The future of environmental sustainability in the Taita Hills, Kenya: assessing potential impacts of agricultural expansion and climate change

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The indigenous cloud forests in the Taita Hills have suffered substantial degradation for several centuries due to agricultural expansion. Currently, only 1% of the original forested area remains preserved. Furthermore, climate change imposes an imminent threat for local economy and environmental sustainability. In such circumstances, elaborating tools to conciliate socioeconomic growth and natural resources conservation is an enormous challenge. This article tackles essential aspects for understanding the ongoing agricultural activities in the Taita Hills and their potential environmental consequences in the future. Initially, an alternative method is proposed to reduce uncertainties and costs for estimating agricultural water demand. The main characteristic of the approach proposed in this study is the use of satellite data to overcome data availability limitations. Furthermore, a modelling framework was designed to delineate agricultural expansion projections and evaluate the future impacts of agriculture on soil erosion and irrigation water demand. The results indicate that if current trends persist, agricultural areas will occupy roughly 60% of the study area by 2030. Rainfall erosivity is likely to increase during April and November due to climate change and slight decrease during March and May. Although the simulations indicate that climate change will likely increase total annual rainfall volumes during the following decades, irrigation requirements will continue to increase due to agricultural expansion. By 2030, new cropland areas may cause an increase of approximately 40% in the annual volume of water necessary for irrigation.

Keywords: Land changes, climate change, simulation models, water resources, soil erosion

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Introduction

The world population has grown from 2.5 billion people in the 1950s to approximately 6.9 billion people in 2010 (UN 2010). The ability of mankind to cultivate crops and raise livestock, together with recent advances in agricultural techniques, is perhaps the main factor that allowed this fast population increase. Nevertheless, agriculture has changed the face of the planet's surface and continues to expand at alarming rates. Currently, almost one-third of the world's land surface is under agricultural use and millions of hectares of natural ecosystems are converted to croplands or pastures every year (Foley et al. 2005). If current trends persist, it is expected that by 2050 around 10 billion hectares of natural ecosystems will be converted to agriculture (Tilman et al. 2001).

The development of the agricultural sector is essential to provide food for the population and combat food insecurity in poor countries. However, the expansion of croplands without logistical and technological planning is a severe threat to the environment. Hence, the dilemma of integrat-

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ing economic and population growth with environmental sustainability is an undeniable issue that needs to be addressed.

Fresh water is perhaps the natural resource mostly affected by agricultural activities. Currently, roughly 70% of freshwater withdraws are used for agriculture (FAO 2005). Although global withdrawals of water resources are still below the critical limit, more than two billion people live in highly water-stressed areas due to the uneven distribution of this resource in time and space (Oki & Kanae 2006). In Kenya, currently over 55% of the rural population do not have access to quality drinkable water (FAO 2005).

Another major environmental problem associated with the expansion of agriculture is soil erosion. Although soil erosion is a natural process, changes in the landscape structure caused by the replacement of natural vegetation are likely to result in accelerated rates of soil loss. Increased erosion rates are directly associated with nutrient loss, which may reduce agricultural productivity (Bakker et al. 2007) and cause water bodies' eutrophication (Istvánovics 2009). In some cases, advanced stages of soil erosion, such as rill and gully erosions, can devastate entire areas, turning them unsuitable for agricultural purposes (Kirkby & Bracken 2009).

Furthermore, variations in precipitation and temperature patterns associated with climate change also have important impacts on the sustainability of agricultural systems. For instance, changes in precipitation volume and intensity may increase the energy available in rainfall for detaching and carrying sediments, accelerating soil erosion. According to Yang et al. (2003), the global average soil erosion is projected to increase approximately 9% by 2090 due to climate change. The climate also exerts great influence on water needs for agriculture. Projections indicate that, without proper investments in water management, climate change may increase global irrigation water needs by roughly 20% by 2080 (Fischer et al. 2007).

Currently, science is facing new challenges to advance in the direction of environmental sustainability. One major challenge lies in the need for understanding the interactions and feedbacks between human activities and the environment (Fig. 1). Hence, interdisciplinary studies are essential to improve our knowledge on the relationships between different components of environmental systems.

Another important challenge is the acquisition of reliable and appropriate data for environmental modelling. For instance, solar radiation, relative

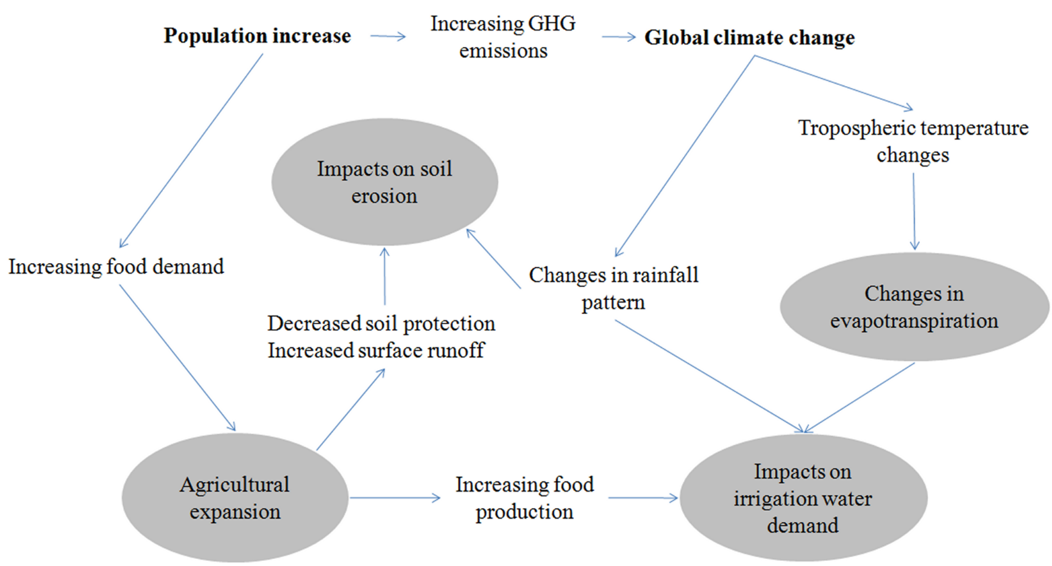


Fig. 1. Flow chart showing a simplified illustration of interactions between agricultural expansion, climate and environment addressed in this article.

humidity and wind speed are some of the variables usually necessary to estimate evapotranspiration (ET). However, assembling and maintaining meteorological stations capable of measuring such variables is, in general, expensive. In many poor regions, meteorological stations are insufficient to acquire the information necessary to represent the spatial-temporal variation of ET. As a result, the irrigation management in such areas is usually inappropriate, increasing the risks of water scarcity and water conflicts.

Therefore, in order to conciliate agricultural systems productivity and environmental sustainability it is imperative to create appropriate tools for monitoring current activities and delineating appropriate strategies for coping with expected changes in the future. This study addresses important elements of this challenge, focusing on environmental issues and methodological drawbacks currently faced in the Taita Hills region, Kenya. The Taita Hills is home for an outstanding diversity of flora and fauna, with a high level of endemism (Burgess et al. 2007). Despite the huge importance of this region from environmental and biological conservation perspectives, the Taita Hills have suffered substantial degradation for several centuries due to agricultural expansion. Hence, the area is considered to have high scientific interest, and there is an urgent need for tools and information that are able to assist the sustainable management of agricultural systems and natural resources. This article presents a series of interdisciplinary studies, which integrate different technologies and modelling techniques aiming to understand specific environmental aspects and delineate future environmental scenarios for the Taita Hills. The specific research problems and objectives are delineated below.

Research problems and objectives

I. The availability of ground meteorological data is extremely limited in the Taita Hills. This limitation is a serious bottleneck for the management of water resources used for irrigation, given that it prevents an accurate assessment of evapotranspiration (ET). To overcome this drawback, the combination of ET models with remote sensing data is considered a promising alternative to obtaining temporally and spatially continuous variables necessary for ET calculation. This study evaluates three empirical ET models using as input land surface temperature data acquired by the MODIS/Terra sensor, aiming to delineate an alternative approach for estimating ET in the Taita Hills.

