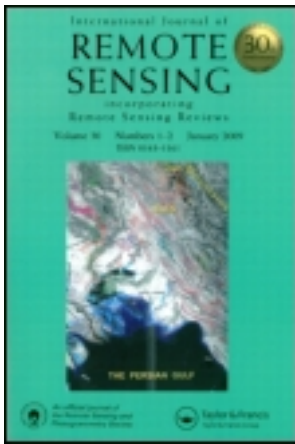


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### A new approach for using time-series remote-sensing images to detect changes in vegetation cover and composition in drylands: a case study of eastern Kenya

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## A new approach for using time-series remote-sensing images to detect changes in vegetation cover and composition in drylands: a case study of eastern Kenya\*

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Vegetation cover and composition are important aspects of the dryland environment because they provide livelihood to humans and also protect soil resources against erosion. Currently, scientists are advancing various techniques for detecting vegetation degradation in the drylands and the possibilities for its control. This study contributed through the testing of time-series mixed-effects modelling of the normalized difference vegetation index (NDVI) and rainfall relationship to trace the footprints of vegetation dynamics in the drylands. The approach aimed at providing guidelines for quick diagnosis of the changes in vegetation cover and composition to trigger necessary action. The mixed-effects technique used in this study is a novel regression approach for simultaneous modelling of the NDVI–rainfall relationship in different dominant vegetation types. Its time-series application with Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI images between 1982 and 2008 was tested in eastern Kenya. The results show how the original dominant vegetation types had been converted to cereal croplands, open grasslands, or reduced to bare ground in a span of 27 years. In some places, it shows how the changes in vegetation composition resulted in the overall loss of vegetation cover. Field validation positively confirmed these observations; thus, indicating that the method was a promising tool for tracing vegetation dynamics in the drylands. In spite of its success, the method was found to be only useful in detecting changes in large areas with dominant vegetation types. The technique can therefore be recommended for regional analysis, and can be used as a first approximation to guide more detailed subsequent analysis.

### 1. Introduction

Vegetation is an important aspect of dryland ecosystems. This is because it buffers the soil against erosion, improves the air quality and is also a major source of human livelihood in terms of food, shelter, fuel, pasture for livestock, medicine and income

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\*This paper came from a workshop entitled ‘*Potentialities and Limitations in the Use of Remote Sensing for Detecting and Monitoring Environmental Change in the Horn of Africa*’. The workshop was organized by Somalia Water and Land Information Management (SWALIM) between 13 and 14 June 2007 at the Holiday Inn in Nairobi, Kenya. SWALIM is a project of the UN-FAO in Somalia ([www.faoswalim.org](http://www.faoswalim.org)).

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(O'Connor *et al.* 2001, Dregne 2002, Ludwig *et al.* 2004, Karnieli *et al.* 2008, Vilela *et al.* 2009). Although the dryland vegetation is important and should be protected, its coverage has been variously reported in the literature to be rapidly declining (Dregne 2002, Obua *et al.* 2006). Data collected from many parts of the world by the Food and Agriculture Organization (FAO) of the United Nations show that its coverage has had a gross decline by millions of hectares since 2000 due to human activities (FAO 2007). Many countries, which have been alarmed by such reports, are instituting policies to conserve/restore their dryland vegetation (Imbernon 1999). This is a positive step that needs to be guided by scientific evidence all the way through policy recommendations, formulations and implementations.

Application of remote sensing is one of the widely used approaches for providing scientific evidence of the environmental change. Its ability to detect changes on the Earth's surface has helped scientists to understand vegetation-cover dynamics and to support the development of land-use/cover policies (Liang 2004). To date, the application of remote-sensing indices in vegetation has dominated the methods for assessing and monitoring changes in vegetation cover. Liang (2004) and Baugh and Groeneveld (2006) have discussed these indices and their applications in various circumstances. Normalized difference vegetation index (NDVI) is one of these indices, with wide applications in the drylands. This is because of its readily available time-series data and its simplicity and robustness, which make its application repeatable in other locations (Tucker *et al.* 2005). Apart from its effectiveness in predicting the surface properties when vegetation canopy is not too dense or sparse, the NDVI also has a good correlation with rainfall, which is one of the limiting factors for growth of the dryland vegetation (Evans and Geerken 2004, Baugh and Groeneveld 2006).

There is a plethora of publications in the literature using the NDVI to monitor vegetation-cover dynamics (Xie *et al.* 2008). However, recent research indicates that there is still untapped potential for the NDVI, which could be useful not only in monitoring changes in vegetation cover, but also in vegetation composition (Evans and Geerken 2004, Wessels *et al.* 2007, Balaghi *et al.* 2008). They suggest that concurrent time-series modelling of the NDVI and climatic data to account for the harmonic relationship between these two quantities can yield time-series residuals that are highly correlated with human-induced changes in vegetation cover (Wessels *et al.* 2007). This approach is currently in application for tracking vegetation-cover loss as an index of human-induced land degradation (Bai *et al.* 2008). While the residuals from such modelling have proven useful in diagnosing changes in vegetation cover, other modelling parameters have not been emphasized. The objective of this study was to analyse the parameters of time-series modelling of the NDVI–rainfall relationship to find out if they could be important in diagnosing changes in vegetation cover and composition.

## 2. Potential of the time-series NDVI–rainfall relationship in detecting vegetation dynamics

The NDVI and rainfall have been shown in the literature to have a harmonic relationship, which can be generally written as:

$$y = f(x, m, c) + e \quad (1)$$

where  $y$  is the vector of the NDVI from different locations in a study area,  $x$  is the corresponding vector of rainfall,  $f$  is the mathematical function for the relationship

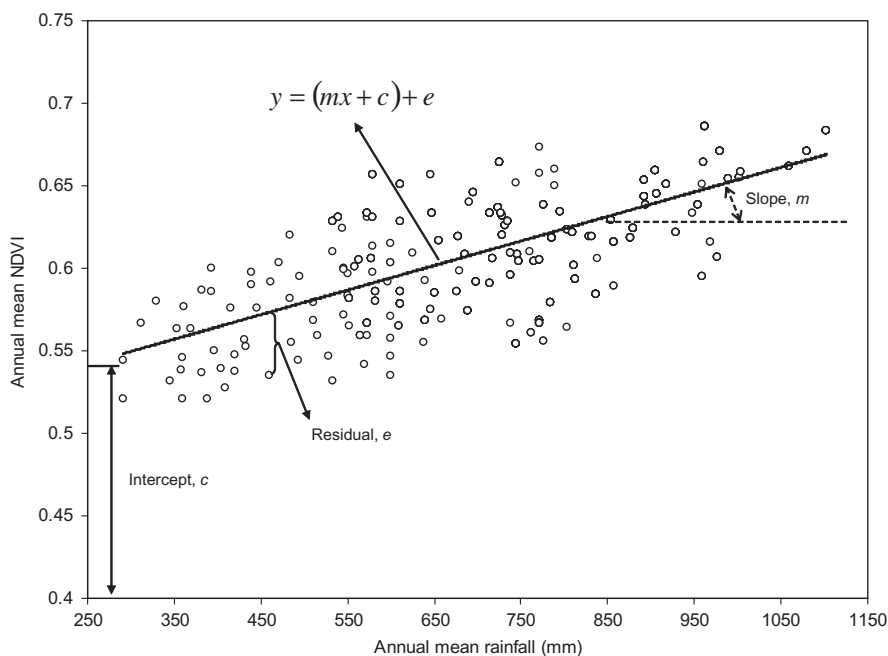


Figure 1. Example of simple linear model for annual maximum NDVI response to annual rainfall amounts in the Upper Athi River basin in eastern Kenya.

between the NDVI and rainfall and  $e$  is a vector of the difference between the predicted and remotely sensed NDVI. Some authors have found a simple linear model for  $f$  (du Plessis 1999, Evans and Geerken 2004), while others have shown that it can also be a non-linear model (Prince *et al.* 2007). Whichever model type it is,  $f$  contains at least two fitting parameters ( $m$  and  $c$ ), which are related to the vegetation–rainfall characteristics. As an illustration, consider a simple linear model for the NDVI–rainfall relationship shown in figure 1. It contains a parameter  $m$  representing the slope and another parameter  $c$  for the  $y$ -axis intercept (figure 1). The slope, which is the ratio of the change in the NDVI to the corresponding change in rainfall, is an index of the rate of the NDVI response to rainfall. It is a potential indicator of how fast the vegetation responds to rainfall. The parameter  $c$ , which is the intercept, is the minimum NDVI when rainfall is very low. It is a possible indicator of the minimum NDVI during dry periods.

