agriculture

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The Impact of a Warming Micro-Climate on Muooni Farmers of Kenya

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Academic Editors: Annelie Holzkämper and Sibylle Stöckli
Received: 26 May 2016; Accepted: 2 March 2017; Published: 7 March 2017

Abstract: Rainfed agriculture has become highly vulnerable to the depleting water resources in most arid and semi-arid tropics (ASATs) under the effect of climate change. The impact has certainly been very high in Muooni catchment where more than 99% of the natural forest has been cleared. The warming micro-climate is accelerated by extended deforestation, unsustainable irrigation, and water over-abstraction in the catchment by eucalyptus and other exotic trees. The dwindling crop yields add to the farmer's suffering. Farming communities have created various innovative ways of coping with a warming environment to increase their agriculture resiliency. These include, among others, rain water management, reforestation and agro-forestry. To what extent have these practices been disturbed by the increasing temperatures, and decreasing rainfalls and river discharges in Muooni catchment? This study used statistical forecast techniques to unveil the past, current and future variations of the micro-climate in Muooni catchment, and relevant factors determining farmers' vulnerability to drought. Muooni catchment is warming by 0.8 to 1.2 °C in a century as a result of a changing micro-climate. These changes are mainly driven by deforestation due to the high urbanization rate and agricultural practices in Muooni catchment. Centennial rainfall is subsequently plummeting at 30 to 50 mm while discharges are decreasing from 0.01 to 0.05 $m^3 \cdot s^{-1}$, with unmet water demands of 30% to 95% and above. In view of the current trends of the population growth and urbanization in Muooni, agricultural expansion is seriously threatened if no appropriate policy, extension service and science based emergency measures are put in place by the Government of Kenya.

Keywords: micro-climate change; climate adaptation; vulnerability to drought

1. Introduction

Regional climate change projections performed by Hulme et al. (2001) [1] indicate that from 1900 to 2100 the variations of temperatures in Africa range between 0.2 °C per decade (for the lowest scenario—B1) to 0.5 °C per decade (for the high scenario—A2). Some parts of East Africa record increased rainfall of 5% to 20% in December–February, and decreases of 5% to 10% in June–August. Meanwhile, rainfed agriculture has become highly vulnerable to the depleting water resources' effects under the warming micro-climate. The latter is ushered on by extended deforestation [2]. The 2007/2008 Human Development Report (HDR) mentions five (5) interactive transmission mechanisms of farmers' vulnerability to climate risks in East Africa. These encompass: (1) the collapse of ecosystems; (2) increased exposure to coastal flooding and extreme weather events; (3) heightened water insecurity; (4) reduced agricultural productivity; and (5) increased health risks [3]. Climate change, deforestation and poverty are thus increasingly disturbing life-supporting ecosystems and the services on which agriculture relies. The agricultural production in most arid and semi-arid tropics (ASATs) is seriously affected by the changing weather patterns and climate trends, and particularly by the unpredictability of rainfall [4]. African communities also face the inequitable distribution of rainfall, which often is coupled with the recurrence of droughts and flash floods. The latter adds to the existing water scarcity tragedy and dwindling crop yields [5]. "While the processes are already apparent in many countries, breaching the 2 °C threshold would mark a qualitative shift: it would mark a transition to far greater ecological, social and economic damage" [2]. If the current trajectory of water resources degradation keeps its pace, this water crisis will have serious consequences on the living styles of people and economic systems that depend on the availability of quality water and its temporal distribution [1]. The lack of access to safe water and irrigation will hinder human development and welfare, thus leading to enhanced poverty in many parts of East Africa, Kenya in particular [6]. Agricultural water development is hence, a prerequisite for ensuring food security and alleviating poverty in Kenyan ASATs [7].

Farming communities have created various innovative ways of coping with a warming environment to increase soil moisture and agriculture resiliency. These include among others rain water management, reforestation and agro-forestry. They enhance rainwater infiltration into the soil and increase groundwater reserves [8,9]. Tree planting has therefore been strategically combined with agricultural crops to safeguard rainfed agriculture in most of ASATs of eastern Kenya [10,11]. Yet, this strategy is sometimes unsustainable; it comes with some side effects, such as water over-abstraction in the catchment by eucalyptus and other invasive trees planted near water bodies [12]. To what extent have temperatures, rainfalls and river discharges changed in the last five decades in Muooni catchment? What is the prospect for the future farming water therein? This study provides critical answers to these questions.

This study uses an evaluative design based on auto regressive moving average (ARIMA) model to address these questions. It simulates the past, present and future variations of the micro-climate of Muooni catchment. It specifically seeks to: (i) predict the extent to which rainfall, temperature and discharge have changed in Muooni catchment from 1971 to 2010; (ii) foresee their future trend from 2011 to 2030; and (iii) determine farmers' vulnerability to drought as well as the related sensitivity of the farms and farmers' adaptive capacity. The elasticities of temperature, rainfall and discharge in the upper and lower sub-catchments of Muooni are first computed based on the ARIMA model. Then, a trend-shift technique utilizing non parametric tests and PP-Plots is employed to ascertain the revealed hydro-climatic changes for the period 1971–2010 and 2011–2030. This provides a plausible explanation of the need for alternative water saving strategies and other climate adaptation mechanisms used by smallholder farmers in Kenya to supplement their irrigation water. Prior to presenting and discussing these results a description of the study area and the prediction model are presented, following this short introduction. Thereafter comes the presentation of the main results and their discussion, followed by conclusions and key recommendations of the study.

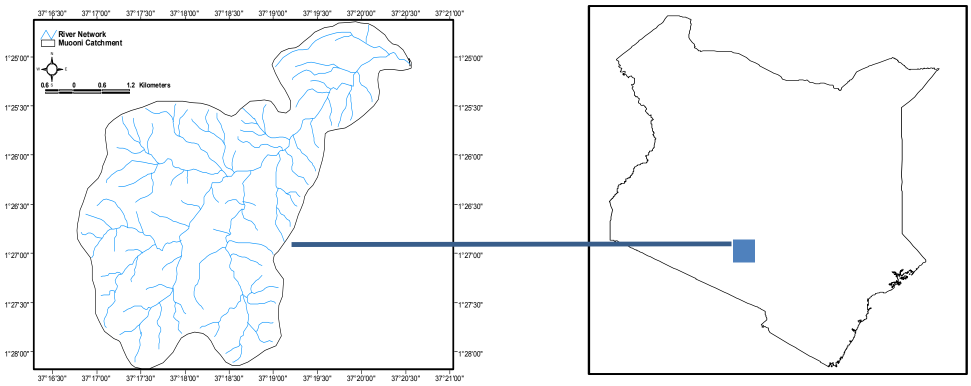
2. Materials and Methods

2.1. Study Area

2.1.1. Geographical Setting and Topography

Muooni catchment belongs to the eastern highlands topographic area, one of the most important mountainous ecosystems of Kenyan drylands [12]. This small catchment (of 25 km^2) is located in the eastern region of Kenya, within Machakos County, Mitaboni location of Kathiani Division. It rises between 1434 m (near Kathiani) and 2005 m (at Mutondoni) and is bound by latitudes 1.24° S and 1.28° S, and longitudes 37.16° E and 37.20° E in the 37th Meridian (Figure 1).