II. Despite the large importance of agricultural activities for the economy and food security in the Taita Hills, the expansion of croplands imposes serious threats for the environment. Understanding the driving forces, tendencies and patterns of land changes is an essential step for elaborating policies that can conciliate land use allocation and natural resources conservation. This article investigates the role of landscape attributes and infrastructure components as driving forces of agricultural expansion in the Taita Hills and simulates future landscape scenarios up to the year 2030.

III. Land use and soil erosion are closely linked with each other and with local climate. The expansion of agricultural areas in the Taita Hills and changes in precipitation patterns associated with climate change are imminent threats for soil conservation. In this context mathematical models and scenario exercises are useful tools to assist stakeholders in delineating soil conservation practices that are consistent with plausible environmental changes in the future. One of the objectives of this study is to investigate the potential impacts of future agricultural expansion and climate change on soil erosion in the Taita Hills.

IV. In Africa, as well as in most parts of the world, the agricultural sector is the main consumer of water resources. As agricultural areas increase in the Taita Hills, there is an escalating concern regarding the sustainable use of water resources. Furthermore, future changes in temperature and rainfall patterns may affect the water requirements for agricultural activities. Understanding the relations between these components is crucial to identify potential risks of water resources depletion and delineate appropriate public policies to deal with the problem. This study evaluates prospective changes on irrigation water requirements caused by future agricultural expansion and climate change.

Study area

The Taita Hills are the northernmost part of the Eastern Arc Mountains of Kenya and Tanzania, situated in the middle of the Tsavo plains in the Coast Province, Kenya (Fig. 2). The Eastern Arc

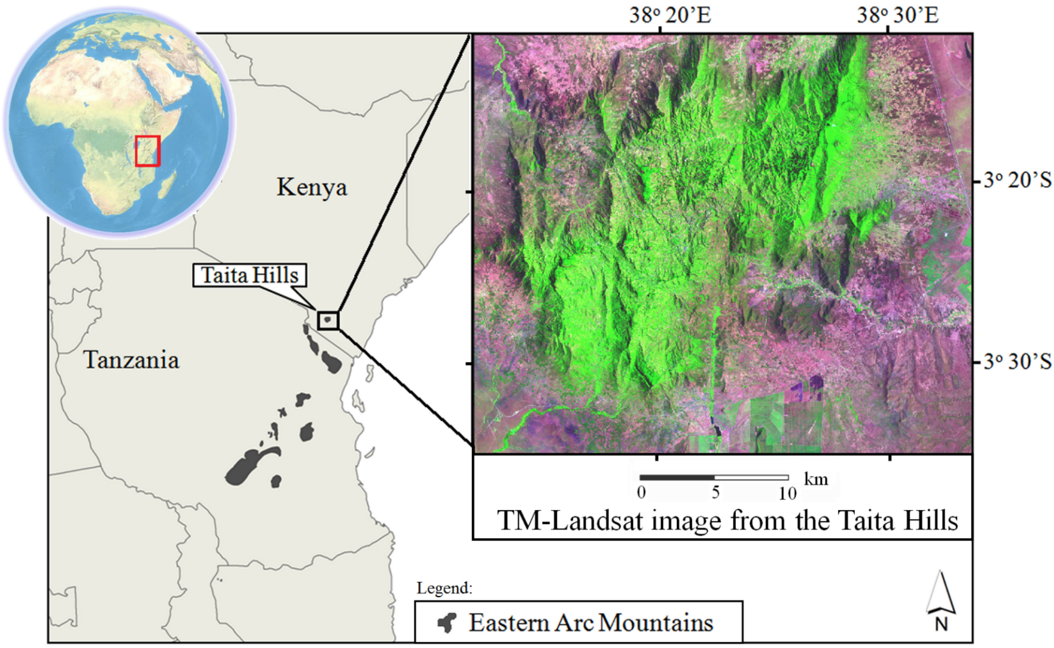


Fig. 2. Geographical location of the study area shown in a TM-Landsat image from April 3, 2001.

Mountains sustain some of the richest concentrations of endemic animals and plants on Earth, and thus it is considered one of the world's 25 biodiversity hotspots (Myers et al. 2000).

The Taita Hills cover an area of approximately 850 km^2. The population of the whole Taita-Taveta county has grown from 90,146 persons in 1962 to approximately 280,000 in the year 2009 (KNBS 2010). According to Clark (2010), population growth has been a central driving factor behind rising environmental pressure. The indigenous cloud forests have suffered substantial loss and degradation for several centuries as abundant rainfall and rich soils have created good conditions for agriculture. Between 1955 and 2004, approximately half of the cloud forests in the hills have been cleared for agricultural lands (Pellikka et al. 2009). Population growth and increasing areas under cultivation for subsistence farming have caused scarcity of available land in the hills and contributed to the clearance of new agricultural land in the lowlands (Clark 2010). Currently, it is estimated that only 1% of the original forested area remains preserved (Pellikka et al. 2009).

The agriculture in the hills is characterised by intensive small-scale subsistence farming. In the lower highland zone and in upper midland zone, the typical crops are maize, beans, peas, potatoes, cabbages, tomatoes, cassava and banana (Jaetzold & Schmidt 1983; Soini 2005). In the slopes and lower parts of the hills with average annual rainfall between 600 and 900 mm, early maturing maize, sorghum and millet species are cultivated. In the lower midland zones with average rainfall between 500 and 700 mm, dryland maize varieties and onions are cultivated, among others.

Supplementary irrigation practice is common, especially in the highlands, and profitable production is highly dependent on the availability of water resources (Jaetzold & Schmidt 1983). Despite the small average farm size, the income of many families in the Taita Hills relies solely on agricultural production. Although the technological level of farmers is not high, many carry out basic soil conservation practices, such as terraces.

Methods

Alternative methods for estimating reference evapotranspiration

In order to identify feasible approaches for estimating reference ET (ETo) in the Taita Hills, three empirical ETo models that require only air temperature data were evaluated, namely the Hargreaves (Hargreaves & Samani 1985), the Thornthwaite (Thornthwaite 1948) and the Blaney-Criddle (Blaney & Criddle 1962) methods.

To overcome the low data availability from ground meteorological stations, this study made use of land surface temperature (LST) data obtained from the MODIS sensor, on board of Terra and Aqua satellites (Wang et al. 2005). In order to clearly distinguish this approach, when LST data is used in replacement of air temperature data from ground stations, the Hargreaves, the Thornthwaite and the Blaney-Criddle models will be hereafter denominated as Hargreaves-LST, Thornthwaite-LST, and Blaney-Criddle-LST, respectively.

The empirical equations were calibrated using as a reference the FAO Penman–Monteith (FAO-PM) method. The FAO-PM method is recommended as the standard ETo method and has been accepted by the scientific community as the most precise, this is because of its good results when compared with other equations in different regions worldwide (Cai et al. 2007; Jabloun & Sahli 2008). Although the FAO-PM method also carries intrinsic uncertainties and errors, it has behaved well under a variety of climatic conditions, and for this reason the use of such methods to calibrate or validate empirical equations has been widely recommended (Allen et al. 1998; Gavilán et al. 2006).

The meteorological data necessary for the FAO-PM equations were obtained from a synoptic station placed at Voi town and operated by the Kenya meteorological department. ETo values were also calculated for this exact point using the empirical models and MODIS LST data. The calibration parameters were defined using the following equation (Allen et al. 1998):

$$ETo_{cal} = a + b \cdot ETo_{LST} \tag{1}$$

where ETo_{cal} represents the calibrated ETo values, in which the calibration parameters a and b are determined by regression analysis using as a reference the FAO-PM method; ETo_{lst} is the ETo values estimated using the empirical models and MODIS LST as input. The estimates obtained by each model were compared using standard statistics and linear regression analysis (Douglas et al. 2009). Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were calculated using the equations described below:

$$RMSE = \left(\frac{1}{n}\sum_{1}^{n}(ETo_{cal} - ETo_{R})^2\right)^{0.5} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{1}^{n}\left|ETo_{cal} - ETo_{R}\right| \tag{3}$$

Agricultural expansion modelling in the Taita Hills

This study integrated remote sensing, GIS techniques and a spatially explicit simulation model of landscape dynamics, DINAMICA-EGO (Soares-Filho et al. 2007), to assess the agricultural expansion driving forces in the study area and simulate future scenarios of land use. A general description of the applied method is illustrated in Figure 3.