By using the modelling parameters  $m$  and  $c$  for different vegetation types in a study area, it is possible to identify vegetation types with high NDVI during dry or wet periods and those that respond quickly/slowly to rainfall. It may be possible to detect significant changes of the dominant vegetation types in the study area based on changes in the intercept and slope parameters, especially if the modelling is temporally repeated for each location in a study area. This study tested this hypothesis in detecting changes in vegetation composition in the Upper Athi River basin in eastern Kenya.

Apart from using the NDVI–rainfall relationship to detect the changes in vegetation composition, the relationship was also used to assess the changes in vegetation cover. The approach of using the trend of time-series residuals from the NDVI–rainfall model, which was developed by Evans and Geerken (2004) and later improved by Wessels *et al.* (2007), was applied in this study. According to this approach, a

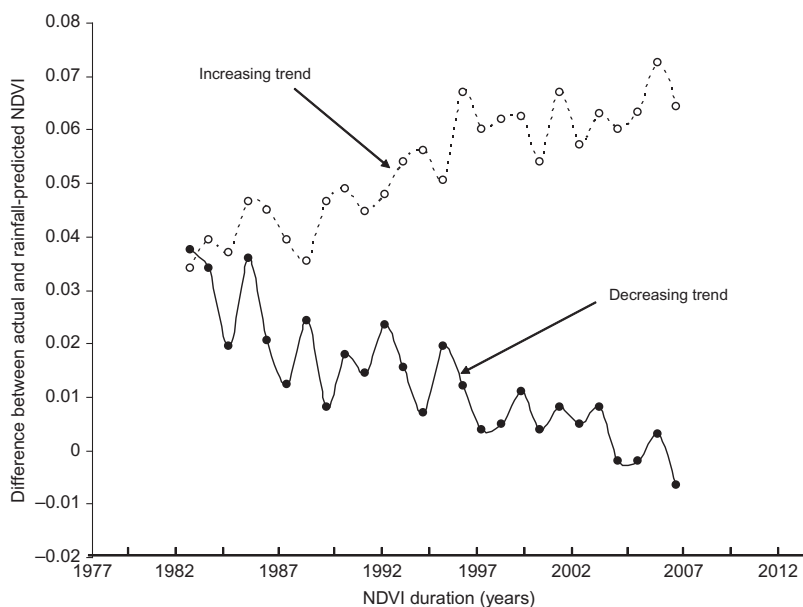


Figure 2. Example of time-series trend of residuals from NDVI–rainfall modelling for detecting changes in vegetation cover.

significant gradual increase of the residuals in a given area over time is taken to indicate an increase in vegetation cover, while a gradual decrease indicates a decline in vegetation cover. In order to use this approach, the NDVI–rainfall relationship for a particular area is first modelled, and then its residuals are extracted. The process is repeated over time, and the trend of the residuals analysed for any gradual increase or decrease. Figure 2 shows examples of two locations in the Upper Athi River basin. Analysis of their NDVI–rainfall relationship gave residuals with an increasing trend between 1982 and 2007 for one location, and a declining trend for the other location during the same period.

In the application of the residual trends to assess changes in vegetation cover, the significant increase of the residuals implies that the oscillations of vegetation dynamics gradually increase above the corresponding climatic oscillations. Since the NDVI and climate are assumed to have a harmonic relationship, unequal increase of the NDVI signals above those for climate in a given area may be explained by a possible increase in vegetation cover (due to forestation, etc.) (Evans and Geerken 2004, Wessels *et al.* 2007). Similarly, areas with declining residuals may be those in which declining vegetation cover oscillated below the corresponding climate signals. This study also tested the potential of these residuals trend in monitoring changes in vegetation cover.

### 3. Materials and methods

#### 3.1 Study area

The study was carried out in the Upper Athi River basin in eastern Kenya. The study area stretches from latitude 1°09' to 1°59' S and from longitude 36°56' to 37°45' E,

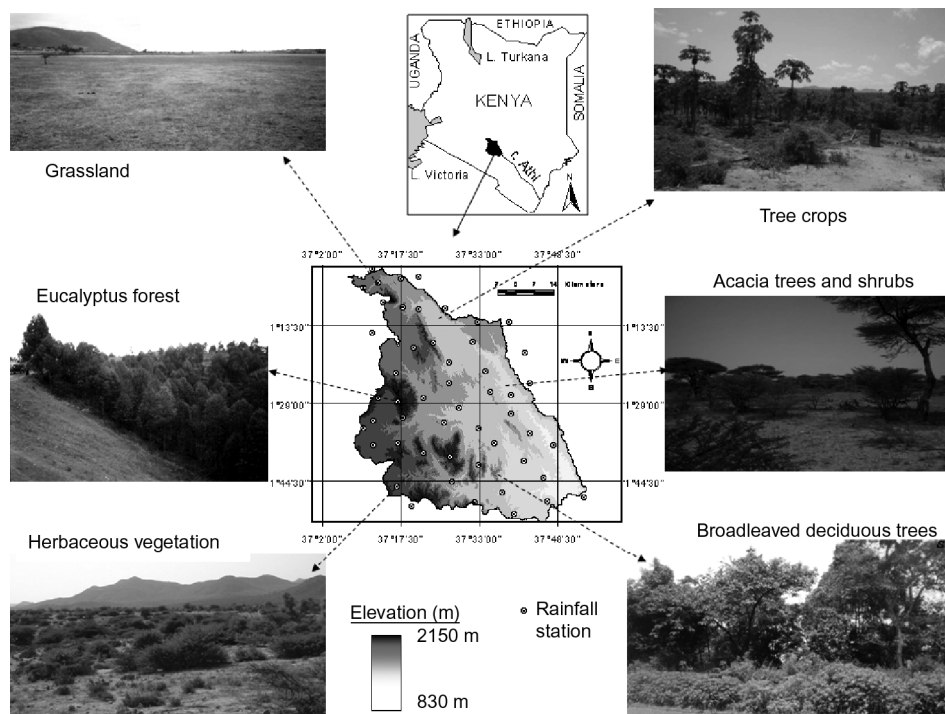


Figure 3. The study area (latitude  $1^{\circ}09'$  to  $1^{\circ}59'$  S, longitude  $36^{\circ}56'$  to  $37^{\circ}45'$  E) and some common vegetation types. The photographs were taken between 12 and 30 May 2008.

and covers 4513 km<sup>2</sup> (figure 3). It is almost flat (slope  $<2\%$ ) in the midland areas (altitudes 1000–1500 m above sea level (a.s.l.)), gently sloping ( $2\% < \text{slope} < 20\%$ ) in the lowlands ( $<1000$  m a.s.l.) and has steep slopes ( $>20\%$ ) in the uplands ( $>1500$  m a.s.l.). More than 50 years ago, the high-altitude areas were covered with indigenous broadleaved deciduous forests, the midland areas dominated by herbaceous vegetation and savannah shrubs in the lowlands (Ojany and Ogendo 1973, Jaetzold and Schmidt 1983, Tiffen *et al.* 1995, Omuto 2008). However, some of these original land-cover types have already been converted to croplands, others developed for human settlement and others replanted with *Eucalyptus* trees or reduced to open grasslands (figure 3). These changes in vegetation make the study area a good candidate for testing the potential of time-series remote sensing in detecting changes in vegetation cover and composition. The area has a bimodal rainfall pattern in which 60% of annual rainfall falls between March and June and the remaining 40% between October and December. In general, about 67% of the area will receive less than 800 mm of rainfall on average in a year. These are the areas where the altitude is less than 2000 m. The remaining 33% of the area receives an average annual rainfall amount of 1100 mm, which is mainly in the mountainous areas (where altitude  $>2000$  m). Although the high-rainfall highland areas were covered with forest vegetation, their proportion was low in comparison to the lowland areas (figure 3). The study area therefore provided a large range in vegetation cover within which the method could be evaluated.