From a hydrological point of view, Muooni belongs to the Athi Basin, one of the 6 major river basins of Kenya, which is administered by the Regional Office of the Water Resources Management Authority (WRMA) in Machakos. The area is situated between the Iveti forest (from the source) and Kyevaluki and Uuni hills (in the east) [13]. The catchment is shared by three administrative sub-locations, namely Isyukoni, Mbee and Kaewa. It is mainly populated by the Akamba agriculturalists and livestock keepers, of the Bantu ethnic group, whose total population was estimated to 25,000 people in 2010, with an average density of 1000 heads per km^2 [14]. The Akamba people have intensively cultivated the land, even up to the top hills, to feed such a growing population [13]. There is no doubt that soil erosion, water stress and food insecurity are major concerns of Muooni farmers.



Muooni Catchment Republic of Kenya

Figure 1. Muooni catchment area in the map of Kenya and East Africa [14].

2.1.2. Agro-Climatic Conditions

Muooni catchment belongs to medium upper midland agro-ecological zone, which is potential for sunflower and maize cropping. Climatic conditions vary from arid to semi-arid [15]. Annual temperatures range between 12 °C and 23 °C, the average temperature being 17.5 °C. Mean annual rainfall was estimated to 540 mm from 1968 to 2006 with a reliability of 66%. However, during the last five years, annual rainfall varied between 626 mm and 783 mm. This rainfall is bimodal, falling during the long rains (from April to May) and the short rains (from November to December). This rainfall regime is also dominated by two main dry "monsoon" seasons (January–February and June–September) [16]. Additional rainfall comes from the trade effects of south-eastern winds blowing on slopes. Rainfall patterns are spatially uniform, even during extreme periods of drought and wetness, but they are highly influenced by the seasonal movements of the African "Inter Tropical Convergence Zone" (ITCZ) [17]. The El Niño Southern Oscillation (ENSO) always affects agricultural water and land-use in the catchment, mainly in terms of rainfall and irrigation water volumes, and crop treatments. The short rainy season becomes either extremely wet or totally dry following the El Niño–La Niña cycle [17].

The mean annual evapo-transpiration (ET) computed by Jaetzold et al. (2007) [15] was about 1622 mm in Machakos County. This abnormal ET value may be attributed to the fact that some irrigation schemes (like Kahuti in Muooni environs) carry large water volumes from dams outside the catchment. A part from this irrigation abstraction, the ET value might have been influenced by the recurrent soil moisture deficits occurring since pre-colonial times during dryspells, which might have depleted soil moisture storage in some parts of the catchment, and thus affecting groundwater recharge and water balance. Jaetzold et al. (2007) [15] used sophisticated models of soil-water-dynamics (like MARCROP, WOFOST and CERES) that included climatic, soil-hydraulic and plant physiological parameters to generate these evapo-transpiration values. These models were calibrated and validated to: (1) delineate the stage-specific development of crops/plants (including yield sensitive aspects); (2) estimate/calculate morphological development of plant parts (e.g., roots); and (3) estimate/calculate yield parameters in correlation to soil water balances (being most important in particular in tropical dry lands).

2.2. Research Methods

2.2.1. Sampling Methods and Techniques of Data Collection

The selection of Muooni catchment was mainly explained by the need for building scenarios of farmers' vulnerability and capability to drought and flood. The catchment was subdivided in two homogenous Ecological Functional Units (EFU), namely the Upper Sub-Catchment Area (USCA) and the Lower Sub-Catchment Area (LSCA) [18]. Primary meteorological data (for rainfall, temperatures) were mainly collected from the Kenya meteorological department Hydrological data (for discharge and streamflow) were retrieved from the WRMA stations as well as relevant ministerial archives (i.e., Kenya Meteorological Department (KMD) and the Department of Resource Surveys and Remote Sensing (DRSRS)). Discharge (streamflow) data obtained from the WRMA office in Machakos ranged from 1971 to 2010. Additionnal primary data on discharge were measured in situ from April to August 2011, at 6 river points, using Seba Hydrometrie current meter. During the same period, the researcher gathered once a month proxy data on soil moisture were equally measured at 30 field points using a Theta Probe ML2x soil moisture meter and 30 soil cans. These data were complemented by administration of on-farm survey questionnaires to 101 farmers to understand their water challenges and saving strategies. Besides, a Focus Group Discussion (FGD) and in-depth interviews took place in Kathiani Town and involved 13 key informants and 20 local administration officers, respectively, to unveil community strategies and public policies regarding disaster management.

2.2.2. Techniques of Data Analysis

Data collected were analyzed to achieve the above stated objectives, namely: (i) to predict the extent to which rainfall, temperature and discharge have changed in Muooni catchment from 1971 to 2030; and (ii) to determine farmers' vulnerability to drought as well as the related sensitivity of the farms and farmers' adaptive capacity.

Hydro-Climatic Prediction

This study used hydro-climatic statistical forecasting and trendshift techniques to predict seasonal time series temperature, rainfall and discharge in Muooni catchment from 1971 to 2030 for both USCA and LSCA clusters. A "Seasonal Autoregressive Integrated Moving Averages" (SARIMA) model was utilized to generate seasonal, annual and centennial forecasts of rainfall, temperature and streamflow in Muooni supported by "Mean Average Percentage Error" (MAPE), "Autocorrelation Function" (ACF), and "Partial Autocorrelation Function" (PACF). A comparison of various trendshift detection techniques shed light on the changes of these hydro-climatic variables [19]. These included Mann-Whitney Pettitt Test and Marginal Homogeneity Test and P-P/Q-Q Plots, among others [20].

(a) SARIMA Stochastic Model Specification

The Seasonal Auto Regressive Integrated Moving Average (SARIMA) model was used for time series analysis. It integrated 2 models in a single one to estimate both regular and seasonal regression parameters. The SARIMA encompassed an autoregressive (AR) model and a moving average (MA) model, which assumed that the time series hydro-climatic variables (X_t) were nonstationary. These variables needed thus to undergo successive differencing, depending on the degree of autoregression (AR) and its impact on the residual error. To generate MA values, the backward shift operator B was defined as a set of successive values (β_0, β_1, β_2, ... , *for the* X_t *regression coefficients, and* α_0, α_1, α_2, ... , *for the AR autoregressive coefficients*) for an observed lag length (Equation (1)) [21]:

$$X_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \varepsilon_t \tag{1}$$

where, ε_t, is a set of successive residual values (ε_1, ε_2, ...) representing the AR model given by Equation (2) [21]:

$$\varepsilon_t = X_t - \alpha_0 - \alpha_1\, \varepsilon_{t-1} - \alpha_2\, \varepsilon_{t-2} \text{ for } t \geq 3 \quad (2)$$

where, α_i, is a set of autoregressive (AR) model coefficients usually represented by the vector A.

The residual value in any prediction model is ideally very small if the model is unbiased, meaning a model having an error term closer to zero (0) with a variance closer to one (1). Yet, this is hardly the case when dealing with time series [22]. ARIMA models are hence based on the assumption that any time series (Y) is a product of secular trend (T), seasonality (S), the cyclical irregular movement (C) and other irregular fluctuations (I). Therefore, one cannot expect an immediate best fitting line (comprising a white noise or ideal error term close to 0) after a first regression or prediction of time series. A certain lag length shall then be observed prior to getting a stationary series and smooth trendline [23]. One way of doing so is by removing autoregressive and autocorrelated errors, and/or solving problems related to heteroskedasticity and multicollinearity.