The Land Use-Cover Change (LUCC) model receives as inputs land use transition rates, landscape variables and landscape parameters. The landscape parameters are intrinsic spatially distributed features, such as soil type and slope, which are kept constant during the simulation process. The landscape variables are spatial-temporal dynamic features that are subjected to changes by decision makers, for instance roads and protected areas. Ten landscape attributes (variables/parameters) were used as inputs for the model.

Land use global transition rates refer to the total amount of changes for each type of land use/land cover transition given in the simulation period, without taking into account the spatial distribution of such changes. The transition rates were calculated by cross-tabulation, which produced as output a transition matrix between the land cover maps from 1987 and 2003. The dates of the land cover maps were chosen based on two criteria. The first criterion was that the landscape changes between the initial and final landscape should accurately represent the ongoing land change activities in the study area. That is to say, the agricultural expansion rates between 1987 and 2003 were assumed to retrieve a consistent figure of the current trends. The second criterion relied on the availability of cloud free satellite images to assemble the land cover maps. According to a study carried out by Clark (2010), between 1987 and 2003 cropland has expanded by 10,478 ha, reflecting an expansion rate of approximately 650 ha year^{-1}.

The local transition probabilities, different from the global transition rates, are calculated for each grid cell considering the natural and anthropogenic characteristics of the site. The transition proba-

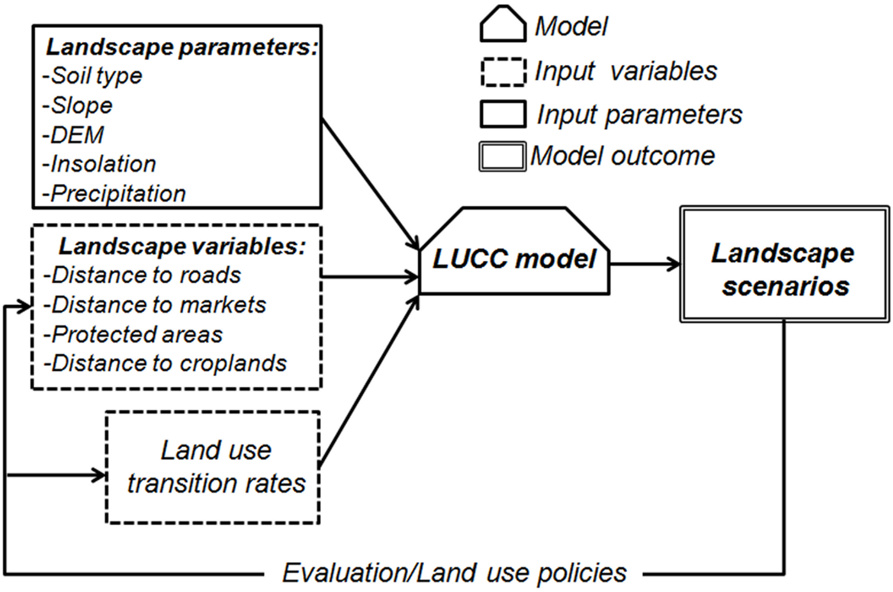


Fig. 3. General description of the modeling framework, in which landscape attributes obtained using remote sensing and GIS techniques are used as inputs for a LUCC model. The model evaluates the role of each attribute in the land changes and simulates future landscape scenarios (adapted from Maeda et al. 2011a).

bility of each cell was calculated in DINAMICA-EGO using the weights of evidence (WoE) method (Soares-Filho et al. 2002; Almeida et al. 2008). The WoE is a Bayesian method in which the effect of each landscape variable on a transition is calculated independently of a combined solution (Soares-Filho et al. 2002). The spatial probability of a transition is given by the following equation (Bonham-Carter 1994):

$$P_{x,y}\{T/V_1 \cap V_2 \cap \ldots \cap V_n\} = \frac{O\{T\} \times e^{\sum_{i=1}^{n} W^{+}_{x,y}}}{1 + O\{T\} \times \sum_{j=1}^{t} e^{\sum_{i=1}^{n} W^{+}_{x,y}}}, \quad (4)$$

where $P_{x,y}$ is the probability of transition in a cell with coordinates x,y; T represents the land use/land cover transition; V_n accounts for all possible landscape variables i selected to explain transition T; $O\{T\}$ is the odd of a transition, represented by the ratio between a determined transition probability and the complementary probability of non-occurrence, described by equation 5:

$$O\{T\} = \frac{P\{T\}}{P\{\bar{T}\}}, \quad (5)$$

where $P\{T\}$ is the probability of occurrence of transition T, given by the number of cells where the concerned land use/land cover transition occurred divided by the total number of cells in the study area; $P\{\bar{T}\}$ is the probability of non-occurrence of transition T, given by the number of cells where the concerned land use/land cover transition is absent divided by the total number of cells in the study area, and $W^{+}_{x,y}$ is the weight of evidence for a determined landscape variable range, defined by the following equation:

$$W+ = \log_e \frac{P\{Vi/T\}}{P\{Vi/\bar{T}\}}, \quad (6)$$

where $P\{V_i/T\}$ is the probability of occurring variable V_i in face of the previous presence of transition T, given by the number of cells where both V_i and T are found divided by the total number of cells where T is found and $P\{V_i/\bar{T}\}$ accounts for the probability of occurring variable V_i in face of the previous absence of transition T, given by the number of cells where both V_i and are found divided by the total number of cells where T is not found.

The W^+ values represent the attraction between a determined landscape transition and a certain variable. The higher the W^+ value is, the greater is the probability of a certain transition to take place. On the other hand, negative W^+ values indicate

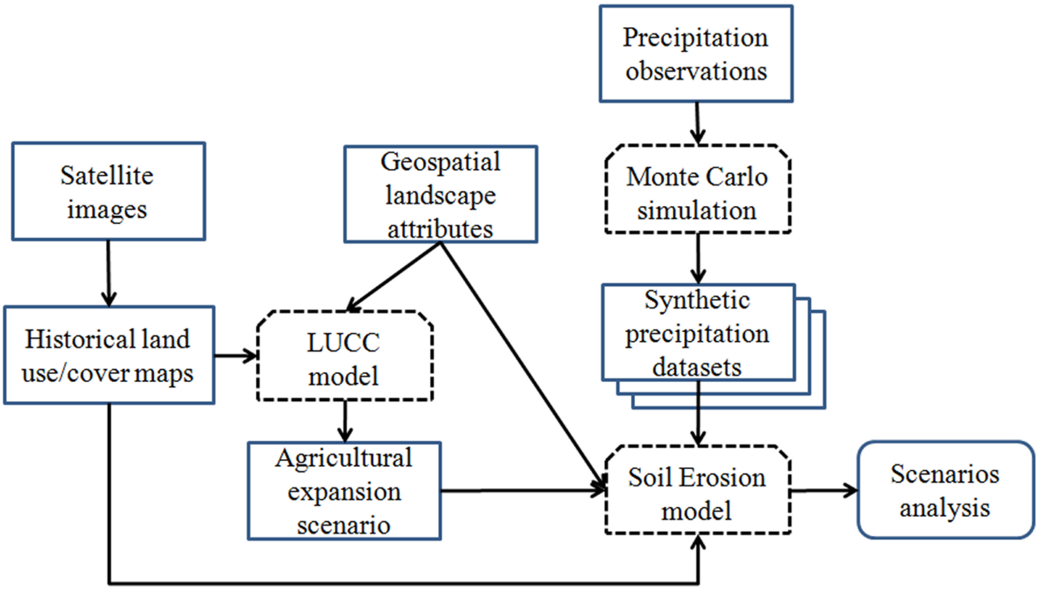


Fig. 4. Flow chart illustrating the integrated modelling framework concept used to estimate the impacts of agricultural expansion and climate change on soil erosion (adapted from Maeda et al. 2010b).

lower probability of a determined transition occurring in the presence of the respective variable range. Based on the W^+ values of each range for every considered variable, DINAMICA-EGO generates a spatially explicit probability map, in which the cell receives as attributes the probability for a determined transition.