### 3.2 Data

The data used for assessing vegetation dynamics were time-series NDVI images, rainfall amounts and a land-cover map. The NDVI images comprised 10 day composite maximum Advanced Very High Resolution Radiometer (AVHRR) images from January 1982 to December 2008 and 16 day composite maximum Moderate Resolution Imaging Spectroradiometer (MODIS) images from January 2000 to December 2008. The AVHRR images had a spatial resolution of 8000 m and were downloaded from <http://earlywarning.usgs.gov/adds/datatheme.php> on 8 January 2009. The MODIS images had a spatial resolution of 250 m and were downloaded from <http://pekko.geog.umd.edu/usda/apps> on 2 February 2009. The MODIS images were used to test if the spatial resolution could influence the accuracy of the proposed method. All NDVI images were already geometrically corrected, and only minor adjustments were made to convert the image digital numbers to NDVI values, as recommended in the accompanying metafiles. These adjustments were done using ILWIS software (Koolhoven *et al.* 2007). Figure 4 shows box-plot summaries of the average NDVI for the whole study area and selected samples of the mean annual NDVI images. The summaries were obtained using R Computing Environment software (R Development Core Team 2008). The image samples not only showed that there were higher NDVI magnitudes in 1982 or 2000 than in 2008, but also gave the impression of how the NDVI characteristics spatially varied in the study area.

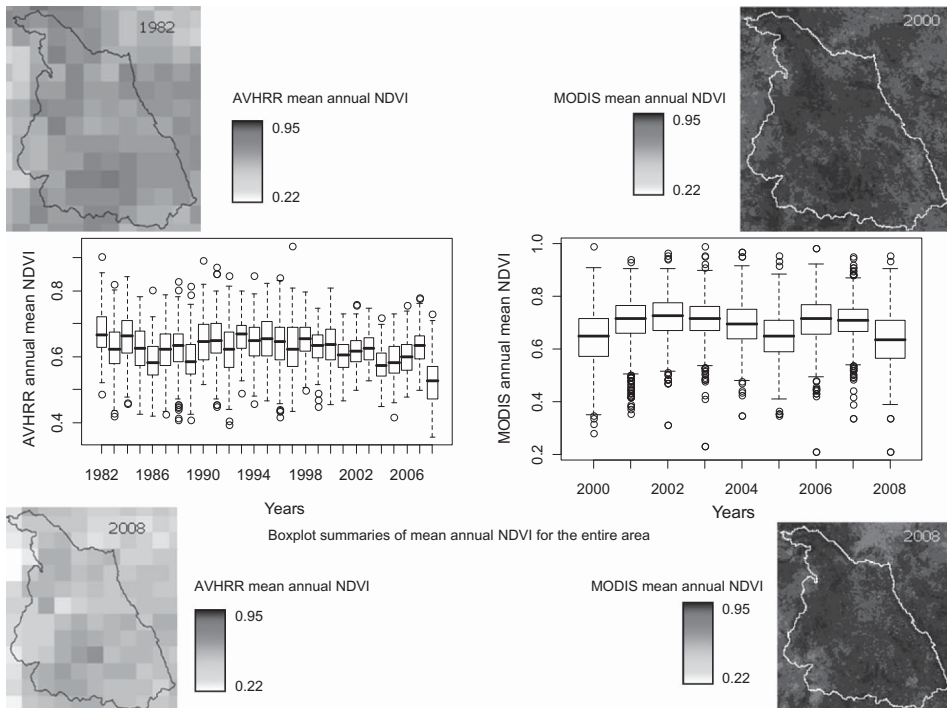


Figure 4. Preliminary analysis of time-series annual maximum NDVI in the Upper Athi River basin in eastern Kenya. The numerical signposts are arranged as follows, from bottom to top: minimum, first quartile, second quartile, third quartile and maximum. Open circles are extreme values.

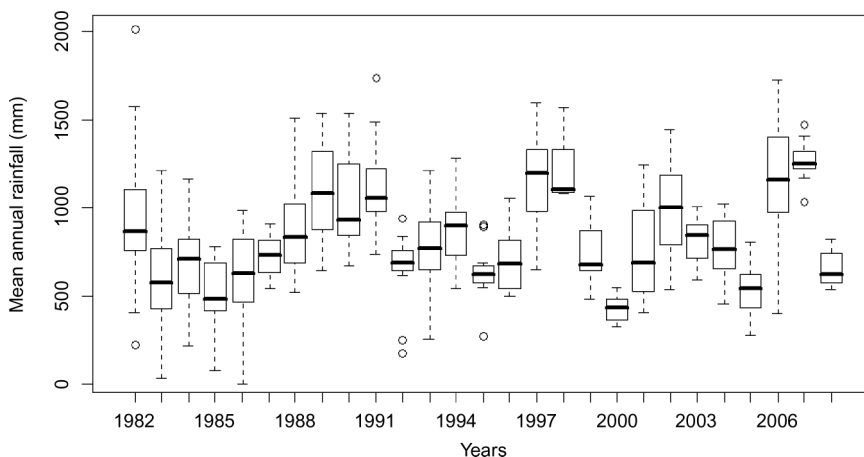


Figure 5. Preliminary analysis of time-series annual rainfall amounts in the Upper Athi River basin in eastern Kenya. The numerical signposts are arranged as follows, from bottom to top: minimum, first quartile, second quartile, third quartile and maximum. Open circles are extreme values.

The time-series rainfall data were monthly rainfall amounts for 52 recording stations in the study area (figure 3). The rainfall records were from January 1982 to December 2008 and were obtained from the Kenya Meteorological Department ([www.meteo.go.ke](http://www.meteo.go.ke)). A box-plot summary of the rainfall data is given in figure 5.

Although the annual mean NDVI and cyclical rainfall patterns in figures 4 and 5 looked similar, further preliminary analysis of their harmonic relationships was carried out using monthly standardized anomalies. These anomalies were used because they can remove seasonal variations and short-term biases, which can mask important patterns in a time-series signal (Nikken 1999). They were determined using:

$$\text{standardized anomaly}_{ij} = \frac{(z_{ij} - \bar{z}_j)}{\sigma_{z_j}}, \quad i = 1, 2, \dots, 27, \quad j = 1, 2, \dots, 12 \quad (2)$$

where  $z_{ij}$  is the mean monthly rainfall amount/NDVI for month  $j$  in year  $i$ ,  $\bar{z}_j$  is the long-term mean monthly rainfall amount/NDVI and  $\sigma_{z_j}$  is the standard deviation for the monthly rainfall amount/NDVI. Equation (2) was implemented in the R Computing Environment software (R Development Core Team 2008). The anomalies showed that the NDVI and rainfall signals seemed to have had a harmonic relationship between 1982 and 1999 (figure 6). However, after 1999, the NDVI signals generally dipped in spite of the available rainfall. This unique response was perhaps due to the changes in vegetation characteristics around this time. Although some authors using similar time-series NDVI data have argued against satellite sensor artefacts in the data (Kaufmann *et al.* 2000, Tucker *et al.* 2005), the possibility of sensor-related problems was also not totally ignored as having contributed to the observed unique dipping of the NDVI.

