasons. Short rains occur from November to January and long rains from March to June. Average annual rainfall ranges from 500 to 1,300 mm and mean annual temperature varies from 15ºC to 25ºC, resulting in a wide range of agro-ecological conditions (MoA, 1987). Drought events do happen in cycles of four or five years, normally in runs of two or more seasons, and they have great impact on food security (Tiffen *et al.*, 1994). Almost half of the total surface of the study area is under agricultural use (6,615 km^2). Agriculture is represented mainly by subsistence-oriented mixed farming systems that include both crop and livestock production, although some coffee and cotton are cultivated in the area as cash crops. Maize is the most important staple crop, but a wide variety of other food crops are grown (beans, millet and sorghum), vegetables (tomatoes and kales), fruit trees (orange, banana, mango and pawpaw) and tubers (cassava). For all crops, yields are generally low and crop failure is a common problem.

Table 2.1. **Soil properties for the main soil groups in Machakos and Makueni districts (average values for the upper 30 cm (MoA, 1987; Onduru et al., 2001))**

Soil Class	Water Holding Capacity (Vol %)	Bulk Density (kg/l)	SOC (%)	Clay (%)	pH	CEC (meq/100g)
typic Eutrustox	8.3	1.32	1.16	35	6.9	9.3
rhodic Paleustalfs	9.2	1.43	0.53	17	6.2	9.0
ultic Haplustalfs	13.3	1.25	0.87	46	6.5	9.8
oxic Paleustults	19.1	1.36	0.44	53	6.4	11.8

Soil nutrient management through application of manure and chemical fertilizer is practiced by farmers. However, due to the relatively high prices of chemical fertilizer, this is only applied on plots that are of good quality and have less risk of crop failure; manure is more often applied on plots that do have some kind of land problem (de Jager, 2007). Soil conservation practices have been implemented in the area since colonial times (Tiffen *et al.,* 1994). While in the 1930s the building of erosion control structures was enforced after severe land degradation took place, nowadays the majority of the farmers (almost 75%) voluntarily maintain these structures and the area is well known for the widespread use of terrace cultivation. Other soil and water conservation measures commonly used are strips, contour farming and ridging (de Jager, 2007; Tiffen *et al.*, 1994). Irrigation is hardly available for the majority of the farmers but some cases exist in locations neighboring the Athi river. Access to simple small-scale irrigation allows the cultivation of vegetables such as chili peppers, tomatoes, onions and eggplant for commercial production. In such cases, where water and marketing constraints are alleviated, farmers directly respond by applying higher doses of mineral and organic fertilizer. This change in farm management results in higher and more stable yields and higher financial returns (de Jager, 2007).

2.2.2 Methodology

To predict the spatial distribution of topsoil SOC and texture in the study area, the spatial variability of the soils was interpreted using the concepts of the soil forming factors equation described by Jenny (1941). Jenny's equation states that soil formation is a function of climate, organisms (including vegetation), relief, parent material and time. A limited number of soil observations were taken in terraced maize fields and analyzed for the targeted soil properties. Auxiliary information on the various soil forming factors was collected (remotely sensed imagery, digital elevation models, geology, geomorphology, etc.) and used as explanatory variables to perform a step-wise multiple regression analysis, which established the relationship between the measured soil properties and the soil forming factors. Next the residuals were calculated and interpolated using kriging to incorporate the spatial correlation of the errors of the linear regression model. The final maps were obtained by combining the regression models with the interpolation of the residuals in a regression kriging approach. Cross-validation was performed to establish the prediction accuracy of the maps.

2.2.3 Sampling procedure

Because the digital soil map was intended for the assessment of agricultural productivity on terraced fields and of arable farming in particular maize production, natural areas (51% of the total study area) were masked out and excluded from the analysis using the FAO-Africover map (www.africover.org). Clusters of four sample points were distributed throughout the area in a manner that could both maximize the coverage of sampling and capture the spatial correlation of the soil properties. Fields within the cluster were on average 1,500 meters apart. Sampling in clusters also facilitated the data collection process, since accessibility is a problem in most of the study area. Land use and management variation was reduced by taking samples on terraced fields under maize production. The coordinates of each sampling location were determined with a global positioning system. To avoid the effects of within field variation, five top soil (0-30cm) samples were taken in each field and mixed thoroughly into a composite sample. Samples were analyzed in the laboratories of the Kenya Soil Survey for SOC and texture. SOC was determined using the total organic carbon colorimetric method and clay content was established with the hydrometer method. Laboratory consistency was also assessed by submitting 50% of the samples as duplicates with randomly numbered labels.

2.2.3 Auxiliary data

With Jenny's equation in mind, various sources of auxiliary data were retrieved and analyzed in order to capture the spatial variation of the soil forming factors in the study area. Data on climate, organisms, relief and parent material were used to establish the correlation between the environmental variables and the targeted soil properties (Figure 2.2).

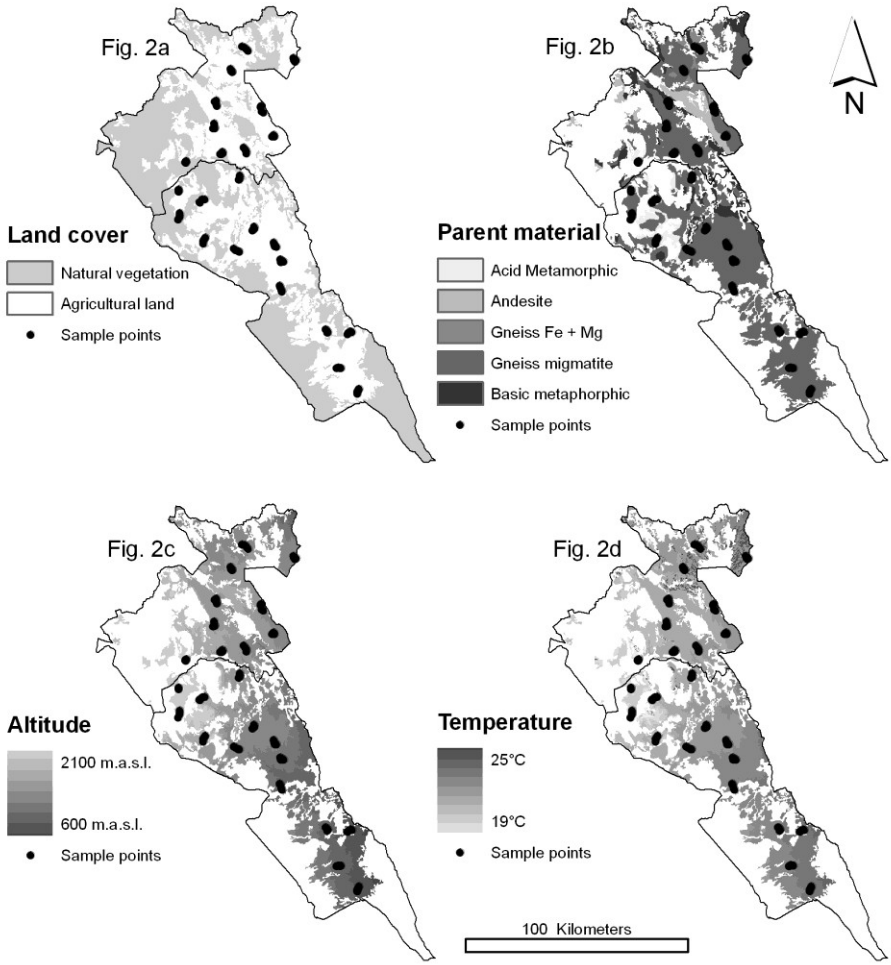

Figure 2.2. **Sampling scheme and spatial distribution of auxiliary data a) land cover; b) parent material; c) altitude and d) mean temperature for Machakos and Makueni districts**

Climate

In terms of climate, data were obtained from the weather stations of Katumani (1.517° S and 37.267° E; 1,680 meters above sea level) in Machakos district, and Kiboko (2.283° S and 37.700° E; 1,540 meters above sea level) in Makueni district. To integrate indices of local climate into the analysis, daily records of 1987 were used as input for a mechanistic model for climate interpolation (Baigorria Paz, 2005), which models climate spatial variation based on terrain characteristics. With this model, maps of average solar radiation and annual temperature were generated. The study area is in close proximity to the Equator and solar radiation is rather uniform. However, mean temperature increases considerably to the west as altitude decreases.

Organisms

As an indicator of organic matter contribution to soil formation, the Normalized Difference Vegetation Index (NDVI) was used as an auxiliary variable. The NDVI is a surrogate for biomass presence obtained from the relationship between Red and Near Infra Red (NIR) radiation and is calculated as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

As a higher NDVI value reflects higher biomass, this index is also indirectly an indicator of water availability. The index was calculated from Landsat imagery, with the Global Orthorectified Landsat Datasets (30 m resolution) for three decades: 1970's MSS, 1990's TM, and 2000's ETM+. Neighborhood statistics were applied on each of the NDVI maps, calculating the average value in a 3x3 cell rectangle in order to reduce the effects of positional error of the reference points and short distance effects. The sum of the three decades NDVI was also assessed for each resolution and incorporated in the analysis.

Relief

Altitude, slope and aspect were derived from the seamless global coverage 3 arc second (~90m) digital elevation model derived from the Shuttle Radar Topography Mission[1]. Aspect was corrected using the cosine function to avoid an unrealistic discontinuity at 0 and 360 degrees and have a better estimate of the relative east and west deviation. In addition, other landscape attributes were calculated. Slope position class was assessed based on the Topographic Position Index (Weiss, 2001; Jennes, 2005) using a neighborhood of 5 kilometers. In this case, slope position was characterized in six classes, namely ridge; upper slope; middle slope; flat slope; lower slope and valley. Also using the Topographic Position

[1] Downloadable from: http://edc.usgs.gov/products/elevation/srtmbil.html

Index, landforms were classified in seven categories: canyons with deeply incised streams; mid-slope drainages or shallow valleys; U-shaped valleys; plains; open slopes; upper slopes (mesas); and mountain tops or high ridges.

Geomorphological processes causing redistribution of water and soil material across the landscape have an important influence on soil variability and were included in the analysis in the form of spatial patterns of water accumulation, erosion and deposition. The LAPSUS modeling framework (Claessens *et al*., 2006; Schoorl and Veldkamp, 2001) and the DEM were used in this exercise to disaggregate soil units by differences in contributing area (CA, also called drainage or catchment area) and local slope. CA is calculated as the area contributing flow to a cell. This topographic attribute is related to soil moisture and can also be associated with the intensity and frequency of processes involving water accumulation (*e.g*. water erosion by runoff). For our analysis, a multiple flow routing algorithm (Quinn *et al*. 1991) was used with a P factor of 4. The P factor is a weighting factor for convergence: the higher the value, the more convergent the flow is routed towards the drainage system. Values for CA were truncated at 200 grid cells, to avoid the extremely large values in the streams. In addition, the topographic wetness index (TWI) was calculated with LAPSUS and included in the analysis. This index is an indicator of water and sediment movement in the landscape and describes the spatial distribution and extent of zones of saturation for runoff generation as a function of upslope contributing area and local slope (Wilson and Gallant 2000; Claessens *et al*., 2006). It can be written as:

$$TWI = \ln\left(\frac{CA}{\tan(S)}\right),$$

where CA is the contributing area in m^2/m, and S is the local slope in degrees. Fixed maximum cut-off values were used for these indices to exclude the drainage pattern from the analysis. Sinks in the DEM were eliminated prior to the calculations.

Parent material

A general physiographic soil map at a scale of 1:250,000 was developed by Van Engelen and Wen (1995). From this map, the main geological classes were derived based on lithology: migmatite gneiss, andesites, intermediate igneous and metamorphic rock.

2.2.4 Model Description

By means of regression kriging (Hengl *et al*., 2004) the entire set of explanatory variables generated from the auxiliary data regarding climate, NDVI, relief and parent material was used for the spatial prediction of SOC and clay content. The models for the selected soil properties were obtained with step-wise multiple regression analysis. Categorical variables were introduced in the regression analysis as binary variables using the delta-function that equals 1 if a location is within a particular unit and 0 otherwise. The structural analysis of the regression residuals at observation points provided the semi-variograms which were used to perform regression kriging. Therefore, the prediction of the targeted soil properties was finally given by combining the function obtained with the linear regression (a constant with a varying trend) with the interpolated residual. The final maps were obtained with the Gstat geostatistical package (Pebesma, 2004). To examine the improvement of the prediction achieved by incorporating the regression equation and interpolation of the residuals, the model performance was calculated by comparing the spatial average of the ratio of the kriging variance and that of the observations as follows:

$$\text{model performance} = 1 - \frac{\text{spatial average of kriging variance}}{\text{sample variance of observations}}$$

2.2.5 Validation

The prediction accuracy of the resulting maps was evaluated by cross-validation. In order to do this, the field dataset was partitioned in sub-samples corresponding to the field clusters. The performance of the models was evaluated by executing several repetitions of regression kriging in which, each time, a single cluster of points was temporally removed from the dataset. This cluster (or sub-sample) temporally removed was the set of points used as a validation set, while the remaining samples from the other clusters were used to estimate the regression coefficients and to interpolate the residuals. Thus, SOC and clay content were predicted at the cluster locations without using the observations in the cluster. The process was repeated for every cluster. Differences between observed and predicted values were computed with the Mean Error (ME), Root Mean Square Error (RMSE) and the Standardized Root Mean Square Error (SRMSE), using the following equation, where *n* equals the number of sample points.

$$\text{ME} = 1/n\sum_{i=1}^{n}(obs_i - pred_i)$$

$$\text{RMSE} = \sqrt{1/n\sum_{i=1}^{n}(obs_i} - pred_i)^2$$

$$\text{SRMSE} = \sqrt{1/n\sum_{i=1}^{n}(obs_i} - pred_i)^2 / pred\,\mathrm{var}_i$$

The resulting maps were also compared with those of the general physiographic soil map at a scale of 1:250,000 (Van Engelen and Wen, 1995). This soil map consists of units discriminated by their particular pattern of landform, lithology, slope, parent material and soil. The units are described by a representative soil profile identified by experts from existing soil survey reports.

2.3 Results and discussion

During field work in February 2006, 95 terraced maize fields were sampled (Fig. 2.2[a]). The samples correspond to 24 clusters distributed over the study area. Each cluster consisted of four fields (except one cluster with only three fields), separated from each other by approximately one kilometer.

2.3.1 Descriptive statistics

The results of the laboratory analysis of the 95 composite soil samples (Table 2.2) indicate that SOC in the topsoil is low (<1.3%) for the whole study area. This is probably a consequence of the intense agricultural use of the existing farming systems and the lack of inputs. In contrast, textural variation in the area is large with textures ranging from sandy clay to loamy sands. Both dependent variables depict a normal distribution and SOC and clay have a positive correlation of 0.61. The consistency test of the laboratory with duplicate samples showed an R^2 of 0.75 for SOC and R^2 of 0.84 for clay content. Details on the absolute measurement errors can be seen in Table 2.3. Descriptive statistics of the auxiliary variables used in the regression analysis are shown in Table 2.4 for continuous variables and Table 2.5 for categorical variables. The categorical variables show that most of the agricultural area is on the flat plains of a large metamorphic unit that extends across the districts.

Table 2.2. Summary statistics for SOC and texture analysis of terraced maize fields in Machakos and Makueni districts

Soil Properties (%)	Mean	Std. Dev	Min	Max	Skewness
SOC	0.84	0.21	0.27	1.33	-0.5
Clay	27	10	8	57	0.3
Sand	64	11	35	88	-0.2

Table 2.3. Summary statistics for measurement errors of SOC and Clay in samples from terraced maize fields in Machakos and Makueni districts

Soil Properties (%)	Mean	Mode	Min	Max	Variance
SOC	0.09	0.04	0.00	0.30	0.004
Clay	3	0	0	18	12

Table 2.4. Descriptive statistics of continuous auxiliary variables in the agricultural area of Machakos and Makueni districts

Category	Variable	Code	Mean	St.Dev.	Corr. Coeff SOC	Corr. Coeff. Clay
Climate	Mean Temperature	T	21.8	0.6	-.006	-.332*
	Solar Radiation	SRad	20.1	0.6	-.059	-.061
Topography	Altitude	Alt	1133	239	-.054	.418*
	Slope	Sl	3.3	3.3	.099	.236*
	Aspect (corrected cos)	Asp	0.2	0.7	.166	.034
Flow accumulation	Topographical Wetness Index	TWI	10.9	4.5	.054	-.085
	Contributing Area	CA	20	49	-.164	.035
Vegetation	NDVI (1970)	$NDVI_{70}$	-0.08	0.04	-.082	-.035
	NDVI (1990)	$NDVI_{90}$	0.17	0.09	.117	.085
	NDVI (2000)	$NDVI_{00}$	-0.09	0.09	-.086	-.007
	NDVI (sum)	$NDVI_{sum}$	-0.02	0.16	.003	.037

Table 2.5. Descriptive statistics of categorical auxiliary variables in the agricultural area of Machakos and Makueni districts

Category	Variable	Code	% of area	SOC		Clay	
				average	st.dev.	average	st.dev
Slope position	Flat	Sp_f	56	0.88	0.20	27	9
	Lower slope	Sp_l	19	0.77	0.25	24	9
	Upper slope	Sp_u	11	0.82	0.19	27	9
	Ridge	Sp_r	5	0.75	0.22	24	10
	Middle slope	Sp_m	5	0.98	0.17	37	10
	Valley	Sp_v	4	0.72	0.29	27	4
Land form	Plains	Lf_p	75	0.85	0.21	26	9
	U-shaped valleys	Lf_u	8	0.86	0.12	34	12
	Canyons, deeply incised streams	Lf_c	4	0.5	0.1	21	7
	Mid-slope drainages, shallow valleys	Lf_d	3	0.92	-	36	-
	Upper slopes, mesas	Lf_m	3	0.96	0.06	40	1
	Mountain tops, high ridges	Lf_t	3	0.84	0.23	31	13
	Open slopes	Lf_o	3	0.93	0.09	35	4
Geology	Gneiss migmatite	G_g	79	0.83	0.21	26	9
	Andesite	G_a	11	0.99	-	34	-
	Intermediate igneous	G i	6	0.96	-	36	-
	Metamorphic	G_m	4	0.85	0.23	36	10

2.3.2 SOC regression model

The regression model predicting SOC was obtained with a step-wise linear regression (entry significance of 0.5; removal significance of 0.1):

$$SOC_{regression} = 0.841 - 0.252 * \delta(Lf_{m}) - 0.359 * \delta(Lf_{u}) - 0.332 * \delta(Lf_{c}) + 0.185 * \delta(Sp_{m}) + 0.067 * Asp$$

The analysis of variance (ANOVA) is given in Table 2.6. The regression accounts for 21% of the variance (Figure 2.3) with a RMSE of 0.19 and a SRMSE of 7.76. SOC levels for the upper slope (mesa), u-shaped valleys and canyons are smaller than for the rest of the study area. In addition, areas located on middle slope positions have larger SOC contents. Notice that the union of these three landforms and the slope position represent just about 20% of the area of interest, therefore SOC in the remaining 80% of the area is given by a combination of the constant value (0.84) and aspect, which is positively correlated to SOC. This relationship means that areas with an East exposure present higher SOC levels than those in the West, which can probably be explained by a smaller evapo-transpiration rate on the slopes oriented to the East.

Table 2.6. ANOVA of the regression model for predicting SOC on terraced maize fields in Machakos and Makueni district

	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.903	5	0.181	4.784	.001
Residual	3.361	89	0.038		
Total	4.264	94			

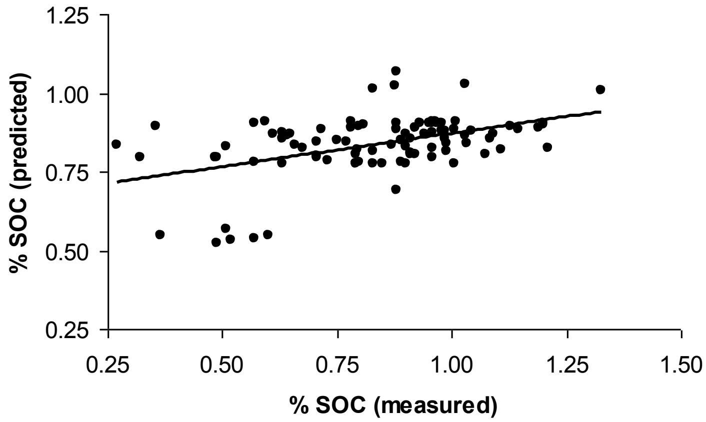

Figure 2.3. **Linear regression for soil organic carbon model for terraced maize fields in Machakos en Makueni districts.**

2.3.3 Clay regression model

The clay regression model was developed with the same methodology used for SOC:

$$Clay\ \% = -3.95 + 0.018 * Alt - 9.8 * NDVI_{70} - 18.4 * \delta(Lf_{m}) + 8.63 * \delta(Sp_{m})$$

The ANOVA results are presented in Table 2.7. This model accounts for 35% of the variance (Figure 2.4) with a RMSE of 0.19 and a SRMSE of 7.76. In the case of the clay model, areas located in the landform upper slope (or mesa) present a negative correlation with clay content while areas located in middle slope position have a larger clay content. These two classes correspond to nearly 11% of the total area. The same relationship exists between these classes and SOC, which is consistent with the positive correlation between clay and SOC. Though $NDVI_{70}$ appears in the equation, its contribution is very small and in terms of texture classes it is more or less irrelevant. Hence, altitude accounts for most of the variation in clay content in this area, describing a positive correlation. This can be explained because elevated areas present larger rainfall which facilitates weathering processes, but also because the higher parts in this region are generally older in geological terms; consequently, longer time of exposure has permitted chemical decomposition of minerals for clay formation.

Table 2.7 **ANOVA of the regression model for predicting clay content on terraced maize fields in Machakos and Makueni districts**

	Sum of Squares	df	Mean Square	F	Sig.
Regression	3027.686	4	756.921	11.895	.000(d)
Residual	5727.051	90	63.634		
Total	8754.737	94			

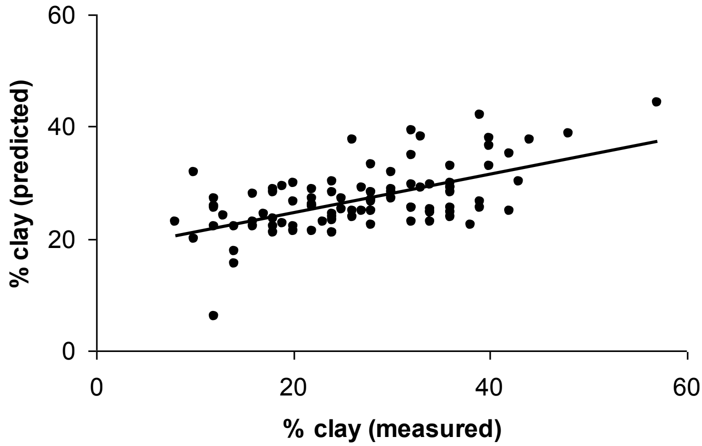

Figure 2.4 **Linear regression for clay content model for terraced maize fields in Machakos en Makueni districts.**

2.3.4 Spatial interpolation

A structural analysis of the data points produced semivariograms for SOC and clay residuals (Figure 2.5). The semivariograms were fitted by a spherical model with a range of 33 km for SOC and 30 km for clay. The semivariogram for the SOC residual has a nugget value of 0.020 $\%^2$, which is almost half the total variance (0.042 $\%^2$), meaning that the combined effect of short distance spatial variation and measurement error is substantial. In this case, the variance of the measurement error is 0.002 $\%^2$; therefore, the short distance error accounts for almost 90 % of the nugget variance. In the semivariogram of clay content residual, the nugget variance is 30 $\%^2$ and the sill value is 70 $\%^2$. Since the semivariance of the measurement error is 6.2, short distance error in this case accounts for 80 % of the nugget variance.

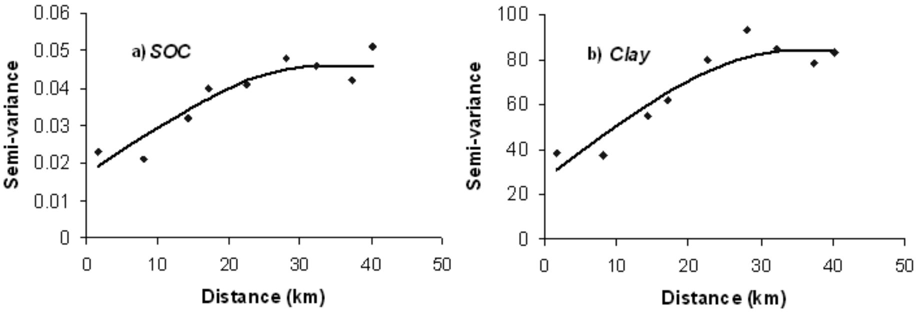

Figure 2.5 **Semivariogram for a) SOC and b) Clay content for terraced maize fields in Machakos en Makueni districts.**

Table 2.8. **Descriptive statistics for the SOC and clay maps obtained with regression kriging**

Soil Properties	Mean (%)	Min (%)	Max (%)	Variance (%^{2})
SOC	0.82	0.28	1.21	0.02
SOC var	0.04	0.03	0.08	0.00
Clay	25	0	65	38
Clay var	58	0	252	123

Although the measurement error will influence the prediction accuracy of the regression model for both soil properties, most of the variance is given by the short distance spatial variation. In this case, this refers to distances of approximately one kilometer. The maps obtained with regression kriging of predicted SOC and clay content are presented in Figures 2.6 and 2.7. The descriptive statistics are in Table 2.8. In the case of SOC, the variance in the observations was 0.045 %^{2} while the spatial average of the kriging variance was 0.039 %^{2}. Consequently, we conclude that the model using regression kriging explains only 13 % of the variation in SOC, which is smaller than the variance explained by the regression model (21 %). This can be explained by the fact that the R^2 of the regression model is a somewhat overoptimistic measure because it does not include the uncertainty in the estimated regression coefficients, whereas the regression kriging variance does (Hengl *et al.*, 2004). The RMSE for the calibration points was 0.16% with a SRMSE of 1.63. For clay content, the sample variance of the observations is 93.0 %^{2} and the spatial average of the kriging variance is 58.4 %^{2}. Consequently, the model performance of regression kriging for clay content is 37 %, which is greater than the variance explained by the regression only. The RMSE for the calibration points was 6.32% with a SRMSE of 0.92. Thus, in this case accuracy was improved by interpolation of the residuals.

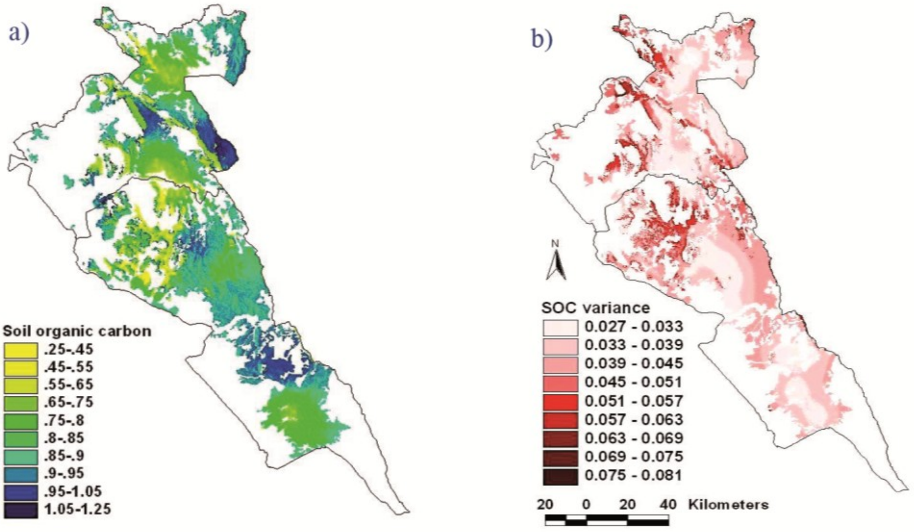

Figure 2.6 **a) Predicted SOC and b) SOC variance (regression kriging) for terraced maize fields in Machakos en Makueni districts.**

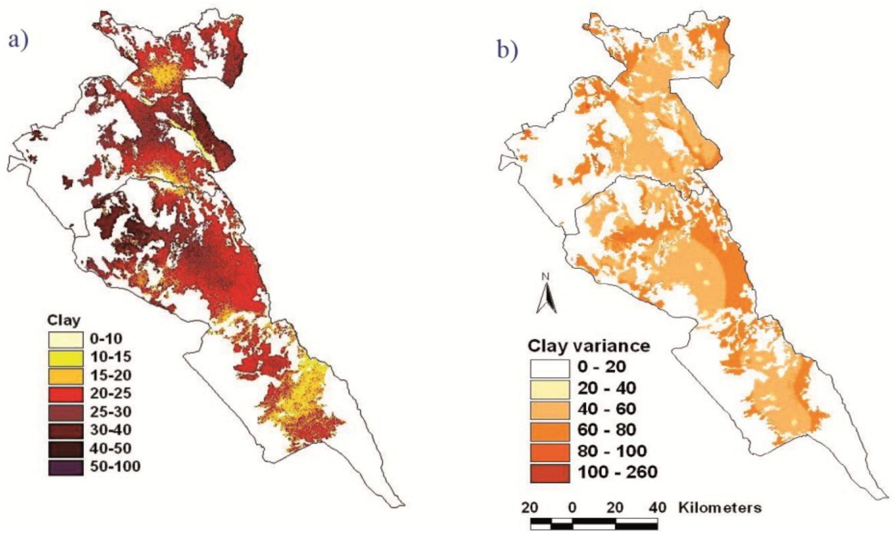

Figure 2.7 **a) Predicted clay content and b) clay content variance (regression kriging) for terraced maize fields in Machakos en Makueni districts.**

2.3.5 Cross-validation

Results from the cross-validation are presented in Table 2.9. In the case of ME, both values are close to zero and suggest an unbiased prediction. The RMSE values are slightly smaller than the standard deviation of the observed sample values (0.21 % and 9.65 % for SOC and clay respectively). This means that by using the information of the explanatory data and the spatial correlation of the residuals we can obtain a better estimation than just using the average value of the observations as a prediction. However, when comparing these values it is important to be aware that the improvement is in the order of 9 % for SOC and 20 % for clay, which is less than the model performances. In addition, the values of the SRMSE are close to one, which indicates that the prediction error variance is a realistic assessment of the observed accuracy; therefore the accuracy of the map seems well estimated by the regression kriging variance.