After defining the weight of each landscape variable, transition probability maps are created for every simulated year. Based on spatial probabilities, new agricultural patches are stochastically allocated using two algorithms: 'expander' and 'patcher'. The *expander* function performs the expansion of previously existing patches of a certain class. The *patcher* function, in turn, is designed to generate new patches through a seed formation mechanism (Soares-Filho et al. 2002).

Assessment of potential impacts on soil erosion

Future agricultural expansion and climate change scenarios were used to evaluate their potential impacts on soil erosion in the Taita Hills. To achieve this objective a modelling framework was assembled by coupling a landscape dynamic simulation model, an erosion model and synthetic precipitation datasets generated through a stochastic weather generator. This approach aimed to evaluate how agricultural expansion, together with climate change, can modify the variables of a widely used soil erosion model, allowing a qualitative assessment of the impacts of these changes for soil conservation.

The soil erosion model used was the Universal Soil Loss Equation (USLE) (Wischmeier & Smith 1978). Remote sensing and GIS techniques were combined to provide the necessary inputs for the modelling framework. A flow chart illustrating the components of the modelling framework is presented in Figure 4.

The USLE and its revised version, RUSLE (Renard et al. 1997), have been extensively used worldwide during the last decades (Kinnell 2010). Even though these models are known for their simplicity, their effectiveness has been demonstrated in many recent studies (e.g. Beskow et al. 2009; Nigel & Rughooputh 2010), including several studies in Kenya (e.g. Angima et al. 2003; Mutua et al. 2006). The USLE is given as:

$$A = R \times K \times LS \times C \times P \quad (7)$$

where A is the annual average soil loss [t ha^{-1} ano^{-1}], R is the rainfall erosivity factor [MJ mm ha^{-1}

h^{-1}], *K* is soil erodibility [t ha h MJ^{-1} mm^{-1}], *L* and *S* are the topographical factor [–], *C* is the vegetation cover factor [–], and *P* represents erosion control practices [–].

Provided the fact that the *K* and *LS* factors are intrinsic characteristics of the landscape, they can be kept constant in all simulated scenarios. On the other hand, land changes directly affect the *C* factor. These changes were analysed by evaluating the average *C* factor value in the study area during 1987, 2003 and in the simulated scenario for 2030. The potential impacts of agricultural expansion for soil conservation were also assessed by analysing the spatial distribution of croplands in relation to the *K* and *LS* factors. Possible changes on the *P* factor were not addressed in the present study.

The rainfall erosivity factor (*R*) is a numerical index that expresses the capacity of the rain to erode a soil (Wischmeier & Smith 1978). Hence, the *R* factor is directly affected by changes in precipitation pattern. These changes were evaluated at monthly and yearly time steps. Additionally, the soil erosion potential was calculated by excluding the anthropogenic variables from the USLE equation (*C* and *P*). This approach is needed to clearly understand the role of external factors in the system without the influence of the changes in the landscape cause by human activities.

Although the USLE provides a simple and useful tool for soil conservation, studies commonly neglect the calibration and validation of this model. Given the absence of reliable data for calibration, the presented study did not attempt to provide soil loss estimation figures. Instead, the evaluation of the soil erosion potential among the different scenarios was based mainly on a comparative analysis of changes, following the procedure proposed by Kepner et al. (2004) and Miller et al. (2002). Such procedure assumes that, using percent change observations, the parameters incorporated in an eventual calibration would be partially or totally cancelled, providing more realistic figures than absolute values of soil loss. The absolute changes in soil erosion potential were analysed only qualitatively, taking into account the spatio-temporal distribution of changes.

The *R* factor was calculated using the method proposed by Renard and Freimund (1994), and recently applied by Beskow et al. (2009). The method is based on an empirical relationship between rainfall erosivity and the Fournier Index (*FI*). The *FI* indicates climatic aggressiveness, which has a high correlation with the amount of sediment washed into the stream by surface runoff.

Future climatic conditions were simulated using a stochastic weather generator. Three greenhouse-gas emission scenarios were considered (SRES, Special Report on Emissions Scenarios): SRA1B, SRA2 and SRB1 (Nakicenovic et al. 2000). For each scenario, a respective synthetic precipitation datasets was created: SyA1B, SyA2 and SyB1. The data necessary for this procedure were obtained from the IPCC data distribution centre (*http://www.ipcc-data.org*). A detailed description of the procedures used to generate the synthetic climate datasets are described in Maeda et al. (2010b).

The *K* factor was calculated using the method proposed by Williams & Renard (1983). This approach was chosen for being broadly used in recent studies (e.g. Xiaodan et al. 2004; Rahman et al. 2009) and for requiring input variables that are commonly available worldwide. The data necessary for calculating the *K* factor were obtained from the Soil and Terrain Database for Kenya (KENSOTER), which provides a harmonized set of soil parameter estimates for Kenya (Batjes & Gicheru 2004).

The topographical factor (LS) was calculated in the software USLE2D (Van Oost et al. 2000), using the algorithm proposed by Wischmeier and Smith (1978). This calculation was performed based on a 20 m spatial resolution DEM.

Assessment of potential impacts on irrigation water requirement

In this last assessment, agricultural expansion and climate change scenarios were used to evaluate their potential impacts on Irrigation Water Requirements (IWR). Remote sensing and GIS techniques were combined to provide the necessary inputs for the modelling framework described in Figure 5.

Crop water requirement (CWR) is defined as the amount of water required to compensate the ET loss from a cropped field (Allen et al. 1998). In cases where all the water needed for optimal growth of the crop is provided by rainfall, irrigation is not required and the IWR is zero. In cases where all water has to be supplied by irrigation the IWR is equal to the crop ET (ETc). However, when part of the CWR is supplied by rainfall and the remaining part by irrigation, the IWR is equal to the difference between the ETc and the Effective Pre-

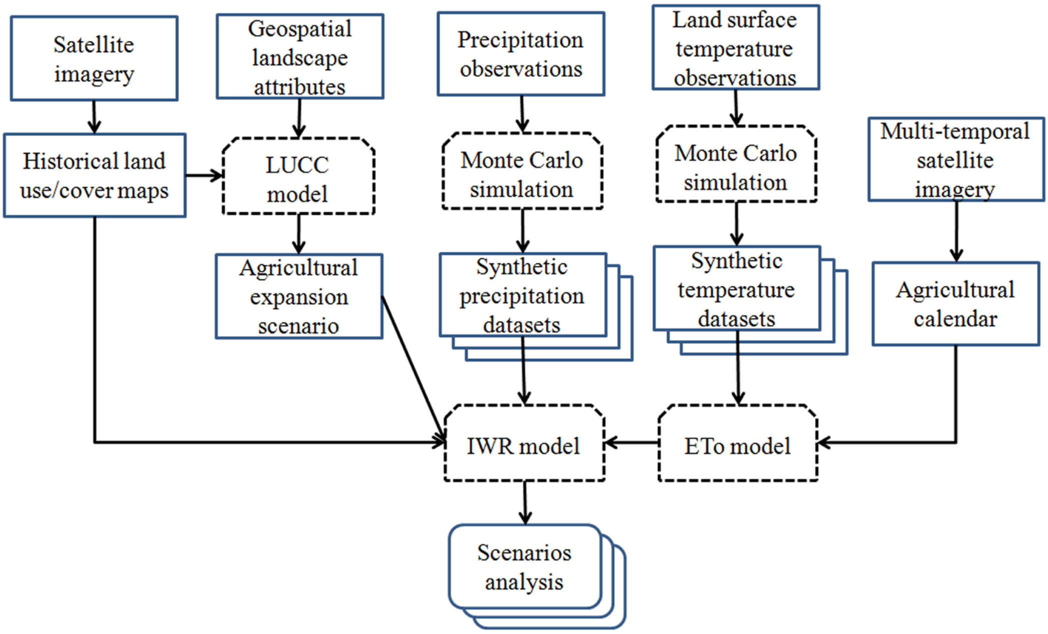


Fig. 5. Flow chart illustrating the integrated modelling framework concept used in assessing the potential impacts of agricultural expansion and climate change on irrigation water requirements (adapted from Maeda et al. 2011b).

cipitation (Peff). In such cases, the IWR was computed using the following equation (FAO 1997):

$$IWR_m = (Kc_m \times ETo_m \times 30) - Peff_m \qquad (8)$$

where: IWR_m = monthly average crop water requirement in month *m*, [mm]; Kc_m= crop coefficient in month *m*, [–]; ETo_m= mean daily reference evapotranspiration in month *m*, [mm day^{-1}]; $Peff_m$ = average effective precipitation in month *m*, [mm].