The land-cover map consisted of 13 dominant vegetation types mapped at a scale of 1: 100 000. It was developed by Africover in 1998 ([www.africover.org](http://www.africover.org), downloaded on



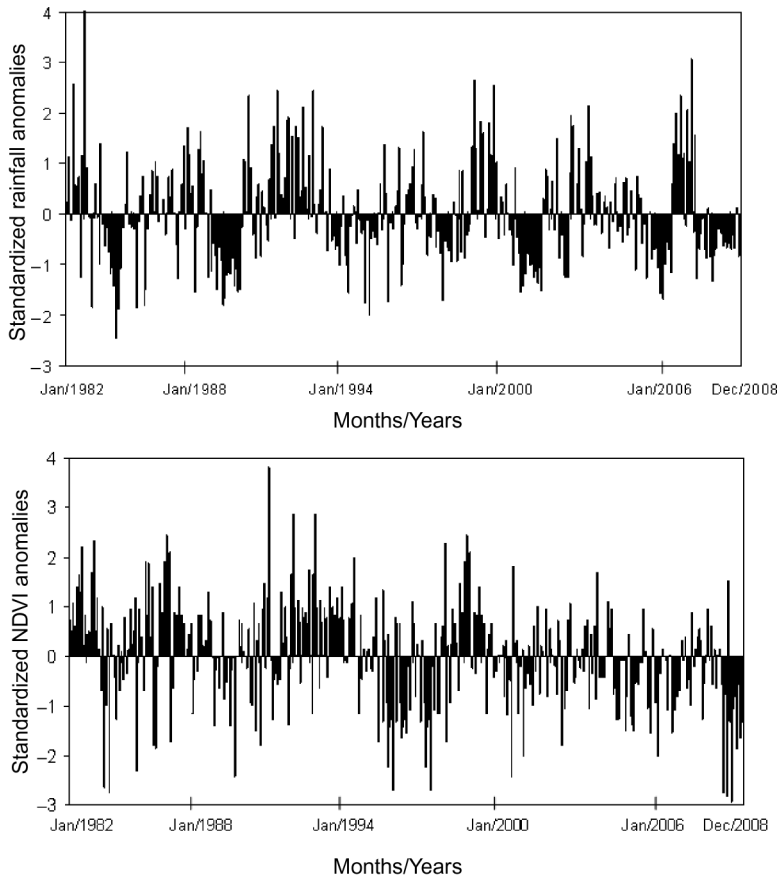


Figure 6. Time-series anomalies for NDVI and rainfall.

2 January 2009). A summary of vegetation types in the map is given in table 1, where it shows that most of the study area was already cropland by 1998. The indigenous forest (mostly deciduous broadleaved trees) on the highlands and woodland vegetation (mainly *Acacia* trees) in the midlands of this land-cover map were also observed by Owako (1971) and Ojany and Ogendo (1973) in the late 1940s. It was therefore likely that these vegetation types had remained intact between the late 1940s and 1998. Similarly, the wooded grassland and some parts of grassland observed in 1998 in the south of the study area (in what is locally known as the Kapiti planes) were also noted by Jaetzold and Schimdt (1983) and Ojany and Ogendo (1973). Again, they could also be assumed to have remained intact between the 1970s and 1998. All these areas with intact vegetation provided the necessary control for checking the accuracy of the proposed method.

In addition to the time-series NDVI and rainfall data, this study also used the 90 m Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) to extrapolate monthly rainfall amounts for facilitating pixel-based analysis of the NDVI–rainfall relationships. The DEM was used in extrapolating rainfall amounts because of the known relationship between rainfall amounts and altitude in east

Table 1. Vegetation types in the study area and their general classification.

Code	Africover description	Dominant vegetation type	Vegetation class	Area (%)
1	Continuous closed to very open herbaceous vegetation	Grass and forbs	Grassland	7.5
2	Medium to high thicket with emergents	<i>Commiphora</i> spp.	Bushland	0.7
3	Medium to high shrubland with open medium to tall herbaceous and emergents (65–40%)	<i>Grevillea</i> spp.	Dry shrubland	6.4
4	Forest with shrubs	<i>Eucalyptus</i>	Forest	3.7
5	Woodland with shrubs	<i>Acacia</i> spp.	Woodland	9.1
6	Broadleaved deciduous woodland with open herbaceous layer and sparse shrubs (65–40%)	<i>Podocarpus</i> , <i>Grewia</i> , <i>Premna</i> and <i>Combretum</i> spp.	Indigenous forest	9.2
7	Open woody vegetation with herbaceous layer	<i>Balanites</i> and <i>Rhus</i> spp.	Wooded grassland	6.8
8	Closed to very open herbaceous vegetation with sparse shrubs on temporarily flooded land. Water quality: fresh water	<i>Lantana</i> spp.	Wet shrubland	0.4
9	Industrial and/or other area(s)		Bare	0.3
10	Rain-fed herbaceous crop(s)	Cereals	Cereals	52.3
11	Rain-fed herbaceous crop(s) dominant crop: industrial crops – sisal ( <i>agave</i> spp.)	Sisal	Sisal	0.3
12	Permanently cropped area with rain-fed shrub crop(s). Dominant crop: fruits and nuts – pineapple ( <i>Ananas comosus</i> (L.) Merr.). Crop cover: orchard(s)	Banana / Pineapple	Shrub-crops	0.3
13	Permanently cropped area with rain-fed shrub crop(s). Dominant crop: beverage – coffee ( <i>coffea</i> spp.). Crop cover: orchard(s)	Coffee	Coffee	0.6
14	Permanently cropped area with small-sized field(s) of rain-fed tree crop(s) (one additional crop) (herbaceous terrestrial crop with simultaneous period). Crop cover: orchard(s)	Mangoes/Pawpaw	Tree-crops	2.6

Africa (Omuto 2008, Omuto and Vargas 2009). The DEM was downloaded from <http://srtm.usgs.gov> on 15 December 2008. Its application in extrapolating rainfall amounts was achieved through the regression kriging method (Hengl *et al.* 2007, Omuto 2008). To check the extrapolation accuracy, a holdout cross-validation was first carried out. Then the entire dataset for the month was used to produce the image of the rainfall amount for that month. The cross-validation tests involved using 2/3 of each month's rainfall amount for extrapolation and testing the output on the remaining 1/3. Its results showed that the correlation between the actual and predicted monthly rainfall datasets were between 70–90% (figure 7).

### 3.3 Time-series modelling of the NDVI–rainfall relationship

Before application of the mixed-effects modelling, the NDVI and rainfall statistical characteristics (annual maximum or minimum, semi-annual mean, coefficient of variation, etc.) were first determined. The statistical characteristics for the NDVI were then correlated with the corresponding rainfall characteristics to identify the best combination that could give the highest Pearson correlation for most pixels in the study area. After testing all NDVI and rainfall statistics, the 6 month (or 0.5 year) maximum NDVI and 6 month accumulated rainfall were found to give the highest correlation ( $>0.72\%$ ) for over 90% of the pixels in the study area. The spatial and temporal distributions of the 6 month maximum NDVI and corresponding rainfall amounts were also found to be nearly the same. Thus, a linear model was chosen for equation (1). This linear model was then analysed with the mixed-effects modelling for different vegetation types from the land-cover map (Pinheiro and Bates 2000, Omuto *et al.* 2006).