Equation (2) recognizes the existence of autoregressive errors in the ARIMA model due to an error term in time $t-2$ thus affecting the error of time $t-1$, which in turn affects the error term of the prediction period (t). This is what leads to the non-stationarity of the time series. The latter is generally represented by a large number of high peaks and dips in the time series. Seasonal ARIMA (SARIMA) method is applied for correction of the non-stationarity issue both in the regular and the seasonal AR time series (Equation (3)). MA operators are then included in the model to help smoothing these time series and get a best fitting line for successive X_t values of the stationary series. In a nutshell, differencing both regular and seasonal AR series enabled removing first the secular trend (in the regular series) and then seasonalities (in the seasonal series) so as to obtain stationarity, and a white residual error or noise that has a mean closer to zero (0) with a variance closer to one (1) [24]. Thence, the general linear SARIMA model is Auto-Regressive (AR) to order p (or P) and Moving Average (MA) to order q (or Q) and operates on the d^{th} (or D^{th}) difference of X_t to obtain stationarity. The seasonal ARIMA model of order (p, d, q) (P, D, Q) can thus be represented as polynomials of order p, d and q (for regular series), and P, D and Q (for seasonal series), respectively. For successive X_t values of the stationary series, the SARIMA model for a given region can be written in compact form as Equation (3) [25]:

$$(1 - B)^d (1 - B^s)^D\, \phi(B)\, \Phi(B)\, X_t = \theta(B)\, \Theta(B) a_t \quad (3)$$

where,

d and D are the order of the first differencing component for removing the trend (for regular series) and the seasonality (for seasonal series), respectively;
s is the period of the season (in this case s = 4 for quarterly seasons in a year);
$\phi(B)$ and $\theta(B)$ are AR and MA operators for regular series represented as polynomials of order p and q, respectively;
$\Phi(B)$ and $\Theta(B)$ are AR and MA operators for the seasonal series represented as polynomials of order P and Q, respectively.

For fitting the SARIMA model to the time series a three-stage ARIMA procedure was followed: (1) model identification: determining the autoregressive (AR) and moving average (MA) processes; (2) model estimation: combining the parameters of both processes in the same model to predict the trend; (3) model diagnostics: assessing the stochastic process stationarity. However, this procedure required at least 50 observations to ensure stationarity, otherwise series might remain non-stationary [26]. That is a general weakness of all ARIMA models: the requirement for a large number of data points for estimating short time series. This was clearly depicted by a series of correlograms (or autocorrelation plots) developed from the original time series of almost all hydro-climatic variables in both sub-catchment areas. They displayed an autocorrelation problem with non-stationary series for many successive lags, beginning at lag 1. For that reason, the SARIMA model was associated with Ljung-Box statistic to enable fitting the time series of hydro-climatic models in a record lag time. This procedure was used to test whether parameters corresponding to the coefficient of the moving average operator ($\theta(B)$ and $\Theta(B)$) were significantly different from 0% at 95% confidence interval.

Ljung and Box suggested an iterative approach that maximizes optimality and comprehensiveness of the family of models obtained from moderate sample sizes using the following Q^* statistic for autocorrelation [27].

$$Q* \; = \; N(N+2)\sum_{k=1}^{m}(N-k)^{-1} \; r_k^2 \tag{4}$$

where,

N is the number of observations in the series;
r_k is an AR of lag k the first differencing component for removing the autocorrelation problem;
m-p-q is the number of degrees of freedom of the fitting model for AR and MA of p and q orders.

In practice, the model building process used for ARIMA and Ljung-Box includes an Auto-Correlation Function (ACF) and a Partial Auto-Correlation Function (PACF) [28]. ACF is used to gather information concerning the seasonal and non-seasonal AR and MA operators, and measure the amount of linear dependency between observations in a time series. Serial dependency on intermediate elements within the lag is removed via the PACF, an extension of the ACF. The identification of the appropriate parametric time series model depends on the shape of the ACF and PACF. If the ACF estimates of other than integer multiple of s (the period of the season) failed to damp out, this suggested that stationarity was to be obtained through non-seasonal differencing. If however the sample PACF damped out at lags that were multiple of s, that revealed the need for a seasonal MA component into the model, otherwise other lags may imply a non-seasonal MA term. Thereafter, the model diagnostic checking would be done by means of the Residual Auto-Correlation Function (RACF) to determine whether residuals were white noise. In this study, the filter model was based on the poorest goodness of fit that was limited to four models: a linear one, the logarithm, the exponential and power ones. Predicted values were saved along with their upper and lower limits, and the noise residuals.

(b) Model Selection and Validation

An automatic selection criterion was used to keep the model as simple as possible and at the same time provide a goodness of fit to the data series. The normalized Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC) are the most commonly used automatic criteria for selecting regressors (or explanatory variables) to balance between the conflicting model simplicity with its statistical goodness of fit. The AIC mathematical expression is given by Equation (5) [29]:

$$AIC \; = \; \frac{N}{n}\,(-2lnML) + \; 2k \tag{5}$$

where,

$lnML$ denotes the maximized log likelihood function;
N is the number of observations of non-stationary series;
n is the number of differenced series (N-d);
k is the number of independently adjusted parameters.

However, the BIC provides a minimum AIC value to discriminate models and is likewise estimated by the maximum likelihood (ML) method as Equation (6) [30]:

$$BIC = (-2lnML) + k\; ln(n) \tag{6}$$

The utilization of the minimum AIC in the BIC reinforced and complemented the model construction at its identification, estimation and diagnostic stages, since AIC model tended to overestimate the order of autoregression. Hence, the BIC slightly better discriminated the models than could the AIC. Finally, model fit measures were utilized to assess the strengths of the estimated hydro-climatic models.

(c) Model Correction

The following fit measures were utilized in this study to assess the strengths of the estimated hydro-climatic models: Stationary R-squared; R-squared; the root mean square error (RMSE); the mean absolute percentage error (MAPE); the mean absolute error (MAE); and the maximum absolute error (MaxAE). These measures were supported by the Bayes information criterion (BIC), the residual autocorrelation function (ACF) and residual partial autocorrelation function (PACF) for the purpose of comparing models and selecting the best fitting trendline. The best-fitting models were automatically identified, estimated and corrected by solving several statistical problems related to time series, including the prediction bias, autoregressive and autocorrelated errors, heteroskedasticity, and multicollinearity. It shall be noted that all baseline data collected (January 1971–December 2010) and their forecasts (JF 1971-OND 2030) were benchmarked as maximum, minimum and averages to allow comparison of hydro-climatic variability over the prediction period (January 1971 to December 2030).

Trendshift Detection and Occurrence Likelihood

After forecasting, statistical trendshift techniques were employed to ascertain the significance of changes in temperatures, rainfall and discharges in both ecological functional units (EFUs) of Muooni catchment. Techniques for detecting inter-seasonal variations' shift encompassed statistical tests such as the median test, Kruskal-Wallis H-test, Two-sample Kolmogorov-Smirnov test, and Mann-Whitney U-test. However, techniques for detecting inter-annual trendshift included Mann-Whitney Pettitt and marginal homogeneity tests [19]. These results gave a broad idea on the micro-climate and hydrological changes observed in Muooni catchment.

Thereafter, probability distributions were plotted to confirm (or infirm) any assumption of shifting trend in the behaviour of hydro-climatic variables assessed in the catchments. The resulting P-P Plots consisted of cumulative relative frequencies of observed values (or observed percentiles) of hydro-climatic variables assessed against cumulative density probabilities of expected values (or expected percentiles) of the same variables. Probability distributions used to that effect often comprehended uniform, exponential, normal/Student's *t*, lognormal and Weibull distributions. This statistical validation of the predictions was linked to spatial data analysis that depicted changes in land-use/cover and soil moisture. It added a qualitative value to the assessment and enable defining the likelihood of occurrence of climatic events predicted earlier in Muooni catchment. This procedure mainly took into consideration the significance of rainfall patterns and biodiversity population change in each EFU of the catchment, namely the upper sub-catchment area (USCA) and/or in the lower sub-catchment area (LSCA). Then, a probability ranging from less than 25% to above 95% was assigned to each factor based on its likelihood of occurrence. This led to contextualizing the predicted changes in a particular sub-catchment environment of the study area.