The *Peff* is defined as the fraction of rainfall retained in the root zone, which can be effectively used by the plants. That is, the portion of precipitation that is not lost by runoff, evaporation or deep percolation. The monthly total rainfall was converted to *Peff* using a simplified method proposed by Brouwer and Heibloem (1986), which is based on empirical observations and requires only the total monthly volume of precipitation.

The Hargreaves model was chosen to estimate the ETo in the study area. The *Kc* values were obtained from tables recommended by FAO (Allen et al. 1998). Nevertheless, to assign the appropriate *Kc* values it is essential to identify the agriculture calendar in the study area, that is, the period of the year when crops are planted, grown and harvested. For this, monthly Normalized Difference Vegetation Index (NDVI) obtained from MODIS satellite imagery were used to identify the phenological stages of croplands during the year.

A stochastic weather generator was used to estimate future precipitation and temperature conditions. Three SRES greenhouse-gas emission scenarios were considered: SRA1B, SRA2 and SRB1 (Nakicenovic et al. 2000). For each scenario, a respective synthetic precipitation and temperature datasets were created: SyA1B, SyA2 and SyB1. For a detailed description of this method, please refer to Maeda et al. (2011b).

Results

Remote sensing based methods for estimating evapotranspiration

The results obtained in the evaluation of the ETo models are summarized in Table 1. The global average RMSE and MAE are fairly homogeneous for each of the evaluated models. The RMSE ranged from 0.47 mm day^{-1}, with the Hargreaves-LST

Table 1. Summary of the results obtained from the models' error analysis and linear regression analysis

	Hargreaves-LST	Thornthwaite-LST	Blaney-Criddle-LST
Correlation coefficient (R)	0.67	0.66	0.55
RMSE (mm day^{-1})	0.47	0.49	0.53
MAE (mm day^{-1})	0.39	0.42	0.46
Calibration parameter (a)	3.221	3.507	–1.980
Calibration parameter (b)	0.497	0.543	1.379

model, to 0.53 mm day^{-1}, with the Blaney-Criddle-LST model. The MAE achieved similar figures, ranging from 0.39 mm day^{-1}, with the Hargreaves-LST model, to 0.46 mm day^{-1}, with the Blaney-Criddle-LST model.

The monthly errors obtained by the tested models, in comparison with the reference method, are presented in Figure 6. Although the monthly performance of the models is uniform between March and July, important differences are observed in January, February and between August and December (Fig. 6). In particular for the Blaney-Criddle-LST model, it is possible to notice a clear increase of the RMSE and MAE in January, November and December. The Blaney-Criddle-LST model performed better in months when air temperature was closely related to LST, but had its performance reduced in months when air temperature and LST are less correlated. However, the Hargreaves-LST model was more efficient in minimizing the effects of the differences observed between air temperature and LST during November, December and January. The model performed well during these months, retrieving RMSEs of 0.51, 0.61 and 0.51 mm day^{-1}, respectively.

Considering the results achieved in this study and comparisons with previous research, it is concluded that the Blaney-Criddle-LST model is not appropriated for this region when using the proposed methodology. However, the Hargreaves-LST model achieved the best results in the linear regression and in the analysis of errors. The results obtained using the Hargreaves-LST are compatible with the errors observed by Gavilán et al. (2006), which evaluated the Hargreaves equation under semiarid conditions in southern Spain, finding RMSE ranging from 0.46 to 1.65 mm d^{-1}. Furthermore, the correlation coefficients obtained by the Hargreaves-LST and Thornthwaite-LST models are consistent with the results reported by Narongrit

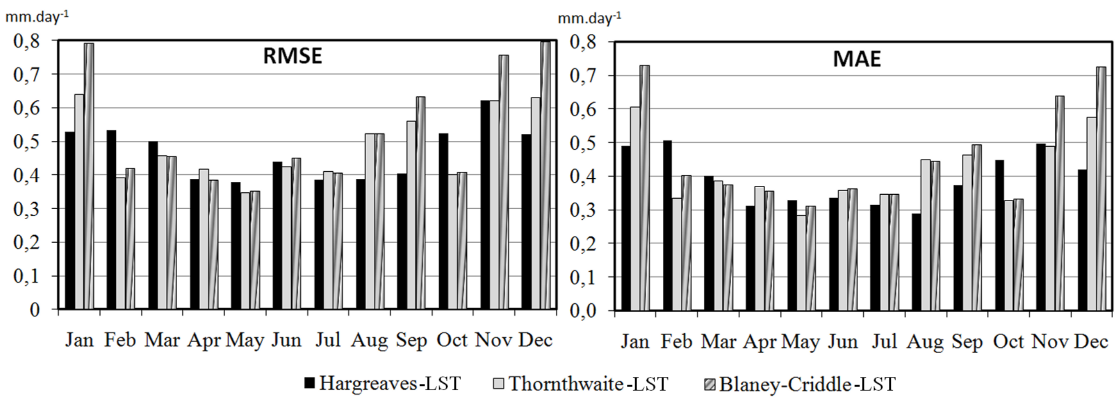


Fig. 6. Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The errors are used to quantify the differences between the ETo estimated using the reference method (FAO-PM) and the estimates obtained using the empirical models parameterized using MODIS LST data (adapted from Maeda et al. 2011a).

and Yasuoka (2003), which achieved R^2 of 0.57 and 0.60 when comparing these respective models with the FAO-PM method.

The driving forces of agricultural expansion and scenarios for 2030

The highest conversion rates were observed in the transition from woodlands to agriculture. However, considering absolute numbers, shrubland areas are the most affected, given that currently they represent the predominant vegetation type in the region. The small regions covered with broadleaved forests were nearly untouched, presenting low conversion rates, the total area decreased from 7.7 to 6.9 km² during the observed period.