Mixed-effects modelling is a unique regression analysis that simultaneously determines the average regression parameters for an entire population and parameters for individual groups (e.g. vegetation types) in the population. The approach behaves like a hybrid regression of a single model for the whole landscape, on the one hand, and multiple models for each group in the landscape, on the other hand. Consequently, it integrates the advantages of these two modelling extremes and gives very robust

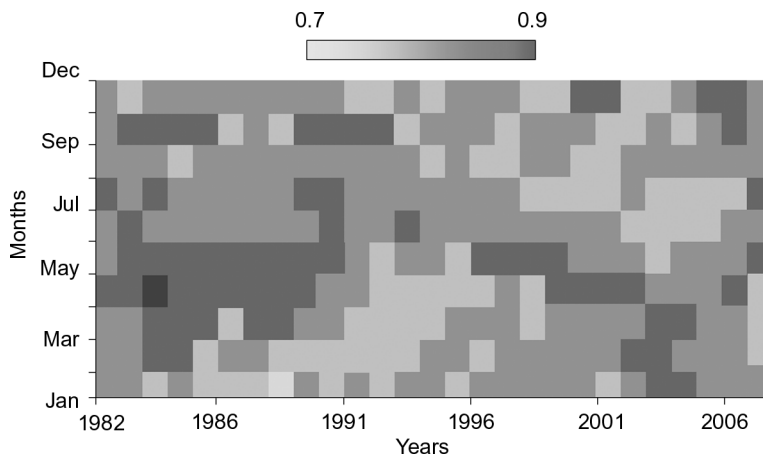


Figure 7. Correlation between time-series predicted and measured monthly rainfall amounts.

statistical estimates (Pinheiro and Bates 2000, Omuto *et al.* 2006). Its modelling representation of equation (1) is:

$$\begin{aligned} y_i &= f_i(x, \phi) + e_i \\ \phi_i &= \mathbf{D}\boldsymbol{\beta} + \mathbf{B}\mathbf{b}_i \quad i = 1, 2, 3, \dots, 13 \\ \mathbf{b}_i &\sim N(0, \boldsymbol{\Psi}), \quad e_i \sim N(0, \sigma^2) \end{aligned} \quad (3)$$

where  $i$  is the number of vegetation classes in the land-cover map,  $\phi$  is the vector of regression parameters,  $N$  is the symbol of normal distribution,  $\sigma$  is the standard deviation,  $\boldsymbol{\beta}$  is a vector of the whole study area average estimates of the model's slope and intercept (also known as fixed effects),  $\mathbf{b}$  is a vector of random deviations of the slope and intercept in each vegetation class around the fixed effects (also known as random effects),  $\mathbf{D}$  and  $\mathbf{B}$  are design matrices for solving equation (3) and  $\boldsymbol{\Psi}$  is a variance–covariance matrix for the random effects (Laird and Ware 1982). Pinheiro and Bates (2000) and Omuto *et al.* (2006) have given detailed information on how to solve equation (3) and obtain its regression parameters. In this study, the solution was implemented using the R Computing Environment software (R Development Core Team 2008).

Equation (3) was determined for every 6 months from January 1982 to December 2008. Its resultant time-series residuals were used to determine the change in vegetation cover while the time-series random effects were used to assess the temporal change in vegetation composition. For the random effects, their time-series similarities or differences between the vegetation classes were used to identify the time when the vegetation composition changed and possible changes between different vegetation types. The assumption used was that the concurrent time-series patterns of the random effects implied similar vegetation types, while separate time-series patterns implied different vegetation types. The general framework given in figure 8 was used to implement these analyses. Validation of the results was carried out by comparing two photographs/high-resolution images of the same area taken at two different dates.

## 4. Results

### 4.1 The NDVI–rainfall model parameters

Mixed-effects modelling estimated the regression parameters for the NDVI–rainfall relationship in every dominant vegetation type in the study area. Figure 9 shows an example of its output in the first half of 1994. It shows the population average estimates of the regression parameters (i.e. intercept = 0.4490 and slope = 0.0007) and regression parameters for indigenous forest, grass and *Acacia* vegetation types. The regression parameters for these vegetation types were estimated as random deviations from the population average estimates; hence, they were known as random effects. The estimation was carried out such that vegetation types with regression parameters lower than the population averages had positive random effects, while vegetation types with parameters higher than the population average estimates had negative random effects (Pinheiro and Bates 2000). For example, random effects for the intercept parameters were positive for grass (0.0785 = 0.449 – 0.3705) and *Acacia* (0.0308), because their curves were lower than the population average, while that for indigenous forest was negative (–0.0688), because its curve was above the average curve (figure 9). Where the random effects were zero implied that the model characteristics for that vegetation

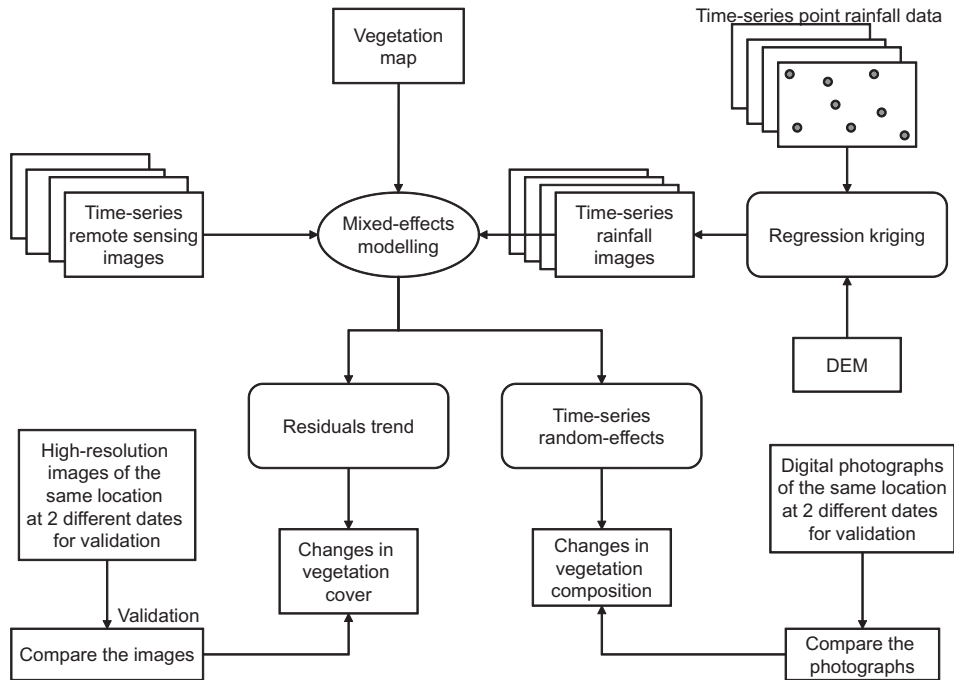


Figure 8. Conceptual framework for time-series mixed-effects modelling for detecting vegetation dynamics.

type were similar to the population average. This is illustrated in figure 9 for the slope parameter for indigenous forest and *Acacia*, which had parallel curves to that of the population average.

The random effects from the NDVI–rainfall modelling were obtained for different dominant vegetation types from 1982 to 2008 (figure 10). The results show that the random effects for the intercept parameter for areas without vegetation (bare), cereals and grass were mostly positive (figure 10). Since the intercept parameter in the NDVI–rainfall relationship was used to reflect the minimum NDVI during dry periods, its random-effect results among bare areas, grass and cereals imply that these vegetation types often had the lowest NDVI signals during dry periods. As for banana, sisal and indigenous forest, their intercept random effects had the highest negative values; implying that they remained fairly green throughout the years. In terms of the slope parameter, grass, coffee, cereals and *Lantana camara* had the largest negative random effects (figure 10). Like the intercept, the slope parameter was used to reflect the rate of vegetation response to rainfall. Hence, its random-effect results among grass, coffee, cereals and *L. camara* suggest that these vegetation types had the fastest response to rainfall in the study area. Other vegetation types such as *Acacia* and *Commiphora* had near-zero random effects and were likely to have had the average response to rainfall and the average NDVI during dry periods in the study area.