Farmers' Vulnerability to Drought in Muooni

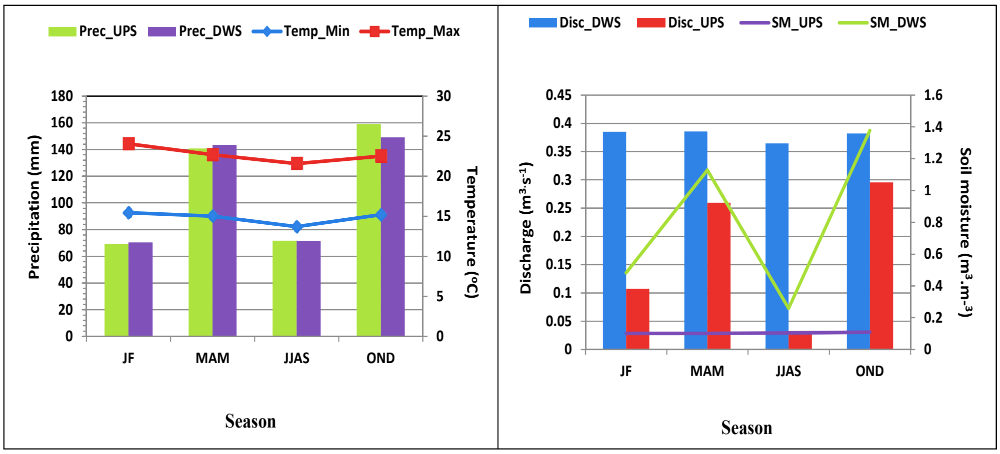
The study also used Hydro-geomorphologic impacts and risks assessment (HIRA) technique to analyze anthropogenic factors and externalities affecting fertile land and water availability in Muooni catchment [31]. This technique was particularly useful for recording significant land-use activities and hydro-geomorphologic risks randomly occurring on farmlands and in the whole catchment. The analysis was based on the significance of hydro-geomorphologic impacts (or risks) of each farming activity (or environmental externality) going on in Muooni catchment. These were interpreted in terms of sedimentation of the river and its dam as well as water over-abstraction from the catchment and the dam reservoir, leading to high rates of unmet water demands in agriculture and other productive sectors. The catchment degradation was basically related to the soil erosion problems leading to the sedimentation of Muooni River and its dam, and to subsequent depletion of soil moisture and the low productivity of agricultural lands. Farmer's poverty and illiteracy as well as other socio-economic risks and the uncertainty of agricultural water and production were among key drivers of their vulnerability to the warming micro-climate in Muooni.

3. Results

3.1. Hydro-Climatic Prediction for Muooni Catchment

3.1.1. Descriptive Hydro-Climatic Statistics

High deviations in temperatures, discharges and soil moisture were observed during almost all the seasons, except for rainfall, which presented high variations during the long dry season (JJAS) and short rainy season (OND) (Figure 2).



Legend:
Prec_UPS = Precipitation upstream
Prec_DWS = Precipitation downstream
Temp_Max = Maximum temperature
Temp_Min = Minimum temperature
JF = January-February dry season
MAM = March-April-May rainy season

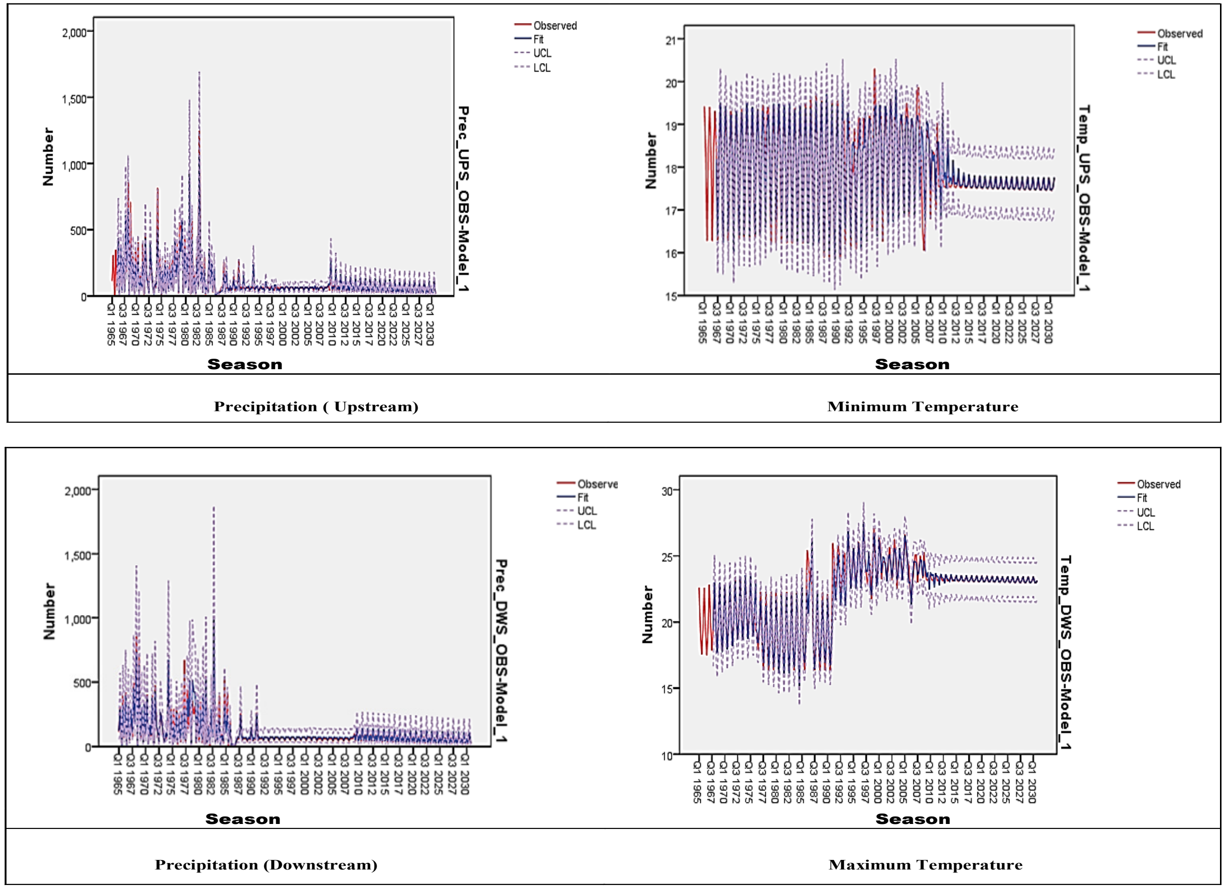
Legend:
Disc_UPS = Discharge upstream
Disc _ DWS = Discharge downstream
SM_UPS = Soil moisture upstream
SM _ DWS = Soil moisture downstream
JJAS = June-July-August-September dry season
OND = October-November-December rainy season

Figure 2. Seasonal hydro-climatograph of Muooni catchment (1971–2010) [32].

All selected variables characterizing each hydro-ecological zone presented different trends depending on the type of data collected. Temperature and discharge upstream were naturally lower than downstream, and a change in their minimum value would clearly be captured upstream than downstream, while the change of maximum values would be easily sensed downstream rather than upstream. This assumption helped clustering farmers' vulnerability to changes in temperature, rainfall and discharges by sub-catchment to shed more light on their perceived resiliency to hydro-climatic changes going on in the catchment.