The SOC estimation of the general physiographic soil map (Van Engelen and Wen, 1995) compared with the observed SOC values showed a ME of 0.29 % and RMSE of 0.46 %. In the case of clay content, the ME is 2.6 % and RMSE of 16.0 %. Therefore, the error measures are greater for the physiographic soil map than for the digital soil map, which suggests an improved estimation. However, the comparison is not entirely objective because the digital soil map is evaluated by cross-validation, which implies that the observations were used to calibrate the DSM model.

2.3.6 Model performance

In this case study, environmental variables used to develop the regression models could only explain 21 % and 35 % of the soil variation for SOC and clay content, respectively. When using the spatial correlation of the residuals with regression kriging, the model performance deteriorated for SOC from 21 % to only 13 %, while for clay it improved to 37%. The worsening and marginal improvement are due to the fact that the variance explained by the regression models does not include the uncertainty in the estimated regression coefficients, which leads to overoptimistic results, particularly in the stepwise regression procedures employed here (Copas, 1983). Similar performance results were obtained with the cross-validation. In fact, the cross-validation results were slightly poorer than the model performances, which may be explained from the fact that we removed entire clusters of observations for cross-validation to prevent that the interpolated values would be based on observations very nearby. However, this removal also meant that fewer observations were used in the interpolation than the actual observation points available, and that in the cross-validation assessment nearest observation sites were always remote.

Table 2.9. Cross-validation results Mean Error (ME), Root Mean Square Error (RMSE) and the Standardized Root Mean Square Error (SRMSE)

Soil Properties	ME (%)	RMSE (%)	SRMSE
SOC	0.01	0.21	1.02
Clay	0.26	8.61	1.01

In the case of SOC, model performance is inferior to those reported in previous studies (Florinsky *et al*., 2002; Gessler *et al*., 2000; Hengl *et al*., 2004; McKenzie and Ryan, 1999; Ryan *et al*., 2000). Using regression analysis of terrain attributes to estimate SOC Gessler *et al*. (2000) found an R^2 of 0.78 and Florinsky *et al*. (2002) an R^2 of 0.37. These cases were performed in North America in relatively small areas (sampling intensity of 1 and 328 observations per km^2 respectively) with a clearly known and uniform land use history, namely a natural reserve in the case of Gessler *et al*. (2000) and an agricultural field managed with precision agriculture in Florinsky *et al*. (2002). In addition, the digital elevation models used to derive the terrain attributes in these cases had a resolution of less than 15 m. Other studies from McKenzie and Ryan (1999) and Ryan *et al*. (2000) used the environmental correlation of soil forming factors and 165 soil samples in two different areas of 500 km^2 in Australia, and found R^2 of 0.54 and 0.39 for SOC. The first case refers to a forest in a mountainous area, while in the second case relief and land use are slightly more complex. Both cases used a 25 m resolution DEM. Finally, Hengl *et al*. (2004) reported a case study in Croatia with an R^2 of 0.33 for SOC using regression kriging with terrain attributes derived from a 100 m resolution DEM in combination with soil units. In this case 0.05 observations per km^2 were obtained and SOC in the area showed large variation, from 2% to 33%. In contrast to the case in Kenya, our sampling intensity was 5 times less intense (0.01 observation per km^2) and SOC content was generally small for the whole area (below 1.32%), presenting a small variation range of merely 1%. Note also that all samples were taken from the terraced maize fields which reduced the variation in the population.

Regarding clay content, our results are worse than those reported by McKenzie and Austin (1993) but very similar to the clay-elevation correlation coefficient reported in McBratney *et al*. (2000). The latter is consistent with our model, in which the variation of texture is mostly explained by elevation as well. On the other hand Ziadat (2005) reported a digital soil mapping exercise carried out in Jordan in a 148 km^2 area with 15 observations per km^2. Using terrain relief parameters derived from a 20 m resolution DEM they performed step-wise linear regression and used an unsupervised classification algorithm to predict soil depth, water holding capacity, cover type and soil texture, and found that the ability of terrain attributes to predict soil attributes was poor, with a maximum R^2 of 0.19 for surface cover percentage.

The performance of the spatial analyses also depends on the spatial structure of the properties of interest. Previous research has reported that SOC often has strong spatial structure (Kravchenko *et al*., 2006[b]), but this is normally the case for precision agriculture studies, where samples are taken up to 100 m apart from each other. In our case, both targeted soil properties present a large nugget to sill ratio (> 0.6), which is an indication that the spatial structure of these properties in the area is weak. Furthermore, studies have found that SOC presents different spatial structure and dependence in conventional and organic farming. Therefore, when studying the spatial dependence of SOC, long term management should be included as an explanatory variable in the analysis (Kravchenko *et al*., 2006[a]). However, in the Kenyan case there was no other data available than the NDVI images to include this variable in a spatially exhaustive manner. Even though most agricultural areas can be classified as mixed farming systems with low endowments and we tried to minimize land use effects by sampling on maize fields only, we know from farm surveys that there are important differences in farm management across the study area that can affect soil properties, particularly regarding SOC. This is especially true for parts that are intensively terraced, which not only have better management practices, but where soil redistribution processes also have different dynamics. The interpolation of the residuals of SOC illustrated that the spatial distribution of the errors was related with land use. Underestimation of SOC occurs in the highly terraced areas around Machakos town, in the fields on the river terraces of Athi River and also in areas where recent irrigated agriculture has taken place. From direct field observations it is possible to identify these areas as zones where more developed agricultural systems occur, which probably have higher levels of endowments than the rest of the district and better nutrient management. On the other hand, the areas which appear with an overestimation of SOC, in reality present marginal farming systems and -in some cases- display severe erosion features. Thus, evidently there are circumstances in which land use management history plays a key role and this might weaken model predictions in this case.

Regarding relief, topography is among the main driving factors of soil distribution and spatial variation and terrain attributes derived from digital elevation models have proven good predictors of soil properties (Florinsky *et al*., 2002; Gessler *et al*., 2000; McKenzie and Austin, 1993; Odeh and McBratney, 2000; Ziadat, 2005). Moreover, topography is considered as the primary factor that simultaneously affects the spatial distribution of both SOC and soil texture (Kravchenko et al., 2006a). Therefore, we expected it to be a robust explanatory variable in this study. Although altitude and a limited number of classes of slope and landform appeared as explanatory variables in the final models, relief parameters in this case did not strongly explain the spatial variation of the targeted soil properties. A possible explanation for this is the coarse resolution of the DEM used, which meant that key features such as terraces are not well represented. The resolution of the DEM has to be adequate for the terrain, and in our case study the 90 m DEM was employed for the climate interpolator model and to derive slope and aspect parameters. Nevertheless, it has been found that at resolutions coarser than 40 m, terrain variables start behaving erratically and rapidly lose their predictive power (Gessler *et al.,* 2000; McKenzie and Ryan, 1999) and certain landscape features become less discernible. Hence, this fact could be affecting the predictive capability of the generated variables. Decreasing the horizontal resolution of the DEM produces effects such as smaller slope gradients on steeper slopes, steeper slope gradients on flatter slopes, narrower ranges in curvatures, larger specific catchment areas in upper landscape positions, and smaller specific catchment areas values in lower landscape positions (Thompson *et al*., 2001). Nevertheless, terrain attributes can still show a trend of how landscape processes affect soil properties if other parameters are stable and still useful for spatial prediction. For this reason, Ziadat (2005) suggests that when doing digital soil mapping in large areas, subdividing the surface in watersheds is a promising approach. In the Kenyan case, a partitioning of the area in smaller geomorphological or geological units could also be considered.

From an operational point of view, the selection of the explanatory variables remains rather arbitrary. Even in an environment with relatively little data available, an almost infinite number of explanatory variables can be defined that characterize the key soil forming processes. Insight in the agro-ecological conditions in the region may help to select the most important ones. But to achieve an accurate prediction model by means of digital soil mapping, the quality of the environmental data used for the regression analysis has to be adequate. Nowadays, a considerable amount of data is digitally available at low cost or even free of charge. However, the resolution at which data is offered varies significantly and is usually coarse for places like Africa. In this case study, we did not want to make an a-priori selection of the variables and as a result a large number of variables were defined of which only a few were selected in the final models.

This study is still constrained by the limited number of samples and auxiliary information. New sampling techniques through proximal sensing with spectrometry allow for a rapid assessment and increased sampling without jeopardizing the available resources (Shepherd and Markus, 2002). In addition, new improved land cover maps, climate data and digital elevation models are released that allow for a better insight in the soil forming factors.

Finally, it is important to keep in mind that soil maps are developed for a specific purpose. In land use analysis SOC and clay content can be used as an estimation of soil fertility and water holding capacity for crop growth simulation models. Therefore, it is interesting to evaluate how sensitive crop production models are to these parameters and compare the model performance with an input map generated by digital soil mapping techniques and one originating from conventional soil mapping.

2.4 Conclusions

Given the complex characteristics of the study area and the limited number of observations used for the analysis, the regression models obtained for SOC and clay are satisfactory. The ME and RMSE for the digital soil map are even higher than for the physiographic soil map. However, the model performance and cross-validation statistics show that the resulting maps are not very accurate and only marginally better than just taking the sample mean to predict the soil property for all locations in the Machakos and Makueni districts. Apparently, important processes which have a dominant effect on the spatial variation in SOC and clay were not adequately represented by the explanatory variables. Moreover, the low sampling density of only one observation per 140 square km meant that spatial interpolation with kriging also could not markedly improve the maps. In spite of the poor quality of the resulting maps, we do believe that digital soil mapping is a promising methodology for exploratory soil surveys and is not constrained to (semi-)detailed soil surveys. Digital soil mapping can be used for the spatial prediction of individual soil properties in large areas, creating maps in digital format in a rapid, effective, efficient, and low cost manner. The methodology incorporates soil scientific knowledge and provides a consistent logical framework to the mapping of continuous surfaces in a quantitative approach, but there is no generic method for spatial prediction. There is a wide array of statistical methods available and their use is flexible, depending on the characteristics of each application (extent of the study area, spatial variation, resolution and quality of auxiliary data available, spatial structure of the soil properties, sampling intensity, etc.) In small scale digital soil mapping the extent of the study area will generally lead to more complex interrelationships of the soil forming factors. In particular, it should be noted that in large areas soil forming processes are rarely uniform and considerations at watershed level should be taken. In addition, in these type of areas some factors can vary greatly over short distances, but this variation can only be captured if the auxiliary data used for the environmental correlation is adequate.

Chapter 3

Linking Nutrient Monitoring and Trade-Off Analysis for Policy Assessment

Submitted to:
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3.1 Introduction

Estimates of population growth in the next decades show major challenges for the improvement of agricultural systems. Not only food production will have to reach historical levels in order to feed the growing population, but this will have to be accomplished under a growing pressure on limited resources such as land, water, and fertilizer. Effective agricultural policies are an essential tool in the transformation of global agriculture. The demand for efficient production systems can only be fulfilled through a combination of technology development with efficient policies. Scientists have developed many approaches to evaluate the performance of agricultural systems (*e.g.,* Bouma *et al.* 2007). Normally these approaches look at biophysical and economic indicators such as pesticide leaching (Aylmore and Di 2000), soil nutrient balances (Stoorvogel *et al.* 1993), erosion (Foster *et al.* 1996), livelihoods and poverty (Kristjanson *et al.* 2005). The quantification and monitoring of these indicators allow policy makers to have an idea of the present situation of the systems and, in some cases, it makes possible to target an array of options for their improvement. However, although it is important for policy making to look at these indicators separately and *ex post*, it is very important to be able to look at the indicators in an *ex ante* and integrated manner. Only through the latter we can evaluate policies and technologies for agricultural development properly. A number of quantitative modeling tools have been developed to provide these *ex-ante* assessments to guide decision makers to make informed choices between present and future outcomes. However, the proper methods for linking the various tools are still under debate (Ewert *et al.* 2011; Antle and Stoorvogel 2006).

Low productivity in African farming systems is related to many factors like poverty, lack of inputs, weather cycles, human health problems, and political instability. One of the key factors that has been identified to be a serious threat to many agricultural systems in sub-Saharan Africa is soil fertility decline. Although the process is less visible compared to other soil degradation processes like erosion, there is an increasing awareness that soil fertility decline is a significant problem for agricultural development in sub-Saharan Africa (Koning and Smaling 2005; Bouma *et al.* 2007). Already in the early 1990s, Stoorvogel *et al.* (1993) developed a nutrient accounting methodology at the regional level to assess soil fertility changes by quantifying nutrient inputs and outputs. They estimated negative soil nutrient balances for most farming systems with average annual losses per hectare for sub-Saharan Africa of 22 kg for nitrogen, 2.5 kg for phosphorus and 15 kg for potassium. The initial methods for calculating nutrient balances were later refined and downscaled to the farm level within NUTMON (De Jager *et al.* 1998[a] and 1998[b]; Van Den Bosch *et al.* 1998a and 1998b). NUTMON studies have been carried out in diverse places all over the world such as Kenya (De Jager *et al.* 2001, Gachimbi *et al.* 2005, Onduru *et al.* 2007), Ethiopia (Haileslassie *et al.* 2005, Van Beek *et al.* 2009), Vietnam (Phong *et al.* 2011), and India

(Surendran and Murugappan, 2007[a], 2007[b], 2010). These nutrient balances have given a clear message to the scientific community and policy makers and provided the basis for *ex post* evaluation to appraise the current farming systems. However, the analysis does not allow for an *ex ante* evaluation as it lacks the interaction between nutrient inputs and production out puts and their relationship with the socio-economic environment. Recent advances in data acquisition and modeling allow for the development of integrated assessment methods that combine biophysical simulation models with econometric models, and have also improved the capability to characterize the interactions between spatially varying bio-physical conditions and economic behavior (*e.g.,* Pautsch *et al.* 2001; Antle and Capalbo 2001; Antle *et al.* 2003; Wu *et al.* 2004; Lubowski *et al.* 2006). In this context the Trade-off Analysis (TOA) (Antle and Capalbo 2001; Stoorvogel *et al.* 2001, 2004a) was developed to provide a participatory approach to the integrated assessment of agricultural systems. Together with the methodology, software was developed to implement spatially-explicit agricultural systems models for the analysis.

This paper aims to show how results from nutrient balances studies can be used in integrated assessment to evaluate policy and technology interventions. To do this we will link NUTMON and TOA. Through this linkage it is possible to exploit the complementarities of the two methodologies to target adequate policies for agricultural development. The linkage of these two methodologies is proposed as a novel way to implement regional analysis based on models of site-specific environmental and economic interactions. In the methodology section we will describe NUTMON and TOA in detail and show how the two methodologies are connected. Subsequently, we will illustrate this linkage with an application for the mixed farming systems in Machakos and Makueni districts (Eastern Province, Kenya) hereafter referred to as the Machakos study area, where previous NUTMON studies provided survey data. In the discussion and conclusion section we will discuss the possible advantages and implications of linking the two approaches.

3.2 Methodology

3.2.1 NUTMON

General description

NUTMON is an integrated, multi-disciplinary methodology which works at the farm level, targeting different actors in the process of managing natural resources, particularly those related to soil fertility (De Jager *et al.* 1998[a], Van Den Bosch *et al.* 1998[a]). This methodology includes a selection of well described standardize techniques to characterize and monitor farming systems and their agro-ecological conditions, focusing at the plot and the farm level where most of the decisions regarding farm management are taken. Because the methodology is intended to monitor nutrient balances, it also includes records of specific characteristics of the farming systems, such as crop-livestock interactions, that are not registered in traditional farm surveys. In addition, NUTMON has software that provides a systematic way to manage the acquired data, resulting in standard descriptions and analyses of the farming systems. NUTMON is a participatory methodology that allows farmers and researchers to jointly analyze the environmental and financial sustainability of the farming systems.

Conceptual model

NUTMON uses a standard conceptual model of the farming system to describe the farm resources through an inventory of nutrient stocks and flows (Figure 3.1). The conceptual model sub-divides the farm in various units and identifies different nutrient flows. The units represent nutrient pools while different flows describe the processes that relocate them.

The units are grouped into a number of basic components: Household (HH), Farm Section Units (FSU), Primary Production Units (PPU), Secondary Production Units (SPU), Redistribution Units (RU), Stock (STOCK) and the external world (EXT). HH is characterized by consumer and labor units including their gender, age distribution, and education, as well as capital stocks. Land resources are described by FSUs which are land units that are considered homogeneous with well described characteristics. PPUs are the basic units of analysis and are defined as cropping activities of one or more crops in well-defined fields over a specific period. A single FSU can contain one or more PPUs. The animals present in the farm are described as SPUs which are groups of animals of the same species under similar management conditions in relation to feeding, confinement, grazing, etc. The places within the farm where nutrients are accumulated and frequently reallocated (such as stables, corrals, dung hills, garbage heaps, compost pits, and latrines) are called the RUs. The STOCK is the temporary storage of crop products and residues, as well as inputs. Finally, EXT comprises everything outside the farm limits including *e.g.,* markets and neighbors.

Assessing the nutrient balance

The farm inventory starts with the drawing of farm sketches along with the farmers, to show the spatial location and configuration of the different units within the farm. During data collection, the various flows within the units and outside the farm boundaries are visualized and registered in close collaboration with the household members. Transect walks and local soil classification results in a description of the basic FSUs at the farm. The participatory approach guarantees that the FSUs are also recognized by the farmer which is crucial for the future development and implementation of potential interventions.

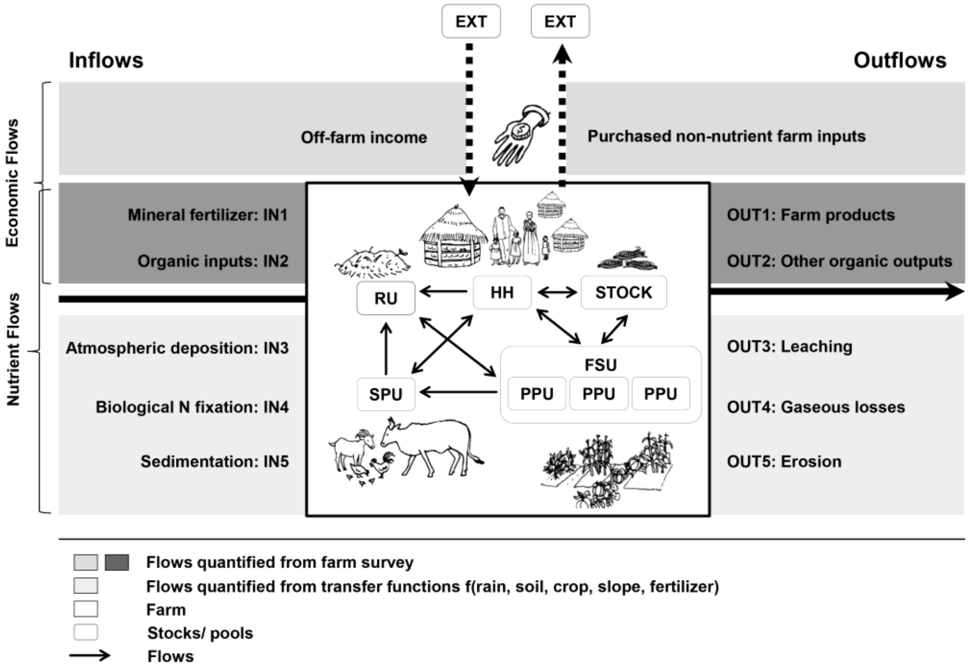

Figure 3.1 NUTMON conceptual model of the farming system

A standard structured questionnaire is used for monitoring soil nutrient flows on the farms. Typically, farm management is monitored during one or two growing seasons through frequent (*e.g.*, bi-weekly or monthly) visits to the farm. Table 3.1 provides an overview of the key information that is collected during the survey. The NUTMON software facilitates the entry, checking and handling of the survey data. The soil nutrient balance is estimated on the basis of five nutrient inputs and five nutrient outputs (Figure 3.1). Some of these flows (including mineral and organic fertilizer application, harvest of farm products and residues) are quantified during monitoring based on information provided by the household members during the farm survey. Other flows, such as atmospheric deposition, biological fixation, leaching, and gaseous losses, are more difficult to quantify and are derived from transfer functions (Stoorvogel and Smaling 1990; Smaling *et al.* 1993, Van Den Bosch *et al.* 1998[a]). Based on the nutrient flows entering and leaving PPUs and the farm, the NUTMON software calculates nutrient balances for the PPUs and the farm for a determined period as the net difference of inputs and outputs. The balances indicate whether soil fertility is declining or whether nutrient stocks are building up. The estimation of total nutrient stocks is based on soil samples and allows flows to be related to available stocks.

Table 3.1 Main information categories included in the questionnaire (van den Bosch *et al.* , 1998)

	Information group	Type of information
Farm Inventory	General farm data	Geographical situation, land ownership etc
	Demographic structure of the household	Identification of all persons at the farm, sex, age and occupation
	PPUs	Identification of parcels and parcel sizes
	SPUs	Identification of animal groups
	Sketch of the farm	Sketch of farm infrastructure with FSUs and PPUs
	Other compartments	Identification of RUs
	Implements and machinery	Identification of implements, number and age
Input-output monitoring	PPUs	Identification of the fields and crops present at the time of monitoring
	Input PPUs	Quantity and source of fertilizers, seeds, manure, crop residues, feeds, pesticides, labor, traction etc.
	Output PPUs	Quantity and destination of harvested products and crop residues
	SPUs	Number of animals born, purchased, gifts, consumed, died
	Inputs in SPUs	Quantity and source of fodder, concentrates, veterinary services, labor, etc
	Output SPUs	Quantity and destination of milk, eggs, hides, skins, hiring out of animals, traction
	Average confinement of the animals	Confinement to fields, pastures, fallows, farm yards, kraals and outside the farm
	Redistribution of manure	Quantity and destination of manure
	Inputs and outputs food stock	Book keeping of staple food in stock
	Family labor	For each person: days spent on crops, livestock, general farm, household, off-farm activities
Input-output cash flows	Off-farm income	Estimated off-farm income and amount invested in farm activities
	Output of cash-flows	Hired labor, purchase of mineral and organic fertilizer, feeds and amendments, Purchase of staple food
	Price data base	Collection of price distribution of all products to be used as a reference

Together with the information of the individual flows, the analysis shows where nutrient use efficiencies are low and how the system can be improved (De Jager *et al.* 1998[a]; Gachimbi *et al.* 2005; Van Den Bosch *et al.* 1998[a]; Van Den Bosch *et al.* 2001). Through the registration of cash flows and prices, NUTMON can also evaluate the economic performance of the farms and the individual activities.

Interpreting the soil nutrient balances

NUTMON provides insight into the nutrient dynamics of farming systems (Van Den Bosch *et al.* 2001). As such, NUTMON contributes to the development of different integrated nutrient management technologies that can be tested in subsequent farm experimentation (Gachimbi *et al.* 2005). The results are discussed with farmers to illustrate the effects of management practices on soil fertility and to identify some possible solutions such as improving manure use, applying erosion control methods, cultivating N-fixing crops, composting, and fallowing. It should be noted that the development of potential interventions requires expert judgment of both scientists and farmers, but that they also need further testing in the field. NUTMON was developed to evaluate existing systems *ex post* and does not include essential feedbacks (between *e.g.,* agricultural inputs and production) to evaluate alternative systems. To use these results at the regional level, farmers' field schools can be implemented or stakeholder meetings can be organized, in which researchers and farmers are able to share their findings and start experimentation under different agro-ecological conditions. Although nutrient balances are useful in targeting potential interventions that may resolve the major constraints of the farming systems, the methodology does not allow for the evaluation of these interventions, which is fundamental for the development of better policies. However, the information generated in the soil nutrient balances studies is a solid base for further research.

3.2.2 Trade-Off Analysis

General description

TOA (Antle and Capalbo 2001; Stoorvogel *et al.* 2001 and 2004[a]) is a participatory approach developed to perform integrated assessment of agricultural systems and to provide a decision support tool for agricultural and environmental policy analysis. In this type of assessment, the farming systems are characterized in both bio-physical and economic terms by means of quantitative (sustainability) indicators. The relationship between these indicators is established in the form of tradeoffs curves and the analysis is done by looking at how these tradeoffs are affected by alternative technology and policy scenarios. TOA combines biophysical models (normally crop production and environmental) with econometric production models (*e.g.,* Salasya 2005; Marenya and Barrett 2009). The econometric production models include input demand and output supply functions that are estimated using actual farm survey data. The model specification is similar to conventional econometric production models, except that in the case of TOA the site-specific effects of soils, climate and input use on production are represented in the input demand and output supply functions by crop inherent productivities, hereafter called *inprods*. These *inprods* are yield predictions obtained from crop growth simulation models with average management and site-specific soil and climate data. In the econometric models, *inprods* are interpreted as an indicator for the site-specific productivity potential expected by farmers. Once the econometric production models are estimated, they are later used to parameterize a simulation model of farm land use and management decisions on a site-specific basis. TOA includes software to model the system and to simulate tradeoffs under alternative scenarios (Stoorvogel *et al,* 2004[a]). The results of the analysis can be presented as two-dimensional tradeoff graphs, tables and maps, which are all forms that can be easily communicated to stakeholders and policy makers.

Indicators, trade-offs, and scenarios

TOA is a participatory methodology and requires collaborative work among stakeholders, policy makers and scientists to formulate the research priority settings. Together they must identify a limited number of key quantifiable indicators for the region under study, what kind of tradeoffs can occur, what are possible technology and policy scenarios to be evaluated, and so on. The indicators, trade-offs and scenarios need to be defined in an early stage of the process as they may require specific research activities to be included in the analysis.

The choice of relevant indicators depends basically on the local agro-ecological conditions, the particular interest of the stakeholders and the type of scenarios to be evaluated. These indicators include economic performance (*e.g.* annual net returns, poverty index, food security, and risk) and environmental performance (*e.g.* soil organic matter content and other indicators of soil quality, soil erosion, chemical leaching, and human health.). Subsequently, the tradeoff curves are constructed by varying a particular variable of interest like grain price and see how the relationship between key indicators (*e.g*. income *vs.* pesticide leaching) is affected. In this way, the tradeoff curves represent the principle of opportunity cost among scarce resources. Finally, the effects of technology scenarios, such as the introduction of a new crop variety, or a change in policy, are evaluated in terms of their effect on the tradeoff curve compared to a so called "base scenario". The alternative scenarios are constructed by varying certain model parameters in model simulation.

Data requirements

A considerable amount of site-specific data is needed to implement TOA. Firstly, TOA requires experimental data to calibrate the biophysical simulation models to assess *inprods* and environmental impacts. Secondly, detailed information on soil and climate conditions is required to run the calibrated biophysical models. Thirdly, the economic simulation model needs to be calibrated for which farm survey data are required to describe the current agricultural practices and decision making. Finally, additional information may be needed for the formulation of alternative scenarios. TOA is a spatially explicit methodology and soil and climate information is included in the analysis. As mention in the previous section, soil and climate data are used as inputs of the biophysical models of crop (and livestock) production as well as in the environmental models. In addition, site-specific farm data are required to estimate the behavioral parameters of the econometric-process models including data on variable inputs and outputs (*e.g.* seed quantity, fertilizer use, production of crops and residues), and fixed factors (*e.g.* land size, equipment, household characteristics). In some cases, depending on the indicators, tradeoffs and scenarios of interest to stakeholders, additional experimental data may be needed to calibrate simulation models to assess crop growth, land degradation, or alternative technologies. Probably, data collection is the most limiting factor for this type of analysis. The rapid turnover of policy analysis leaves little room for extensive data collection.

Model estimation

A strong point of TOA is the use of different disciplinary models in the analysis that are linked. These models can be sub-divided in three main groups: (i) production models to estimate the inherent productivity of specific fields, (ii) econometric production models to understand farmers' behavior, and iii) environmental process models to estimate the environmental impact of farmers activities. Although it is extremely difficult to calibrate a regional integrated assessment model, the individual models can be calibrated. The calibration of the models for the local conditions of the study area takes place in the model estimation phase (Stoorvogel *et al.* 2004a).

The crop production models (and potentially livestock models) are used in TOA to capture the spatial and temporal variation of the land (soil and climate) through the *inprods*. The TOA software calculates *inprods* using calibrated crop growth simulation models from the DSSAT suite of models (Jones *et al.* 2003). In these calculations the soil and weather conditions on the farms can either be measured or derived from a GIS database. The *inprods* are used as indicators for the productivity of farmers' fields in the economic models as a manner to explain the variation in management decisions made by the farmers. The calibration therefore focuses on the relative differences in productivity and not on the absolute level of the estimates. The calibration of the crop growth simulation models can either be through field experiments or through a selection of crop varieties in the crop growth simulation model that explain most of the variation observed in the field.

Subsequently, the estimation of the econometric production models is carried out using the farm survey data and the *inprod* indexes of the surveyed farms. Parameters for price distributions and other exogenous variables of the production models are also estimated using the survey data (Antle and Capalbo 2001). The econometric production models are then composed by a series of input demand and output supply equations representing farmers' crop choice and input use as functions of economic variables (input and output prices, farm characteristics) and the biophysical variables (*inprods*). The environmental impact models need to be calibrated following their own specific procedures depending on the process or indicator.

Model simulation and environmental impact assessment

Crop and econometric production models described above are finally used to parameterize an econometric simulation model that predicts crop choice, input demand and output supply on a site-specific basis (Stoorvogel *et al.* 2001 and 2004a). Although with TOA it is possible to run the simulation for the original survey fields at their exact locations, the model also has the option to draw fields randomly from the area, thus creating a new sample of fields which allows the extrapolation and stratification of the area. In order to do this, the TOA samples a set of fields from the area by creating a random set of coordinates and verifying the selected coordinates against a set of user-defined spatial conditions (e.g. soil type, altitude). If the location is accepted, a field size is drawn from a given distribution of field size and the *inprod* of that particular field is assessed using the crop growth simulation model (Stoorvogel *et al.* 2004a). Next, the actual simulation of land use and input use begins. Each individual simulation run starts with drawing input and output prices from the distributions after which land use and input use decisions are simulated.