#### 4.2 Change in vegetation composition

The estimated random effects from the NDVI–rainfall relationships varied both in time and space. For example, the intercept random effects were largely negative

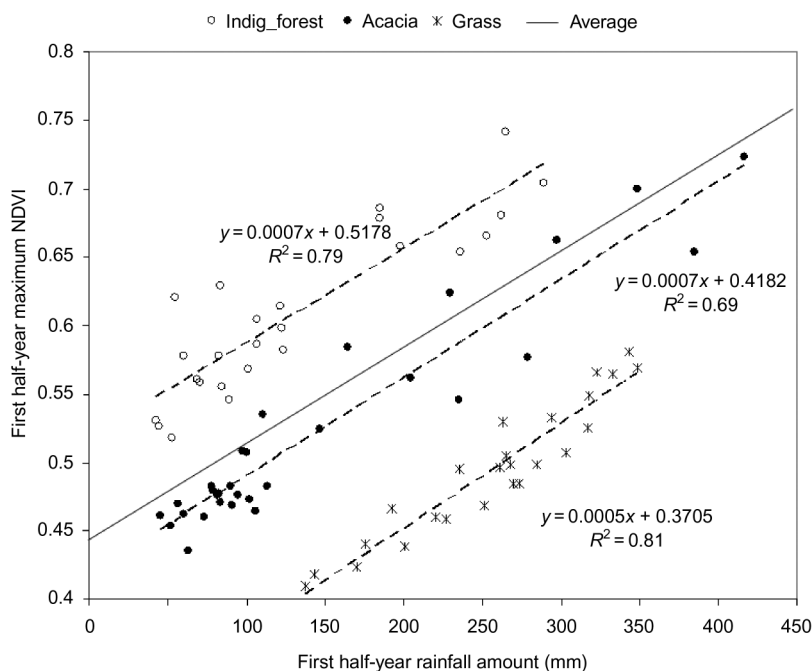


Figure 9. Example of mixed-effects output for the NDVI–rainfall relationship.

among the highland vegetation (altitude >2000 m) most of the time between 1982 and 1988 (figure 11(a)). Since they indexed the minimum NDVI during dry periods, it could be said that the highlands remained vegetated between 1982 and 1988. After 1988, the intercept random effects fluctuated far below 0, which implied that, although the original highland vegetation seemed to have changed, they still remained vegetated. For the lowland vegetation, the intercept random effects were mostly positive, while the slope random effects were negative. Furthermore, their time-series oscillations kept changing from positive to negative without any definite pattern. This implies that the lowland vegetation had the most remarkable change in vegetation composition between 1982 and 2008 in comparison to the highland vegetation.

Further pixel-by-pixel assessment of the time-series pattern of the random effects was carried out to establish the performance of the mixed-effects parameters in detecting changes in vegetation composition. As an example, the time-series random effects for three different locations in the study area (Ndulaya, Manyani and Syomuunyu) were extracted and graphically analysed (figure 11(b)). In the land-cover map, the three locations fell under *Balanites aegyptiaca*. Their random effects coincided between 1982 and 2002, implying that they all had *B. aegyptiaca* as the dominant vegetation during this period. After 2002, the random effects in Ndulaya began deviating from their counterparts in Manyani and Syomuunyu. The deviations were quite pronounced between 2003 and 2005, minimal in 2006 and then increased again after 2006 (figure 11(b)). These deviations imply change of the NDVI response to rainfall, perhaps due to change in vegetation composition from *B. aegyptiaca* to another dominant vegetation type.

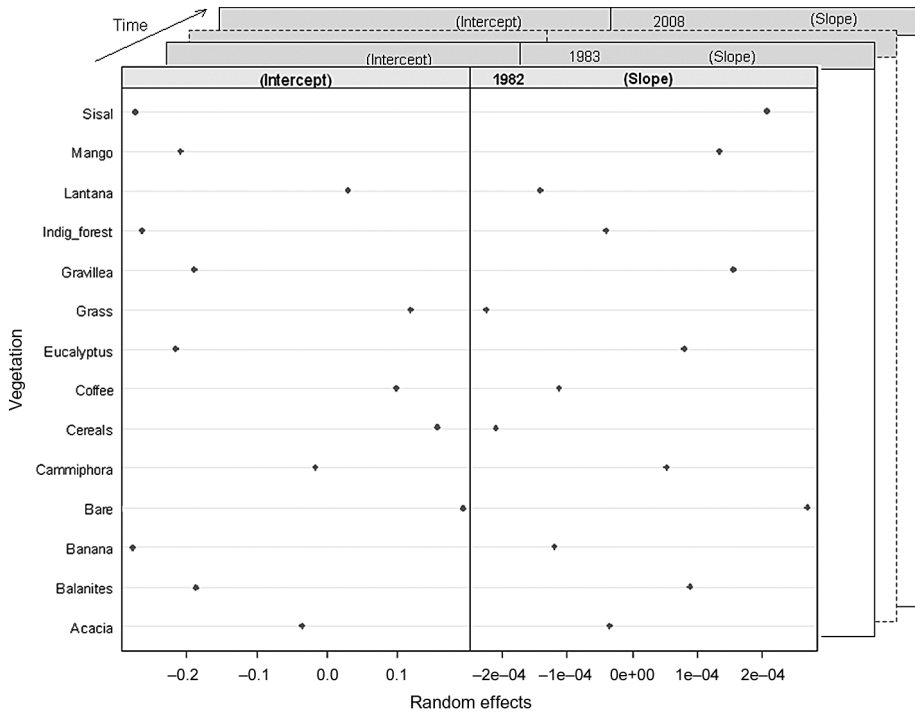


Figure 10. Random effects for the NDVI–rainfall relationship in the study area at different times between 1982 and 2008.

In another example, the random effects at Iiuni in the southeast of the study were also graphically analysed. The area had been classified as small plots of maize crops in the land-cover map by Africover ([www.africover.org](http://www.africover.org)) in 1998. A time-series pattern of its random effects showed that, between 1982 and 1995, it had oscillations similar to those for grass in its neighbourhood areas. After 1995, the random effects deviated from the characteristics for grass and behaved like the characteristics for maize crops (figure 12(a)). This pattern was positively confirmed with digital photographs of the area taken with nearly similar backgrounds in 1996 and 2008 (figure 12(b)). The photographs and the classification by Africover corroborate the results obtained from the time-series pattern of the random effects.

The above pixel-by-pixel assessment of the time-series random effects was done for all vegetation types in the study area. The results show that the majority of changes in vegetation composition consisted of transitions to grass, crops (mainly cereals) and *Eucalyptus* in some places. In the central and eastern parts of the study area, most changes involved movement from *Acacia* and *Commiphora* to cereal crops. In the northwest and southeast, the changes were mainly from tree vegetation to grass. There were a few changes in the highlands (in the west, north and south) and mainly involved change from indigenous forest to *Eucalyptus* trees. This was likely because most high-altitude areas had been demarcated by the Kenyan government as protected forests in the late 1980s and later reforested with *Eucalyptus* (Tiffen *et al.* 1995).