3.1.2. Predicted Hydro-Climatic Trends in Muooni

Muooni catchment experiences decreasing trend of rainfall and river discharges with increasing mean seasonal and annual temperatures. Table 1 presents the results of the seasonal autoregressive integrated moving average (SARIMA) model for the two EFUs of Muooni catchment as displayed in Figure 3.



Legend :

Obser = Observed trendline
Ft = The best fitting trendline
UCL = Upper Class value
LCL = Lower Class value
Q_1 2003 = First Quarter of the year 2003 (= first season of the year)
Q_3 2003 = Third Quarter of the year 2003 (= third season of the year)

Figure 3. The general trend of observed and expected hydro-climatic variables in Muooni.

Table 1. Seasonal hydro-climatic forecast for the upper and lower Muooni (1971–2030).

Dependent Variable	**Fit Model** [a]						**Model Fit Statistics**			**Ljung-Box Q(18)**			**Residual Autocorrelation** [b]	
	ARIMA	Estimate	SE	MAPE	t	Sig.	Stationary R^2	R^2	Normal BIC	Statistics	df	Sig.	ACF	PACF
Prec_UPS														
MA	(002)(011)	−0.178	0.061	17.82	−2.935	0.000	0.865	0.864	8.135	42.925	15	0.000	−0.008	−0.010
Seasonal MA		0.396	0.061		6.476	0.000								
Trendline		−0.018	0.061		−2.935	0.004	-	0.877	-	-	-	-	-	-
Constant		51.2	0.178		32.819	0.000								
Prec_DWS														
MA	(002)(101)	−0.289	0.63	27.97	−4.559	0.000	0.877	0.746	8.466	61.874	15	0.000	0.23	0.14
Seasonal AR		0.975	0.018		54.342	0.000								
Seasonal MA		0.598	0.064		9.409	0.000								
Constant		5.533	0.289		19.16	0.000								
Trendline		−0.029	0.064		−3.355	0.000	-	0.863	-	-	-	-	-	-
Constant		55.553	0.289		79.643	0.000								
Temp_Max														
MA	(003)(011)	−0.774	0.060	2.131	−12.803	0.000	0.598	0.863	−0.023	21.004	14	0.102	−0.27	−0.27
Seasonal MA		0.599	0.063		9.449	0.000								
Trendline		0.003	0.0007		9.078	0.000	-	0.863	-	-	-	-	-	-
Constant		22.05	0.003		61.383	0.000								
Temp_Min														
AR	(404)	0.972	0.013	1.214	74.384	0.000	0.839	0.839	−1.741	21.786	14	0.083	0.072	0.071
MA		−0.368	0.048		−7.717	0.000								
Constant		18.125	0.341		53.166	0.000								
Trendline		0.002	0.054		4.346	0.000	-	0.839	-	-	-	-	-	-
Constant		18.125	0.341		53.166	0.000								
Disc_UPS														
MA	(002)(011)	0.582	0.053	39.14	11.082	0.000	0.492	0.955	−1.612	35.051	15	0.002	0.181	0.180
Seasonal MA		0.420	0.078		5.401	0.000								
Trendline		−0.018	0.019		−2.821	0.005	-	0.627	-	-	-	-	-	-
Constant		4.488	0.053		11.082	0.000								
Disc_DWS														
AR	(102)(011)	0.310	0.066	39.14	4.720	0.000	0.896	0.719	−0.371	48.273	15	0.000	−0.025	−0.025
MA		−0.313	0.065		−4.795	0.000								
Seasonal MA		0.438	0.061		7.176	0.000								
Trendline		−0.012	0.065		−4.795	0.000	-	0.667	-	-	-	-	-	-
Constant		6.657	0.314		7.176	0.000								

[a] Trendline derived from the worst-fitting models with the highest stationary R^2 and natural log transformation at lag 1. [b] Residual autocorrelation at lag 2. Prec_UPS = Rainfall upstream; Prec_DWS = Rainfall downstream; Temp_Max = Maximum temperature; Temp_Min = Minimum temperature Temp_Max; Disc_UPS = Discharge upstream; Disc_DWS = Discharge downstream.

Temperature and Rainfall Trends

Seasonal forecasts displayed in Table 1 reveal that maximum temperatures in Muoni record increases of 0.003 °C every quarter (R^2 = 0.863) while minimum temperatures will rise by 0.002 °C per quarter (R^2 = 0.839). Annual rainfall will decrease downstream and upstream by 0.018 mm (R^2 = 0.877) and 0.029 mm (R^2 = 0.863) per quarter, respectively. Hence, centennial mean temperatures will increase by 0.8 to 1.2 °C per century, respectively. This warming will be accompanied by subsequent shortages of mean rainfall of about 7.2 mm per century (upstream) to 11.6 mm per century (downstream).

Predicted Discharges and Streamflow

Muooni River's daily streamflow was estimated to 12,812.34 m^3 in 2010. The river peaks in May and December, and falls in February and September. Consistent high flows are observed downstream rather than upstream, except during the long dry season (June to September). However, these streamflows are expected to decrease to 0.012 $m^3 \cdot s^{-1}$ (R^2 = 0.667) downstream and 0.018 $m^3 \cdot s^{-1}$ (R^2 = 0.627) and upstream, respectively. These variations will negatively affect in-stream water flow in Muooni.

It is worth noting that the rating curves for Muooni River were so much biased with a probability (PAME) averaging 40%. Nonetheless, using these biased rating curves, daily discharges for the year 2010 were averaging 0.0915 and 0.2237 $m^3 \cdot s^{-1}$ upstream and downstream respectively, with decreasing rates by unit of gauge height of 0.05% upstream (R^2 = 0.627, PAME = 39.1%) and 0.3% downstream (R^2 = 0.667, PAME = 39.1%). Based on these streamflows, from 1971 to 2010, Muooni river had a total duration ranging from 10% to 25% of the flow period (Figure 4). This is a clear indication that Muooni river waters are depleting every year under the effects of a changing environment in the catchment.

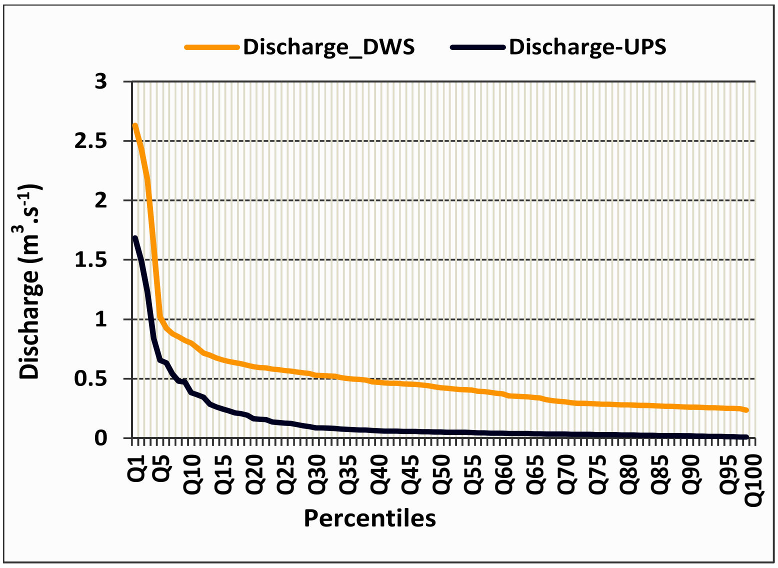


Figure 4. Monthly flow duration in Muooni catchment.