The output of the econometric simulation model includes land use and land management for each of the fields, under different conditions (the tradeoff points) and for several repetitions. This output can subsequently be the input for the environmental process model that estimates the impact of specific decisions on that location in terms of, e.g. erosion or any other environmental process. This process is repeated for each scenario. Outcomes can be displayed spatially as maps or they can also be aggregated to construct regional tradeoff curves.

3.2.3 The linkage of NUTMON and TOA

Most of the NUTMON studies have been carried out in semi-subsistence agricultural systems, which are the dominant type of agriculture in the poorest and most environmentally vulnerable regions of the world. To characterize these systems in bio-physical and economic terms is crucial for quantitative analysis and for the development of modeling tools for integrated assessment.

The NUTMON methodology is complementary to TOA, because it provides a systematic approach to data collection, but more important is that former NUTMON studies carried out in different places of the world already provide solid data sets and sound conclusions regarding management interventions from farmer interaction and stakeholders meetings. This information is very valuable for the implementation of TOA, which also requires considerable resources, stakeholder meetings, data collection, modeling, etc. Similarly, the TOA also adds value to NUTMON by offering the possibility to quantitatively evaluate the policy and technology scenarios targeted with the farm nutrient balances. Figure 3.2 illustrates the key points where NUTMON and TOA can be linked: a) stakeholder input for research priority setting, b) farm data acquisition and c) a readily available environmental impact model for the cases where soil nutrient depletion has been identified as a key sustainability indicator.

a) TOA research priority setting

Establishing effective inter-disciplinary work is not a straightforward process and can be highly time consuming. Since NUTMON is a participatory approach, involving active stakeholder contribution by means of farmer field schools, farm experimentation and meetings, etc., the available NUTMON studies have already made great progress in relation to the collective effort of gathering knowledge of farmers, extension officers and researchers. The NUTMON studies not only have created great awareness and understanding among the different actors and stakeholders of the problem of soil nutrient depletion, but they have also brought together sufficient information to fully accomplish the initial phase of TOA. This includes the definition of the research priority settings and the sustainability indicators, the detection of alternative management practices, and the formulation of the possible scenarios for evaluation. In addition, they have pointed out the different disciplines that will be involved in the research, the models that will be needed and have facilitated the definition of the units of analysis.

b) Farm data acquisition

Like all regional integrated assessment models, the TOA methodology requires a large amount of detailed data to implement the disciplinary models successfully and data collection and acquisition is perhaps the most costly and time-consuming part of the methodology. In this respect, NUTMON provides a systematic and comprehensive approach to characterize and collect farm data for both inputs and outputs of the agricultural systems. The biophysical data (soil and climate) for the TOA analysis is normally not included in the NUTMON studies, and these can be obtained directly from exploratory soil surveys and records from weather stations, although they rarely are available for individual farms. Other options are to do specific data collection at the farm level or to use new efficient ways for data collection using interpolation of weather data (Baigorria-Paz 2005) or digital soil mapping (Mora-Vallejo *et al.* 2008). On the other hand, the estimation of the econometric production models requires field and farm-level data collected with periodic farm survey. Records of input use data should be done frequently enough so that recall errors are minimized.

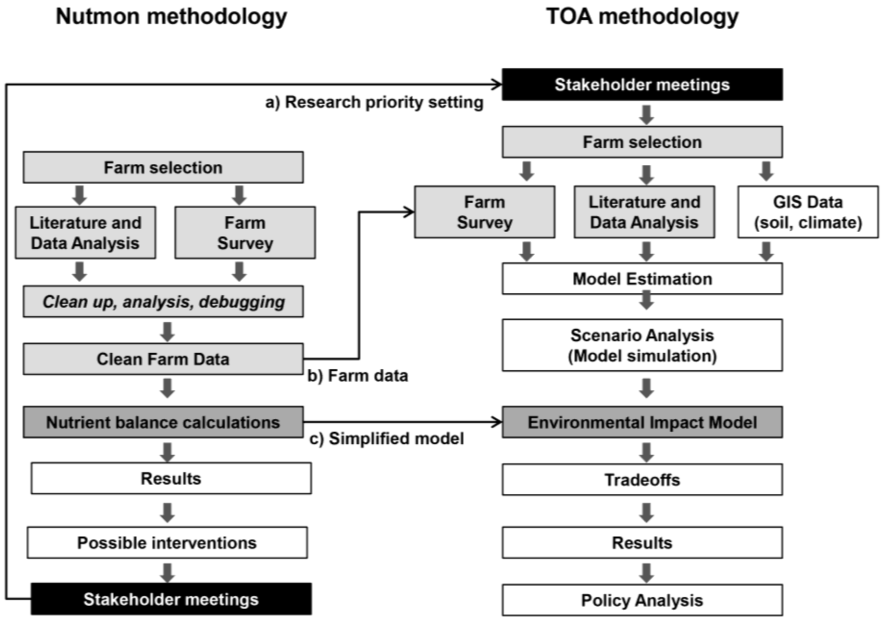

Figure 3.2 Linkage between the NUTMON and Trade-off analysis methodologies

In this respect available data from sources such as an agricultural census have proved to be inaccurate because they are based on recall. In addition, they typically lack data on input use and other necessary information about farm production systems. Other studies that deal with a small number of "representative" farms are not adequate for econometric estimation because they do not provide enough insight on the variability within the population of farms. For these reasons, the design of the NUTMON methodology, based on regularly monitoring of input and output with the relevant economic information, is highly suitable for the estimation of the econometric model in TOA.

Several NUTMON surveys are available for different relevant study areas that have been previously prioritized in the research agenda by governments and donors (De Jager *et al.* 1998a). These surveys capture the complexity and variability of the study areas by making clusters of farms representing the different agro-ecological conditions, management groups (*e.g.* conventional and low-input endowment), and technology scenarios (*e.g.* irrigation). Furthermore, the farms are also selected in a participatory process assuring cooperation and interest from the household members in the research and the following activities. The NUTMON surveys store data on a monthly basis and have been carried out for periods of at least a year (covering in many cases two growing seasons). Therefore, all the specific information required to estimate the econometric model for TOA can be found in these surveys. Field data is added from the PPU reports, which include the flows of inputs and outputs from every production unit and their attached prices. Crop presence records in each field facilitate the characterization of the existing cropping systems to be modeled. Besides the farm survey database, NUTMON uses a background data module that includes additional information required for the analysis like nutrient content in crops and residues, dry matter content, soil properties, calibration of local units of measurement, among others, incorporated as actual local values or as default values derived from literature. Finally, NUTMON presents a user friendly Data Processing Module, in which all data can be easily managed, extracted and exported in a format that is readily available for the TOA assessments. With this module it is possible to link different NUTMON data sets and make them compatible by setting the units of analysis -such as currency and weight measures- in a single system. Model runs (to assess the nutrient balances or economic indicators) can be performed for determined periods, and when done in a seasonal basis, the results confer a clear illustration of the dynamics of each growing period. These data are the key input variables for modeling tools aiming to assess the behavior of these systems over time. Semi-subsistence agricultural systems have certain characteristics that make modeling them more difficult than the systems typical of more commercially-oriented agriculture. Among these features are a low degree of specialization and high degree of diversification; mixed crop-livestock systems; inter-cropping; high rates of crop failure; extremely small field size and seasonal reconfiguration of sub-parcels within fields; limited or zero use of purchased inputs; high transportation and other transaction costs; and the lack of formal markets.

c) Environmental model

In previous applications the TOA has been linked to models for pesticide leaching, carbon sequestration, human health impact, and erosion (Crissman *et al.* 1998; Stoorvogel *et al.* 2004b; Antle *et al.* 2005; Diagana *et al.* 2006; Antle *et al.* 2007; Antle *et al.* 2008). To study the environmental effects of the Machakos' farming systems, the NUTMON framework provided the basis for dealing with soil fertility issues by characterizing the farm systems in terms of distinct units and quantifiable flows. In this TOA application, the NUTMON model is used to calculate nutrient budgets at the parcel level which are later aggregated at the farm level.

3.3 A TOA application for the mixed farming systems of Kenya

3.3.1 Study area

To illustrate how NUTMON and TOA can be linked we will present a case study for the Machakos study area. Until the late 70s Machakos suffered acute land degradation due to high population pressure, erratic rainfall and recurrent droughts. Initially, predictions for this area were doomed, but farmers adoption of control measures such as terracing were able to revert the degradation processes and Machakos became one of the few examples where despite the increasing population pressure agricultural productivity and per capita income could also increase (Barbier 2000; Tiffen *et al.* 1994; Zaal and Oostendorpt 2002). However, recent studies of nutrient balances in Machakos revealed that continuous farming with low levels of external inputs still has negative impact on soil fertility (De Jager *et al.* 2001; De Jager *et al.* 2004; Gachimbi *et al.* 2005). Although alternative policies and technological interventions have been proposed (*e.g.* RoK 2004), the economic and environmental impacts of these alternatives have not been evaluated.

The study area is 13,500 km^2 and includes both Machakos and Makueni districts. Makueni district is situated in the southern part, and was formerly part of Machakos district but separated in 1992 for administrative purposes. Altitude ranges from 400 to 2,100 meters above sea level and climate is classified as semi-arid, with low, highly variable rainfall, distributed in two rainy seasons. The short rains occur from November to January and are usually more reliable than the long rain season, which takes place from March to June. Annual rainfall ranges from 500 to 1,300 mm and mean annual temperature varies from 15ºC to 25ºC, resulting in a wide range of agro-ecological conditions (MoA 1987). Drought events occur in cycles of four or five years, normally in runs of two or more seasons, having great impact on food security (Tiffen *et al.* 1994). Soils are generally deep to very deep, friable, with textures ranging from sandy clay loam to sandy clay. According to USDA Soil Taxonomy (Soil Survey Staff 1975), soils are classified as typic Eutrustox, ultic Haplustalfs, oxic Paleustults and rhodic Paleustalfs. The inherent soil fertility is very poor with low soil organic matter contents (<2%) and deficiencies in nitrogen and phosphorus. Superficial runoff is not common, though erosion can take place at the beginning of the planting season when the land is still bare and heavy rains occur (MoA 1987; Onduru *et al.* 2001). Almost half of the area is under agricultural use. Agriculture is the major economic sector, represented by semi-subsistence farming systems that include both crop and livestock production, although some coffee and cotton are cultivated as cash crops. Livestock is free grazing in the dryer areas and kept in more intensive zero-grazing units in the more humid areas. Maize is the most important staple crop, but a wide variety of other food crops are grown (beans, millet and sorghum), vegetables (tomatoes and kales), fruit trees (orange, banana, mango and pawpaw) and tubers (cassava). For all crops, yields are generally low and, particularly for maize, crop failure is common.

Farmers practice soil nutrient management through the application of manure and chemical fertilizer. Whereas fertilizer use is constrained to better endowed plots with lower risk of crop failure, manure is more often applied on plots that do have some kind of land problem (De Jager *et al.* 2004). Soil conservation practices have been implemented in the area since colonial times and the area is well known for the widespread use of terracing. Other soil and water conservation measures commonly used are strips, contour farming and ridging (De Jager *et al.* 2004; Tiffen *et al.* 1994).

The majority of farms has no access to irrigation. Only in a few locations neighboring the Athi river irrigation occurs. In these areas, access to simple small-scale irrigation allows the cultivation of vegetables such as chili peppers, tomatoes, onions and eggplant for commercial production. In cases where water and marketing constraints are alleviated farmers directly respond by applying higher doses of mineral and organic fertilizer. This change in farm management results in higher and more stable yields and higher financial returns (De Jager *et al.* 2004). In De Jager *et al.* (2001) a full description of the study area and its farming systems is given.

3.3.2 Input data

Former two NUTMON projects (LEINUTS in 1997-1998 and NUTSAL in 1999-2001) provided survey of 121 farms. The farms are clustered around 6 villages selected on the basis of agro-ecological conditions, farming systems, population density and soil fertility management (Gachimbi *et al.* 2005). The clusters are considered representative of the majority of the farming systems in the area, both for rain-fed agriculture (Machakos, Kionyweni, Kasikeu, Kiomo) and irrigated agriculture (Matuu, Kibwezi). Within the framework of NUTMON's participatory approach, village meetings were held in each of the clusters and farmers identified a list of practices for appropriate soil fertility management in terms of crop, soil and water management (Gachimbi *et al.* 2005). Basic information on the farm characteristics of each cluster can be found in Table 3.2.

Weather data were available from the weather stations of Katumani (1.517^o S and 37.267^o E; 1,680 meters above sea level) in Machakos district, and Kiboko (2.283^o S and 37.700^o E; 1,540 meters above sea level) in Makueni district. These stations provided daily data on solar radiation, minimum and maximum temperatures and rainfall for the periods 1986 to 1989 in Katumani and 1980 to 1989 in Kiboko. Weather data were interpolated using a simple linear regression with altitude. In addition monthly averages for temperature and rainfall were derived from the FAOCLIM database (FAO, 2001a). Soil data were obtained with digital soil mapping techniques (Mora-Vallejo *et al.* 2008).

Table 3.2 Farm characterization of the study area

	Machakos	Kionyweni	Kasikeu	Kiomo	Matuu	Kibwezi
Farm Size (ha)	2.78	3.14	3.08	7.84	1.55	4.31
	(1.43)	(3.24)	(2.06)	(7.10)	(0.74)	(4.16)
Family size	8.68	8.17	7.25	7.33	8.92	7.87
	(3.16)	(2.90)	(3.99)	(2.19)	(2.93)	(3.03)
% mixed system	26.16	60.12	34.91	46.09	19.10	25.60
	(44)	(49)	(48)	(50)	(39)	(44)
% maize system	25.58	22.11	37.26	36.09	31.74	10.63
	(44)	(42)	(48)	(48)	(47)	(31)
% beans system	16.86	0.62	8.49	7.39	12.00	–
	(37)	(7.86)	(28)	(26)	(33)	
% vegetable systems	7.56	–	3.30	–	33.94	55.07
	(26)		(18)		(47)	(50)
% pasture	23.84	17.15	16.04	10.43	3.23	8.70
	(43)	(38)	(37)	(31)	(18)	(28)
TLU per farm	1.30	2.90	1.64	2.06	2.87	0.98
	(1.11)	(3.18)	(0.82)	(2.52)	(5.63)	(0.40)
Manure production (dry kg/TLU/month)	214	152	150	216	245	291
	(131)	(229)	(131)	(65)	(232)	(50)
Manure use (dry kg season^{-1})	567.66	152.24	738.20	1050.74	103.81	287.75
	(748.05)	(439.54)	(926.69)	(1221.70)	(169.28)	(183.4)
Fertilizer use (kg season^{-1})	12.09	18.83	39.65		9.00	17.95
	(20.33)	(24.94)	(54.15)	2.00 (-)	(11.71)	(30.20)

Note: Standard deviation in parentheses

3.3.3 Indicators and scenarios

NUTMON studies identified a number of economic and environmental indicators including agricultural production, net returns, nutrient depletion and food security (De Jager *et al.* 2004; Gachimbi *et al.* 2005). Possible interventions to reduce soil nutrient depletion have been recognized in various stakeholder meetings with farmers and extension officers, such as improving manure management, introducing zero-grazing units, increasing the use of inorganic fertilizer, improving crop rotation, education in soil and water conservation techniques and improving the commodity market (De Jager *et al.* 2004). Many of these potential interventions are also confirmed by the Kenyan Government in its Strategy for Revitalizing Agriculture (RoK 2004).

In this illustration, we will evaluate with TOA only two interventions (or scenarios) proposed by NUTMON studies for the farming systems of Machakos. The first scenario is a decrease in the price of mineral fertilizer. Poor access to fertilizer due to deficient infrastructure and weak markets, inadequate packing and overpricing has been identified as an important problem faced by farmers in many diagnoses in the region (Jayne *et al.* 2003). The majority of the farmers indicate that they do not apply fertilizer because simply they cannot afford it. Consequently, policies to lower fertilizer prices are considered to address soil fertility decline. A second scenario deals with the consequences of better use of animal manure. Zero-grazing units have been promoted in the area as a manner to improve soil fertility with the existing resources of the farm (Onduru *et al.* 2008). In addition, current manure management on the farm coincides with large losses of nutrients where relatively simple measures can improve the efficiency (*e.g.* Tittonell *et al.* 2010). Tradeoffs in this example will be constructed by varying the price of maize, being this one of the main commodities in the region with highly volatile prices.

3.3.4 Model setup

The semi-subsistence farming systems of Machakos presented some new challenges for the setup of the economic simulation model. The incorporation of the *inprods* in TOA has been found to be a useful procedure to incorporate soil and climate information into econometric process models, but the use of this technique with semi-subsistence farming systems, that involve a large number of crops and complex intercrops, was difficult because crop models for all of these crops and intercrops do not exist. Other features typical of the semi-subsistence farming systems are high rates of crop failure, interactions between crops and livestock systems, and the use of non-essential inputs such as fertilizer, hired labor and pesticides. Details on the implementation of the econometric simulation model can be found in Antle (2011). In the Machakos case finally six main cropping systems were identified for which econometric models were estimated to describe input demand and output supply: mixed (intercrop), maize, bean, vegetable, Napier grass, and livestock. The *inprods* of maize, beans and tomato were used for model estimation and simulation. The models were calibrated using the survey data and experiments carried out in the region (*e.g.* Fertilizer Use Recommendation Project in MoA 1987). The characterization of the cropping systems in these six groups also facilitated the calculation of nutrient flows using the nutrient balances as defined in NUTMON (Van Den Bosch *et al.* 1998a).

3.3.5 Model simulation and scenario analysis

The simulation runs were performed with a sample of 500 farms randomly taken from the area. As maize prices are highly variable in the region, tradeoff curves were constructed by varying the mean maize price from -75% to +100%. Besides the base scenario that represents the observed production conditions two alternative scenarios were evaluated that specifically aim at the reduction of soil nutrient depletion. A fertilizer scenario deals with the fertilizer prices in Kenya. The high farm gate prices of fertilizer are frequently considered to be the main cause for lack of fertilizer use (RoK 2004). In the scenario definition the mean fertilizer price is reduced in 50% resulting in mean fertilizer prices that roughly correspond to the world market price (Jayne *et al*, 2003). Secondly, the manure scenario considers improved manure handling. Current manure management practices are considered to be inefficient with various, relatively easy solutions to improve their efficiency (Place *et al.* 2003; Onduru *et al.* 2008; Tittonell *et al.* 2010). In the manure scenario we assume that these improved management practices are adopted and result in doubling manure use efficiency and demand in all cropping systems.

3.3.6 Results

Figure 3.3 illustrates that under current management conditions and prices (*i.e.* the base scenario), seasonal net returns and nutrient depletion vary widely, but in general results show low returns from agriculture (<150,000 KS$ ha^{-1}) and high N-depletion rates (average losses of 32 kg N ha^{-1}). The variation can be explained by the variation in agro-ecological conditions in the area but also by the variation in input and output prices that farmers face. In the rain fed farming systems (Machakos, Kionyweni and Kasikeu) higher net returns are correlated with higher soil nutrient depletion. In these systems, net returns are the result of high productivity associated with favorable agro-ecological conditions. However, the nutrient inputs into these systems are low, thus productivity is sustained by mining soil nutrient stocks. The situation is different for the extensive farms of Kiomo and the farming systems with irrigation, where there is no clear correlation between net returns and nutrient depletion. In irrigation systems net returns are generally higher than those of the rain fed systems, probably because the net returns for vegetable production are higher. Nutrient depletion rates vary widely in these systems, and low depletion rates are possible with high net returns when the production of vegetables is more intensive and uses more external nutrient inputs.

In Figure 3.4 we can look at the relationship between the indicators of farm income and nutrient depletion, comparing the base scenario to the two alternative scenarios of decreasing fertilizer price and increasing manure use efficiency, while varying maize prices. The results are presented as the aggregated tradeoffs curves. These curves show contrary to what is generally believed that the manure scenario has little impact on nutrient depletion rates and that the effect of reducing the fertilizer price is positive but also modest. The fluctuation in maize prices however, has quite an influence on the relationship between net returns and nutrient depletion. Model results show that with observed maize prices, farmers allocate nearly 60% of the farm area to maize mixed (maize intercropped) systems in equal shares.

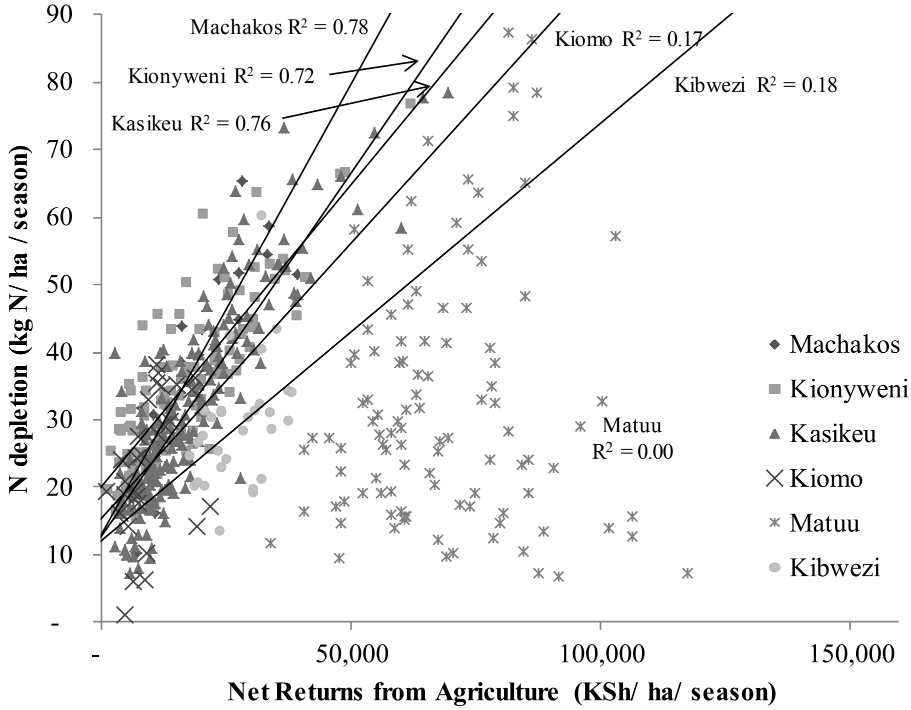

Figure 3.3 **Relationship between Net Returns from Agriculture and N depletion under observed prices and management conditions in the different farm clusters of Machakos, Kenya**

With increasing maize prices, farmers tend to capitalize the circumstances and the mixed system is gradually replaced by the maize monocrop up to 70% of the land allocated to maize and less than 10% to mixed crops. On the contrary, when maize prices decrease more land is allocated to the mixed system (40%) rather than maize (10%). These changes in land allocation have a large impact on the soil nutrient balances, because maize is a very nutrient demanding crop and, as mentioned before, the use of external inputs is low in these systems. Although with increased maize prices fertilizer use doubles and manure use increases up to 30% on the maize systems, these nutrient additions are not sufficient to offset the increases in nutrient losses from grain and by-product removal, leaching and denitrification.

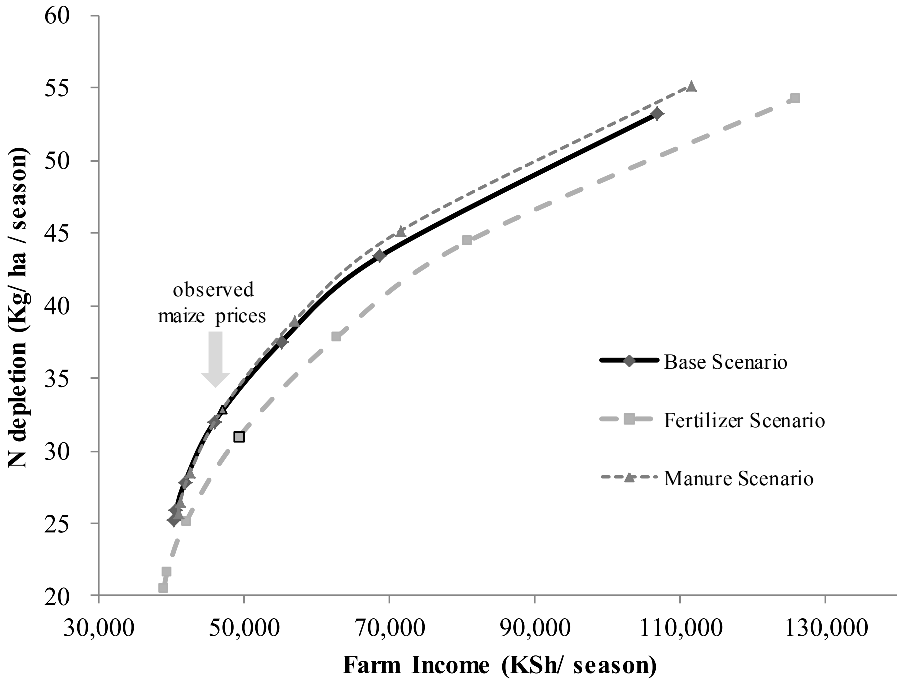

Figure 3.4 **Trade-offs between N-depletion and Farm Income in Machakos study area under three different scenarios. Tradeoff curves are constructed by varying the maize price (-75%, -50%, -25%, observed price, + 25%, +50%, +100%)**

The variation of the nutrient depletion across the area can be seen in Figure 3.5. These maps are constructed with the interpolation of the results of the different scenarios for the 500 farms sampled in the simulation runs. The non-agricultural areas have been excluded from the analysis. This figure shows substantial spatial variation of nutrient depletion in the Machakos study area, and that the spatial distribution changes with each scenario and with changes in maize prices.

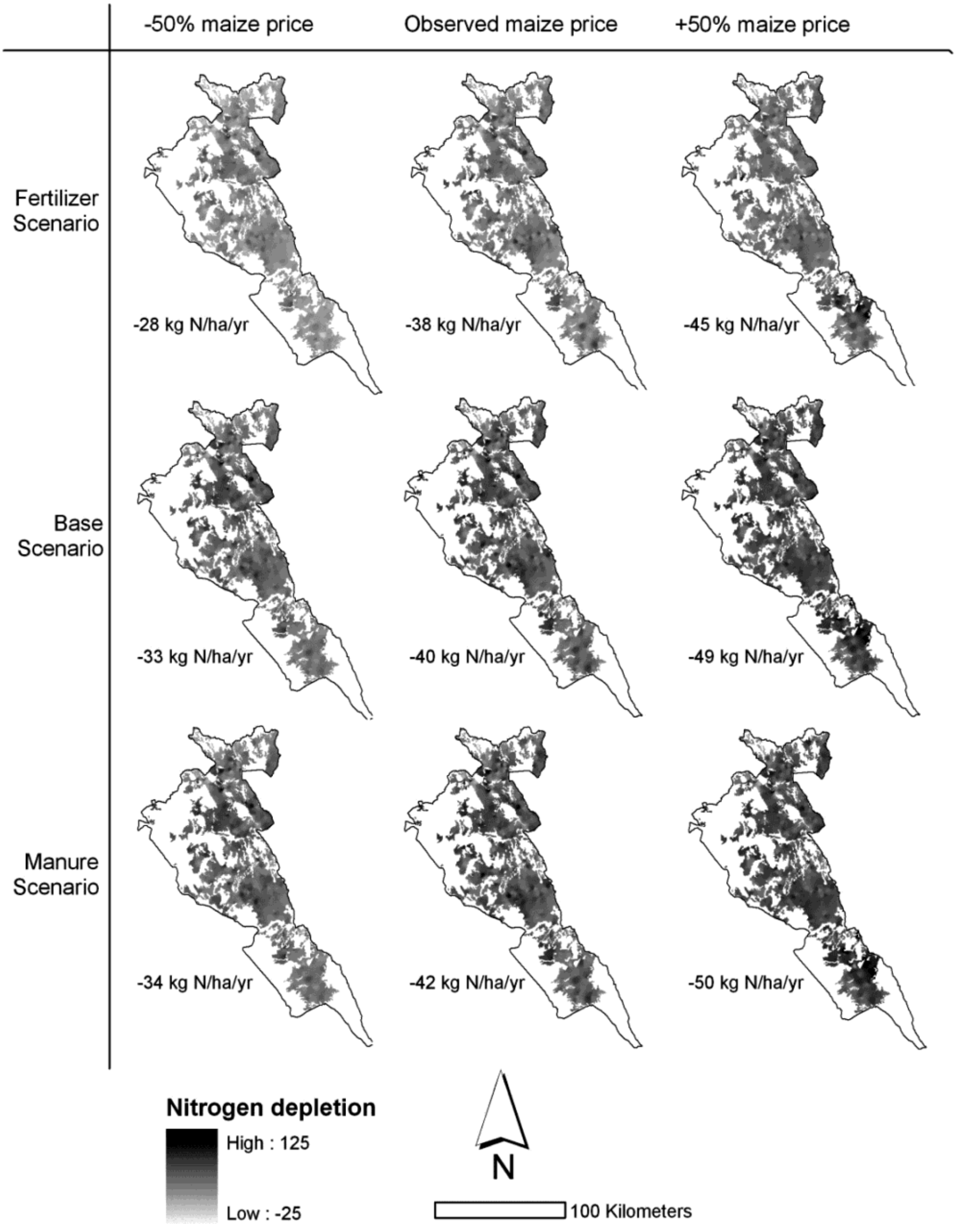

Figure 3.5 **Soil N depletion in Machakos study area under different scenarios with varying maize prices**

While the fertilizer scenario appears to be the most beneficial and it is possible to identify large areas where depletion is low, areas with serious depletion rates are found in all cases. The spatial variation suggests that interventions would be more effective if they go together with policies that direct these interventions to the areas where the problem is most severe.

As we can see from this illustration, the linkage of NUTMON and TOA provides new insights on the problem of soil fertility. Furthermore, this type of integrated analysis is a novel manner to use the findings of NUTMON previous studies and take them into the policy level. Although soil fertility is a problem that farmers themselves have identified as constraining agricultural development, it is also a long term problem. Their daily struggle dealing with short term problems and poverty in practice leaves them little space for INM improvements. Therefore, if we want to effectively produce changes in their management, policies that accompany and direct farmers in this process have to be implemented. For this reason, researchers should be able to produce recommendations not only for the farmers but also better information for the policy makers, and this can be done by means of an integrated assessment.