The most relevant W^+ values obtained during the model calibration are shown in Fig. 7. This information represents the attraction between a determined landscape transition and a certain land-

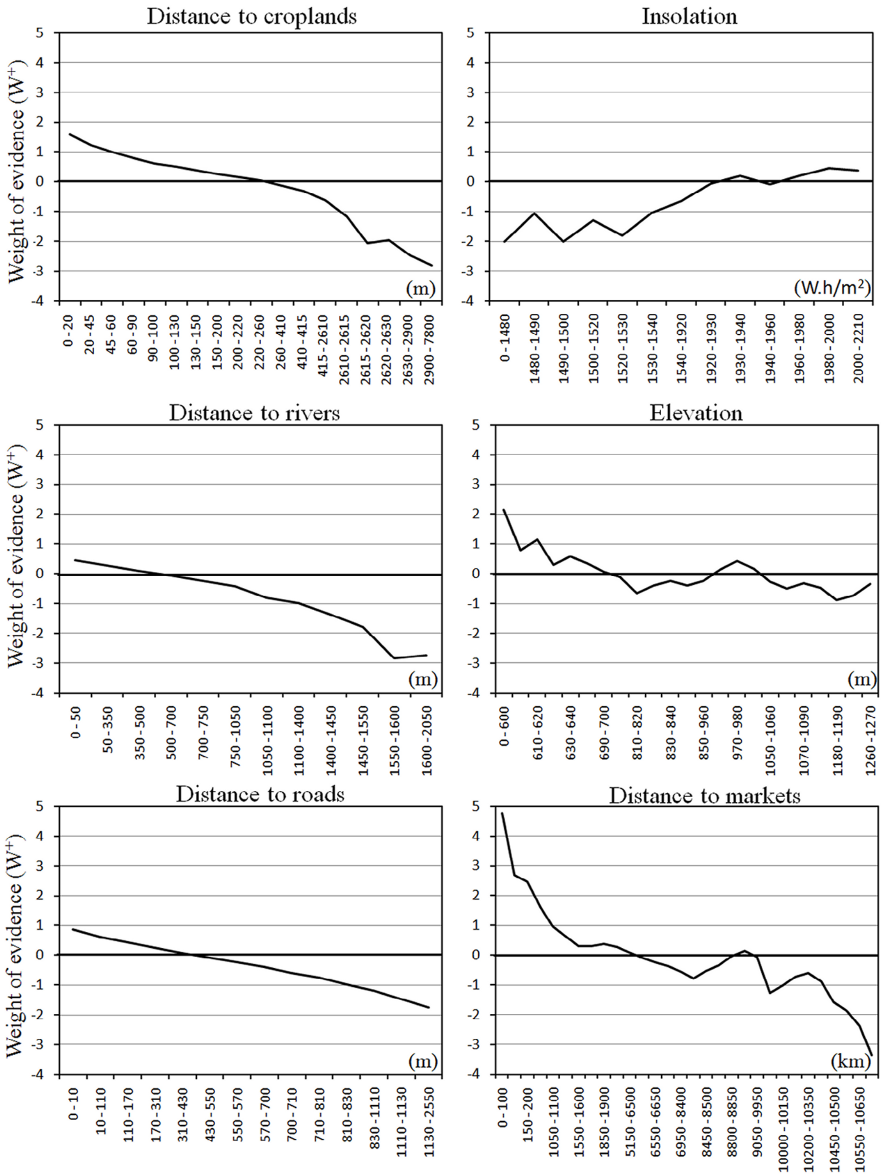


Fig. 7. W+ values attributed for each range of six landscape attributes most related to the 'shrublands to croplands' transition (adapted from Maeda et al. 2010a).

scape attribute. Distance to rivers, insolation, distance to croplands, DEM, distance to roads and distant to markets were particularly associated with the land-use transitions. The distance to croplands is an important driving factor for all transitions indicating that the proximity to previously established croplands is a key factor for agricultural expansion in this region.

Although areas close to rivers did not retrieve high positive W^+ values, the importance of water bodies for croplands is clearly reflected in regions distant from rivers, where high negative W^+ values are observed. Hence, the results indicate that patches further than 1 km from water bodies have lower probability of being converted to cropland. Distance to roads also presents a clear pattern in influencing the transition from shrublands to croplands. Nevertheless, this attribute did not retrieve very high W^+ values, possibly due to the fact that the Taita Hills comprise a relatively dense road network, diminishing the contrast between areas nearby and away from roads. The distance to markets, here represented by the Euclidean distance to the main villages, was the most representative driving force for the agricultural expansion.

After the model is calibrated and the role of each landscape variable is defined, transition probability maps are created for each simulated year. The spatial probabilities are used to guide the distribution of new simulated agricultural patches, which are stochastically allocated by the 'expander' and 'patcher' algorithms. In Figure 8, the land use maps for 1987 and 2003 are displayed (upper left and upper right) together with the land use maps for 2030 resulted from the simulation. It is observed that, in 1987, croplands were already clearly established along highlands (central area in the maps). This is explained by the favourable climatic and edaphic conditions for agricultural activities (e.g. high precipitation rates), which resulted in the clearance of large areas of forest during the last century. Cropland areas expanded to

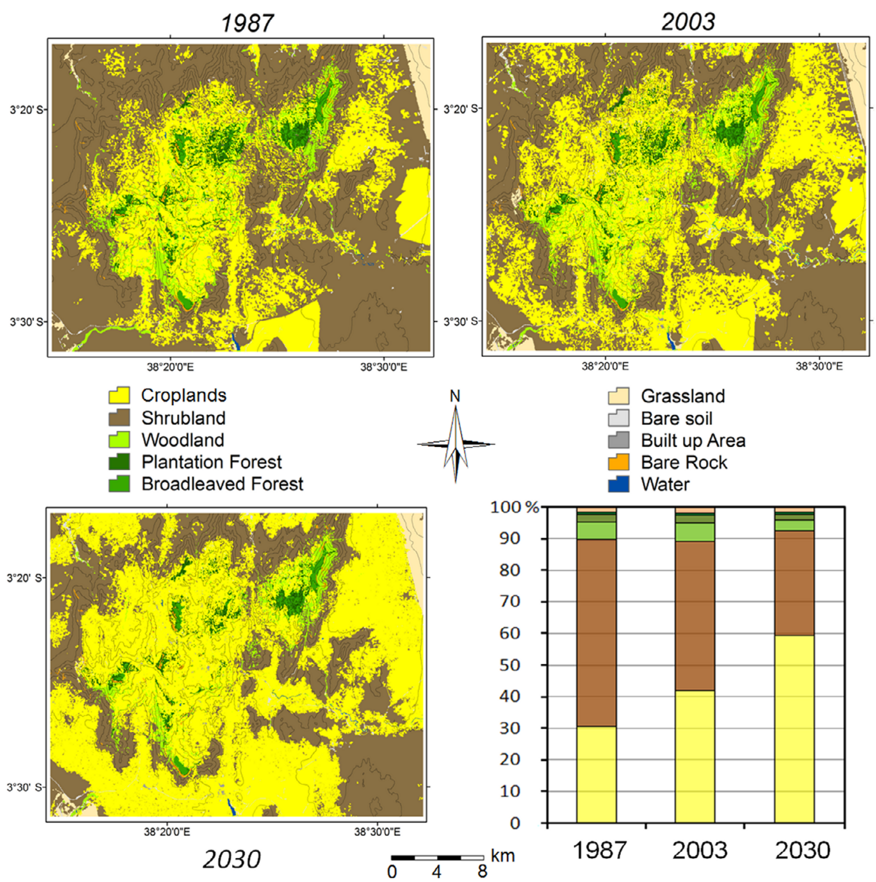


Fig. 8. Land use maps for 1987 and 2003 (upper left and upper right) and simulated scenario for 2030 (lower left) (adapted from Maeda et al. 2010b).

around 515 km^2 in 2030, corresponding to about 60% of the study area. This represents an increase of 40% in comparison to the year 2003, when croplands occupied around 365 km^2.

Potential impacts on soil erosion by 2030

The results show that agricultural patches established during the last decades were carefully settled in areas with favourable topography from the soil conservation perspective, i.e. lower LS factor. This pattern was reinforced after 1987, when the availability of space in the hills was scarce and the agriculture started expanding to flat areas along the foothills. In the agricultural expansion simulated for 2030, a slight increase is noted in cropland patches settled in areas with LS factor between 1 and 10, whereas the most significant increase was again in areas with a topographic factor between 0 and 1.

The soil erodibility factor in the study area varied from 0.0139 to 0.0307, allowing the distinction of eight different erodibility classes. Because soil erodibility figures may vary according to the method used for calculation, the results were analysed only in a comparative base, taking into account the soil erodibility range found in the study area. In 1987 and 2003 agricultural areas were established mainly in soils with medium erodibility (0.0205–0.0255). The simulated agricultural expansion for 2030 was also higher in these soils. The low occurrence of agricultural activities in soils with higher erosivity is explained firstly by the low area occupied by these soils in the study area and secondly by the fact that such soils, together with climatic variables, create unfavourable conditions for agricultural practices. Therefore, the results indicate that agricultural activities are unlikely to expand into areas with higher soil erodibility.