Although the above time-series analysis of random effects using AVHRR NDVI images seemed to identify changes in vegetation composition, there were cases that it

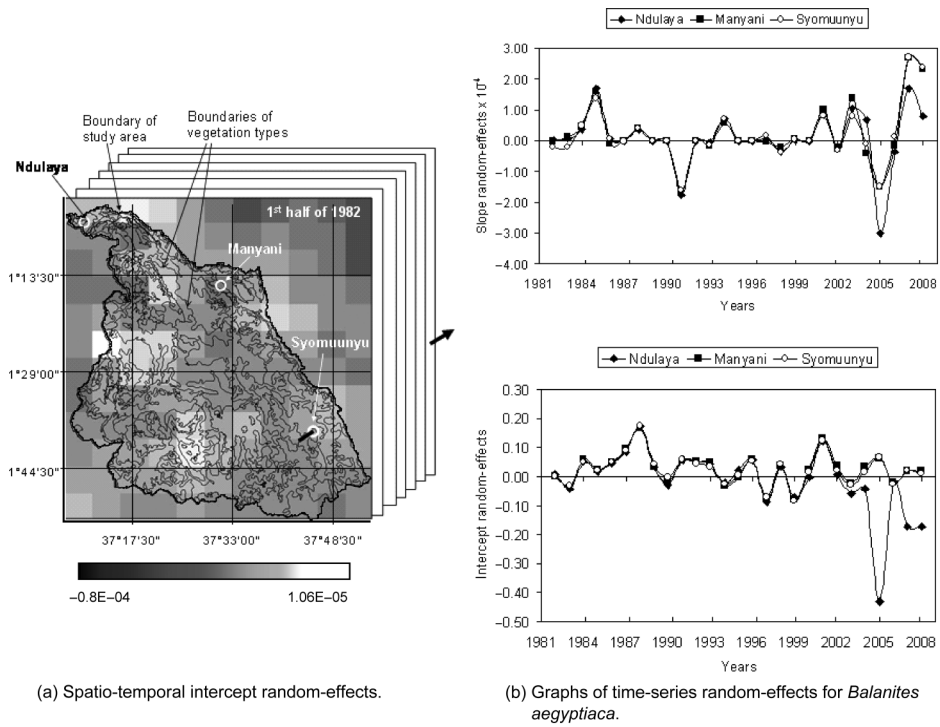


Figure 11. Integral analysis of random effects for detecting change in vegetation composition.

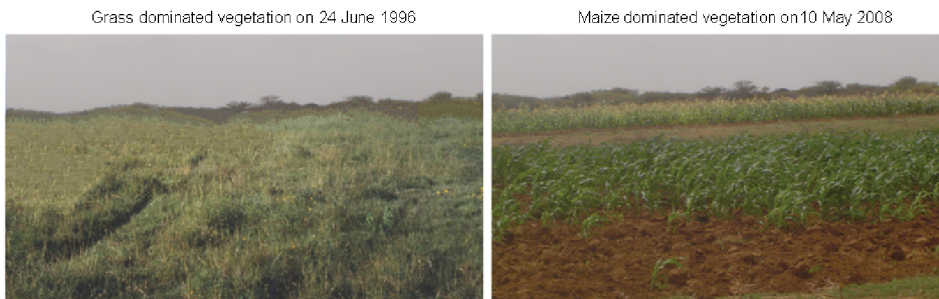
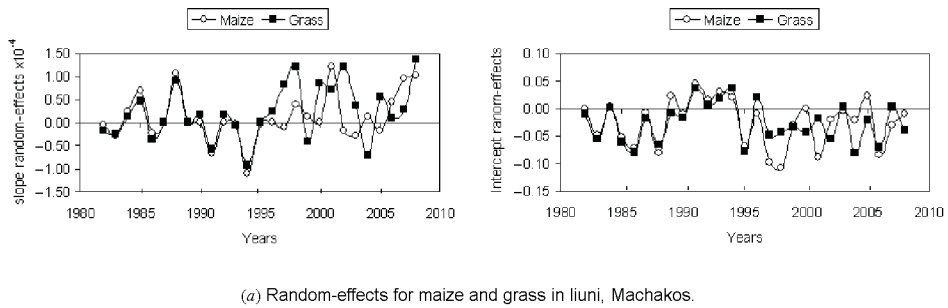
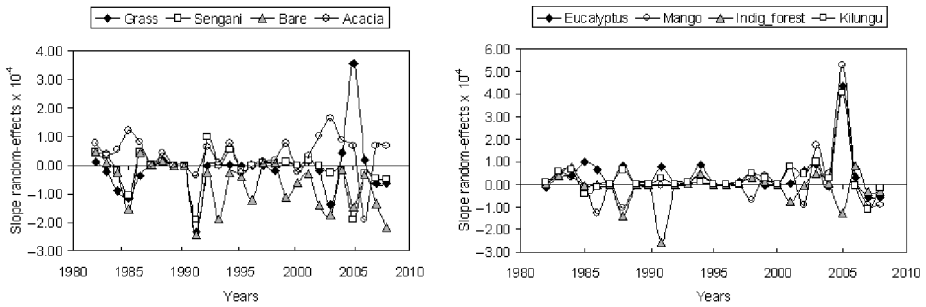


Figure 12. Validation of mixed-effects output for the NDVI-rainfall relationship in Iiuni.





(a) Slope random-effects around Sengani (north of study area).

(b) Slope random-effects around Kilungu (south of study area).



(c) 16 May 2008 photograph of Sengani.



(d) 19 May 2008 photograph of Kilungu.

Figure 13. Comparison of mixed-effects output for the NDVI–rainfall relationship in Sengani and Kilungu.

did not properly identify. For example, a polygon of *Acacia* in Sengani in the north of the study area had mixed responses in which the time-series random effects alternated between those for grass, *Acacia* and bare ground (figures 13(a) and (c)). Similarly, in Kilungu in the south, an area with mangoes and maize crops also had the time-series random effects, which oscillated between the characteristics for *Eucalyptus*, mangoes and indigenous forest (figures 13(b) and (d)). It was not immediately clear whether vegetation composition in these areas was changing as depicted by the time-series random effects or whether the random effects were not able to detect their transitions.

In trying to find the cause of lack of clear distinction of some of the cases that were not properly identified by AVHRR images, analysis of the time-series random effects was repeated using MODIS NDVI images. The results demonstrated that, in spite of the shorter time-series duration in MODIS than in AVHRR images, the MODIS-based analysis successfully detected changes in vegetation composition in some locations. It showed the change in vegetation composition from grass to maize cropland after 2003 in a small parcel of land that was next to the Konza ranch in the southwest of the study area. These two adjacent plots were distinctly represented in two different pixels in the MODIS NDVI images. In the AVHRR NDVI image, they all belonged to one pixel of grass that did not reflect any change in vegetation composition between 1982 and 2008. The MODIS NDVI image also showed a change in vegetation composition from indigenous forest to maize crop in a field on the slopes of the Kilungu hills and to grass and tree crops in some strips of bushlands along the Athi River. In general, the MODIS NDVI images could detect changes in vegetation

composition in homogeneous fields that were between 250 and 8000 m long. They also detected changes in vegetation composition in some border fields between different vegetation types (e.g. grass fields between Machakos urban centre and the adjacent Kiima Kiwe forest in the west of the study area) and some fields on the slopes of the mountainous areas (e.g. maize fields on the slopes of the Kilungu hills). The AVHRR's lack of clear determination of these fields was largely due to its low spatial resolution images.

The fields that were not properly identified by MODIS and AVHRR NDVI images were mainly those of mixed vegetation types and of relatively small sizes, but with uniform vegetation types (e.g. plots of crops and trees in abandoned/silted water-pans).