While NUTMON methodology targets potential interventions to improve management on individual farms, the TOA methodology allows the evaluation of these interventions on a population of farms. In this way, it is possible to upscale NUTMON results from the farm to the regional level. It is common that surveys conclude with a "shopping list" of interventions to deal with the problem of soil fertility. These general recommendations have been repeatedly suggested for different cases in various regions in Africa, but attempts to implement them fail to reverse the negative trend in soil fertility. With the NUTMON-TOA approach we can look at these interventions carefully and assess the impact of their implementation on the actual farming systems. For example, reducing mineral fertilizer price is frequently suggested as a silver bullet solution against soil nutrient depletion, but with the Machakos case study we can observe that the comprehensive evaluation of this intervention shows that even if it may ameliorate soil fertility in certain locations, the problem will still not be solved in all places, and at the regional level the contribution of this measure is modest. Moreover, results show that fluctuating maize prices have great impact on soil nutrient balances and this fact has never been considered before when analyzing soil fertility decline. Maize is the main staple food and the most important source of calories for Kenyan livelihoods, therefore the government has continuously intended to control and influence the maize market in order to encourage production while keeping low costs for consumers. However, price policies for this crop have always focused on food security and no attention has been given to their environmental consequences on sustainability.

On the other hand, the linkage of NUTMON and TOA allows viewing the outcomes of NUTMON studies from a different perspective. NUTMON results are visualized as schematized farm nutrient flow charts that show the main flows, gains and losses of nutrients within the farms. While these results at the farm level are a powerful tool to work along with farmers, at the policy level farm charts are not enough and results need to be offered for the population of farms. The link of NUTMON with TOA makes possible to present the aggregated results over strata or over the entire area. Since TOA is a spatially explicit tool and incorporates the spatial environmental differences of the population of farms in the analysis, spatially explicit results can also be displayed in the form of maps. These maps are simple, appealing and informative visualization tools for policy makers and help to provide key answers to questions like where are the critical areas that need urgent intervention, which areas are doing better and why, and which policies will work for one area but will be of no use in other.

3.4 Discussion and conclusion

The main hypothesis of this paper is that the NUTMON methodology is complementary to the TOA methodology and by linking the two it is possible to use nutrient balances as sustainability indicators for policy analysis. This hypothesis is confirmed with the Machakos case study.

This illustration shows that NUTMON surveys are of great value for an integrated assessment such as TOA and that both methodologies can benefit from each other. The key objectives of NUTMON studies are to determine current rates of change in soil fertility and together with farmers identify the main processes driving the soil nutrient balances in order to develop more sustainable farming practices. But this methodology cannot be used to evaluate either the long-term solutions or the short-term interventions that may reverse the land degradation (Vanlauwe and Giller, 2006). Although the use of soil nutrient balances is a widespread practice (Scoones and Toulmin, 1998; Warren, 2002; Roy *et al.* 2003), the connection to a policy oriented tool was still absent.

Linking NUTMON survey with TOA allows the evaluation of the impacts of policy and technology scenarios on nutrient depletion or other sustainability indicators that are of interest to stakeholders and policy makers in the study area. Likewise, TOA benefits from NUTMON because it provides an excellent standardized base of farm data and environmental models. The setup of TOA requires quite an amount of stakeholder input to identify indicators and scenarios, and the implementation of models requires extensive data collection. Previous NUTMON studies provide all the detailed, spatially referenced survey data needed to successfully implement the spatially-explicit modeling approach of TOA. In addition, NUTMON even provides the conceptual model for the evaluation of the environmental impact through the assessment of soil nutrient balances. On the contrary, starting from scratch would be time consuming and expensive.

Many other quantitative modeling tools have been developed to assess the effects of agricultural technologies and policies but most of them use data aggregated across farms to carry out the analysis of a "representative" farm for a group of farms in a region (Holden, 2005). Although the representative farm construct may be appropriate for some types of policy analysis, its use does not allow to take into account the spatial differences of the environmental and economic conditions, and how they affect the (spatial) distribution of the outcomes that are used to quantify key indicators for policy analysis, such as vulnerability, poverty, and environmental risk (Just and Antle, 1990; Antle and Stoorvogel, 2006; Salasya and Stoorvogel, 2010). As illustrated with the Machakos case study, with the NUTMON-TOA approach it is possible to evaluate integrated management practices at the farm level, and subsequently aggregate the results for a population of farms (village or regional level) to finally develop complementary policies for a determined area and this is important for policy analysis. In this respect we could find that the level of aggregation could provide different answers to the same question. Although key explanatory variables and their links can change at different levels of aggregation, and there are other considerations to make when generalizing across level and scale (Gibson et al 2000, Van Passel et al 2012), the aggregation process implemented in TOA is based on statistical analysis which provides sound results (Antle et al 1998, Antle 2011).

It should be noted that in this example only two alternative scenarios were evaluated, but in practice other alternatives to improve farmers' livelihoods have been suggested in several policy documents. Further research could address the evaluation of these policy documents to explore whether these general recommendations will in fact have the intended impact on site specific problems. In addition, this paper is based on a single case study in Machakos in Kenya, which focus mainly on soil fertility. There are several NUTMON studies all over the world that provide all the basic data to study this and other sustainability relevant indicators. Although other applications may require an additional linkage with other environmental impact models, the base for this linkage has been established with this case.

Finally, when looking at model results it should be considered that some aspects are not yet included in the simulations, such as the integration of dynamic simulation in the analysis to capture essential feedbacks (e.g. the effect of increased fertilizer use on productivity, crop rotations, etc.) and processes (*e.g.* the soil organic matter dynamics) . These issues remain as a great challenge for further development of this type of research.

Chapter 4

Integrated Assessment of Agricultural Interventions

Published as:

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4.1 Introduction

Kenya's population has reached almost 40 million inhabitants and more than 70% of the people depend on agriculture. However, the contribution of the agricultural sector to the country's Gross Domestic Product is only 25% (FAO 2012a). From the total agricultural output, 75% comes from small-holder subsistence systems (IFAD 2012).

Although agricultural production in Kenya has doubled in the last two decades, the country has suffered from economic stagnation with estimates of economic growth of only 1.5% while the population is growing at a rate of 2.5%. For this reason, the poverty rate has also remained constant with more than half of the population living below the poverty line and/or unable to meet their daily requirements of food intake (IFAD 2012). According to the Millennium Project (UN-MP 2005), an economic growth of at least 7% is required if the Millennium Development Goals (MDGs) are to be met by 2015. Because agriculture is the main economic activity in the country, it is often designated as the engine for this growth. Moreover, increasing agricultural production is key to combat malnutrition. The government of Kenya has acknowledged this situation and recognizes that agriculture needs to be revitalized if economic growth is to be achieved. The government has therefore included this matter in several national strategy documents: the Economic Recovery Strategy (ERS) in 2003 (RoK 2003), the Strategy for Revitalizing Agriculture 2004-2014 (SRA) in 2004 (RoK 2004), and, most recently, the Kenya Vision 2030 (RoK 2007a) which is in line with the MDGs. Specifically the SRA comprises a list of nation-wide interventions to be implemented by the government to increase agricultural productivity and improve the conditions of Kenyan livelihoods. The SRA promises a Green Revolution in Kenya. However, the possible impacts of the suggested interventions have not yet been evaluated.

Various tools for regional land use analysis are available (*e.g.,* Heerink *et al.* 2001; Harris 2002; Matthews 2007; van Ittersum *et al.* 2008). The Trade-off Analysis (TOA) (Stoorvogel *et al.* 2004*a*) is one of these methodologies specifically developed to perform an ex-ante evaluation of the impact of agricultural policies and technology interventions on the farming systems of a certain region. The TOA is based on an integrated assessment in which crop growth simulation models, econometric production models and environmental impact assessment models are integrated. Recently, TOA has been linked to the NUTMON methodology (Mora-Vallejo *et al.* 2012). NUTMON is a multi-disciplinary approach designed to study soil nutrient balances and flows at the farm level (De Jager *et al.* 1998, Van Den Bosch *et al*, 1998a). This methodology offers a selection of well described standardized techniques to characterize and monitor farming systems. The linkage of NUTMON and TOA methodologies allows regional analysis based on models of site-specific environmental and economic interactions. NUTMON studies have been carried out in several areas of Kenya (Van Den Bosch *et al.* 1998*b*; De Jager *et al.* 2001; Gachimbi *et al*. 2005; De Jager *et al.* 2006; Onduru *et al.* 2007).

In this paper, we will evaluate the economic and environmental consequences of a set of selected agricultural interventions proposed in the SRA with the TOA methodology. We will focus on those interventions that are relevant to soil nutrient balances and agricultural production. The potential impact of these interventions will be assessed on the semi-subsistence farming systems of Machakos and Makueni Districts (Easter Province, Kenya) where previous NUTMON studies provided sufficient data for the analysis.

4.2 Materials and methods

4.2.1 Area description

The Machakos study area (Fig. 4.1) is a hilly drought-prone farming area of nearly 13,500 km^2 located 50 km south of the capitol of Kenya, Nairobi. It includes both Machakos and Makueni districts, Makueni being formerly part of Machakos district but separated in 1992 for administrative purposes. Machakos became quite famous after the publication of the book "More people, less erosion" by Tiffen *et al.* (1994). In this book, the authors take the Machakos case to illustrate how population pressure not always has a negative impact on land resources, but it can also stimulate farmers to adopt innovative land management techniques that reverse the process of acute land degradation, while increasing agricultural productivity and per capita income. Many studies have been carried out in the area since (Babier 2000; Warren 2002, Zaal and Oostendorp 2002; Mortimore and Tiffen 2004) and question the "benefits" of population pressure over land (Siedenburg 2006; Tiffen and Mortimore 2006; Malakoff 2011).

Land degradation started in Machakos during colonial times, when the existing high potential agricultural areas were reserved for the white settlements and the local population was forced to migrate to the fragile environment of the semi-arid lands. In the late 1930s authorities recognized signs of massive erosion and degradation that resulted in poverty. From then until independence, the environmental concern of the authorities led to enforced interventions to stop land degradation in the region. Initially, drastic measures were implemented such as mandatory destocking through cattle sales and compulsory communal work involving terracing and grass-planting. Gradually, voluntary terracing and other soil conservation practices were adopted by the local farmers and maintained after they reclaimed their disputed land in the late 60s (Tiffen *et al.* 1994). As a result, within a few decades the farming systems shifted from unsustainable to a more sustainable agriculture, a process that has also been described as "the Machakos Miracle" (Zaal and Oostendorp 2002).

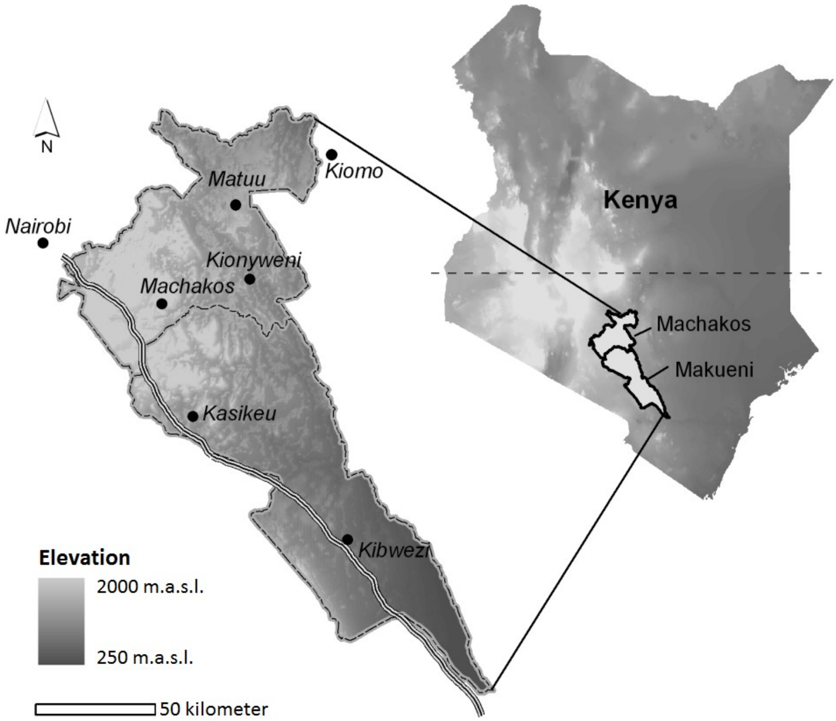


Figure 4.1 Location of the Machakos study area

Despite these optimistic views about Machakos, at present many farmers in the area still face enormous difficulties to sustain their livelihoods with poverty rates ranging from 40 to 90 percent (Thornton *et al.* 2002) with an average of 66% (RoK 2005). In addition, although some forms of land degradation have been prevented, the effects of the population pressure on the fragile environment are still being felt, including pollution from the industries, destruction of forests, soil erosion and desertification. Although less visible, recent studies of soil nutrient balances in Machakos established that yields are low, nutrient balances are generally negative, and agricultural production is still threatened by soil fertility decline (De Jager *et al.* 2006).

The Machakos study area presents a large variation in biophysical and socio-economic conditions. Altitude ranges from 400 to 2,100 meters above sea level, climate is classified as semi-arid with low and highly variable rainfall distributed in two rainy seasons. Mean annual rainfall varies in from 500 mm in the lower parts to 1,300 mm in the higher parts with significant annual variation (Tiffen *et al.* 1994). Mean annual temperature ranges from 15ºC to 25ºC. Soils are generally deep to very deep, with soil texture classes ranging from sandy clay loam to sandy clay. The inherent soil fertility is very poor with common deficiencies in nitrogen and phosphorus. Soil organic carbon content is very low (<2%). According to USDA Soil Taxonomy (Soil Survey Staff 1975), soils are classified as typic Eutrustox, ultic Haplustalfs, oxic Paleustults and rhodic Paleustalfs (Ministry of Agriculture 1987).

Approximately 50% of the area is dedicated to agriculture, which is the main economic sector in this region. Farmers also obtain a considerable part of their income from non-farming activities inside and outside the district as well (Tiffen *et al.* 1994; De Jager *et al.* 1998; Oale 2011). The mountainous areas offer better conditions for agricultural development in terms of rainfall and market opportunities and for that reason they are more densely populated than the plains to the south. Agriculture is represented by semi-subsistence farming systems that include both crop and livestock production. These type of systems have typical characteristics like a low degree of specialization and a high degree of diversification; mixed crop-livestock systems; inter-cropping; high rates of crop failure; small field size and seasonal reconfiguration of sub-parcels within fields; limited or zero use of purchased inputs; high transportation and other transaction costs; and lack of formal markets. Maize is the most important staple crop but a wide variety of other food (*e.g.,* beans, tomatoes, kales, orange and cassava) and cash crops (*e.g.,* coffee and tea) are grown. At present some farmers have access to small-scale irrigation that allows the cultivation of vegetables for commercial production. Livestock is managed mostly as free grazing, although intensive zero-grazing units are proliferating in the region.

4.2.2 The TOA methodology

The TOA methodology was developed to evaluate the potential impacts of different policy instruments and technological interventions on agricultural systems (Stoorvogel *et al.* 2004*a*; Antle *et al.* 2009). TOA was designed for the integrated analysis of trade-offs between different sustainability indicators dealing with *e.g.*, economic, environmental and human health effects of agricultural systems. This analysis is based on econometric production models characterized with input demand and output supply functions that are estimated using actual farm survey data. The model specification is similar to conventional econometric production models, except that site-specific effects of soils and climate on production and input use are represented by crop inherent productivities. These inherent productivities are yield predictions obtained from crop growth simulation models with average management and site-specific soil and climate data, and are interpreted in the economic models as representations of the site-specific productivity potential known to the farmers. The econometric production models are estimated and used to parameterize a model that simulates farm land use and management decisions on a site-specific basis for a particular region.

A TOA application starts with a joint discussion with various stakeholders or, as in this case, a particular policy document, to define the key sustainability indicators and a number of possible interventions. An inventory of soil and climate data provides a description of the bio-physical environment and a farm survey provides data on farm management and production. The data are used to parameterize crop models, estimate inherent productivities of the survey farms, and estimate the econometric production models. The models are then used to simulate agricultural management under a number of alternative scenarios, such as changes in the bio-physical environment (*e.g.*, climate change), agricultural management, and economic conditions (*e.g.*, price and policy changes). Each simulation is carried out for a sample of farms that represents the population of farms in the region, so the results can be used to evaluate total regional impacts as well as the spatial distribution of impacts. The site-specific changes in land use and management can further be evaluated using environmental impact models to assess pesticide leaching (Stoorvogel *et al.* 2004*b*), soil erosion (Antle *et al.* 2005), carbon sequestration (Antle *et al.* 2007), and soil nutrient depletion (Mora-Vallejo *et al.* 2012).

4.2.3 Farm survey

Various dynamic farm surveys have been carried out in Machakos in the context of different NUTMON projects (Kinyanjui *et al.* 2000; Onduru *et al.* 2001; De Jager *et al.* 2001; Gachimbi *et al.* 2002; Gachimbi *et al.* 2005; De Jager *et al.* 2006). The surveys provided monthly input and output data for 121 farms with numerous fields and for various crop cycles resulting in a total of 2424 observations. These farms were located in six clusters based on specific bio-physical conditions, farming systems, population density and soil fertility management (Gachimbi *et al.* 2005). The clusters (Fig. 4.1) represent the majority of farming systems in the area including both rain-fed agriculture (found in all villages) and irrigated agriculture (found in Matuu and Kibwezi). Table 4.1 shows the main characteristics of the farming systems in each of the clusters. These farming systems are complex for modeling purposes and often include both monocrops of important cash crops such as maize and vegetables, and intercrops of primarily subsistence crops. Based on the survey data, the cropping systems were classified for the simulation model into five important systems: a mixed (or intercropped) system (often including maize, beans, vegetables and root crops), mono-cropped maize, mono-cropped beans, vegetables, and grasses. Additionally, livestock products (milk and manure) were incorporated in the analysis with livestock consuming crop residues and producing milk and manure, with manure being applied to crops in the next season.

Table 4.1 **Farm characterization of the study area**

	Machakos	Kionyweni	Kasikeu	Kiomo	Matuu	Kibwezi
Farm Size (ha)	2.78	3.14	3.08	7.84	1.55	4.31
	(1.43)	(3.24)	(2.06)	(7.10)	(0.74)	(4.16)
Family size	8.68	8.17	7.25	7.33	8.92	7.87
	(3.16)	(2.90)	(3.99)	(2.19)	(2.93)	(3.03)
% mixed system	26.16	60.12	34.91	46.09	19.10	25.60
	(44)	(49)	(48)	(50)	(39)	(44)
% maize system	25.58	22.11	37.26	36.09	31.74	10.63
	(44)	(42)	(48)	(48)	(47)	(31)
% beans system	16.86	0.62	8.49	7.39	12.00	–
	(37)	(7.86)	(28)	(26)	(33)	
% vegetable systems	7.56	–	3.30	–	33.94	55.07
	(26)		(18)		(47)	(50)
% pasture	23.84	17.15	16.04	10.43	3.23	8.70
	(43)	(38)	(37)	(31)	(18)	(28)
TLU per farm	1.30	2.90	1.64	2.06	2.87	0.98
	(1.11)	(3.18)	(0.82)	(2.52)	(5.63)	(0.40)
Manure production (dry kg/TLU/month)	214	152	150	216	245	291
	(131)	(229)	(131)	(65)	(232)	(50)
Manure use (dry kg season^{-1})	567.66	152.24	738.20	1050.74	103.81	287.75
	(748.05)	(439.54)	(926.69)	(1221.70)	(169.28)	(183.4)
Fertilizer use (kg season^{-1})	12.09	18.83	39.65		9.00	17.95
	(20.33)	(24.94)	(54.15)	2.00 (-)	(11.71)	(30.20)

Note: Standard deviation in parentheses
*TLU: Tropical Livestock Unit (equivalent to 250 kg of live weight)

Although with TOA it is possible to run the simulations of the scenarios for the original survey fields at their exact locations, the model also has the option to draw fields randomly from the area, thus creating a new sample of fields which allows the extrapolation and stratification of the area. In order to do this, the TOA samples a set of fields from the area by creating a random set of coordinates and verifying the selected coordinates against a set of user-defined spatial conditions (*e.g.,* soil type, altitude). If the location is accepted, a field size is drawn from a given distribution of field size and the inherent productivities of that particular field are assessed using the crop growth simulation model (Stoorvogel *et al.*

2004a). Next, the actual simulation of land use and input use begins. In this case, the simulation runs were performed for a sample of 500 farms randomly taken from the area.

4.2.4 Indicators

The SRA recognizes several factors that constrain the growth of agriculture in Kenya in a wide variety of different fields, ranging from the incidence of HIV/AIDS, land policy, credit to natural disasters, pests and diseases, and the low adoption levels of modern technologies. In this line, the government identifies five critical areas that require public action to stimulate the desired transformation of the agricultural sector: 1) reform of the legal and regulatory framework governing agricultural operations, 2) promotion of research and technology development, 3) reform of the extension service system, 4) a market-based agricultural credit and inputs system, and 5) promotion of domestic processing of agricultural produce. Some specific actions proposed to increase agricultural production include investing in soil health (*e.g.* use of mineral and organic fertilizer, soil conservation measures); promoting small-scale water management (*e.g.* smallholder irrigation schemes, livestock water); improving seed, agricultural extension and agricultural research. These actions have also been mentioned in the MDGs project (UN-MP, 2005) and are confirmed in the Kenya Vision 2030 document (RoK, 2007a). The main objectives of the SRA are to increase farm income, reduce poverty, and maintain or improve soil fertility of the subsistence farming systems. Accordingly, the indicators chosen for the comparative analysis are farm income, net returns to agriculture, poverty, and soil nutrient depletion.

<u>Farm income</u> is defined as the returns to crops and livestock in Kenyan Shillings (KSh/season). It is calculated as the difference between the value of all outputs (including crop products and residues, milk, manure) and the costs (either cash or opportunity cost) of all inputs excluding land and family labor (including seed, mineral and organic fertilizer, pesticides, and hired labor). Although the exchange rate of the KSh varied significantly during the survey it approximately corresponds to 1 US$ = 60 KSh.

<u>Net returns to agriculture</u> is farm income divided by the cropped area of the farm and it is given in KSh per hectare per season.

<u>Poverty</u> is the headcount poverty rate defined as the percentage of households below a poverty line of one US$ per day per person. We follow here the definition of poverty as it is being used by the World Bank (2001) and the SRA. This indicator includes net returns from agricultural activities and off-farm income.

<u>Soil nutrient depletion</u> is the indicator for the decline in soil fertility, described as the seasonal losses of nitrogen in kg per hectare. It is calculated according to the NUTMON methodology in terms of distinct farm units and nutrient flows (De Jager *et al.* 1998; Van Den Bosch *et al.* 1998a). The model calculates nutrient budgets at the field level. Some

flows are estimated by the production model (*e.g.*, crop products and fertilizer use) and then translated to nutrient flows by multiplying them by the respective nutrient contents. Other flows are more difficult to assess (*e.g.*, leaching and denitrification) and are calculated by simple statistical models.

4.2.5 Tradeoff curves

In this type of modeling approaches there is always an uncertainty about a number of model parameters that are highly dynamic. For example, changes in input and output prices and other parameters can be used to generate variations in management that, in turn, induce new tradeoffs between economic and environmental outcomes. A good example for Kenya is the highly variable price of maize.

Maize is grown in the majority of cultivable land in Kenya, it is the main staple food and the most important source of calories for Kenyan livelihoods. For this reason, maize availability has been equated to food security, and food policies in Kenya have historically given excessive attention to this crop. The government has intended to control and influence the maize market, but policy makers have to struggle with two competing objectives, which are a) ensuring adequate returns for domestic maize price and encourage production, while b) keeping low costs for consumers and attain food security (Nyoro *et al*. 2007). For that reason, the maize market has been subject to several reforms since the 1980s, shifting from a state oriented economy towards an increased participation of the private sector, with resulting fluctuations in maize prices (Jayne and Argwings-Kodhek 1997). A recent food policy document in Kenya is the National Food and Nutrition Policy draft (NFNP), which has changed the attention from maize for self-sufficiency to promote food diversity and access (RoK 2007b). Among other measures, this draft proposes gradual removal of import duties on maize. Although studies show that domestic maize prices in the main markets of Kenya have been on an upward trend since 2002, with even sharp increases from 2008 (Kirimi 2009), this type of policies encourage the entrance of maize from Uganda and Tanzania, which will have an effect on local prices. In order to incorporate the high variability of maize prices in Kenya in the analysis, we included seven tradeoff points by varying the maize price from a 75% decrease up to a 100% increase in the average maize prices. These price increases are in the range of actual price fluctuations in Kenya in the past years. For instance, from August 2010 to July 2011 prices increased with 200% (FAO, 2012b).

4.2.6 Scenarios

The results of various scenarios will be compared to the base scenario that refers to the actual situation in the region during the NUTMON studies. The SRA lists a large number of different interventions. In this study we will focus the analysis on four technical scenarios that are considered key from a production point of view: 1) fertilizer prices, 2) manure availability, 3) integrated nutrient management, and 4) drought resistant crop varieties.

Fertilizer prices are generally considered to be a major constraint to the increase of food production in Kenya. An increase in food production can only take place if the depleted soil nutrient stock is replenished with external nutrient inputs (Stoorvogel *et al.* 1999; UN-MP 2005; Vanlauwe and Giller 2006). But the use of mineral fertilizer is normally limited because of its high price (Alene *et al.* 2008). African farmers pay considerably higher fertilizer prices than farmers in the rest of the world. In the case of Kenya, the farm-gate price is roughly twice the fertilizer price at Mombasa port (Ariga and Jayne 2011). This difference is the result of an inefficient domestic marketing structure which incurs in additional costs such as transaction costs among market actors, transport, handling, storage, taxes, and fees (Ariga and Jayne 2011). Therefore, the SRA aims to improve fertilizer accessibility by decreasing transaction costs, improving the infrastructure and marketing of the inputs, and by removing taxes on agricultural inputs and outputs. These measures combined would reduce the farm-gate prices of inputs such as fertilizer. The Kenya Vision 2030 also includes a flagship proposal to develop and implement a fertilizer cost reduction program. With TOA we will examine what would happen in Machakos if a reform of the fertilizer market takes place and the policy to lower the farm-gate price of mineral fertilizers succeeds. In this fertilizer scenario, the fertilizer price was reduced by 25% of the current price assuming that the most important regulatory and coordination problems in the domestic market are resolved; by 50% to represent the case in which the local price is close to the world market price; and by 75% supposing subsidies to inputs could be implemented or there is a reduction in the world price.

Manure is frequently seen as one of the key solutions to soil fertility decline in the case of subsistence farming where farmers lack resources to purchase external inputs. While increasing the use of inorganic fertilizer is a straightforward manner to improve nutrient balances within the systems, farmers should also be encouraged to take full advantage of the organic nutrient resources available in their own farms. The incorporation of organic materials not only supplies nutrients to the crops, but it also improves soil physical properties, such as water retention and soil structure. However, the implementation of organic practices is not simple because in small-scale farming the availability of organic waste is typically limited and several alternative uses are possible. For example, fodder and crop residues are not only valuable as cattle feed but also have alternative uses such as fuel, building material, mulching and green manure or they can be burned for pest and weed control or for ash reincorporation (Dudal 2001). Likewise, animal manure can be collected and stored for composting or fuel or it can be directly applied to the crops as organic fertilizer. In general, composting is very labor intensive and its use is limited. Moreover, farmers lack of the proper tools to handle manure, so they prefer to apply it in the fields close to the homestead and the stable, creating strong gradients of soil fertility within the farms (Tittonell *et al.* 2005*a*). At present less than 25% of the Kenyan farmers make use of manure and compost (RoK 2004) and the nutrient use efficiency is low (Tittonell *et al.* 2005*b*, Tittonell *et al.* 2010). In relation to this, the SRA claims that successful agricultural intensification also requires a better integration of the crop and livestock production systems. Therefore, one alternative that has generally been suggested to promote nutrient recycling is shifting livestock management from free-grazing to zero-grazing units. Assuming that an effective extension service would be able to support this transformation in Machakos resulting in a substantial increase in the use of manure, we created a manure scenario in which we modified the model parameters related to manure use, doubling the efficiency in manure production as well as doubling the demand of manure in all the cropping systems.

As productive land is becoming increasingly scarce, agricultural growth in Kenya has to be achieved by increasing the output per unit of land. A variety of Integrated Nutrient Management (INM) technologies have been developed to improve production through an increase in soil fertility. These technologies are designed to reduce nutrient losses *(e.g.,* erosion control measures, use of crop residues, agro-forestry, and household waste recycling) or to add nutrients to the system (*e.g.,* application of inorganic fertilizer, use of concentrates for livestock feeding, adding organic inputs from outside the farm, and use of leguminous species) (Stoorvogel 1999). INM generally incorporates mineral fertilizer to add nutrients and organic soil amendments to increase soil organic matter. Whether these alternative technologies are adopted by farmers depends in part on the policy environment (De Jager 2005). Policy instruments that may encourage better land use management (*e.g.*, market liberalization, tax reduction, price regulation and subsidies) have been discussed (Scoones and Toulmin 1998 and 1999). Many reports conclude with a “shopping list” of interventions to deal with the problem of soil fertility decline. These general measures have been repeatedly suggested for different cases in various regions in Africa, but attempts to implement them have not reversed the negative trend in soil fertility (De Jager 2005). To represent these types of interventions, an INM scenario was created which combines a 50 percent reduction in the price of fertilizer and a 100 percent increase in manure use efficiency.

The SRA mentions that the use of improved seeds has remained low in Kenya and that it is especially limited in small-scale farming systems. Therefore, an alternative to increase agricultural production and improve food security within the country is to encourage the use of improved crop varieties among small-scale farmers, particularly in the use of improved maize seeds. Although farmers' adoption of new varieties of maize in Kenya is particularly high in the high potential areas, where the use of hybrid seed can be up to 90%, adoption rates are drastically lower (about 10%) in the semi-arid and lowland environments such as in Machakos Region (Hassan 1998; Bett *et al.* 1989). Low adoption rates of new varieties and technologies can be explained by the lack of affordable credit, inadequate linkages between researchers, extension services and farmers, and also the lack of demand driven research which takes into account farmers' various concerns such as risk avoidance or labor and capital constraints.