The average R factor for the study area was approximately 3040 MJ mm ha^{-1} h^{-1} $year^{-1}$ when considering current climate conditions. This result is consistent with figures obtained in other semi-arid regions. Da Silva (2004) found that erosivity varied from 2000 to 4000 MJ mm ha^{-1} h^{-1} $year^{-1}$ in semi-arid regions in the north-east of Brazil. However, in regions with high topographic heterogeneity, such as the Taita Hills, it is crucial to consider local variations at detailed spatial scales.

The erosivity values obtained in the SyA2 scenario resulted in the most evident differences in comparison with current conditions. In January, March, May and December the changes in precipitation resulted in a clear but slight decrease in rainfall erosivity. The erosivity reduction during these months varied from 4 to 120 MJ mm ha^{-1} h^{-1} $month^{-1}$. However, still for the SyA2 scenario, a large increase was observed in April (280 MJ mm ha^{-1} h^{-1} $month^{-1}$) and November (260 MJ mm ha^{-1} h^{-1} $month^{-1}$).

For the SyB1 scenario, the increases in rainfall erosivity during April and November were lower, approximately 217 and 40 MJ mm ha^{-1} h^{-1} $month^{-1}$, respectively. A slight decrease was also observed during March, May and December, but in contrast with the SyA2 scenario, the erosivity during January was almost constant, with a minor increase of 27 MJ mm ha^{-1} h^{-1} $month^{-1}$. The SyA1B was the most conservative scenario, although clear changes are still present. Namely, it showed the highest erosivity increases during January and December, while it confirmed the tendency of a decrease in erosivity during March and May.

In general, it is plausible to assert that the climate changes simulated for the study area are likely to decrease rainfall erosivity during March and May due to a slight reduction in precipitation rates in these months. However, the model indicates the possibility of an increase, of much higher magnitudes during April and November. The disagreements between the simulated scenarios in January and December indicate higher uncertainties during these months. For June, July, August and September rainfall erosivity values are likely to continue to be very low.

For all scenarios it is noted that low or no change occurs in the lowlands (roughly 500 m above sea level). The changes, however, start to be more evident along areas higher than 1000 m a.s.l., where average precipitation rates are higher. In particular for the SyA2 scenario, changes are very high above 1500 m, reaching absolute differences up to 1500 MJ mm ha^{-1} h^{-1} $year^{-1}$ when compared with current conditions.

Potential impacts on irrigation water requirement by 2030

Spatial and temporal variations on ETo are strong both in the lowlands and in the hills. In general ETo is higher in the months of September and October, and reaches the lowest values between April and June. The correlation between ETo and altitude varies according to season and altitude range. ETo follows more closely the changes in the alti-

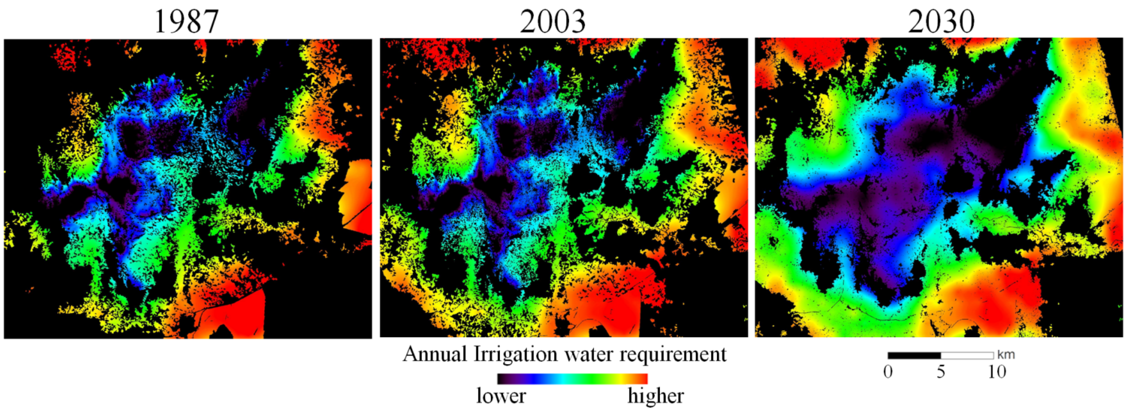


Fig. 9. Annual irrigation water requirement maps for 1987, 2003 and 2030. The black areas in the map represent regions where no agricultural activities are taking place (adapted from Maeda et al. 2011b).

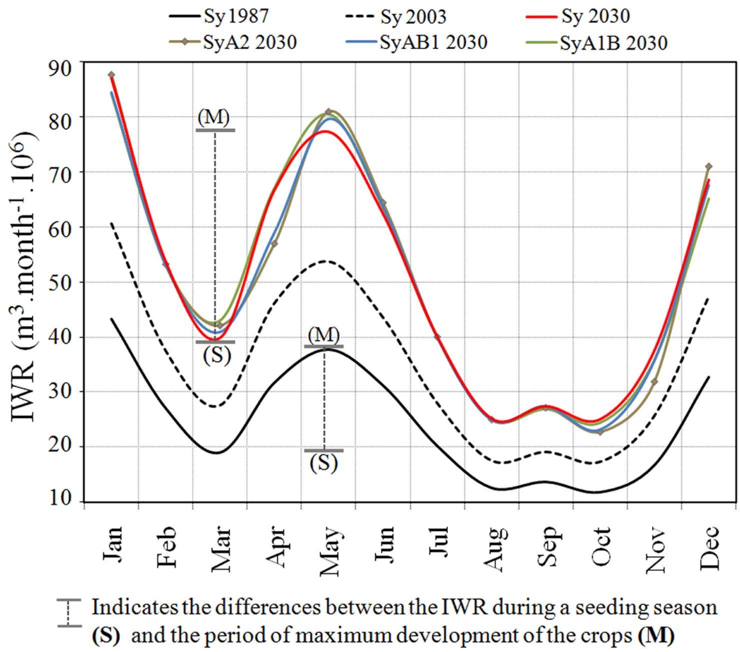
tude in October than in May. In May, the variation ranges from 4.5 to 5.4 mm day^{-1} while in October the variation is from 5.3 to 6.9 mm day^{-1}. From 1987 to 2003, a large number of cropland patches were created in areas with ETo between 5.7 and 5.9 mm day^{-1}, while few new patches were implemented in areas with lower ETo (<5 mm day^{-1}). This tendency was strongly sustained during the scenario simulated for 2030. Hence, it is feasible to assert that by 2030 new croplands are likely to take place in areas where ETo values are historically higher.

Considering an invariable climate condition, the agricultural expansion observed between 1987 and 2003 resulted in an IWR increase of 42%. An integrated analysis of this result with the historical precipitation volumes in the study area indicates that the agricultural expansion has likely reached unsustainable levels from the water resources point of view. That is to say, by 2003 the annual average precipitation volume in the entire study area (~390 million m^3 year^{-1}) was already insufficient to meet the water resource requirements necessary to achieve optimal crop production in every agricultural property.

Among the scenarios simulated for 2030, the scenario considering current climate conditions resulted in the highest annual IWR volume, reaching approximately 610 million m^3 year^{-1}. All the climate change scenarios (SyA1B, SyA2 and SyB1) caused a slight reduction in the IWR when compared with current conditions. Therefore, the results indicate that the climate change tendencies up to 2030 are likely to decrease the total annual volume of IWR in this study area. A comparison between the annual IWR maps for 1987, 2003 and 2030, considering they Sy scenario, is presented in Figure 9.

Figure 10 shows the monthly IWR values for all simulated scenarios. The increase in IWR caused by the agricultural expansion component is clearly identified in an offset of the curves among different years. Considering only the curves for the year 2030, the climate changes simulated in the SyA1B, SyB1 and SyA2 datasets indicate a tendency of increase in the IWR during March and May when compared with a scenario with unchanged climate conditions (Sy2030). This tendency is inverted in April and November, when a slight decrease is observed in the IWR. During the other months, the IWR is kept relatively constant among the different climate scenarios. In these cases, eventual increases in the temperature were likely to be compensated by increases in rainfall volume, keeping the IWR constant. From the practical point of view, the results indicate a higher water demand during the seeding season, in February/March, and during the period of maximum development of the crops, in May. Climate changes are likely to decrease the water demand for irrigation during both crop growing seasons in April and November.