Summary of Predicted Hydro-Climatic Changes in Muooni catchment

All baseline data collected (January 1971–December 2010) and their forecasts (January 2011–January 2030) were benchmarked as maximum, minimum and averages to allow comparison of changes in hydro-climatic variables over the period starting from January 1971 up to December 2030 (Table 2). Results show that high temperature increases will be recorded over all the seasons, while rainfall will drastically decrease during the long rainy season (MAM) by 15.4% to increase during the long dry season (JJAS) by almost a similar variation (14.5%). The short rainy and dry seasons will experience some decreases in rainfall, which may not be statistically very significant. The estimated change fields for monthly rainfall, temperatures and river discharges in both sub-catchments of Muooni are presented below (Table 3).

Table 2. Hydro-climatic variables benchmarked in Muooni catchment (1971–2030).

Variables	OBSERVED (1971–2010)			PREDICTED (2011–2030)			Expected Variation (%)
	Min	Max	Average	Min	Max	Average	
Average Daily Temperature (°C)/Season							
Jan–Feb (JF)	15.44	24.03	19.73	15.63	24.10	19.87	+00.68
Mar–Apr–May (MAM)	15.01	22.66	18.84	15.07	22.70	18.89	+00.24
Jul–Jul–Aug–Sep (JJAS)	13.69	21.57	17.63	13.83	21.60	17.72	+00.48
Oct–Nov–Dec (OND)	15.18	22.49	18.84	15.60	22.50	19.05	+01.11
Average Seasonal Rainfall (mm)/Season							
Jan–Feb (JF)	56.14	83.65	69.89	62.89	71.75	67.32	−03.68
Mar–Apr–May (MAM)	98.42	185.74	142.08	88.95	151.39	120.17	−15.42
Jul–Jul–Aug–Sep (JJAS)	62.02	81.23	71.62	81.99	82.06	82.03	+14.52
Oct–Nov–Dec (OND)	108.35	199.75	154.05	90.70	151.32	121.01	−02.15
Rainfall in Record Drought Years (mm/month)							
1987 (Archive)	2.29	24.16	19.72				
2009 (Recent)	4.11	22.38	19.48				
Rainfall in Record Wet Years (mm/month)							
1981 (Archive)	2.21	280.7	65.41				
2010 (Recent)	6.8	338.4	103.47				
Discharge in Record Drought Years (m^3/s)							
1987 (Archive)	0.002	0.267	0.106				
2009 (Recent)	0.001	0.081	0.053				
Discharge in Record Wet Years (m^3/s)							
1981 (Archive)	0.067	2.111	0.386				
2010 (Recent)	0.009	1.576	0.415				

Table 3. Predicted monthly hydro-climatic changes in Muooni catchment (2011–2030).

Month	Upstream			Downstream		
	ΔT_{min} (%)	ΔP (%)	ΔD (%)	ΔT_{max} (%)	ΔP (%)	ΔD (%)
January	+0.31	+3.10	+0.04	+0.52	+0.031	0.00
February	−0.37	−0.53	−0.04	−0.21	−0.03	0.00
March	+0.18	−8.08	−0.01	+1.06	−13.33	−1.41
April	+0.13	−3.35	−0.03	+0.61	−3.83	−3.78
May	−0.07	−3.99	−0.01	−0.50	−7.92	−0.79
June	+0.21	+6.03	+0.01	+0.19	+0.83	+0.06
July	+0.16	+5.04	+0.01	+0.82	+7.18	+0.08
August	−0.09	+4.05	0.00	−0.10	+7.32	+0.06
September	+0.20	−0.60	0.00	+0.09	−1.67	−0.09
October	+0.546	−0.133	−0.03	+0.39	−2.19	−0.16
November	+0.55	−1.96	−0.14	+0.47	−7.69	−0.81
December	−0.014	−0.052	−0.15	−0.27	−3.03	−0.24

Notes: ΔT_{max} = Change in maximum temperature; ΔT_{min} = Change in minimum temperature; ΔP = Change in Rainfall; ΔD = Change in Discharge.

3.1.3. Hydro-Climatic Trendshift Likelihood in Muooni Catchment

The perceived shifting trends of the selected hydro-climatic variables in Muooni sub-catchments were tested for both inter-annual and inter-seasonal variations. These shifting trends were clearly detected in the upper and lower sub-catchments, even though the extent at which these variables' behaviour shifted differed in intensity from one EFU to another (Figure 5). In effect, the cumulative probability for observed temperature was remarkably different from expected one in Muooni catchment. Observed cumulative probabilities were higher toward the upper percentiles and lesser toward the lower percentiles, while their expected counterparts were higher in the lower percentiles and lesser in the upper percentiles for all the selected variables, both upstream and downstream.

Shifting Inter-Annual Trend

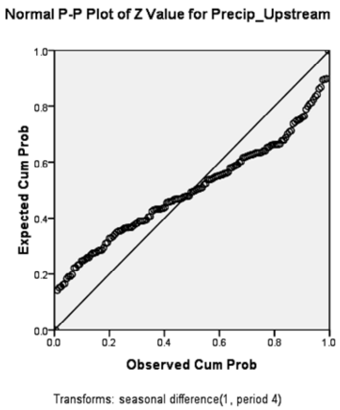
Non-parametric hypothesis tests utilized in this study confirmed the inter-annual trendshift across all the variables tested in Muooni catchment. First, Mann-Whitney Pettitt test revealed that there was a change in the behaviour of all the variables at a certain time within the period under examination (1971–2030). All the variables, except for maximum temperatures, had Z statistics above 2 with p-values lesser than 5% significance interval. The analysis proceeded to a rejection of the null hypothesis stating that the distribution of the two sets of data were homogeneous over the period under study. Hence, the alternative hypothesis upholding trendshift was accepted.

The Marginal Homogeneity test likewise, revealed a lack of homogeneity in the behaviour of all the variables, as the MH statistics were below -3 for rainfall upstream (MH = -9.52; sig. = 0.0) and rainfall downstream (MH = -11.08; sig. = 0.0), and higher than 3 for the remaining variables. This implied that the two sets of data (1971–2010, and 2011–2030) were heterogeneous and that the null hypothesis supporting consistent homogeneity was rejected in all the cases. The study concluded that there was a likelihood of inter-annual trendshift in the behaviour of almost all hydro-climatic variables in Muooni catchment.

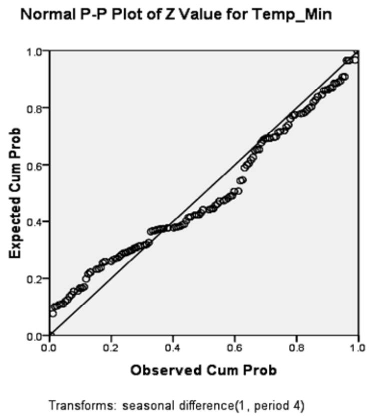
Inter-Seasonal Variations' Shifting Trend

The median test for inter-seasonal variations invalidated the null hypothesis stating that the two populations tested in Muooni catchment had similar median discharges upstream and downstream (Chi-Square = 148; n = 148; sig. = 0.0). This hypothesis test confirmed the inter-seasonal variation of discharges in this catchment in the course of climate change. However, when it came to rainfall and temperatures the null hypothesis could not be rejected as the chi-square statistics was slightly below the limit. This lack of significance meant that if there was shift, it may have occurred by chance, not as a result of climate change. The analysis thus upheld the homogeneity of distributions of temperatures and rainfall across the seasons.