Most farming in the region of Machakos is rain fed. Given the low soil fertility and the unfavorable weather conditions in the area, poor harvests and total crop failure are generally accepted as a fact of life (Gachimbi *et al.* 2002). Because rainfall is highly unreliable, farmers are unwilling to invest their limited capital in seeds of a high yielding variety, because these usually need sufficient water to realize their yield potential. Participatory research in the Machakos area has shown that farmers recognized drought and the resulting crop failure as the most important constraint to agricultural production (Bett *et al.* 1989; Banziger and Diallo 2001), followed by low soil fertility and pests. We therefore created a scenario that would simulate the introduction of maize varieties resistant to drought and low levels of soil nitrogen. To evaluate this alternative with the TOA, we explored the effects of doubling the probability of crop success. In our model setup, crop failure was accounted for by incorporating the probability of crop success in the simulation of expected returns. Further details on the modeling of crop failure are provided in Antle *et al.* (2005).

4.3 Results and Discussion

4.3.1 General

As mentioned in the SRA, the sustainability indicators (Table 4.2) in the Machakos study area exhibit major environmental and social problems in all clusters. Low farm income, low net returns from agricultural activities and high levels of poverty occur together with high soil nutrient depletion rates. Although there are differences between the clusters, the percentage of households below the poverty line is very high for the whole area. The average income in the clusters is strongly correlated to the poverty rate (R^2=0.96) indicating comparable income distributions. The only cluster that depicts better indicators for farm income and poverty is Matuu, where vegetables are grown for the regional market. Nevertheless, in the area of Kibwezi, which also vegetable production under irrigation, incomes are almost as low (and poverty levels as high) as the clusters with little or no vegetable production. Larger farm size is associated with lower net returns per hectare because farming activities are less intensive. That is the case for the Kiomo area, with the lowest net returns from agricultural activities. Kionyweni shows the highest poverty rate, where low farm income coincide with small off-farm income.

Table 4.2 **Evaluation of the sustainability indicators in the Machakos study area under current conditions (standard deviation in parenthesis)**

	Machakos	Kionyweni	Kasikeu	Kiomo	Matuu	Kibwezi
Farm Income	38,5	26,9	29,4	41,1	97,6	45,3
(1,000 KSh)	(19,9)	(20,0)	(20,4)	(24,1)	(33,9)	(19,4)
Net Ret from Agr.	17,9	16,5	17,5	9,7	71,0	27,5
(KSh/ha)	(9,5)	(11,8)	(11,6)	(5,1)	(21,5)	(6,2)
	88	90	83	81	46	76
Poverty (%)	(20)	(24)	(28)	(29)	(38)	(36)
N depletion	37	35	31	23	32	29
(kg N/ha)	(14)	(13)	(14)	(10)	(19)	(9)

The farm characteristics of this area also indicate that the farming systems are more subsistence oriented, with a large portion of the farm area dedicated to mixed crops and no vegetables. In the following text we will discuss the impact on the study area of changing maize prices and the various scenarios on the sustainability indicators.

4.3.2 Trade-off curves with varying maize prices

To measure the consequences of varying maize prices in the Machakos study area we selected the indicators of nutrient depletion and net returns to agriculture on a per-hectare basis (Figure 4.2). First, we can observe that trade-off curves are different for each cluster of farms. In the clusters that are more maize dependent like Machakos, Kionyweni and Kasikeu, net returns are around KSh 17,000 under current conditions and remain around that range if maize prices decrease. If maize prices increase, Machakos and Kionyweni reach net returns up to KSh 50,000 while Kasikeu makes net returns of nearly KSh 40,000. For these three clusters nutrient depletion rates vary with changes in maize prices, being higher in Machakos if prices of maize increase. Kasikeu has the lower depletion rates. The farms of Kiomo present the lowest net returns per hectare, ranging from KSh 7,000 to 30,000 with varying maize prices. However, these farms are much larger in size than those of the other clusters. Depletion rates in Kiomo are also low. In the case of the clusters that are producing vegetables like Matuu and Kibwezi, the changes in maize price have a large impact on net returns and nutrient depletion.

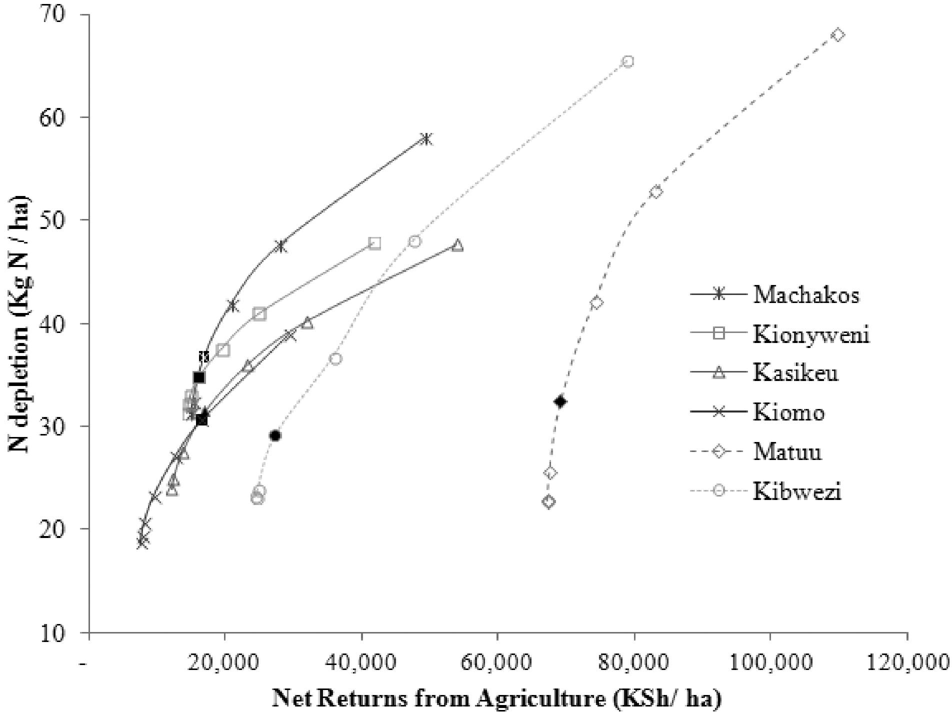


Figure 4.2 **Effects of varying maize prices on N depletion and Net Returns from Agriculture in the farm clusters of Machakos under current management conditions (Base scenario). Solid filled marker indicates de observed maize price.**

Net returns are higher in Matuu (KSh 90,000 to 154,000) that in Kibwezi (KSh 40,000 to 130,000) with similar depletion rates for both clusters (23 to 65 kg N). Notice that in all clusters and increase in maize price will result in higher nutrient depletion. What is seen in the results of the simulation is that when maize prices increase, all the clusters increase their share of mono-cropped maize, especially in Machakos, Kionyweni and Kasikeu where mono-cropped takes up more than half of the area with higher maize prices. This increase goes together with only slight increases in manure and fertilizer application, and because maize is a very nutrient demanding crop, nutrient depletion takes place. When maize prices decrease, the area under maize decreases as well, but decreases from 50% to 75% of the price have almost no effect on the indicators in all clusters because all farms will always have a share of maize for home consumption, despite the price. For this reason, all clusters react more to increases in maize price and the decrease in price has less influence.

4.3.3 Scenarios

Figure 4.3 illustrates the relationship between nutrient depletion and farm income on a seasonal base for the scenarios proposed in the SRA under evaluation, with prices of maize varying from a 75% decrease to 100% increase. First, the graph shows clearly that nutrient depletion will take place in all possible scenarios and at any maize price.

Fertilizer use in Kenya has been strongly restricted by poor access, high costs and low quality. With the collapse of farmers' cooperative societies and organizations that depended on direct government support for trade, it became difficult to obtain agricultural inputs in rural areas, or they simply became unaffordable for many farmers. Although in the Machakos area the use of fertilizer is positively related to net returns, the application rates are below the recommended rates. At the observed fertilizer prices, farmers apply on average 27 kg of fertilizer per hectare each season, but applications can be as little as 7 kg in farms of Kiomo and up to 47 kg in Matuu. Although a decrease in the fertilizer price has a positive impact on nutrient balances, the problem of soil fertility decline is by no means solved by decreasing fertilizer price. With observed maize prices, a reduction of 25% in the fertilizer price has very little effect on nutrient depletion and if the price is lowered by 75% nutrient depletion is reduced by 6% only. With varying maize prices, we observe that increases in the price of maize will result in higher depletion and increased farm income. A decrease in maize price results in less depletion, but also lowers farm income.

Manure applications in the Machakos area vary from 0.3 to nearly one ton per hectare per season. These rates are not related to farm income, net returns to agriculture or the amount of livestock available. Results from the simulation show that if an increase in the efficiency of manure use occurs, it will not produce the desired effects on the sustainability indicators proposed in the Strategy. In a manure scenario, farm income increase nearly KSh 2,000 per season compared to those of the base scenario, but, as the application of manure increases, depletion rates will slightly worsen (1 to 2 kg N ha^{-1}). This is explained because under this scenario the land allocation of maize monocrop is higher than in the base scenario, and the nutrient addition from manure does not offset the increases in nutrient outputs from maize production. The modest impact of increasing manure use efficiency is not surprising if we consider that in the base scenario farmers are applying on average nearly 540 kg of manure per hectare which represents merely about 3.7 kg N (N content in dry matter = 0.0068). When we simulate an increase in the manure use efficiency, applications will rise to approximately 900 kg of manure per hectare, adding just 2.4 kg N to the system, an amount that is almost negligible compare to the losses in crops and residues. This is especially true if we compare this quantity with the fertilizer scenario in which only inputs of around 100 kg of mineral fertilizer (20 kg of N) start making a difference in the indicators, and still do not manage to substantially decrease soil nutrient mining.

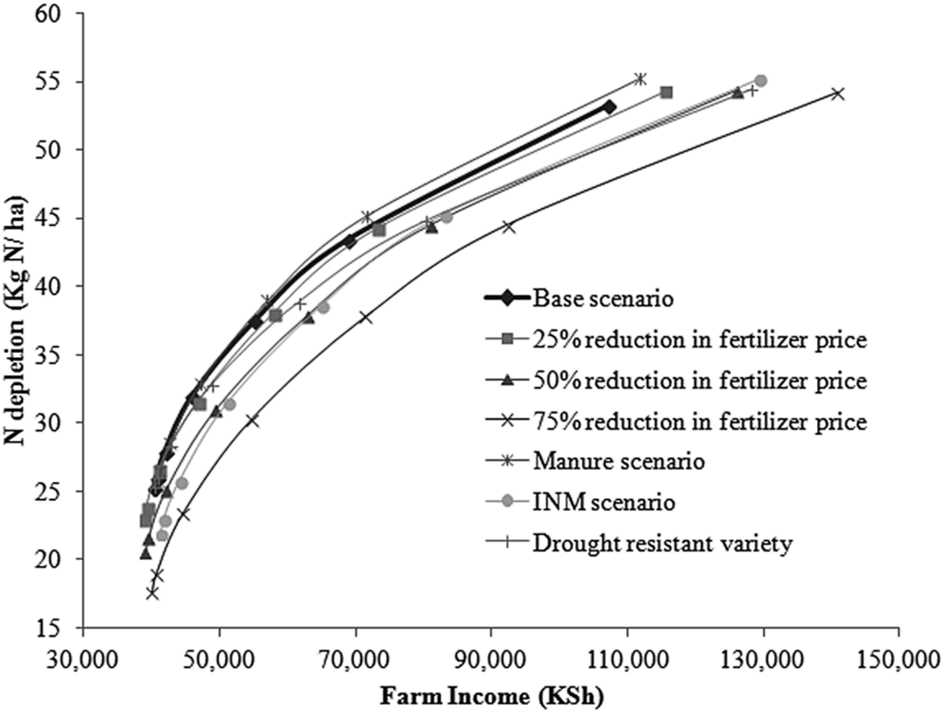


Figure 4.3 Effects in the Machakos study area of the proposed interventions on the indicators of farm income and N depletion with varying maize prices

In addition, if we examine the consequences of changes in maize prices in the manure scenario we can observe that an increase in the price of maize will result in more nutrient depletion.

The INM scenario combines the effects of the fertilizer and the manure scenarios, and the response of the indicators is similar to those described above. The overall additional nutrient input is minimal and does not result in major changes in either the farm income or the soil nutrient balance. In order to make a substantial improvement in the soil nutrient balance or in farm productivity, significant changes in the nutrient inputs are required.

Finally, the introduction of a drought resistant crop variety results in a reduction of crop failure and, consequently, a positive impact on farm income. The drought resistant crop varieties result in a minor increase in nutrient depletion rates (1 to 2 kg of N ha^{-1}) as the higher success of the maize performance increases the net outflow of nutrients. Higher maize prices increase net returns considerably while N depletion is slightly affected.

These results suggest that in order to significantly improve soil fertility and farm income in the Machakos study area the interventions proposed in the SRA are not sufficient and major changes are needed to meet the strategy's goals. This could be a combination of interventions but, more likely, more structural changes are needed to deal with the high population density in combination with the small farm sizes and limited off-farm employment. An increase in the maize price is the one factor that can substantially increase net returns and reduce poverty. This result is illustrated in Figure 4.4, where the cumulative probability of net returns per person under different scenarios with current maize prices (a) is presented as opposed to the effects of varying the maize prices only (b). In this figure calculations are made on a seasonal basis and a threshold value was set at the poverty line (approximately eleven thousand Kenyan Shillings, which correspond to one dollar per day for half a year, i.e., US$183). However, as explained above, soil nutrient depletion increases with higher maize prices, and maize being such an important food crop in Kenya, higher prices are a threat to food security as well. Current production levels of maize only yield minor quantities of crop residues which are all being used to feed livestock. Maize production needs to be raised significantly through improved fertilizer management to increase crop residue production to avail those residues for mulching and the production of compost.

Figure 4.5 and 4.6 show the spatial differences that appear in the study area for the indicators of farm income per person and nutrient depletion per hectare in the fertilizer price and the drought resistant crop scenarios, compared to the base scenario. The fertilizer price is reduced by 50% and maize prices are varied from -50%, observed price and more than 50%. Figure 4.5 illustrates that farm income per person would considerably increase only in the case that a drought resistant maize variety is introduced and the maize price increases. At observed prices the changes are minimal. On the other hand, a decrease in the fertilizer price has almost no beneficial impact on farm income per person at any maize price, suggesting that it is very unlikely that farmers would be willing to apply more fertilizer if they cannot see the economic gains of this intervention. Figure 4.6 shows that the introduction of a new maize variety has minimal detrimental effect on soil nutrient balances at observed and increased maize price. In these cases, more depletion takes place in the farms around Matuu and Kibwezi, which are normally the ones that produce vegetables for the market and would shift to produce more maize, which is a nutrient demanding crop. Conversely, with a reduction by 50% on the fertilizer price there is a positive effect on nutrient balances in all maize prices. The green areas indicate that gains higher than 5 kg of N per hectare would take place compared to the base scenario. Because losses in the base scenario are nearly 40 kg of N on average, nutrient depletion still takes place in all the study area.

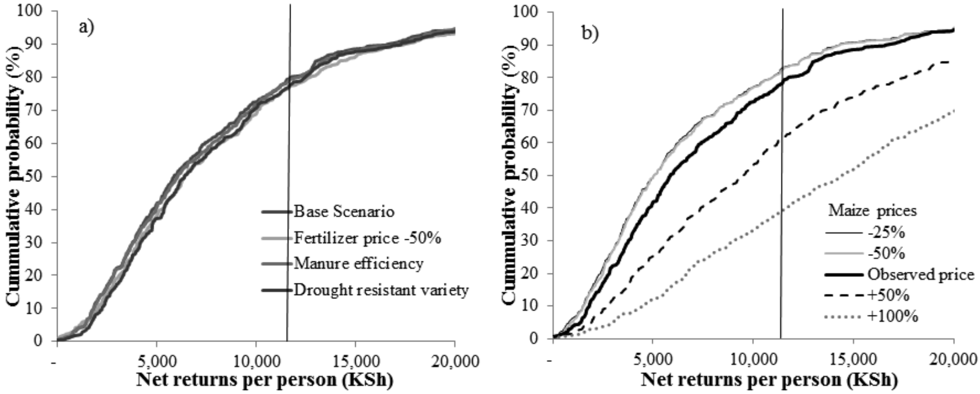


Figure 4.4 **Effect of different scenarios (a) and varying maize price (b) on poverty in the Machakos study area.**

4.4 Conclusions

The Kenyan SRA is a national policy document that addresses the challenge of improving farmers' livelihoods in Kenya. The interventions proposed in this strategy have also been subscribed by other policy documents like the Economic Recovery Strategy, the Millennium Development Goals and the Kenya Vision 2030. However, when we evaluate a few of the most commonly suggested interventions that would improve agricultural production, income and soil nutrient status, we observe that in an area such as the semi-arid lands of Machakos the results raise the question whether these general recommendations will in fact have the intended impact on site specific problems.

For example, the analysis shows that policies reducing the farm gate price of mineral fertilizer will slightly decrease soil nutrient depletion rates in Machakos area, but contrary to what is generally believed, even a substantial decrease in fertilizer price will not eliminate the problem of nutrient mining. Moreover, even if soil fertility can be improved by this type of policy, it appears to have relatively small effects on farm income and poverty. Therefore, policies only oriented to decrease fertilizer farm gate price will fail to reach the goals proposed in the strategy in areas like Machakos. In terms of encouraging management practices that increase the efficiency of manure use (e.g. zero grazing units, composting, manure pit, etc.) we observed that having more manure available make farmers to change their cultivation pattern to a more maize oriented system.

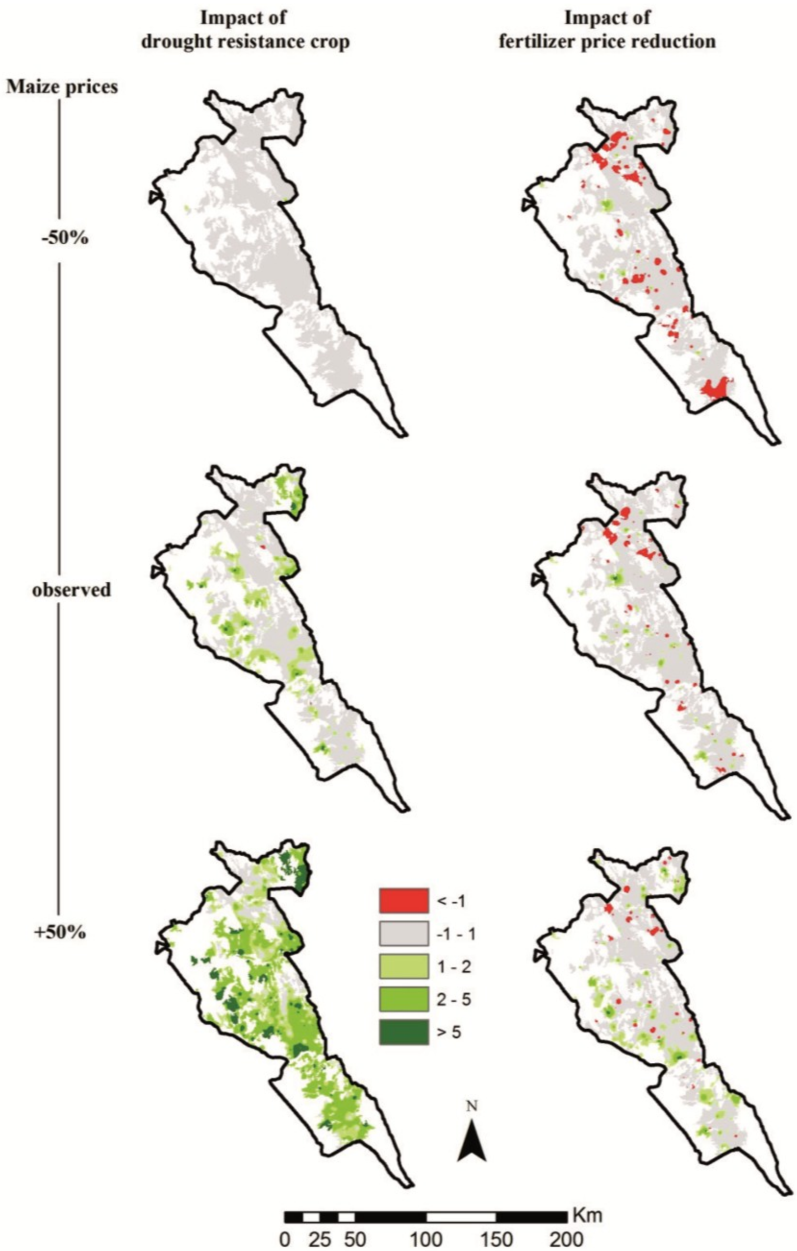


Figure 4.5 **Spatial effects of INM and fertilizer price reduction on net returns (%) with varying maize prices in the Machakos study area**

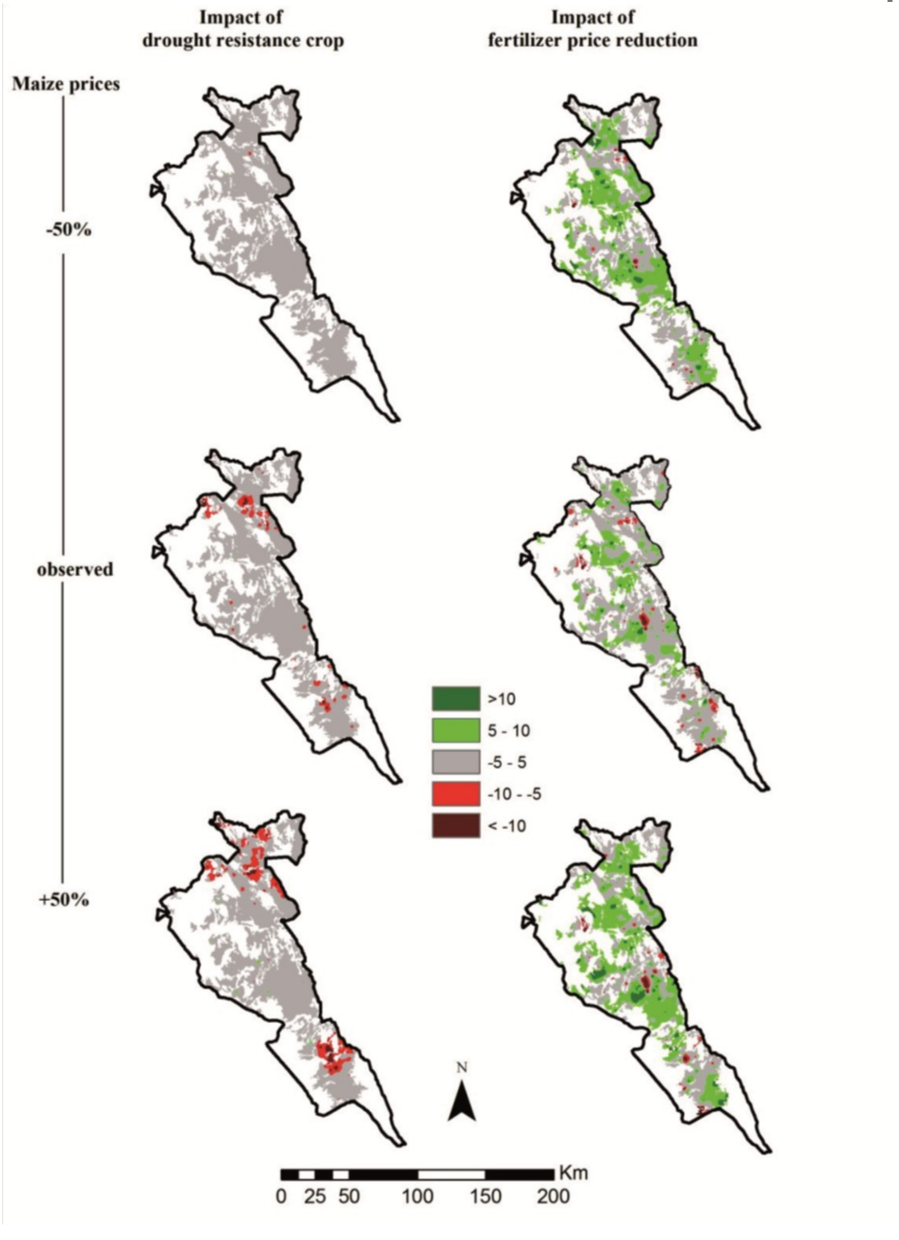


Figure 4.6 **Spatial effects of INM and fertilizer price reduction on nutrient depletion (kg N/ha/yr) with varying maize prices in the Machakos study area**

Although the improvements in fertility management will have some positive impact in production and in net returns, the shift in land allocation results in slightly higher N losses from the system. Calculations indicate that at least 20 kg of N has to be added to the system to produce a significant impact on nutrient depletion. But in order to add this amount of nitrogen through organic fertilizer, applications of more than three tons of manure (dry weight) per hectare are needed. This amount is in the order of 3 to 10 times more than the farmers are currently applying and it is practically unattainable with the present livestock numbers. The analysis also shows that average increases of 200 kg of maize per hectare can be achieved with the introduction of a drought resistant variety. Though this measure would have a positive effect on farm income and poverty, the quantity of maize produced per farm is still far below the requirements of the household members. Moreover, soil nutrient depletion rates would increase in such a scenario. Finally, results illustrate that maize price is the only variable that has the potential to substantially increase income, suggesting that investments that reduce transport costs and increase market efficiency would have beneficial effects. In the light of the recent price increases of maize in Kenya, this result suggests that farmers have benefited from this, but at the expense of soil fertility.

On the other hand, if we look at the individual results for the different farms in the Machakos study area, we can see that even within a relatively small region, spatial differences in farmers' responses coincide with varying responses to incentives. This suggests that although the use of aggregated results (or averages) are informative indicators which clearly represent the situation of the area, the use of maps provides the spatial expression of market and environmental differences and this information can also be used to target the areas that need urgent intervention.

This analysis strongly suggests that the subsistence farming systems of the Machakos area will benefit little from the interventions proposed in the SRA. The resources available to these households are too limited for them to achieve substantial increases in income or prevent the mining of soil nutrients. The extremely small farm size and large family size in the Machakos area also suggest that public policies that promote rural development and increase opportunities off-farm income could have positive impacts on both incomes and the sustainability of agricultural systems.

Agricultural productivity in Kenya comes mostly from smallholder subsistence farmers and varies greatly between farm types and across localities in terms of management, resource allocation, production activities, etc. (Tittonell *et al.*, 2005a). This high degree of heterogeneity suggests that conventional policies will have different impacts in different areas. For example, farmers in high potential areas respond strongly to price incentives (Mose, 2007) but in low potential areas this is not the case, and specific complementary interventions should be taken in order to change farmers' management options. In the case of soil fertility, research has revealed that causes are highly variable and it is related to both biophysical (*e.g.,* agro-ecological zone) and socio-economic factors (*e.g.,* farmer resources, market access, and population density), which together have an important effect on the soil fertility management options (see also De Jager, 2005; Muchena *et al*., 2005; Tittonell *et al.*, 2005a). The heterogeneity of the results is an indication that variability should be taken into account when developing new technologies and policies for particular agricultural systems, and that single interventions based on average outcomes will have limited effectiveness.

Chapter 5

How does the Resolution of Environmental Data Impact Land Use Modeling?

Based on:

Mora-Vallejo, A.M., Stoorvogel, JJ, Antle, J.M., Claessens, L., 2013. How does the resolution of environmental data impact land use modeling? To be submitted.

5.1 Introduction

Environmental problems require a spatially explicit impact analysis. With the on-going advances in geographic information systems (GIS), the increasing availability of remotely sensed data, and the progress in computing power and network storage capacity, it is now possible to develop complex site-specific models that include environmental data in the form of spatially exhaustive continuous maps. For this reason, the demand from the scientific community and the policy makers nowadays is for accurate, up-to-date, spatially referenced information, and the global trend is that environmental data is becoming available at higher resolutions.

In principle, land use models employ soil and climate data as basic inputs of environmental data. The resolution and quality of available environmental data varies widely in the world. In developing countries, where lack of infrastructure and expertise are common constraints, there are still large areas with data of poor quality and low resolution, but even in developed countries it can also be a problem to find appropriate data to upscale models from the field to the regional level. In addition, the classical approach of classified suitability maps with discrete land units is no longer adequate for land use analysis with scenario development, and currently data collection has advanced from qualitative to quantitative research. In this respect, recent initiatives are taking place such as the Digital Soil Map of the World (Sanchez *et al.* 2009) which aims to produce maps of target functional soil properties (*e.g.* clay content, organic carbon) at approximately 90 meter resolution using the present advances in statistics and technologies like remote sensing, infrared spectroscopy, data mining and soil sampling, together with the improved scientific understanding of soils. Activities started in Africa through the Africa Soil Information Service (AfSIS). This is a large-scale, research-based project that is producing maps of geo-referenced soil data for Africa with easy and free access to world-wide users (www.africasoils.net). Regarding weather data, a set of global climate layers (or climate grids) with a spatial resolution of about one square kilometer is freely available for academic and other non-commercial use (www.worldclim.org), and the Reanalysis community (www.reanalyses.org) has developed a comprehensive record of weather and climate changes over time.

While the resolution of available environmental data is increasing, methods to capture spatially explicit socio-economic and land management data are still lacking behind. In general, this type of data are not geo-referenced and demographic, agricultural and price data are usually reported on the basis of an administrative or other arbitrary border, representing a region, district or area, in most cases with no ecological coherence (Antle *et al.* 2001). With the advances of integrated assessment methodologies linking site-specific economic and biophysical models, the demand for spatially referenced demographic and economic data is increasing. However, these types of data are normally highly variable in time and costs associated to data gathering at higher frequency increase as well.