### 4.3 Change in vegetation cover

Trend analysis for the residuals from the time-series mixed-effects modelling of the NDVI–rainfall relationship was also carried out for each pixel in the study area. In the outputs, there were areas in the west and southeast of the study area that had a significant gently increasing trend (figure 14). Therefore, they were associated with improved vegetation cover for the period between 1982 and 2008. In parts of the centre, east and southwest of the study area, the time-series residuals had a significant declining trend (figure 14) and were associated with loss of vegetation cover. In total, about 28% of the study area was found to have had a loss of vegetation cover, 7% had improved vegetation cover and the rest did not have any significant change in vegetation cover between January 1982 and December 2008. The areas with a steep declining trend of the time-series residuals were those in which the difference between actual and

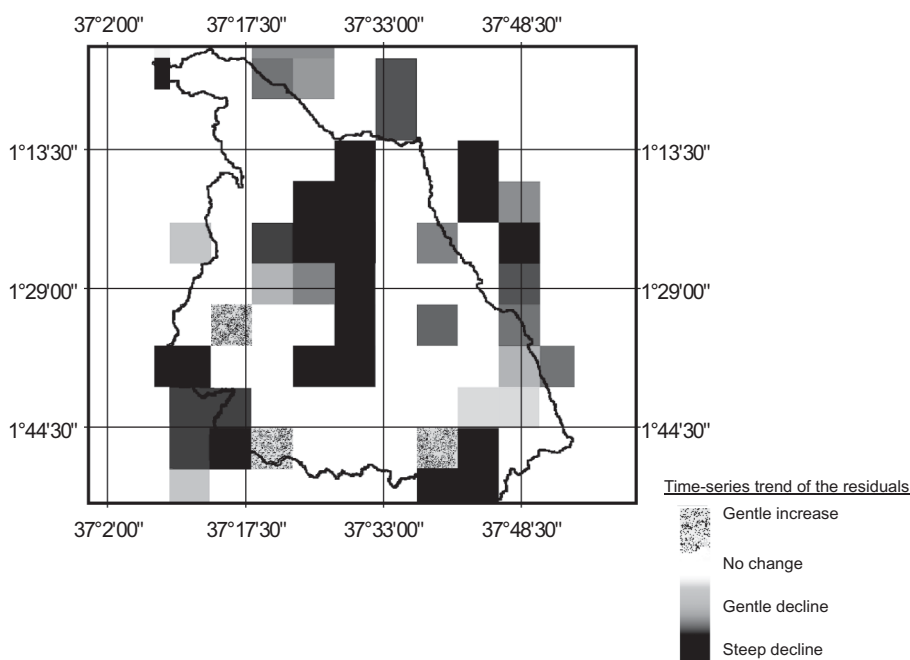


Figure 14. Loss of vegetation cover in the study area using time-series AVHRR NDVI.

predicted NDVI values was very large in a short period of time (figure 2). This implied that they could have rapidly lost their vegetation during that period.

Some of the locations in the study area that had a significant loss of vegetation cover were also found to have had changes in vegetation composition. Examples include west of Ndulaya (in the northwestern tip of the study area), which was dominated by grass and herbaceous vegetation in the 1980s, but which became bare (built-up areas) from 1992. Other examples were Kyanzavi (in the north) and Iiuni (in the centre). In Kyanzavi, the coffee plantation was changed to cereal cropland in 1996, and in Iiuni, the grassland was converted to cereal cropland in 1995. In Mumbuni (in the southern tip of the study area), *Acacia* and *Rhus* trees and shrubs were first changed to grass and forbs in 1992 and then to a mixture of grass and bare areas from 2001. Furthermore, in Lukenya (west of the Mua hills in the west of the study area), indigenous forest was first changed to *Grevillea* in the early 1990s, then to a mixture of *Grevillea* and grass in the late 1990s and lastly to grass from 2001. The vegetation types in Lukenya, Iiuni and Kyanzavi were positively confirmed during the field visit in 2008. In Mumbuni, the area was found covered with grass and sparse *Acacia* shrubs contrary to grass and bare areas, as predicted by the time-series analysis of the random effects.

Trend analysis of the residuals using the MODIS did not identify any area with significant change in vegetation cover. Perhaps this was because of its short time-series imagery (from 2000 to 2008). Other studies have shown that changes in the land cover in the study area mainly started occurring from the late 1980s (Tiffen *et al.* 1995, Omuto 2008). Therefore, it was possible that without the 1980s images, the MODIS could not have captured any significant change in vegetation cover.

## 5. Discussion and conclusions

Mixed-effects modelling of the NDVI–rainfall relationship was found to be a realistic modelling approach since it recognized the variation of vegetation responses to rainfall (Nicholson *et al.* 1990, Kutiel *et al.* 2000, Xi *et al.* 2008). It enabled possible diagnosis for change in vegetation composition through the random effects, which are statistical realizations with definable probability distribution functions (Pinheiro and Bates 2000). In each location in the study area, the probability distribution of the random effects for the dominant vegetation type was established. Possible changes in vegetation composition in these locations were then reflected as deviations from the established probability distributions. Some of the validation results (e.g. figure 12) confirmed the validity of this approach. Other validation results that were not clearly identified by the approach could have been due to the quality of the input data as illustrated in the differing results obtained from the comparative analysis using AVHRR and MODIS images.

The areas that were found to have a steep decline in vegetation cover were those that had a possible change in vegetation composition. For example, in the centre and northwards, the areas with natural vegetation (*Acacia*, *Commiphora* and grass) were found to have changed to cereals from the late 1980s. Since cereals had a very low NDVI count during dry periods in comparison to natural vegetation (figure 10) and that the study area was largely semi-arid and remained dry most of the time (Tiffen *et al.* 1995, Omuto 2008), the conversion of natural vegetation to cereal croplands could have occasioned the decline in vegetation cover (figure 14).

The areas that had a gentle decline of vegetation cover were mainly areas that did not have a significant change in vegetation composition. For example, Muumandu, Kalanzoni and Kivani in the southwest of the study area, which had a gentle decline of vegetation cover, had tall grass in the late 1980s. In 2004, they were found with short grass whose coverage was less dense than the 1980 grass cover. Similarly, a gentle loss of vegetation cover was also observed in the east of Kamuthwa in the eastern part of the study area, even though the area had been under the *Grevillea* type of trees since the early 1980s (Jama *et al.* 1989, Tiffen *et al.* 1995, Lott *et al.* 2003).

There were also other areas with improved vegetation cover and that were also found to have changed the composition of their dominant vegetation types. The Kiima Kimwe hills in Machakos (west of the study area), the Kilungu forest in Kilome (south of the study area) and Kampi ya Mawe in Makueni (southeast of the study area) (figure 14) were examples in this category. According to the Kenya Forestry Working Group (KFWG 2008), these areas had been demarcated by the Government of Kenya in the mid 1980s as protected forests. The government, through the Ministry of Environment and Natural Resources, replaced the lost vegetation in these areas with *Eucalyptus* trees from around 1990s. It is interesting that the time-series mixed-effects modelling found these areas to have had a change in vegetation composition from indigenous forest to *Eucalyptus* trees and that they also had improved their vegetation cover (figures 3 and 14). These results show that the time-series mixed-effects modelling with reflective remote sensing had some potential in assessing change in vegetation composition and cover. Hence, it can be proposed as a promising tool for tracing the footprints of vegetation dynamics in a study area.

The approach presented in this study was successful in large areas with dominant vegetation types. It was not successful in areas with mixed vegetation types and in areas with small pockets of vegetation (i.e. less than 250 m in spatial resolution). Perhaps this was largely due to the scale of the input data used in the study. The low spatial resolution of the input NDVI images possibly integrated mixed vegetation types in a given area into one single pixel value, thus missing its true NDVI–rainfall relationship.

In spite of the limitations of the input data, the approach is promising. Given that the datasets used in this study are widely available, the approach could be suitable for regional analysis of vegetation cover and composition change in other areas. The method applied here can also be useful as a first approximation to guide further comprehensive analysis involving high-resolution input data. In this regard, the method passes as a useful tool for land condition monitoring and guiding policy decisions on vegetation dynamics in environmental conservation.

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