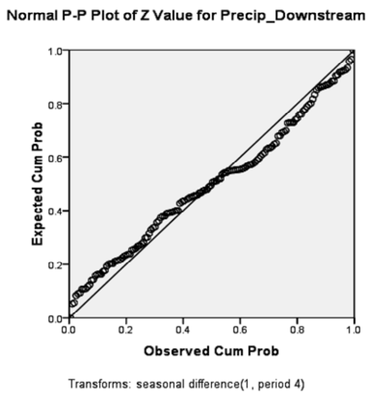
Similar conclusions were derived from the Kruskal-Wallis H-test. The latter could not reject the null hypothesis stating the lack of inter-seasonal variations' shift in almost all the variables tested except for rainfall upstream and downstream (Chi-square = 54.4; n = 37; sig. = 0.0). However, Kolmogorov-Smirnov Test and Mann-Whitney U test rejected the null hypothesis stating that there was no inter-seasonal variations' shift in all the variables tested. Finally, the analysis concluded the fact that was no clear global trend of the variations of all hydro-climatic variables selected in Muooni catchment within each ecological functional units (EFU) across the seasons.



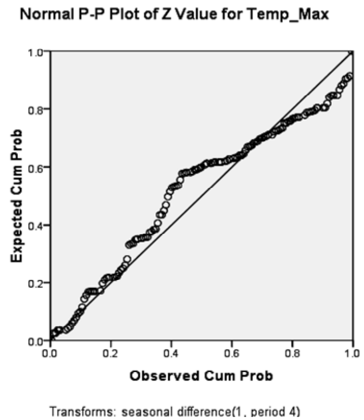
Precipitation (Upstream)



Minimum Temperature



Precipitation (Downstream)



Maximum Temperature

Figure 5. PP-plots for climatic trendshift in Muooni catchment (1971–2010 vs. 2011–2030). Transforms: Seasonal difference (1, period 4). Expected Cum Prob = Expected cumulative probability; Observed Cum Prob = Observed cumulative probability.

Validating Hydro-Climatic Trendshift in Muooni Catchment

PP-plots consolidated the likelihood of inter-seasonal variations' shift in Muooni catchment. Figure 5 remarkably shows hydro-climatic trendshifts in upstream and downstream Muooni catchment but at different intensities. Whereas the observed cumulative frequencies were higher in the upper percentiles and lesser in the lower percentiles, the expected cumulative probability was higher in the lower percentiles and lesser in the upper percentiles for all the selected variables, both upstream and downstream. There were high variations in the intensity of trendshift in seasonal precipitations and discharges upstream as well as maximum temperatures than the remainder of the other variables. Nevertheless, the assumption of shifting trend in the behaviour of hydro-climatic variables assessed was confirmed.

3.2. Farmers' Vulnerability to Drought in Muooni Catchment

3.2.1. Farmers' Exposure to Hydro-Climatic Impacts in Muooni Catchment

The on-farm survey conducted in Muooni catchment shows that 55% of the 101 farmer households were randomly selected in the upper sub-catchment (Kaewa, Lita and Mbee), while the remaining were drawn downstream (from Kauti, Muuoni, Isyukoni, Kyuluni, Ithaene, Mathiane, Mathithu and Muthala). Farmer's household size was established to 5 and 7 people upstream and downstream, respectively. Daily water use per household (farming included) was estimated to 106 and 114 L upstream and downstream, respectively, while a standard household's water use at Muooni Dam site and its environs varied from 250 to 350 L a day [33]. These results gave a clear indication that most farmers were vulnerable to drought, not only because Muooni catchment is a water scarce area but also due to high poverty levels.

Farmers' vulnerability to drought was magnified by the householder's poverty. An average household earned KES 66,180 and 81,744 ($1 = KES 75) per year in the upper and lower zones, respectively. It can be deducted from these results that a farmer living upstream and his relatives earn each a daily income of KES 36 (that is $0.48), while downstream this daily income is estimated to KES 32 (that is $0.43), far below the daily poverty margin of $1.25. These findings are in line with Luwesi (2010) [8], who indicated an average seasonal income of $231 per year (equivalent to KES. 18,480 per quarter in 2010) per farm at Muooni dam site.

Besides, about 35.9% of Muooni farmers interviewed believed that their catchment area was likely to experience acute droughts during a La Niña event, while a handful 1.1% expected an El Niño flood and 29.6% acknowledged high rainfall variability. Also, 19.8% and 5.1% among farmers recognized the effects of the global warming and high wind pressure on their catchment degradation and water stress. Other hydro-geomorphologic impacts and climatic risks randomly occurring in Muooni included the siltation of drainage systems and reservoirs (26.0%), wildfire and deforestation in the catchment (4.1%), gullies (3.7%), and landslides in the catchment (4.0%), to name but a few. These externalities to farming activities were obstructing farmers' efforts to conserve water and soil moisture in their respective sub-catchment areas. The following section provides details on such coping strategies.

3.2.2. Agriculture Vulnerability to Drought in Muooni Catchment

Farmers have resorted to various cropping strategies, which vary in altitude, to face their changing micro-climatic conditions. Coffee, pyrethrum and wheat are intensively cropped in the highly moist soils developed at the hill tops, in addition to maize and sunflower. Unfortunately, these crops mostly fail, owing to the fact that the soils are poorly consolidated and highly susceptible to erosion. Moreover, the rainy seasons are too short for some crops and farmlands are also small by size [21]. With dwindling crop yields, farmers have diversified their farming strategies and sources of livelihood to supplement their incomes. In most cases they have additional crops associated with livestock keeping on high altitudes (1650 to 1800 m) for commercial purpose. These include potatoes, early maturing sorghum, foxtail millet and "marginal crops" like Tepary beans and Tohono Z16 maize [21].

These farmers also sustain their livelihoods through intercropping of both perennial and seasonal crops, owing to the devastating effects of drought (Table 4). Soil moisture measurements taken during the rainy season in the lower sub-catchment confirmed this fact. A maximum volume of about 0.60 $m^3 \cdot m^{-3}$ was measured with more than 25% of the soil samples measuring 0.20 $m^3 \cdot m^{-3}$ and below.

Table 4. Cropping patterns in Muooni catchment.

Main Seasonal Crops	% of Farms Surveyed	Main Perennial Crops	% of farms Surveyed
Maize	75.0%	Coffee	63.2%
Irish Potatoes	47.7%	Banana	77.2%
Sweet Potatoes	59.1%	Sugarcane	36.8%
Cassava	70.5%	Avocado	75.4%
Cow Peas	93.2%	Mango	42.1%
Finger Millets	11.4%	Guava	26.3%
Sorghum	6.8%	Eucalyptus	54.4%
Groundnuts	11.4%	Grevilia	33.3%
French Beans	63.6%	Miraa	0.0%
Other seasonal crops	63.6%	Other perennial crops	14.0%

This soil moisture is even lesser during the normal and dry periods, thus jeopardizing the incomes of at least 75% of farmers who depend on maize and other seasonal crops, notably cow peas (93.2%), cassava (70.5%), French beans and other seasonal crops (63.6%), sweet potatoe (59.1%), and Irish potatoes (47.7%). Besides, Banana (77.2%), avocado (75.4%), coffee (63.2%), mango (42.1%), sugarcane (36.8%) and guava (26.3%) are among key perennial crops associated with the above seasonal ones in Muooni catchment. The linkage between these predictions and spatial data analysis conducted by Luwesi et al. (2012) [16] depicts a drastic change in land-use and cover associated with the depletion of soil moisture. These results consolidate the fact that the changing micro-climate in Muooni catchment has led to the shrinking water supply in most of its hydrographical networks and storage systems.