Hence, acquiring and compiling adequate environmental and economic data for land use modeling requires some effort. While most countries nowadays have large datasets available with e.g. soil and climate information, crop performance, farm characteristics only seldom these data are readily suitable as inputs for modeling. When setting up the models, it is common that the resolution of the data is inappropriate, quality is insufficient, data sets are corrupted or outdated, particular information is missing, data are not in the appropriate format and so on. Consequently, the collection and analysis of additional information and higher resolution data is frequently needed which is often a laborious, costly and time consuming task. While data-intensive research methodologies may be desired or required from a scientific perspective, results meant to inform policy decision making generally have to be available rapidly and at minimal cost, thus limiting the possibility for additional data collection.

In the latter type of analysis, the questions that remain are whether the resolution of the input data influences the outcome of the land use models and to what extent higher resolution data are required to come to a similar, or 'good enough' result for policy advice. When policy makers are interested in general trends or aggregated results only, do we really need detailed high resolution data for the analysis?

In this study we will evaluate the effects of the resolution of environmental data on regional land use analysis using the Tradeoff Analysis Methodology (TOA) (Stoorvogel *et al.* 2003 and 2004) with an application developed for the mixed farming systems of the Machakos study area in Kenya (Mora-Vallejo *et al.* 2012). The TOA is a spatially explicit methodology that integrates bio-physical and economic models to *ex ante* assess a variety of sustainability indicators under scenarios of introducing new technologies and/or policies. We will test the effects of two different (low and high resolution) datasets of soil and climate model inputs on model outcomes. In this case we will focus on the spatial resolution of environmental maps, and temporal resolution is not included in this analysis.

5.2 Materials and methods

5.2.1 The TOA Methodology

The TOA (Stoorvogel *et al.,* 2001, 2004) is a participatory methodology developed to perform integrated assessment of agricultural systems and to provide a decision support tool for agricultural and environmental technology and policy analysis. In this type of assessment, the farming systems are characterized in both bio-physical and economic terms by means of quantitative sustainability indicators. The choice of relevant indicators depends largely on the local agro-ecological conditions of the study area, the particular interest of the stakeholders and the type of scenarios to be evaluated. These indicators can represent the economic performance (*e.g.* annual net returns, poverty index, food security, and risk) and the environmental performance (*e.g.* soil organic matter content and other indicators of soil quality, soil erosion, chemical leaching, and human health). Tradeoff curves can be constructed by varying one (or more) key variables (*e.g.* income) against another (*e.g.* pesticide leaching). In this way, the tradeoff curves represent the principle of opportunity cost among scarce resources. Subsequently, the effects of technology scenarios, such as the introduction of a new crop variety or a change in policy, are evaluated in terms of their effect on the tradeoff curve compared to a so called “base scenario”. The alternative scenarios are constructed by varying certain model parameters in the model simulation runs.

Model set-up

The TOA methodology combines biophysical models (normally crop and livestock production and environmental) with econometric production models. The econometric production models are characterized with input demand and output supply functions that are estimated using actual farm survey data. The model specification is similar to any conventional econometric production model. However, in the case of TOA the site-specific effects of soils, climate and input use on production are represented in the input demand and output supply functions by crop inherent productivities, hereafter *inprods*. The *inprods* are yield predictions obtained from crop growth simulation models with average management settings and site-specific soil, climate and cultivar information. In the econometric models, *inprods* are interpreted as the site-specific productivity potential expected by farmers. Once the econometric production models are estimated, they are later used to parameterize a simulation model of farm land use and management decisions on a site-specific basis. Because TOA is a spatially explicit methodology, environmental information is included in the analysis in the form of maps with their correspondent attribute tables. Soil and climate data are used as inputs for the biophysical models of crop (and livestock) production as well as in the environmental models. In addition, site-specific farm data are required to estimate the behavioral parameters of the econometric-process models including data on variable inputs and outputs (*e.g.* seed quantity, fertilizer use, labour, production of crops, livestock and crop residues) as well as fixed factors for the ‘base system’ (*e.g.* land size, equipment, household characteristics).

Model estimation phase

A strong point of TOA is the use and combination of different disciplinary models in the system analysis. These models can be sub-divided in three main groups: (i) production models to estimate the inherent productivity of specific fields, (ii) econometric production models to understand farmers’ behaviour, and iii) environmental process models to assess the environmental impact of farmers activities. All these models need proper calibration for the local conditions of the study area (Stoorvogel *et al* 2004) and that is done in the model estimation phase. The crop production models (and potentially livestock models) incorporate the spatial and temporal environmental variation (soil and climate) in the analysis with the *inprods*. The TOA software calculates *inprods* using calibrated crop growth simulation models from the DSSAT suite of models (Jones *et al*. 2003). In these calculations, the soil and weather data are determined by the farm location (coordinates). The *inprods* are then used as inputs into the economic models as a spatially explicit variable that explains the management decisions made by the farmers. Subsequently, the estimation of the econometric production models is carried out, using the farm survey data and the *inprods* index of the surveyed farms. Parameters for price distributions and other exogenous variables of the production models are also estimated using the survey data (Antle and Capalbo 2001). The econometric production models are then composed by a series of input demand and output supply equations representing farmers' crop choice and input use as functions of economic variables (input and output prices, farm characteristics) and the biophysical variables (*inprods*). Finally, the environmental process models (*e.g.* land use, pesticide applications, soil erosion) use the management decisions from the econometric simulation model as inputs to estimate the impacts on soil quality, pesticide fate, and other environmental processes of interest for certain management practices.

Model simulation and environmental impact assessment

Crop and econometric production models described above are finally used to parameterize an econometric simulation model that predicts crop choice, input demand and output supply on a site-specific basis (Stoorvogel *et al*. 2001 and 2003). Although with TOA it is possible to run the simulation for the original survey fields at their exact locations, the model also has the option to draw other fields randomly from the study area, thus creating a new sample of fields which allows the extrapolation and stratification of the area. In order to do this, TOA samples a set of fields from the area by creating a random set of coordinates and by verifying the selected coordinates against a set of user-defined spatially explicit conditions for stratification (*e.g.* soil type, altitude). If the location is accepted, a field size is drawn from a given distribution of field sizes and the *inprods* of that particular field are assessed using the crop growth simulation models (Stoorvogel *et al.* 2004). Next, the actual simulation of land use and input use decisions begins. Each individual simulation run starts with drawing input and output prices from the distributions after which land use and input use decisions are simulated. The output of the econometric simulation model includes land use and land management for each of the fields, under different conditions and for several repetitions. This output is subsequently the input for the environmental process model that estimates the impact of specific decisions on that location. This process can be repeated for different scenarios. Outcomes can be displayed spatially as maps or they can also be aggregated to construct regional tradeoff curves or indicators. Environmental impact models used in different TOA applications include pesticide leaching (Stoorvogel *et al.*

2004), soil erosion (Antle *et al.* 2006), carbon sequestration (Antle *et al.* 2007), water redistribution (Claessens *et al.* 2012) and soil nutrient depletion (Mora-Vallejo *et al.* 2012).

5.2.2 A TOA application in the mixed farming systems of Machakos, Kenya

The Machakos study area

The Machakos study area is located in the Eastern Province of Kenya and comprises both Machakos and Makueni districts. The area is nearly 13,500 km^2, from which almost half is under agricultural use, mainly represented by subsistence-oriented mixed farming systems with both crop and livestock production. Maize is the most important staple crop, but a wide variety of other food crops are grown (beans, millet and sorghum), fruit trees (orange, banana, mango and pawpaw), tubers (cassava), and cash crops (vegetables, coffee and cotton) (De Jager *et al*. 2004). Similar to all subsistence farming systems, yields in Machakos are low, crop failure is a common problem and soil nutrient balances are often negative (De Jager *et al*. 2004).

The study area presents significant environmental variation with altitude ranging from 400 to 2,100 meters above sea level. The climate is semi-arid, with low, highly variable rainfall, distributed in two rainy seasons (November- January and March- June), but drought events occur often (Tiffen *et al*. 1994). The mean annual rainfall average ranges from 450 to 2000 mm and mean annual temperature varies from 15ºC to 25ºC (MoA 1987). Soils in this region are generally deep to very deep, friable, with textures varying from sandy clay loam to sandy clay. Though superficial runoff does not frequently occur, water erosion can take place at the beginning of the rainy season when the land is still bare. According to the Soil Taxonomy (Soil Survey Staff 1974), soils are classified as typic Eutrustox, ultic Haplustalfs, oxic Paleustults and rhodic Paleustalfs. Soil inherent fertility is very poor, nitrogen and phosphorus being the most limiting nutrients. In addition, organic carbon content is deficient to poor (<1%) (MoA 1987; Onduru *et al*. 2001).

The socio-economic data to set up this TOA application were compiled from NUTMON studies (De Jager *et al*. 1998[a]; Van Den Bosch *et al.* 1998[a] ; Kinyanjui *et al*. 2000; Onduru *et al*. 2001; De Jager *et al*. 2001; Gachimbi *et al*. 2002; de Jager *et al*. 2004; Gachimbi *et al*. 2005) previously carried out in the area. The NUTMON survey characterizes the area in six clusters of farms representing the different agro-ecological conditions, population density, management group (*e.g.* conventional and low-input endowment) and technology scenarios (*e.g.* irrigation). The main characteristics of these clusters are shown in Table 5.1.

Table 5.1 **Farm characterization for six village clusters in the Machakos study area (Kenya). Standard deviation in parenthesis.**

Variable	Machakos	Kionyweni	Kasikeu	Kiomo	Matuu	Kibwezi
Farm size (ha)	2.8 (1.4)	3.1 (3.2)	3.1 (2.1)	7.8 (7.1)	1.6 (0.7)	4.3 (4.2)
Family size	8.7 (3.2)	8.2 (2.9)	7.3 (4.0)	7.3 (2.2)	8.9 (2.9)	7.9 (3.0)
Mixed system (%)	26 (44)	60 (49)	35 (48)	46 (50)	19 (39)	26 (44)
Maize system (%)	26 (44)	22 (42)	37 (48)	36 (48)	32 (47)	11 (31)
Beans system (%)	17 (37)	1 (8)	8 (28)	7 (26)	12 (33)	–
Vegetable system(%)	8 (26)	–	3 (18)	–	34 (47)	55 (50)
Pasture (%)	24 (43)	17 (38)	16 ((37)	10 (31)	3 (18)	9 (28)
TLU* /farm	1.3 (1.1)	2.9 (3.2)	1.6 (0.8)	2.1 (2.5)	2.9 (5.6)	1.0 (0.4)
Manure production (dry kg/TLU/month)	214 (131)	152 (229)	150 (131)	216 (65)	245 (232)	291 (50)
Manure use (dry kg/season)	919 (863)	320 (356)	420 (625)	449 (663)	604 (593)	545 (784)
Fertilizer use (kg/season)	26 (31)	20 (21)	23 (29)	7 (13)	47 (26)	32 (26)
Off-farm income (1,000Ksh/season)	14.5(24.8)	3.1(6.8)	18.2(26.1)	7.3(10.5)	2.1(5.4)	9.3(13.9)

*TLU: Tropical Livestock Unit (equivalent to 250 kg of live weight)

The use of environmental data in TOA

Soil and climate data are first used in TOA for the calculation of the *inprods*. In the case of Machakos, the farming systems are complex and involve a large number of crops and intercrops in small parcels, presenting a challenge to modeling because models for some of these crops simply do not exist. In Machakos, the *inprods* found to describe best the input demand and output supply for the econometric models were the estimations with simulations for maize and beans production. Additionally the tomato model was used as a reference for the vegetable production. *Inprods* are calculated with DSSAT, which in terms of climate requires daily values of rainfall, minimum and maximum temperature and solar radiation. Regarding soils, data needed are maximum rooting depth and the number and depth of each soil horizon. For every different soil layer quantitative data of volumetric water contents at plant wilting point and field capacity, porosity, texture class, bulk density (dry and moist), organic carbon and nitrogen content, coarse fraction percentage, soil pH and cation exchange capacity are included.

Likewise, *inprods* are calculated in TOA for the model simulation phase, either for the actual surveyed farms or for simulated farms drawn stochastically from the area. In this case the simulation runs were performed with 350 simulated farms spread randomly in the study area. Soil and climate data for the DSSAT models are obtained from the geo-referenced maps with the coordinates of each simulated farm.

Finally soil and climate data are used as input of the environmental impact model. In this case, the environmental sustainability indicator chosen for evaluation in Machakos was soil nitrogen depletion and the model used for the calculations of nutrient balances is a simplified version of NUTMON (De Jager *et al*. 1998[a,b]; Van Den Bosch *et al*. 1998[a,b]). NUTMON characterizes the farming systems in terms of distinct production units and quantifiable flows. The flows are accounted by direct measurement (inputs of inorganic fertilizer and manure and outputs of crop products and crop residues) or transfer functions as listed below. For the calculation of nutrient flows soil and weather maps provide information on mean annual precipitation (P in mm y^{-1}), bulk density (BD in gr cm^{-3}), soil organic carbon (SOC in %) and clay content (%).

Soil mineral Nitrogen stock (kg ha^{-1})

$N_{min} = 2 * 1{,}000 * BD * SOC * 0.02$

Atmospheric Deposition (kg ha^{-1} y^{-1})

$N_{AD} = 0.14 * P^{0.5}$

Non-symbiotic N (kg ha^{-1} y^{-1})

$N_{NSymb} = 2 + (P - 1350) * 0.005$

Leaching if Clay <35 % (kg ha^{-1} y^{-1})

$N_{leach} = [N_{min} + N_{fert}] * ((0.021 * P) + 3.9) * 0.01$

Leaching if 35% < Clay < 55% (kg ha^{-1} y^{-1})

$N_{leach} = [N_{min} + N_{fert}] * ((0.014 * P) + 0.71) * 0.01$

Leaching if Clay >55 % (kg ha^{-1} y^{-1})

$N_{leach} = [N_{min} + N_{fert}] * ((0.0071 * P) + 5.4) * 0.01$

Gaseous losses (N) (kg ha^{-1} y^{-1})

$N_{gas} = [N_{min} + N_{fert}] * (-9.4 + 0.13 * Clay + 0.01 * P) * 0.01$

Environmental data of the Machakos study area were not readily available for the TOA application and high (H) and low (L) resolution maps of soil and climate were produced for this specific purpose (Fig. 5.1). Because the soil map was intended for the assessment of farming systems, natural areas (nearly 50% of the total surface) were excluded from the analysis using the FAO-Africover map (www.africover.org).

Soil data

A low resolution soil map (L_s) was created combining the soil units of the 1:1,000,000 Exploratory Soil Map of Kenya (Sombroek *et al.* 1980) with the representative soil profile descriptions of the Fertilizer Use Recommendation Program (MoA 1987). This soil map (Fig. 5.1a) divides the study area in seven soil units.

In contrast, the high resolution soil map (H_s) was developed combining digital soil mapping (DSM) techniques (McBratney *et al*. 2003) and pedo-transfer functions (Fig. 5.1 b). DSM techniques were used for the assessment of soil organic carbon and clay content in the top soil horizon (0-30 cm) (Mora-Vallejo *et al*. 2008). DSM combines observation data, auxiliary information and expert knowledge to assess in a rapid and cost-effective manner the value of specific soil properties at non-visited locations with a limited sampling size. Soil spatial variability is interpreted using the concepts of the soil forming factors equation (Jenny 1941) which states that soil formation is a function of climate, organisms (including vegetation), relief, parent material and time. Auxiliary data on various soil forming factors are collected (remotely sensed imagery, digital elevation models, geology, geomorphology, etc.) and used as explanatory variables to perform a multiple regression analysis. For the soil map of Machakos, 95 composite soil samples were collected in the field and analyzed for the targeted soil properties. The values of SOC and clay content in the top horizon were obtained using a regression kriging framework (Hengl *et al*. 2004), combining step-wise linear regression models with the interpolation of the residuals. Results showed that SOC in the topsoil was low (<1.3%) for the whole study area with an average value of 0.84 %. In contrast, textural variation was large with textures ranging from sandy clay to loamy sands and average clay of 27%. Subsequently, the missing information for the top soil for the crop growth simulation models was derived from literature and pedo-transfer functions. Soil water content at field capacity and permanent wilting point were estimated according to Saxton *et al.* (1986) as a function of the contents of clay, sand and SOC:

Soil water content at Field Capacity (pF 2.5)

$$\theta_{33} = -0.251 * Sand + 0.195 * Clay + 0.0064 * SOC + 0.0035(Sand*SOC) - 0.016(Clay*SOC) + 0.452\,(Sand*Clay) + 0.299$$

Soil water content at Permanent Wilting Point (pF 4.2)

$$\theta_{1500} = -0.024*Sand + 0.487*Clay + 0.0035*SOC + 0.0029(Sand*SOC) - 0.0076(Clay*SOC) + 0.068\,(Sand*Clay) + 0.031$$

Water content at saturation was taken as a fraction of porosity (Dalgliesh and Foale 1998) according to textural class, being 0.93 for soil classes sand (S), sandy loam (SL) and loamy sand (LS); 0.95 for soil classes loam (L), silty loam (SIL), silt (SI), silty clay loam (SCL) and silty clay (SC); and 0.97 for soil classes clay (C) clay loam (CL), silty clay (SIC) and silty clay loam (SICL). We used a default value of 0.5 for porosity and 6.5 for pH in water. In addition, mineral dry bulk density (BD) was set at 1.3 gr cm^{-3} which is the average value in the region (MoA 1987). BD in moist condition (BD_m) was estimated (Adams 1973; Rawls and Brakensiek 1985) as indicated in the following equation:

$$BD_m = 100 / (SOC *1.78 / 0.224 + (100 – SOC*1.78) / BD$$

Finally, the soil profile descriptions of the soil layers below 30 cm was obtained from the SOTER database of Kenya (1:1,000,000) (Van Engelen 2000) creating a new map with 1,150 different soil units and its associated soil profile description.

Climate data

Climate data were obtained from the weather stations of Katumani (1.517°S; 37.267°E) and Kiboko (2.283°S; 37.700°E), which are located in Machakos and Makueni district respectively. These stations provided daily data on solar radiation, minimum and maximum temperatures and rainfall. Katumani station is located at an altitude of 1627 meters above sea level (m.a.s.l.), with average rainfall of 700 mm and the mean temperature for the growing season is 18.98°C. Kiboko station is located to the south at 988 m.a.s.l. altitude, with average rainfall of 460 mm and the mean temperature of the growing season is 23.2°C. A low resolution climate map (L_c) was created by making a partitioning of the area at 1,200 meters above the sea level with the Digital Elevation Model (DEM). With this delimitation two zones of rain and temperature were created (Fig 5.1c). The high resolution climate map (H_c) was produced by making a further division based on altitude, disaggregating the area in 17 rain zones with annual precipitation ranging from 450 mm to 2,050 mm (Fig 5.1d). Mean temperature was calculated with linear interpolation on the basis of altitude for the two weather stations.

Spatial Sensitivity Analysis

When evaluating the performance of land use models, the effects of different values of a particular variable on a target variable are typically tested by performing a sensitivity analysis. In this type of analysis it is possible to determine if a simulation result is importantly different compared to what was previously assumed by changing the value of one or more independent variables and measuring the effects on a dependent variable. At present, land use analysis incorporates environmental variables (soil and climate) in the form of maps, and therefore not only the changes in the value of the environmental variable can be tested with the model performance, but it is also possible to carry out a sensitivity analysis on the spatial resolution of the input data.

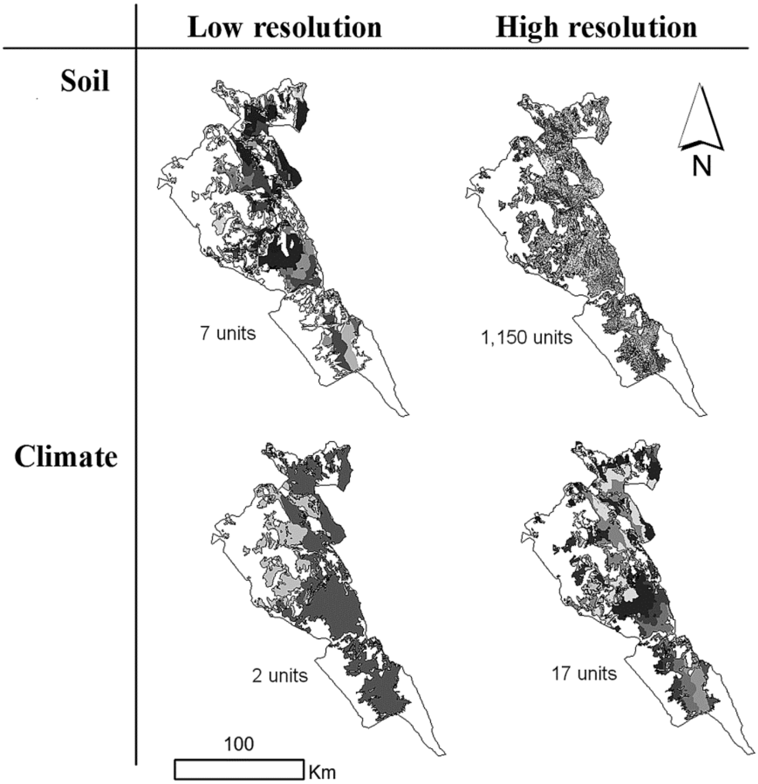


Figure 5.1 **Delineated areas of soil and climate on low and high resolution in the Machakos study area, Kenya (these are mapping units and therefore no legend is provided).**

There are several studies assessing the impact of spatial data resolution on the results of process-based models of erosion, soil fertility, soil moisture, water dynamics, etc. (Borman 2006; Kuo *et al.* 1999; Cotter *et al.* 2003; Gardiner and Meyer 2001; Claessens *et al*. 2005; Mednick 2010; Ruiz-Navarro *et al.* 2012). In this study we will examine the effects of spatial resolution of soil and climate data on a regional integrated assessment with TOA. The model performance will be first tested with the results of the different *inprods* for all the combinations of low and high resolution maps of soil and climate (LsLc, LsHc, HsLc, HsHc). Secondly, we will compare the results of a simulation run for the base scenario and a fertilizer scenario. In Kenya the high farm gate price of fertilizer is frequently considered to be the main cause for lack of fertilizer use (RoK, 2004), and lowering its price (by subsidizing e.g.) is a common recommendation in Africa to reduce soil nutrient depletion.

To define the fertilizer scenario the mean fertilizer price is reduced with approximately 50% resulting in mean fertilizer prices that roughly correspond to the world market price (Jayne *et al.* 2003). As maize prices are highly variable in the region, both the base and the fertilizer scenario will be analyzed with fluctuating maize prices. This is made with the trade-off curves, constructed by varying the mean maize price from -75% to +100%. The indicators chosen for the evaluation are seasonal farm income from agriculture (in Kenya Shillings, KSh excluding off farm income) and nitrogen depletion (Kg ha^{-1} y^{-1}). To quantify the effects of the different resolution map combinations on the model outcomes we will use the root-mean-square deviation (RMSD) as calculated in the following equation, calculated for all n grid cells.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{1,i}-x_{2,i}\right)^2}{n}}$$

5.3 Results and discussion

5.3.1 Effects of environmental data resolutions on inprods

The *inprods* provide a quantitative description of the soil-climate-plant processes and they include the spatial variability of the environmental conditions of the study area in the analysis. The estimation of the average *inprods* with the different soil and climate maps (Table 5.2) shows that for all cropping systems the average yields vary little when changing the resolution of the input data. The standard deviation (*Sd*) is higher for maize and lower for beans when using the low resolution climate map, while in the vegetable system, the *Sd* tends to decrease with decreasing data resolution. However, the variation of the *Sd* is generally small when changing data resolution, hence we would expect that the resolution of environmental input data will have a minor influence on the outputs of the model simulation with TOA. Notice that the response of the *inprods* on changes in soil properties depends on the crop. For example, maize yields are more affected by soil fertility than the bean yields. In the case of vegetables, this cropping system is more intensively managed and less affected by soil fertility.

Table 5.2 Average inprods in the Machakos study area with varying resolution of environmental data. Standard deviation in parenthesis.

Resolution	Maize		Beans		Vegetables No irrigation		Vegetables Irrigated	
HsHc	2206	(718)	1102	(423)	1872	(324)	8551	(794)
HsLc	2321	(921)	1066	(388)	1884	(311)	8167	(691)
LsHc	2249	(657)	1114	(402)	1909	(268)	8741	(693)
LsLc	2350	(866)	1076	(365)	1920	(247)	8339	(643)

Figure 5.2 illustrates the individual effect of soil and climate data resolution on the *inprods*. Regarding soil data (a), it appears that yields of maize and beans are very similar with the low and high resolution maps (R^2= 0.83 and 0.85 respectively) even though in this case we are not aggregating high resolution data for the low resolution map but using two completely different data sources. This can be explained partly because average SOC in the top soil is very similar for the two datasets, though clay content is higher in the low resolution dataset. In the case of the vegetable system, the linearity of the results is weaker (R^2=0.59), especially if irrigation is available (R^2=0.43). This happens because the differences in the clay content of the maps have an effect on the water balances and the vegetable model is more sensitive to water availability.

For example, a small overestimation of *inprods* can be observed with the L_s map, which has higher clay content. In the case of the climate data (b), although there is a high degree of correlation in maize and beans yields for both data sets (R^2=0.76) the low resolution map produces distinct clusters of points at certain yields while with the disaggregated high resolution map the yields are distributed over a wider range. In the Lc map yields of maize and beans are slightly higher than the H_c map. In the vegetable system the linearity decreases and correlation is very low (R^2=0.27) when irrigation is incorporated.

The spatial effects of changing data resolution are illustrated in Figure 5.3 by mapping the *inprods* of maize. As mentioned before, soil data resolution in this case has almost no effect on the estimation of maize *inprods* but the climate map does show differences. While yields in the central part of the area appear similar for both L_c and H_c maps, the L_c results in higher estimation of maize yields in the northern and southern part of the study area than the H_c map. This can be explained because the disaggregation of the climate map results in different rain zones that affect the estimation of maize yields.

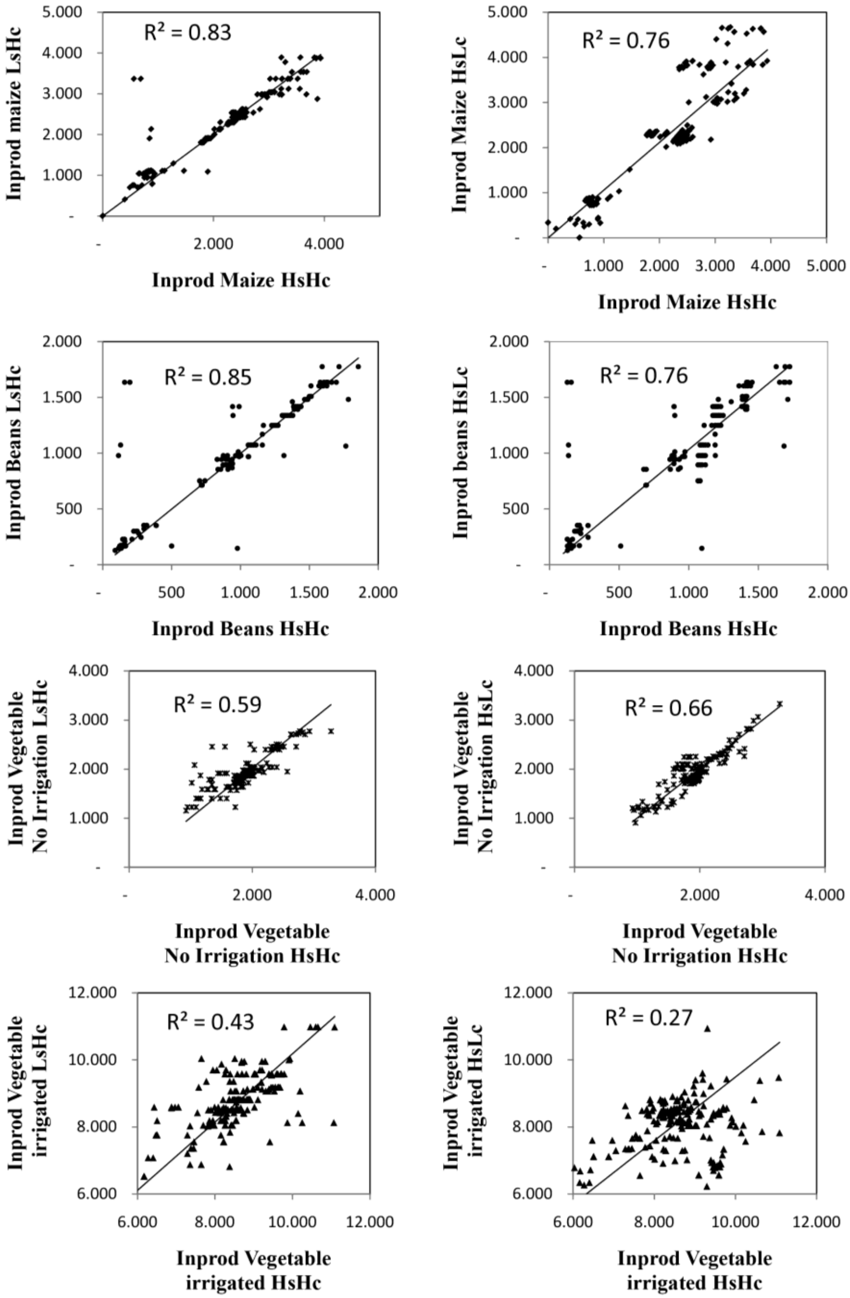


Figure 5.2 **Effect of a) soil and b) climate data resolution on the inprods (kg ha^{-1}) in the Machakos study area**

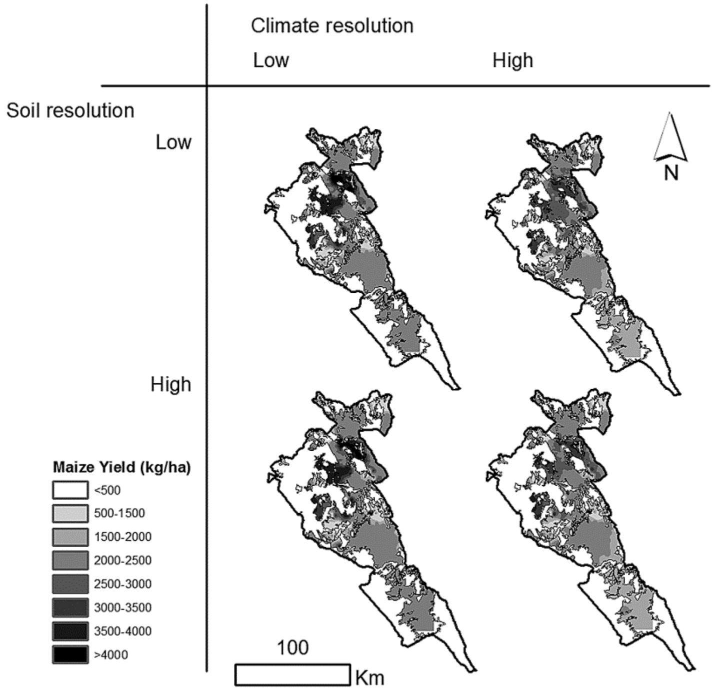


Figure 5.3 **Spatial effects of soil and climate data resolution on the inherent productivity of maize (kg ha^{-1}) in the Machakos study area, Kenya**

5.3.2 Effects of environmental data resolution on model estimation

For the Machakos application of TOA, the econometric production models are estimated with the *inprods* of maize and beans. These *inprods* are used in TOA as exogenous predictors of behavior in the estimation of econometric production models. They provide a statistically useful way to systematically incorporate soils, climate, and genetic information into the estimation of these models. Figure 5.4 illustrates that the correlation of the *inprods* of maize and beans is linear and a decrease in the resolution of the soil map has no effect on this correlation. A decrease in the resolution of climate data has a small effect on the strength of the correlation, but the change is not significant enough to expect changes in the model estimation.