Fig. 10. Monthly irrigation water requirements volume for the entire study area during the years 1987, 2003 and 2030. For the year 2030, four climate scenarios are considered (adapted from Maeda et al. 2011b).



Discussion

The Taita Hills are among the most degraded areas in the Eastern Arc Mountains, having lost approximately 99% of their original forest during the last few centuries (Pellikka et al. 2009). Although this number may sound discouraging, it also makes the Taita Hills a unique learning environment for the protection of more preserved areas in the Eastern Arc, such as Udzungwas, East Usambaras and Ulugurus. Therefore, the causes behind this massive forest loss must not be ignored. In particular, the fact that these highlands have significant importance for providing food and income to local population should be acknowledged.

Previous studies have shown that agriculture was the main cause of forest conversion in the Taita Hills (e.g. Clark 2010). Consequently, it is already known that agricultural activities are actively present in the Taita Hills, and continues to expand. Nevertheless, the answers for other important questions remain unclear or unsolved. To better understand the degradation process in the Eastern Arc it is essential to determine what type of agricultural activities are taking place, to where it may expand in the future and what impacts it will cause. The combined results of this study provide initial arguments to deal with these important questions.

Public policies need to take into consideration the areas where agriculture is more likely to expand in the future. The answer for this question can only be achieved through a detailed assessment of the forces driving the land changes. In this context, this study presents a pioneer assessment of the driving forces of agricultural expansion in the Taita Hills. The results obtained in this analysis closely agree with previous studies carried out in other locations in Kenya. For instance, studying the Narok District in Kenya, Serneels and Lambin (2001) found that the expansion of small-holder agriculture is mainly controlled by proximity to permanent water, land suitability and vicinity to villages.

In addition to delineating agricultural expansion scenarios for the year 2030, this article also addressed potential environmental impacts caused by land changes. The highlands of Kenya and Tanzania are considered natural water towers, given that the higher precipitation rates in these areas historically provide water resources for large regions along the lowlands throughout the year (Aeschbacher et al. 2005; Viviroli & Weingartner 2008). However, the results presented in this study, and confirmed by field work observations, indicate that the average precipitation rates in the Taita Hills are no longer able to provide water resources for the lowlands during the entire year. It is plausible to consider that the changes observed in water resources availability in the Taita Hills are likely to be caused by two main factors. Firstly, the increasing use of water resources for irrigation in the hills might be causing a decrease in rivers' flow, diminishing or in some case depleting the volume of water in the downstream portion of the rivers. The second, but not less important, factor contributing to this issue is likely to be related to changes in the hydrological response of the rivers' basins caused by the replacement of natural vegetation in favour of croplands. Previous studies have shown that land changes may increase surface runoff (e.g. Germer et al. 2010) and have direct impacts on water balance (e.g. Li et al. 2009). These factors can potentially reduce water retention in the watershed, decreasing the flow during the dry seasons.

The replacement of natural vegetation cover will also contribute for accelerated soil erosion. Therefore, the undertaken soil conservations practices must be set as a priority action in the Taita Hills. Although changes in erosion control practices (P factor) were not considered in this study, previous investigations have shown that appropriate land management can significantly decrease soil erosion. For instance, studying soil erosion risk scenarios in Calabria, southern Italy, Terranova et al. (2009) show that erosion control practices can cause a significant reduction of the erosive rate, decreasing from roughly 30 to 12.3 Mg ha^{-1} $year^{-1}$. Feng et al. (2010) demonstrated that soil conservation measures taken by the Chinese government (Grain-for-Green project) significantly decreased soil erosion in the Loess Plateau between the years 1990 and 2005.

Finally, it is important to mention that the issues involving water resources and soil conservation can and should be tackled in an integrated manner. For instance, the adoption of practices to reduce surface runoff, such as terraces, is an important step to avoid soil erosion, and at the same time it enhances water infiltration into the soil, allowing a better recharge of groundwater reservoirs. Furthermore, opting for cultivars capable of maintaining some vegetation protection over the soil for longer periods can contribute to avoiding the direct impact of rainfall in the soil and improve soil structure. These factors not only reduce soil erosion, but also contribute to lower soil evaporation rates and a better water infiltration. In this context, the consolidation of agroforestry systems using native plant species may be highly beneficial to the local agriculture, and an excellent alternative for replacing the eucalyptus plantation forests in the Taita Hills.

Conclusions and further studies

Two general contributions can be highlighted from the results obtained in this study. The first contribution lies in the development and assessment of alternative approaches to improve the acquisition of data related to key aspects of agricultural activities in the Taita Hills. The second relates to the establishment of novel knowledge by delineating unprecedented insights on future environmental scenarios for the region. Considering the above contributions, the results of this study have a large potential to attain researchers, policy makers and local population.

An alternative method for estimating ETo was evaluated by integrating remote sensing data and empirical models. The combined use of the Hargreaves ETo model and MODIS LST data retrieved an average RMSE close to 0.5 mm d^{-1}. This outcome is consistent with results obtained by previous studies reported in the literature using weather data collected by ground stations. Moreover, the errors and uncertainties identified in the use of remote sensing LST can be tolerated considering the reduced weather data collection network in this region. Further studies are necessary to expand this method for other regions in East-Africa. In particular, the spatial variability of the calibration parameters for different climate conditions over East-Africa needs to be identified. Moreover, the method can be significantly improved by using low cost direct methods (e.g. lysimeters) to calibrate the empirical equations.

In relation to the agricultural expansion modelling in the Taita Hills, a connected relation between villages and roads is evident in the definition of new cropland patches. The proximity to already established crop fields is also one of the key factors driving the agricultural expansion. If current trends persist, it is expected that agricultural areas will occupy 60% of the study area by 2030. LUCC simulations indicate that agricultural expansion is likely to take place predominantly in lowlands and foothills throughout the next 20 years. Current trends indicate that the small residual areas of tropical cloud forest, home to a great part of the biodiversity in the Taita Hills, is likely to remain intact throughout the coming years. Nevertheless, the impact of the increasing habitat fragmentation in such biodiversity is a relevant issue that must be addressed in further studies.

The replacement of shrublands and woodlands in favour of croplands expected for the next decades is very likely to reduce the vegetation cover protecting the soil against the direct impact of rainfall, resulting in accelerated soil erosion. By the year 2030, rainfall erosivity is likely to increase during April and November. All scenarios converge to a slight erosivity decrease tendency during March and May. The highest uncertainties were observed in January and December, when some scenarios indicate a small reduction in erosivity while some indicate an increase. Accounting for land changes and climate changes in an integrated manner, it is plausible to conclude that the highlands of the Taita Hills must be prioritized for soil conservation policies during the next 20 years. Although new croplands are likely to be settled in lowlands over the next decades, increases in precipitation volumes are expected to be higher in highlands. Moreover, it was demonstrated that in areas with elevated LS factor, typically in the highlands, increasing rainfall will have significantly higher impacts on soil erosion potential.

Due to the limited availability of non-agricultural land in the highlands, new cropland areas are being settled in areas with low precipitation and higher temperatures. The continuity of this trend is likely to drive agricultural lands to areas with a higher IWR, increasing the spatial dependence on distance to rivers and other water bodies. Although the simulated scenarios indicate that climate change will likely increase annual volumes of rainfall during the following decades, IWR will continue to increase due to agricultural expansion. By 2030, new cropland areas may cause an increase of approximately 40% in the annual volume of water necessary for irrigation.

NOTES

This article is a reduced version of the synopsis of the academic dissertation "Agricultural expansion and climate change in the Taita Hills, Kenya: an assessment of potential environmental impacts", University of Helsinki, 2011.

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