4. Discussion

4.1. Discussion on Hydro-Climatic Trendshift in Muooni Ctachment

From this study results, Muooni catchment is warming at 0.8 to 1.2 °C in a century under the effects of a changing micro-climate. These climatic trends are accompanied by decreased rainfall of about 30 to 50 mm per century. There is also a likelihood of decreasing trend of Muooni river discharges ranging from 0.01 to 0.05 $m^3 \cdot s^{-1}$. As a corollary, Muooni dam's storage capacity has also been decreasing by 6.2% per annum over the period 1987 to 2009. These micro-climatic variabilities have shifted over the years to become normal micro-climate changes. For most climate scientists, the increasing trends of minimum and maximum temperatures in Muooni catchment with subsequent decreases in rainfall and discharges are not surprising. This was previously predicted by Hulme et al. (2001) [2] in their regional climate change projections for Africa. They projected temperature variations of 0.2 °C per decade (for the lowest scenario—B1) to 0.5 °C per decade (for the high—A2), with increased rainfall of 5% to 20% in December–February and decreases of 5% to 10% in June–August. In Muooni, temperature rise may be attributed to the high urbanization rate and agricultural practices, which result in the sequestration and release effects of carbon dioxide (CO_2) from deforestation, dead wood, farm trash, and hedge clippings used for firewood [3,7]. Homesteads within the catchment usually use firewood as their main source of cooking energy. Additional firewood is used for making charcoal, which is an alternative source of cooking energy. This increased demand of cooking energy with high rates of urbanization, especially in the upper sub-catchment area, may have led to the clearing of about 99% of the Iveti forest, and the replacement of indigenous tree species by polycultural exotic tree plantations in other parts of the catchment, since the instauration of the 1980s' rotating "shamba system" decreed by President Arap T. Moi [34–37]. This has resulted into the conversion of wetlands and natural vegetation into croplands and urban settlements, including Iveti Forest, riverine vegetation, savannah and grassland. Urban constructions combined with the clearance of natural vegetation may have enabled surface air temperature to increase under the trade effects of winds, the absorption and release of the highly radiating solar rays at the global scale by concrete materials, soils and water [38,39]. In all the cases, in-depth research needs to be undertaken on any possible cause of increasing temperatures in Muooni and the various determinants of farmers' vulnerability to their warming micro-climate [40].

Moreover, African scientists are recommended to look for "ways that overcome the limits of carbon-intensive growth so that human development is truly sustainable" [41]. These encompass policies and strategies enabling local stakeholders to increase their adaptive capacities and ability to curb climate change impacts. Integrated watershed management (IWM) has been suggested as one such climate proofing tool for achieving efficiency [42,43]. IWM seeks to manage water resources as an economic asset by integrating all costs incurred by competing uses and interdependent interests to achieve high yields at a low cost. It also integrates all types of water users and key stakeholders in water management and catchment development for equitable sharing of the resources [44]. Water is recognized as "a public good with both social and economic values and its management done in a broad and holistic perspective with the appropriate involvement of users at all levels" [45]. Finally, due to the high degree of sector intersection around water, all IWM approaches not only stress the need for economic efficiency of water use and social or developmental equity in access to water, but also for environmental sustainability [46]. This last objective may be challenging but yielding for local farmers' adaptation to their changing micro-climate [47].

4.2. Discussion on Farmers' Vulnerability to Water Disasters

The decreasing trends of river discharges, lower soil moisture and drought severity are shaping the micro-climates and ecological functional units (EFU) of Muooni catchment. While the upper sub-catchment may be prone to higher minimum temperatures, evaporations and transpirations, the lower sub-catchment is likely to experience sporadic flash floods with decreasing maximum temperatures in the near future. Despite several preventive measures aimed at reducing farmers' vulnerability to drought, Wise and Murphy (2012) [48] stress the challenges faced by small scale farmers and women with limited resources in a climate-constrained world. The failure of policies and limited public investments on agricultural development and food production in developing countries are major sources of vulnerability to climate change. Mogaka et al. (2006) [49] attributed this situation to "a combination of the country's very limited natural endowment of water, the high variability with which annual rainfall occurs, the heavy dependence of the economy on water resources, and inadequate preparedness for regularly recurring climate shocks to the economy" [50]. Hence, climate variability and change as well as farmers' inconsistent land use changes, poverty and to some extent their ignorance of physical processes are key determinants of farmers' vulnerability to drought in most arid and semi-arid tropics (ASATs) of Kenya. Besides, the lack of appropriate institutional framework for climate information management, water development and catchment management have led to increased water stress and land degradation among the farming communities [51]. WSP (2011) [52] concludes that the country needs to strengthen its policy instruments and institutions to channel more investments in the development of alternative water resources. These include hydro-political instruments for developing groundwater, rainwater and green water, which may constitute reliable, renewable and drought resistant water sources.

Finally, the projected socio-economic growths and developments in Muooni by Luwesi et al. (2012) [16] clearly show that Muooni catchment enjoys good harvests and water security under above normal rainfall regimes (from April to May). However, this water resource represents only 70% of the total water demand in the catchment under normal rainfall regime (November to March). Severe water crises arise, in some parts of the catchment, under below normal rainfall regime (from June to October) or under normal conditions, when an environmental flow reserve (EFR) of 30% is enforced. This often leads to deficits ranging from 30% to 50% of the total water demand, as it was observed in 2009 and 2012. That crisis often leads to conflicts between agriculturalists and livestock keepers, to the extent that each group is equipped with offensive arms to fight for the appropriation of water sources. The situation worsens when no emergency policy instruments and institutional frameworks are implemented in time. It is therefore crucial to further explore the kind of hydro-political strategies and institutional response needed by farmers to maintain water storage at the desired state in the catchment at all times, and thus minimize the impact of drought on farmers' livelihoods.

5. Conclusions

There is no doubt that farmers living in Eastern Kenya are mostly vulnerable to drought than flood. The high risks of water stress associated to the changing hydro-climatic conditions may be attributed to ill-planned land-use activities and other socio-economic vectors. These in turn are triggered by the global warming, El Niño floods and La Niña droughts. These factors also impact on the farmland productivity and the sedimentation of water channels. Farmers' resiliency largely depends on both their endowed resources and technological capacity to innovate. These factors combined with high investments in climate information systems and water infrastructure may increase the farming community preparedness to water stress and enable the achievement of food security in the ASATs of Kenya in general and Muooni catchment in particular.

In view of the prevailing situation, the government of Kenya needs to assist these farmers with skilled extension service both for climate information dissemination and agricultural innovation to enable them increase their water efficiency and crop productivity. This will help them minimize excessive water losses incurred in farming through evapo-transpiration. The government shall also provide means for measuring and charging all water uses to sustain the cost of maintenance and management of Muooni dam. Finally, public-private partnerships (PPP) are required to facilitate alternative investments in agricultural water development in the catchment through groundwater abstraction, rainwater storage and green water management.

Acknowledgments: We first acknowledge the valuable contributions of various anonymous reviewers and the academic editor of this paper. We are also grateful to the "International Development Research Centre" (IDRC)—Ottawa, Canada—that provided a grant from which a major part of this research was carried out. Information on the centre is available at www.idrc.ca. We also acknowledge the financial, material and technical supports received from the "Center for International Capacity Development" (CICD) of the Universität Siegen (Germany) through the EU funded Project "Capacity Building in Integrated Watershed Management in Eastern Africa (IWMNet/EU Project). Their activities can be found at www.iwmnet.eu.

Author Contributions: This research is part of the dissemination of a PhD study conducted at Kenyatta Universty (Nairobi) by Cush Ngonzo Luwesi under supervision of Chris A. Shisanya and Joy A. Obando.

Conflicts of Interest: The authors declare no conflict of interest under this study. The funding sponsors had no role in the design of the study; in data collection, analysis and interpretation; in the write-up of the manuscript and in the decision to publish the results.

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