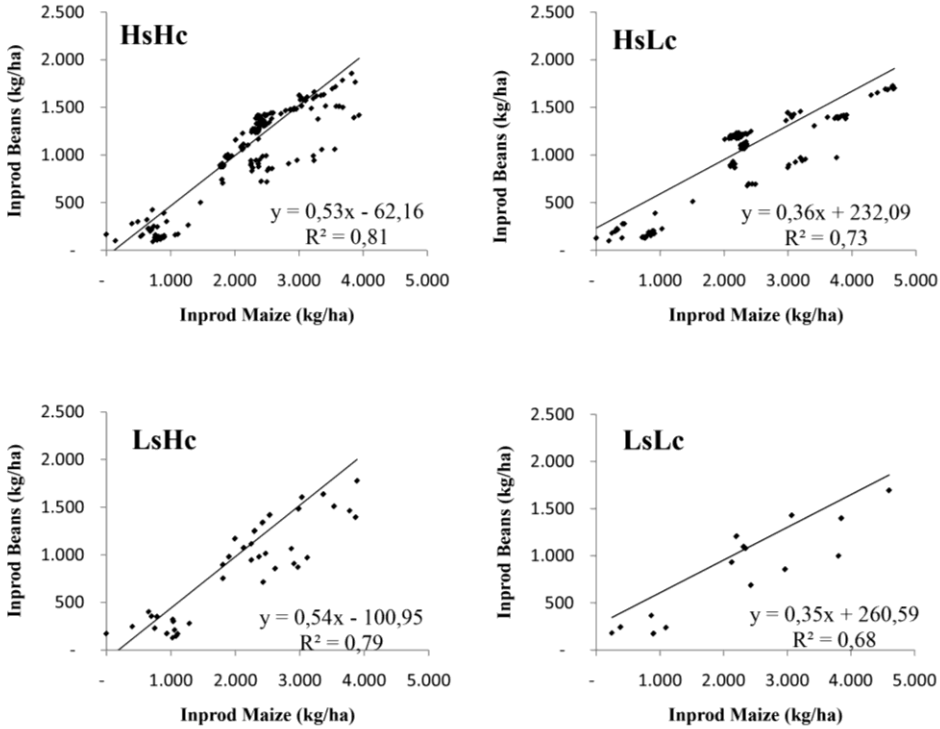


Figure 5.4 **Correlation of maize and beans inprods with changing data resolution in the Machakos study area**

5.3.3 Effects of environmental data resolutions on model simulation results

The results of the model simulation aggregated for the entire study area show that in the base scenario the average farm income is nearly 45,000 KSh and nitrogen depletion is around 33 kg per hectare per season. The base scenario represents the observed production conditions in terms of management and prices. These values are slightly modified in a fertilizer scenario, in which farm income is around 47,000 KSh and nitrogen depletion is 32 kg per hectare. The results of the indicators remain almost unchanged when performing the simulation at different map resolution. If we analyze the aggregated results of both the base and the fertilizer scenario with varying maize prices (Fig 5.5), we can see again that the changes in map resolution do not affect the shape and values of the tradeoff curves.

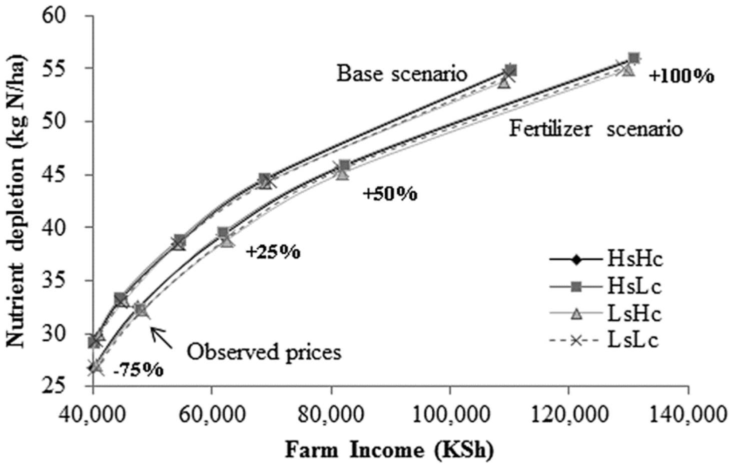


Figure 5.5 **Effects of environmental data resolution on nutrient depletion and farm income in the base and the fertilizer scenarios with varying maize prices (TOP) in the Machakos study area.**

When we look at the results aggregated at the cluster level (Fig 5.6) we can see that there are small differences in the simulation outputs but they do not significantly affect the interpretation of the results. Although as mentioned before the estimation of the *inprods* presented some changes, these differences are more related to the variation (spread) of the *inprods* rather than the average values, and no differences are visible when aggregating the results to the cluster level. The same is the case for the results at the cluster level for the fertilizer scenario.

In Figure 5.7 we mapped the impact of the fertilizer scenario over the base scenario for the sustainability indicators using the L_sL_c and the H_sH_c maps. This figure illustrates that when analyzing the results at the farm level, local differences can be identified.

The effect of the map resolution on the indicators at different scales is clearly illustrated in Figure 5.8 with the calculation of the RMSD of the simulation outputs at the regional, cluster and farm level. To quantify the effects of the different map resolution we analyzed the effect of the climate map alone (H_sH_c-H_sL_c), the soil map alone (H_sH_c-L_sH_c) and both climate and soil map with low resolution (H_sH_c-L_sL_c). The figure shows that the more aggregated the results, the less the resolution of input maps affects the outputs of the model simulation. However, if we want to do an analysis at the farm level, the map resolution needs to be considered.

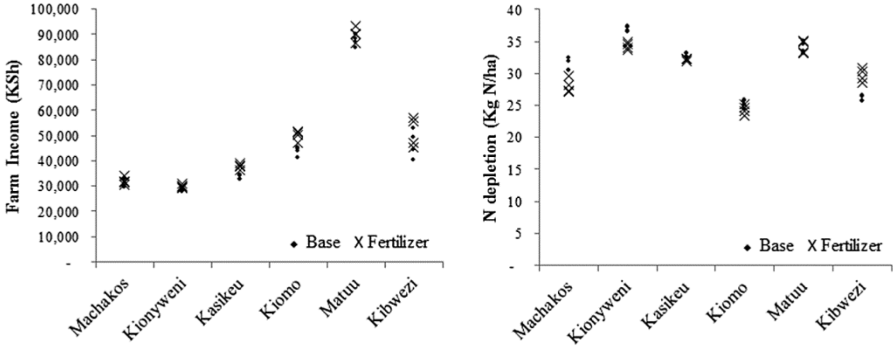


Figure 5.6. **Effects of environmental data resolution on nutrient depletion and farm income in the base scenario aggregated by village cluster in the Machakos study area.**

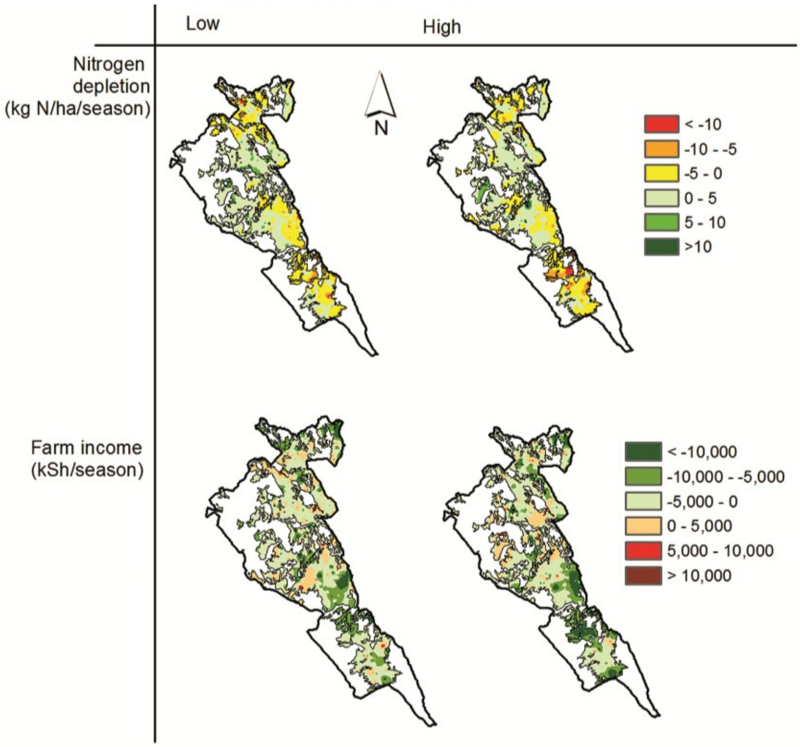


Figure 5.7 **Impact of the fertilizer scenario on nutrient depletion and farm income comparing model outcomes from LsLc to HsHc in the Machakos study area, Kenya.**

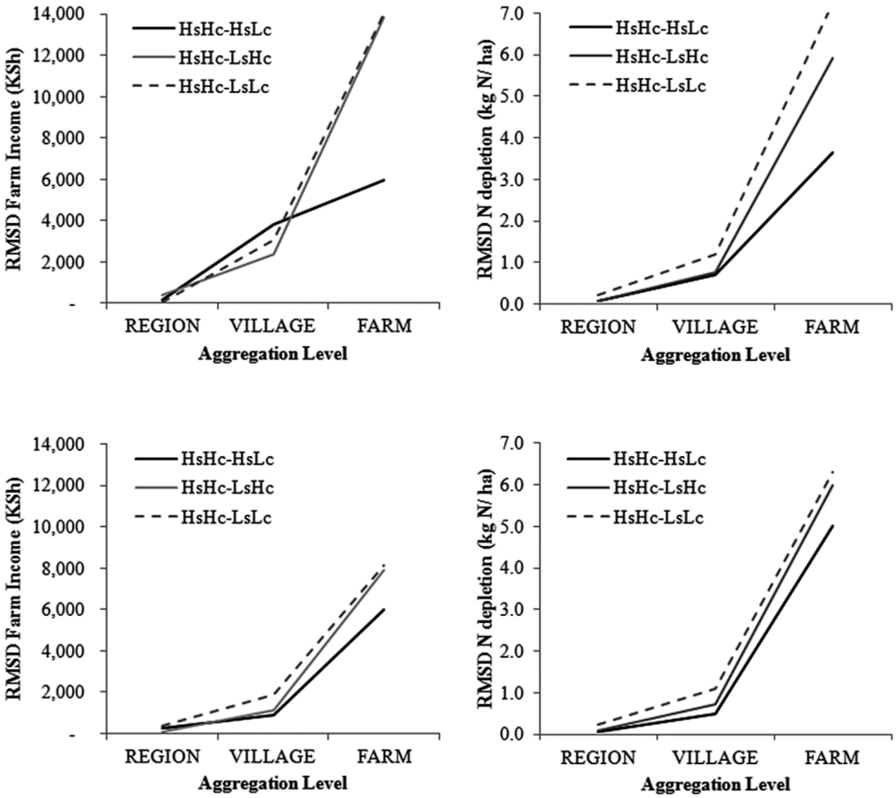


Figure 5.8 **RMSD of the indicators in the base scenario a) and the impact of the fertilizer scenario at different aggregation levels in the Machakos study area**

5.4 Conclusions

The results of this particular Machakos case study suggest that the resolution of the environmental data has very little effect on the outcomes of TOA. The calculation of the *inprods* with the different maps illustrates that the distribution of the results is affected by data resolution, but average values remain almost the same. Furthermore, the aggregated results of the simulation and the tradeoff curves in Machakos are similar for all map resolutions, and therefore using high or low resolution data would not necessarily translate into a different interpretation of the results by e.g. policy makers. In this specific case, we found that the model provides almost the same information when using "good" or "less good" GIS data, and policy makers would probably make the same decisions with any of the maps. If policies or technologies are implemented based on average values for model outcomes, the analysis may equally well be performed with low resolution data. In this respect, the recent developments of the TOA methodology have focused on a minimal data approach model for *ex-ante* impact evaluation with the Tradeoff Analysis model for Multi-Dimensional Impact Assessment (TOA-MD) (Antle 2011), which performs sufficiently accurate with a combination of a priori reasoning and available data. This type of approach has been successfully used for the analysis of technology adoption and payments for environmental services (Antle and Valdivia 2006; Antle and Stoorvogel 2008; Immerzeel *et al.* 2008; Claessens *et al.* 2009), climate change and adaptation impacts (Claessens *et al.* 2012) and adoption of a new maize variety (Antle 2011). However, this type of analysis is not spatially explicit and if spatial patterns or spatial variation in a certain study area are important in the analysis, high resolution environmental data are desirable.

In contrast, other studies on the effects of data resolution on process-based models show very different results. For example, Gardiner and Mayer (2001) tested the sensitivity of RUSLE to data resolution using a base layer of 30 m resolution map aggregated to 285 m in 15 m increments. They found that yield predictions were on average 2 – 300 times the values obtained when the base layer resolution was decreased, and that low resolution soil data led to higher predictions of sediment delivery to streams. In respect to hydrology models, Kuo *et al.* (1999) tested the effects of grid size on run-off and soil moisture and found that increasing grid cell sizes misinterpreted the curvature of the landscape resulting in higher water content and higher evaporation rates for large grid sizes. Claessens *et al.* (2005) found important effects of DEM resolution on the calculation of landscape topographic and hydrological attributes and when modeling landslide hazard and associated soil redistribution with the LAPSUS-LS model, Mednick (2010) also found systematic negative bias in the use of the State Soil Geographic database (STATSGO) in place of the higher resolution Soil Survey Geographic data (SURGO) in long-term hydrologic modeling of rainfall-runoff. Ruiz-Navarro *et al.* (2012) tested the effects of spatial resolution on landscape control of soil fertility and found that each landscape process controlling soil fertility (*e.g.* erosion, water availability) is better represented at different resolutions. These results suggest that special attention on spatial data resolution has to be paid when the analysis includes the use of spatially dependent models. In this case, under or over estimation derived from data resolution effects in the process-based models can lead to great error, especially for land use models and scenario assessment with long term simulation.

In the case of TOA, and based on the results for the Machakos application, the recommendation would be that low resolution data are good enough if the interest is focused on aggregated results, e.g. to inform policy making, but if one wants to look in detail to the farm level and target interventions at this scale, an effort should be made to use higher resolution data. However, obtaining high resolution data is often costly and time consuming and the deliberation should be made whether the type, extent and cost of the evaluated intervention is worth the investment.

Chapter 6

Synthesis

6.1 Introduction

The projected world's population growth and the consequential increasing demand for agricultural products and by-products represent a great challenge for future agricultural production. With the rising pressure over land and water resources, and less people engaged in farming activities, it would be wrong to expect that sustainable agricultural development will happen spontaneously just driven by market forces. If more environmental concern and fair access to food are intended in the process, the future evolution of agriculture will require careful planning, and sound policies and incentives to guide this development. For this reason, policy makers are gradually claiming for more effective tools to assist their decision making process and researchers are working hard to provide them with the proper methodologies and information required (FAO 2009, Godfray *et al.* 2010, van Ittersum *et al.* 2013, van Wart *et al.,* 2013). So the question nowadays is: are we well equipped to make reliable predictions for informed decision making?

Land use systems are certainly complex and the analysis of these systems is currently impossible to do on the basis of one single methodology. In this respect many modeling approaches have been developed (Bouma 1998, Giller *et al.* 2011[b], Britz *et al.,* 2012). Initially, they were in the form of individual models coming from different disciplines (*e.g.* social science, economics, ecology, agronomy) that looked at the biophysical or economic indicators separately. Nowadays the need for a comprehensive analysis of these systems resulted in the development of integrated assessment, in which the connections among the different indicators are included in the analysis. The quantification and monitoring of these indicators together with the understanding of the relationship between different driving factors, allows policy makers to have an idea of the present condition and dynamics of land use systems. If possible changes of these systems can be represented with modelled scenarios , the possible consequences of these changes can be assessed. With this information an array of policy or technology alternatives that increase the opportunities for farmers and the systems' sustainability can be evaluated and the results can be used as inputs for policy makers.

Models are normally used to predict what is likely to happen if a certain decision is made. Currently with the recent developments of geo information systems (GIS), the integration of the spatial variables within models is feasible. In this manner not only "what" is likely to happen can be evaluated but also the "where" question can be addressed. This allows for the identification of location specific interventions or impact analysis.

In particular this research focused on soil fertility decline in the mixed farming systems of Machakos (Kenya). This study area had been subject of numerous studies, most of them focusing on making thorough diagnoses of the systems and identifying their flaws and possible interventions to improve the actual conditions, but they generally failed to evaluate recommendations that could in fact produce the desired changes. Such an evaluation is only possible with an integrated modelling approach that connects and integrates the economic, biophysical and environmental aspects of the system. Hence, two existing methodologies, NUTMON and TOA, were combined to exploit their complementarities and perform integrated analysis in the Machakos systems.

6.2 Research findings

6.2.1 On Biophysical Data

The increasing demand for spatially explicit analysis of environmental problems is calling for accurate, up-to-date, spatially referenced information. In agriculture this is especially true for climate and soil data, which are the basic inputs of land use models (*e.g.* crop growth simulation, environmental models). In this respect, soils are back on the global agenda (Hartemink, 2008) and soil mapping has been considered as one of the pillars to the challenge of sustainable development (Sachs 2009). Soils are important not only to sustain food production, but seven soil functions have been defined to be preserved and restored (EU 2006). These functions are i) production of food and biomass, ii) storing, filtering and transforming compounds, iii) providing habitat and gene pool, iv) providing physical and cultural environment for human activities, v) source of raw materials, vi) acting as a carbon pool, and vii) archive of geological and archeological heritage. Together the main soil threats have been described as erosion, organic matter decline, contamination, salinization, compaction, loss of soil biodiversity, sealing, floods and landslides. With the renovated interest in soils, the demand for detailed, quantitative, high resolution soil data has increased. Traditional soil surveying techniques (USDA 1984, Soil Survey Staff 1993, USDA, 2007) have been gradually replaced by new methods which combine soil survey expertise, information technology, remote sensing, mathematics and statistics. This approach is commonly referred to as digital soil mapping (DSM) (McBratney *et al.,* 2003).

When this research started , the environmental data available for the study area was limited. Regarding weather data records from two weather stations were avilable, which were used to create a simple climate map with seven rain and temperature zones using interpolation techniques combined with the digital elevation model. On the other hand, the soil map was initially created merging the soil units of the 1:1,000,000 Exploratory Soil Map of Kenya (Sombroek *et al.,* 1980) with the representative soil profile descriptions of the Fertilizer Use Recommendation Program (MoA 1987). However, since the map was intended for the spatially explicit analysis of agricultural productivity, we decided to create a new high resolution map testing DSM techniques. To do this we focused in mapping soil organic carbon (SOC) and clay content of the top horizon. These two properties are suitable to derive the top soil's relevant information for crop growth simulation models (soil fertility and water holding capacity).

Results showed that DSM is a promising technique for the spatial prediction of soil properties. Besides, given the complex characteristics of the Machakos study area, the size (13,500 km^2) and the limited number of observations used for the analysis, the regression models obtained for SOC and clay were satisfactory. However, the map's accuracy was low and only marginally better than just taking the sample mean to predict the soil property for all locations.

Creating the high resolution soil map required field work (both time consuming and expensive), and intensive data analysis. Although probably DSM techniques are still more rapid than traditional soil survey, the question was to what extent higher resolution data is essential in land use analysis? Would high resolution data improve model results? In order to answer these questions two different (low and high resolution) datasets of soil and climate were tested as environmental inputs for our NUTMON-TOA approach. The results of this particular case showed that the resolution of the environmental data had very little effect on the model outcomes, and though the distribution of the results is affected by data resolution, average values remain almost the same. This is especially true when we look at the aggregated results of the model simulations, which establish that using high or low resolution data would not necessarily translate into a different interpretation of the results by the policy makers. This result is case study specific, as other studies have demonstrated the strong effects of data scale and data aggregation on modelling and decision making (Kok and Veldkamp, 2011)

6.2.2 On Integrated Assessment

The linkage of NUTMON and TOA methodologies proved to be an excellent combination for the integrated assessment of the Machakos' farming systems.

NUTMON provided a complete descriptive analysis of individual farms, with a full socio-economic characterization, including records of cash and crop flows. In terms of nutrient balances, this information was used to determine current rates of change in soil fertility, identify the main processes driving the soil nutrient flows, and target an array of local interventions that could balance these flows. Adding the TOA methodology allowed to use the economic and biophysical data gathered from NUTMON in a novel innovative manner. First, farm outcomes (together with soil and climate information) were used to calibrate the econometric equations of TOA simulations models, and later the results were transformed into indicators such as Soil Nutrient Depletion, Income, Poverty, Food Security, etc. that are used to perform the *ex-ante* evaluation of possible policy or technology interventions in those systems. For this, NUTMON also made available the environmental impact assessment model of nutrient balances. With the NUTMON-TOA approach we can assess how polices and technologies will affect production, environment, or poverty, and so on, giving direction towards sustainable development pathways.

Since the NUTMON survey data is geo-referenced, with the combination of TOA it was possible to use the data of individual farms of NUTMON and up-scale it to the regional level, creating spatially explicit results that can also be displayed in the form of maps. These maps are a simple, appealing and an informative visualization tool for policy makers, and consequently they will allow policy makers to make informed decisions about the region.

6.2.3 On Policy Analysis

The Kenyan Strategy for Revitalizing Agriculture (2004) is a national policy document that addresses the challenge of improving farmers' livelihoods in Kenya. The interventions proposed in this strategy have also been subscribed by other policy documents like the Economic Recovery Strategy (2003), the Millennium Goal Project (2005) and the Kenya Vision 2030. Therefore, the NUTMON-TOA approach was used to evaluate in the mixed farming systems of Machakos what would be the consequences of a few of the most commonly suggested interventions that are considered to improve agricultural production and soil nutrient status.

The findings, contrary to what is generally believed, show that policies reducing farm gate price of mineral fertilizer decrease soil nutrient depletion rates in Machakos only by little. In addition, farmers do not benefit from this type of policy because the indicators of farm income and poverty remain almost unchanged. At the same time, if we promote to increase the efficiency of manure use by *e.g.* promoting zero grazing units, composting, manure pit, etc. we find that having more manure available will lead farmers to change their cultivation pattern to a more maize-oriented system, which is a highly nutrient depleting crop. Even if economic indicators can slightly improve with this measure, a larger area dedicated to maize will worsen the nitrogen balance situation of Machakos. The same effect occurs if a drought resistant maize variety is introduced, because cultivating more maize has a negative long term impact on soil nutrient balances. What is interesting is to find that maize price is the only variable that has the potential to substantially increase (or decrease) income. This suggests that investments that reduce transport costs and increase the market efficiency would have more beneficial effects rather than changes in on-site management practices. This is a nice example how external factors have more impact on local sustainability than local factors. In the current situation, the resources available in the households of the subsistence farming systems of Machakos are too limited to sustain substantial increases in income or prevent the mining of soil nutrients. The extremely small farm size and large family size also suggest that public policies that promote rural development and increase opportunities of off-farm income could have a larger impact on both income and sustainable development. Price policies (market instruments) have to be improved and other forms of taxation, subsidies, etc. have to be introduced in the policies to evaluate. In the same line, we could argue if the Government should base its intervention on increasing local food production only, or if it would be more effective to direct the effort towards increasing access to food and stimulating rural development in general. This makes our Machakos case study a nice example of how scaling and governance are both interlinked (Kok and Veldkamp, 2011).

On the other hand, the individual results for the different farms in the Machakos study area show that even within a relatively small region, spatial differences in farmers' behavior appear together with varying responsess to incentives. This suggests that although the use of aggregated results (or averages) are an informative indicator which well represents the situation of the area, the use of individual results translated into maps could provide the spatial expression of market or environmental differences, and this information can be used by policy makers to target the areas that need urgent or specific intervention.

6.3 Implications of research findings

Applicability.

This case study confirms the hypothesis that NUTMON and TOA are complementary and that linking these two methodologies can provide important information for policy analysis. These combined methodologies are not only site specific, they are also scale sensitive. Even though these results come from one single case study in Kenya, the procedure is available to be replicated in other places of the world where NUTMON studies have been carried out characterizing different subsistence and semi-subsistence farming systems such as in Ethiopia (Haileslassie *et al.* 2005, Van Beek *et al.* 2009), Vietnam (Phong *et al.* 2011), and India (Surendran and Murugappan, 2007[a], 2007[b], 2010). The developed NUTMON-TOA approach has established a procedure to analyze in depth the sustainability of subsistence and semi-subsistence farming systems. Such tool could be beneficial when trying to give a proper direction to the agricultural development of these systems. In the future not only soil nutrient depletion can be studied but also to other relevant environmental sustainability indicators such as erosion, nitrogen leaching, carbon sequestration, water use efficiency, pollution, and so on.

Contribution to modeling.

Semi-subsistence agriculture remains the dominant type of agriculture in developing countries, especially in the poorest and most environmentally vulnerable regions. These systems present certain characteristics that make modeling them more difficult than systems typical of more commercially-oriented agriculture. Normally semi-subsistence systems have a low degree of specialization and a high degree of diversification, mixing crop-livestock systems with a large number of different types of annual and perennial crops and inter-crops, where crop failure is common. The fields are very small and seasonal reconfiguration of sub-parcels within fields is common. In addition the purchase of inputs is limited, mostly applied to some cash-crops, whereas many farmers apply zero amounts. These characteristics have been taken in account when setting up the econometric models in the case study of Machakos, and this experience is of undeniable value if more cases are to be studied. For example, we simplified the *inprods* variables to only four cropping systems (maize, beans, inter-crop and vegetables) which provide good explanatory variables to the input demand and output supply functions. We also incorporated to the model the high rates of crop failure, the interactions between crops and livestock systems, and the use of non-essential inputs such as fertilizer, hired labor and pesticides.

Resolution of biophysical data.

Although soil organic matter and clay content of the soil map achieved with DSM techniques was acceptable for this application, the sampling density was probably too low to capture important processes which have a dominant effect on the spatial variation of the targeted soil properties. Site specific modelling of erosion and deposition as done by Lesschen et al., (2007) could have enhanced our soil specific data quality. When analyzing the resolution of biophysical data, the results suggest that special attention has to be made when the analysis includes using spatial dependent models. In this case, the under/over estimation derived from data resolution in the process-based models can induce to great error, especially for land use models and scenario assessment with long term simulation. On the other hand, when evaluating econometric models, we found that the model provides almost the same information when using "good" or "less good" GIS data, and policy makers would probably make the same decisions with any of the maps. But this outcome might be different for other regions.

Within our case study we could argue that if policies or technologies are implemented over average values, the analysis may well be performed with low resolution data. In that respect the recent developments of the TOA methodology have focused on a minimal data approach model for *ex-ante* impact evaluation with the Multi-Dimensional Impact Assessment (Antle, 2012) which performs sufficiently accurate analysis with a combination of a priori reasoning and available data. However, if spatial patterns or spatial variation of a certain area are important in the analysis, then high resolution environmental data is desirable.

Site-specific recommendations/ impact evaluation.

In Kenya (and in most Sub-Saharan Africa) agricultural production comes mainly from smallholder subsistence farmers, and varies greatly between farm types and across localities. This high degree of heterogeneity suggests that conventional policies will have different impacts in different locations, and that blanket recommendations are simple not suitable. For example, farmers in high potential areas will positively respond to price incentives (Mose 2007) but in low potential areas specific complementary interventions should be taken into account to change farmers' management. This variability should be taken in account when developing new technologies and policies for particular agricultural systems. The NUTMON-TOA approach was designed specifically to incorporate the spatial variability of the area under study into the analysis and with this approach it is possible to make a site-specific evaluation of possible interventions in a determined area. In the same line, by exploring the consequences of the different interventions, site-specific recommendations can be made.

For example, in the Machakos case, the evaluation of a few of the general interventions that suggested how to improve farming systems, we found that these changes normally will not have the expected results in an area such as Machakos. On the contrary, the variation of the price of maize -one of the major commodities-, has more influence on poverty and food security than any of the suggested improved technologies. This unexpected result illustrates that before chosing interventions the situation has to be analyzed in an integrative manner and for specific locations.

Multi-scale analysis.

The NUTMON-TOA approach allows looking at the study area at different levels. The results can be displayed for individual farms, but can also be aggregated for a population of farms, to the village or the regional level. In this respect we could find that the level of aggregation could provide different answers to the same question, and that yielding detailed site specific recommendations or identifying generic policies that will change farmers' behavior are both possible with this approach. These model properties make the NUTMON-TOA combination a suitable multi-scale governance tool.

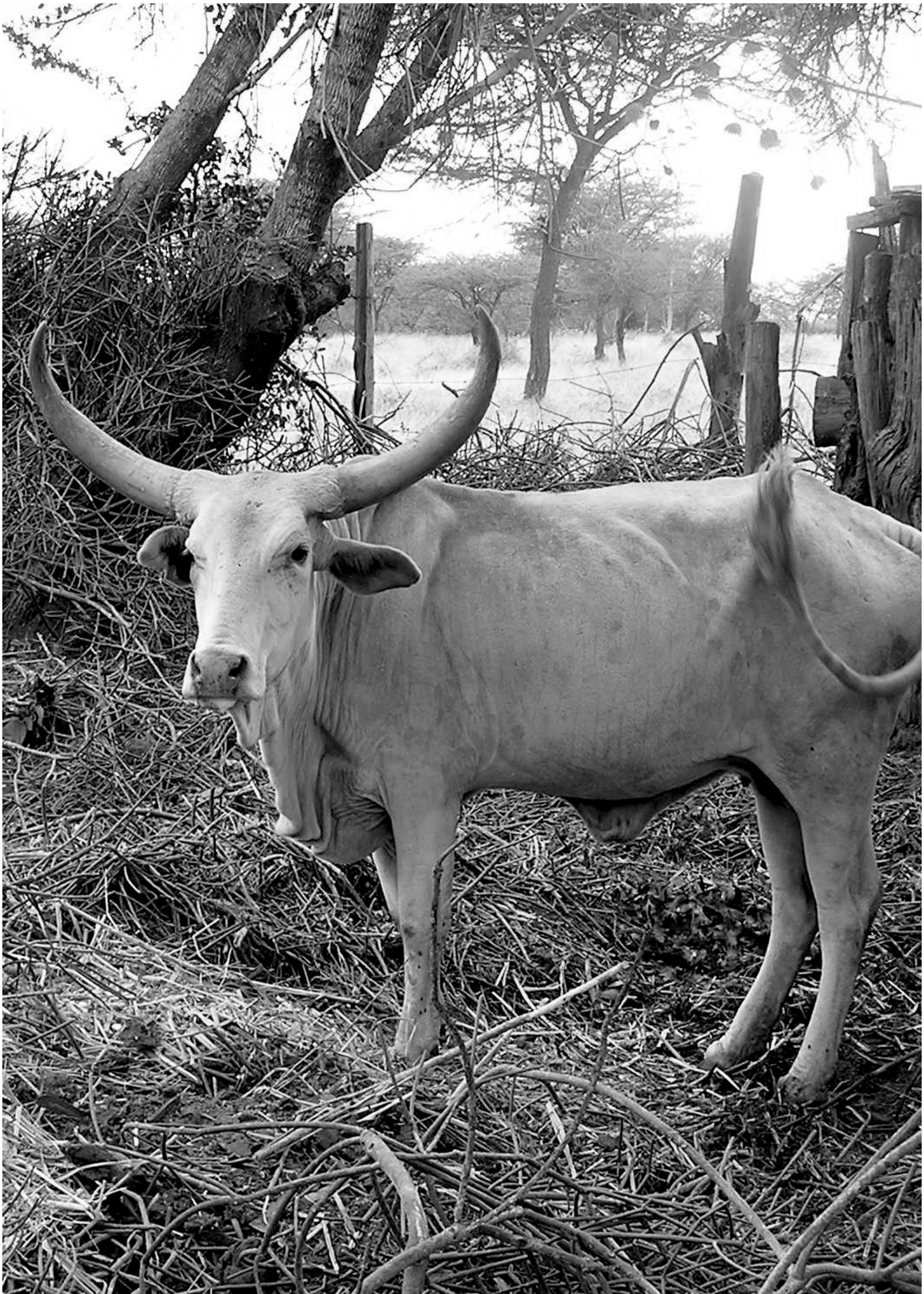
6.4 Future research

Future development of this approach should include the temporal pathway development of the biophysical data, including the effects of changes in environmental conditions (e.g. climate change), soil organic matter dynamics, water redistribution and soil erosion/re-deposition effects. All these factors combined are the landscape legacy effect that may have a long term impact on the system dynamics.

In addition, if long-term effects of policy interventions or technology changes are to be evaluated, this approach should allow the simulation of extended periods of management. In order to do so, considerations have to be made on spatial and temporal dynamics, feedbacks (*e.g.* the effect of increased fertilizer use on productivity), and farmers' capacity to adapt and innovate, and so on. This might require a link with agent based modelling (ABM) to do realistic assessment (Veldkamp, 2009).

Regarding the validation of this type of analysis, issues like sensitivity and uncertainty also have to be addressed.

Finally, this research showed that the resolution of the environmental input data does not always impacts the results of the integrated assessment. In future, research on the sensitivity of the model and the assessment of a certain resolution is needed. In this respect minimum data approaches (Antle *et al.*2010*,* 2014), can be of a promising alternative.



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Summary

Increasing the efficiency of agricultural production is key when addressing poverty and hunger in subsistence farming systems of developing countries. In these regions, changes into more productive and sustainable land use need to be directed by strong public interventions and investments. While policy documents for agricultural improvement often end up with a general “to do” list of recommendations, the actual effects of these technology or policy interventions are seldom evaluated for specific regions or cases. This thesis proposes to combine biophysical and economic research into an integrated assessment which can help to evaluate these recommendations for specific conditions.

Because the assessment of regional policy analysis often requires a large amount of specific data and great efforts in model development, this thesis proposes to use previous research and existing models as a solid base to a new integrated approach. Therefore, new technologies for data gathering such as Digital Soil Mapping (DSM) are tested. DSM techniques appear to be an interesting alternative for traditional soil survey techniques. However, most applications deal with (semi-)detailed soil surveys where soil variability is determined by a limited number of soil forming factors. The question that remains is whether digital soil mapping techniques are equally suitable for exploratory or reconnaissance soil surveys in more extensive areas with limited data availability. In this research we applied digital soil mapping in a 13,500 km^2 study area in Kenya with the main aim to create a reconnaissance soil map to assess clay and soil organic carbon contents in terraced maize fields. Soil spatial variability prediction was based on environmental correlation using the concepts of the soil forming factors equation. During field work, 95 composite soil samples were collected. Auxiliary spatially exhaustive data provided insight on the spatial variation of climate, land cover, topography and parent material. The final digital soil maps were elaborated using regression kriging. The variance explained by the regression kriging models was estimated as 13% and 37% for soil organic carbon and clay respectively. These results were confirmed by cross-validation and provide a significant improvement compared to the existing soil survey.

Nearly 70% of the Kenyan livelihoods depend on agriculture. Because it is the country's main economic activity, increasing agricultural production is crucial to economic growth and food security. However, soil fertility decline is a growing limitation for agricultural development in many sub-Saharan farming systems. In the early 90s the Nutrient Monitoring methodology (Nutmon) was developed to quantify nutrient flows at the farm level. Although Nutmon results can be used to identify new technologies to maintain soil

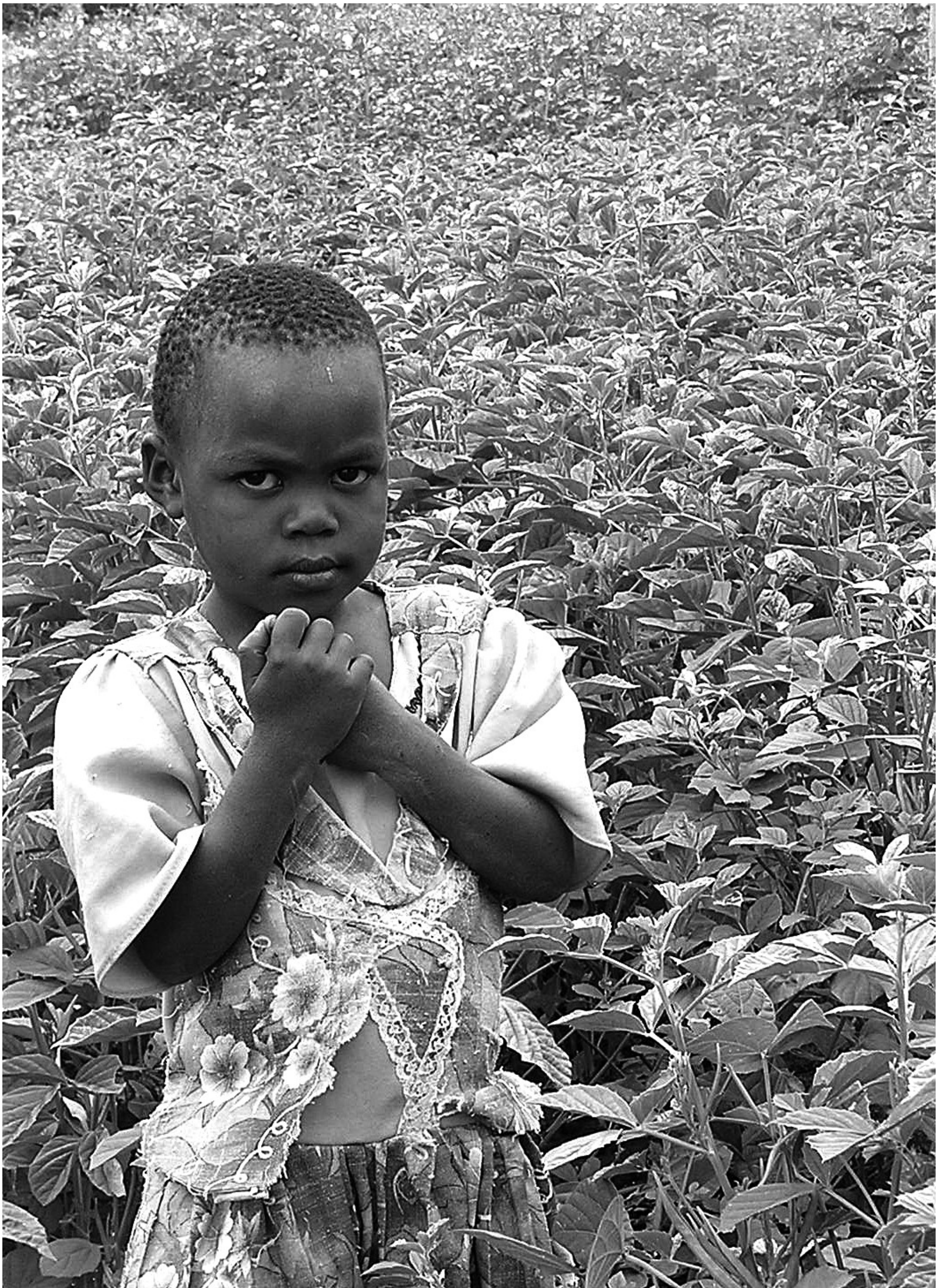
fertility, the methodology does not provide a way to evaluate the potential environmental and economic effects of technologies or policies on regional agriculture. Conversely, the Tradeoff Analysis model (TOA) is a participatory approach developed to perform an integrated assessment of agricultural systems for informed policy decisions, but TOA is constrained by data requirements and it needs linkages to external models to evaluate environmental indicators. In this thesis these two methodologies were linked to implement a participatory regional integrated assessment of agricultural systems. By linking these two approaches it is possible to look at the outcomes of Nutmon studies in a novel manner. At the same time, TOA benefits from Nutmon because it provides an excellent standardized base of farm data and environmental models.

As an illustration of this linkage, an application to the semi-subsistence farming systems in the study area of Machakos (Kenya) was developed. Particular attention was paid to the problem of soil fertility decline. Several policy documents have acknowledged this situation and suggest a list of interventions that should be implemented to enhance Kenyan agriculture. However, the possible impacts of these interventions have not yet been evaluated. In this research we selected agricultural interventions from the Kenyan Strategy to Revitalize Agriculture (SRA) and evaluated the economic and environmental consequences of these interventions with the TOA methodology. Results show that the subsistence farming systems of Machakos will benefit little from the interventions proposed in the SRA. For example, policies oriented to decrease fertilizer farm gate price will fail to increase farm income and reduce nutrient depletion. On the other hand, when management practices that increase the efficiency of manure use are encouraged, a change in the cultivation pattern to a more maize oriented system is observed, an as a result nutrient depletion increases. The price of maize is the only variable that has the potential to substantially increase income, but it also increases nutrient depletion. The resources available to these households are too limited for them to achieve substantial increases in income or prevent the mining of soil nutrients with any of the interventions evaluated.

Results of this type of assessment provide policy makers with reliable information of the possible consequences of their decisions, so they can target effective policy and technology interventions. Policy makers need a clear overview and this can only be achieved if economic, biophysical and environmental indicators are connected. However, advances in geographic information systems, computing power, network storage capacity and the increasing availability of data, allow for the development of complex, site-specific land use models. While the global trend is that environmental data are becoming available at higher resolutions, these data are seldom ready for direct use and compiling adequate data for land use modeling is often a difficult and tedious task. In this context, it is important to explore whether the resolution of input data influences the outcome of the land use models and to what extent higher resolution data are required to come to a similar, or 'good enough' result for policy advice. In this study we evaluated the effects of the resolution (low and high) of soil and climate data on regional land use analysis. Firstly, we evaluated the impact of data resolution on the production potential as assessed by the crop growth simulation models within TOA. Secondly, the impact of these differences in production potential on a simulation run for the base scenario and a fertilizer scenario is assessed using the economic model. As maize prices are highly variable in the area, both scenarios are analyzed with fluctuating maize prices. Farm income and nitrogen depletion are the sustainability indicators under consideration. Results show that the average production potential varies little with different resolution of soil and climate data. In this case of model simulation, the more aggregated the results, the less the resolution of input maps affects the outputs. In this specific case, we found that policy makers will probably make the same decisions irrespective of the resolution of the map. However, if local variability is relevant, the map resolution needs to be considered. Recent developments of the TOA methodology have focused on a minimal data approach, which performs sufficiently accurate analysis with a combination of a priori reasoning and available data. However, if spatial patterns or spatial variation of a certain area are important in the analysis, then high resolution environmental data is desirable.

This case study confirms the hypothesis that NUTMON and TOA are complementary and that linking these two methodologies can provide important information for policy analysis. This approach could be beneficial when trying to give a proper direction to the agricultural development of semi-subsistence farming systems, which remains the dominant type of agriculture in developing countries, especially in the poorest and most environmentally vulnerable regions. These systems have a high degree of heterogeneity, therefore conventional policies will have different impacts in different locations, and blanket recommendations are simple not suitable.

Future development of this approach should include the temporal pathway development of the biophysical data, including the effects of changes in environmental conditions (e.g. climate change), soil organic matter dynamics, water redistribution and soil erosion/re-deposition effects. All these factors combined are the landscape legacy effect that may have a long term impact on the system dynamics. In addition, if long-term effects of policy interventions or technology changes are to be evaluated, this approach should allow the simulation of extended periods of management. In order to do so, considerations have to be made on spatial and temporal dynamics, feedbacks, and farmers' capacity to adapt and innovate, and so on. Regarding the validation of this type of analysis, issues like sensitivity and uncertainty also have to be addressed.



Samenvatting

In de zelfvoorzienende landbouw in ontwikkelingslanden is het verhogen van de efficiëntie van de landbouwproductie noodzakelijk om armoede en honger te bestrijden. Beleidsinterventies en investeringen zijn nodig om landgebruik in deze regio's productiever en duurzamer te maken. Beleidsdocumenten voor landbouwontwikkeling eindigen vaak met een algemene lijst van aanbevelingen. De werkelijke effecten van de voorgestelde technologieën of beleidsinterventies worden echter zelden geëvalueerd voor specifieke regio's of situaties. Dit proefschrift stelt voor om biofysische en economisch onderzoek te combineren in een geïntegreerde analyse zodat deze aanbevelingen voor specifieke condities geëvalueerd kunnen worden.

Omdat de geïntegreerde analyse van regionale studies vaak om een grote hoeveelheid invoergegevens en modelontwikkeling vraagt, stelt dit proefschrift voor om eerder onderzoek en bestaande modellen te gebruiken als een basis voor de nieuwe, geïntegreerde analyse. Daarom zijn nieuwe technologieën voor het verzamelen van gegevens, zoals digitale bodemkartering, getest. Digitale bodemkartering blijkt een interessant alternatief voor de traditionele karteringstechniek. Het wordt echter meestal toegepast in (semi-) gedetailleerde bodemkarteringen waar de bodemdiversiteit bepaald wordt door een beperkt aantal bodemvormende factoren. Het blijft de vraag of de techniek even geschikt is voor karteringen in uitgestrekte gebieden met een beperkte beschikbaarheid van gegevens. In dit onderzoek is de variatie in klei en organische stof in een studiegebied van 13.500 km^2 in Kenia in kaart gebracht met behulp van digitale bodemkartering. De voorspelde ruimtelijke variabiliteit in bodemeigenschappen was gebaseerd op correlaties met omgevingseigenschappen die de verschillende bodemvormende factoren representeren. Tijdens het veldwerk werden mengmonsters van de bovengrond van geterrasseerde mais velden verzameld. Ruimtelijk dekkende gegevens van omgevingsfactoren gaven inzicht in de variatie in klimaat, bodembedekking, topografie en moedermateriaal. De digitale bodemkaarten werden uitgewerkt met behulp van regressie-kriging. De regressie modellen verklaarden respectievelijk 13% en 37% van de variantie in organische stof en klei. Deze resultaten werden bevestigd door een cross-validatie en waren een aanzienlijke verbetering ten opzichte van de bestaande bodemgegevens.

Bijna 70% van de Keniaanse huishoudens is voor het levensonderhoud afhankelijk van de landbouw. Omdat het de belangrijkste economische activiteit van het land is, is het verhogen van de landbouwproductie ook essentieel voor economische groei en voedselzekerheid. De achteruitgang in bodembodemvruchtbaarheid is in toenemende mate een beperking voor de ontwikkeling van landbouwsystemen in sub-Sahara Afrika. In het begin van de negentiger jaren is de Nutmon methodiek ontwikkeld om nutriënten stromen op bedrijfsniveau te kwantificeren. Nutmon resultaten kunnen worden gebruikt om nieuwe technologieën te identificeren die boeren in staat stellen om de bodemvruchtbaarheid te behouden. Nutmon kan echter niet de mogelijke milieu en economische effecten van technologieën of beleid op de regionale landbouw evalueren. Naast Nutmon is er echter ook een participatieve aanpak ontwikkeld om het effect van interventies of nieuwe technologieën te evalueren door een geïntegreerde analyse. De toepassing van dit *Tradeoff Analysis* model (TOA) is echter beperkt door de vereiste invoergegevens. Daarnaast heeft het koppelingen met externe modellen nodig om milieu-indicatoren te evalueren. In dit proefschrift worden Nutmon en TOA gekoppeld voor een participatieve, regionale, geïntegreerde analyse van landbouwsystemen. Door de koppeling van deze twee benaderingen is het mogelijk om de resultaten van Nutmon studies op een nieuwe wijze te bekijken. Tegelijkertijd, profiteert TOA van Nutmon omdat het op een uitstekende gestandaardiseerde manier gegevens verzameld en veranderingen in bodemvruchtbaarheid kan bepalen.

Om de koppeling van deze twee modellen te illustreren is een studie voor complexe semi-zelfvoorzienende landbouwsystemen in een studiegebied van Machakos (Kenia) uitgevoerd. Het probleem van dalende bodemvruchtbaarheid heeft bijzondere aandacht gekregen. Verschillende beleidsdocumenten herkennen het probleem en komen met een lijst van mogelijke maatregelen voor de Keniaanse landbouw. Echter, de mogelijke effecten van deze interventies zijn niet geëvalueerd. In dit onderzoek hebben we verschillende interventies uit de Keniaanse strategie om de landbouw nieuw leven in te blazen (SRA) geselecteerd. De economische en milieu gevolgen van deze maatregelen zijn geëvalueerd met de TOA methodologie. De resultaten laten zien dat de landbouwsystemen in Machakos weinig zullen profiteren van de in de SRA voorgestelde interventies. Beleid gericht op het verlagen van de kunstmestprijs verlagen zal het bedrijfsinkomen niet verhogen en de daling in bodemvruchtbaarheid niet doen afnemen. Ook maatregelen gericht op het verhogen van de efficiëntie van dierlijke mest lijken niet te werken doordat ze leiden tot een uitbreiding van het areaal onder mais dat relatief weinig opbrengt en gepaard gaat met nutriënten verliezen. Het verhogen van de maïs prijs is de enige maatregelen die het inkomen van de boeren verhoogt, maar ook dan zullen de nutriënten verliezen toenemen door een toename van mais areaal. Het lijkt erop dat geen van de voorgestelde maatregelen zowel het inkomen verhoogd alsmede de nutriëntenverliezen stopt door de beperkte middelen van de huishoudens.

Dit soort evaluaties geven beleidsmakers betrouwbare informatie over de mogelijke gevolgen van hun beslissingen zodat ze zich kunnen richten op effectieve interventies in termen van beleid en technologie. Beleidsmakers hebben behoefte aan een duidelijk overzicht waarvoor informatie over economische, biofysische en milieu indicatoren verbonden moet zijn. Echter, de vooruitgang in geografische informatiesystemen, rekenkracht, opslagcapaciteit en de toenemende beschikbaarheid van gegevens, zorgen voor de ontwikkeling van complexe, ruimtelijk expliciete landgebruik modellen. Wereldwijd komen gegevens over onze natuurlijke hulpbronnen en landgebruik steeds vaker op hogere resoluties beschikbaar. Deze gegevens zijn zelden klaar voor direct gebruik en het samenstellen van adequate invoergegevens voor landgebruik modelleren is vaak lastig. Daarom is het van belang te onderzoeken wat het effect van de resolutie van invoergegevens is op het resultaat van de landgebruiksmodellen en in welke mate de hogere resolutie nodig is om een vergelijkbaar of "goed genoeg" resultaat te geven. In deze studie hebben we de effecten van de lage en hoge resolutie bodem en klimaat gegevens op de regionale landgebruiksanalyse geanalyseerd. Ten eerste hebben we het effect van data-resolutie op de landbouwproductie bestudeerd met behulp van de gewasgroei simulatiemodellen binnen TOA. Ten tweede is de invloed van deze verschillen in productiepotentieel op een simulatie voor een basisscenario en een meststof scenario beoordeeld met behulp van het economische model. Aangezien de prijzen van maïs zeer variabel zijn, zijn beide scenario's geanalyseerd met fluctuerende maisprijzen. De duurzaamheid van de systemen is geanalyseerd in termen van het inkomen en de stikstof uitputting van de bodem. De resultaten tonen aan dat de verschillen in resolutie van bodem en klimaat gegevens niet leiden tot grote verschillen in de gemiddelde productie. Als we naar meer geaggregeerde resultaten kijken maakt de resolutie van de invoergegevens minder uit. In dit specifieke geval hebben we vastgesteld dat beleidsmakers waarschijnlijk dezelfde beslissingen nemen, ongeacht de resolutie van de invoergegegevens. Indien de lokale variaties relevanter zijn, dan moet de resolutie van de invoergegevens wel mee worden genomen.

De verdere ontwikkeling van de geïntegreerde analyse zou de temporele dynamiek in biofysische data mee moeten nemen zoals de effecten van klimaatsveranderingen, organische stof dynamiek, water herverdeling in het landschap, en de effecten van bodemerosie en depositie. Gezamenlijk geven deze factoren een erfenis aan het landschap mee die nog in de verre toekomst effecten kan hebben op de dynamiek van deze systemen. Daarnaast zouden de simulaties over meerdere groeiseizoenen moeten plaats vinden om de lange termijn effecten van politieke maatregelen of veranderingen in productie technologieën te evalueren. Om dit verder uit te voeren moet men specifiek kijken naar o.a., de ruimtelijke en temporele dynamiek, terugkoppelingen, en de mogelijkheid van boeren om hun productie systeem aan te passen en te innoveren. Voor de validatie van deze geïntegreerde analyse moet men met name gevoeligheidsanalyse en onzekerheid bekijken.

About the author

Curriculum vitae

Alejandra Mora Vallejo was born in Santiago de Chile on September 23, 1970. She graduated in Agricultural Engineering at *Universidad de Chile* in 1996 and then joined the *Servicio País*, a program developed by the National Foundation for Poverty Alleviation (FNSP) to provide technical assistance to the poorest rural areas in Chile. She was appointed to the Municipality of Rio Ibáñez (Aysen region, Patagonia) where she worked in the elaboration of the County Development Plan, and later in project formulation, fund searching and building local networks. In 1998 she continued working in Rio Ibáñez as a consultant for the National Agriculture Development Institute (INDAP) giving technical assistance to a group of small-scale farmers and collaborating with the Municipality in issues related to productive activities and community development, such as projects on horticulture, forestry, agro-tourism, innovation technology and claims on water rights. In 1999 she moved to Alhué where she became head of the Planning Department of the Municipality. In 2000, she obtained the *Beca Presidente de la República* fellowship from the Chilean Government, and she was accepted in the MSc. Program Soil Inventarization and Land Evaluation at Wageningen University, The Netherlands. She completed her MSc in 2002 with a thesis in system prototyping in Western Kenya. In 2003 she started her PhD in the same group (later the Land Dynamics Group) working on the Tradeoff Analysis model in the subsistence farming systems of Machakos, Kenya. Alejandra returned to Chile in 2007 where she established her home in a farm near the city of Concepción. She has been since dedicated to breeding waterfowl birds and other wild species. In the meantime she has collaborated in several research projects such as in water governance studies with the Water Integrity Network (WIN) and the Environmental Science Centre (EULA) of the *Universidad de Concepción* (2007); Potential of Magellan vegetation under climate change scenarios (2009) at *Universidad de Magallanes*; Scientific Secretary of the International Colloquium of Climate Change in Magellan Region and Antarctica organized by the *Universidad de Magallanes* and the *Instituto Chileno Antartico* (2009), and she also provided technical support for a project on modeling ecological niches of *Sanionia uncinata* in King George Island in Antarctica (2010). In recent years she has also cooperated with technical lectures for veterinary students, and she has just started a reproduction center for native Chilean species with endangered habitats, such as the Torrent duck (*Merganetta armata*), the Pudu deer (*Pudu puda*) and the Magellan Ruddy-headed Goose (*Chloephaga rubidiceps).*

Publications

Antle, J., Meijerink, G., de Jager, A., Stoorvogel, J.J., **Mora-Vallejo, A**. 2005 Econometric- Process Models of Semi-subsistence Agricultural Systems; An Application of the nutrient monitoring data for Machakos, Kenya. Article presented at the Eco-Regional Research Fund workshop on Tradeoff Analysis, Nairobi, Kenya

Mora-Vallejo, A., Claessens, L., Stoorvogel, J.J., and Heuvelink, G.B.M., 2008. Small scale digital soil mapping in Southeastern Kenya. Catena 76, 44-53

Warner, J., Butterworth, J., Wegerich, K., **Mora Vallejo, A**., Martinez, G., & Gouet, C. and Visscher, J.T. 2009. Corruption Risks in Water Licensing with Case Studies from Chile and Kazakhstan. Swedish Water House Report 27, SIWI

Muendo, P., Stoorvogel, J.J., Verdegemc, M.C., **Mora-Vallejo, A**., Verreth, A.J. 2011. Ideotyping integrated aquaculture systems to balance soil nutrients. Journal of Agriculture and Rural Development in the Tropics and Subtropics 112, 157–168

Mora-Vallejo, A.P., Stoorvogel, J.J., Antle, J.M., and De Jager, A., 2013. Linking nutrient monitoring and trade-off analysis for policy assessment. Submitted to Journal of Environmental Management (Minor revision)

Mora-Vallejo, A.P., Stoorvogel, J.J., Antle, J.M., Meijerink, G.W., 2013. Integrated assessment of agricultural interventions in the mixed farming systems of the Machakos region, Kenya. Submitted to Land Use Policy (Minor revision)

Mora-Vallejo, A.P., Stoorvogel, JJ, Antle, J.M., Claessens, L., 2013. How does the resolution of environmental data impact land use modeling? To be submitted

PE&RC Education Certificate

With the training and education activities listed below the PhD candidate has complied with the requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of literature (4.5 ECTS)
- Soil fertility decline in Africa literature review

Writing of project proposal (4.5 ECTS)
- Soil fertility decline in Machakos, Kenya: from diagnosis to intervention

Post-graduate courses (3 ECTS)
- Land science: bringing theory and concepts into practice; South Africa; PERC/LAD (2007)

Invited review of (unpublished) journal manuscript (1 ECTS)
- Agriculture, Ecosystems and Environment: transitions in agro-pastoralist systems East Africa: impacts on food security and poverty (2013)

Deficiency, refresh, brush-up courses (3 ECTS)
- Multifunctional land use (2003)

Competence strengthening / skills courses (3.6 ECTS)
- Trend and ethics in scientific writing; PE&RC (2004)
- Scientific writing; PE&RC (2005)
- Career orientation; PE&RC (2006)
- PhD Competence assessments; PE&RC (2006)

PE&RC Annual meetings, seminars and the PE&RC weekend (3 ECTS)
- PE&RC Day (2003/2004/2005/2006)
- PE&RC Weekend (2004/2006)

Discussion groups / local seminars / other scientific meetings (5.4 ECTS)
- Landslide symposium graduation Lieven Claessens (2005)
- SPAM: Spatial methods (2005/2007)
- World Soil Issues and sustainable development: an agenda for action; 40 years on ISRC – World Soil Information; special seminar 9th (2006)
- Wageningen International: discussion meeting: the millennium village project: thoughts, and afterthought from a Wageningen perspective (2006)

International symposia, workshops and conferences (5 ECTS)
- Tradeoff Analysis workshop; Nairobi, Kenya (2005)
- Pedometrics Conference; Naples, Florida; Digital soil mapping for a tradeoff analysis application in Kenya (2005)

Lecturing / Supervision of practical's / tutorials (3 ECTS)
- Multifunctional land use (2004)
- QUALUS (2004)
- TOA workshop; Nairobi (2004)
- Training mission Makerere University Uganda (2005)

Supervision of a MSc student (3 ECTS)
- Soil variability and landscape in the Machakos district, Kenya

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