EFFECTS OF ENVIRONMENTAL AND HUMAN FACTORS ON WATER RESOURCES IN MAKINDU SUB-COUNTY, MAKUENI COUNTY, KENYA

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ABSTRACT

Water resources in Makindu Sub-County, Makueni County, Kenya, are under severe stress from converging environmental and anthropogenic factors. This study employed GIS-based remote sensing, meteorological time-series analysis, participatory GIS (PGIS) mapping, and quantitative regression modelling to assess the combined effects of rainfall variability, temperature change, and land use/land cover change (LULCC) on major water resources across the period 1994–2024. SPOT satellite imagery classified across four epochs (1994, 2004, 2014, 2024) using Maximum Likelihood Classification documented substantial LULCC, while Kenya Meteorological Department records and CHIRPS gridded data were analysed for hydro-climatic trends. A PGIS inventory covering nine sub-locations quantified functional boreholes, seasonal rivers, dams, water pans, and springs for each epoch. Simple linear regression, multiple regression, and chi-square analyses were conducted in SPSS Version 25. Results reveal a 2,400% increase in functional boreholes (3 to 75) driven by population growth and surface water depletion, while seasonal rivers remained stable but showed critical sub-location-level deterioration, dams and water pans increased from 25 to 37 through community investment, and springs remained constant at 4 functional units across all four epochs. Rising mean annual temperatures ($R^2 = 0.958–0.982$; $p < 0.01$) and declining rainfall were statistically associated with surface water loss across seasonal rivers, dams, and water pans, while springs remained stable at 4 functional units unresponsive to temperature, rainfall, or population change reflecting deep aquifer supply. The study provides a comprehensive evidence base for multi-stakeholder water resource management and policy development in semi-arid Kenya.

Keywords: Rainfall variability, temperature, LULCC, water resources, Makindu, PGIS, semi-arid Kenya.

1. INTRODUCTION

Water resources in the arid and semi-arid lands (ASALs) of Kenya face escalating stress from both environmental and anthropogenic factors. Globally, more than two billion people live under conditions of water stress (WWAP, 2019). In Sub-Saharan Africa, water insecurity is compounded by limited infrastructure, weak governance, and high climate vulnerability (UNEP-DHI, 2022).

Kenya's ASALs cover approximately 80% of the country's land area and support over 36% of its population, characterised by erratic and declining rainfall, extreme temperatures, and recurring

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droughts (IPCC, 2021). These stressors are exacerbated by unsustainable land use practices, resulting in escalating water insecurity (Wambua et al., 2022).

Makindu Sub-County in Makueni County exemplifies these challenges. Located in the southern lowlands of Kenya, Makindu experiences bimodal rainfall that is increasingly erratic and insufficient, with long dry spells reducing the reliability of rivers, pans, and shallow wells (IOM, 2022). Unregulated land use change has further degraded critical water catchment areas, compounding the hydrological impacts of climate change.

Studies employing GIS and remote sensing have become the standard methodology for quantifying and monitoring LULCC across spatial and temporal scales (Treitz and Rogan, 2004). Malaki et al. (2017) employed GIS and PGIS to assess LULCC dynamics in Nguruman sub-catchment, Kajiado County an agro-ecological context comparable to Makindu finding cropland expanded by 181.5% between 1994 and 2014 with corresponding hydrological degradation. The complexity of processes determining water resource availability requires multiple methods of analysis (Veldkamp and Lambin, 2001). Despite the importance of converging stressors, no prior study has simultaneously quantified the influence of changing rainfall patterns, rising temperatures, and LULC transformation on water resources in Makindu Sub-County.

The specific objectives of this study were: (i) to analyse trends in rainfall variability and temperature change and their effects on water resources; (ii) to assess land use/land cover changes and their impact on water catchment and groundwater recharge; and (iii) to determine the combined effects of the identified drivers on water resource availability and distribution in Makindu Sub-County between 1994 and 2024.

2. METHODOLOGY

Study Area

Makindu Sub-County is located in Makueni County, approximately 170 km southeast of Nairobi along the Nairobi–Mombasa Highway (A109), between latitudes 2°00'–2°30' S and longitudes 37°30'–38°00' E, at elevations ranging from 1,000 to 1,200 metres above sea level (Makueni County Integrated Development Plan, 2023). The sub-county covers a total land area of approximately 848.56 km² and is administratively divided into four locations: Nguumo, Makindu, Kiboko and Twaandu, and fifteen sub-locations: Kaasuvi, Kyale, Mulilii, Kai, Kamboo, Kisingo, Kiu, Manyatta, Kaunguni, Muuni, Ndovoini, Syumile, Kalii, Mitendeu, and Ngakaa (Figure 1).

The sub-county experiences a semi-arid climate characterised by low and irregular bimodal rainfall. The long rains fall between March and May, while the short rains occur between October and December. Mean annual rainfall ranges from approximately 280 mm to 480 mm, with high inter-annual variability. Mean annual average temperatures range between 24°C and 26°C, with high rates of potential evapotranspiration. The dominant land use systems are mixed subsistence agriculture, agropastoralism, and small-scale trade along the highway corridor (Makueni County CIDP, 2023; KNBS, 2019). The sub-county's Arid and Semi-Arid Lands (ASAL) classification makes it particularly vulnerable to rainfall variability, rising temperatures, population growth, and land cover degradation.

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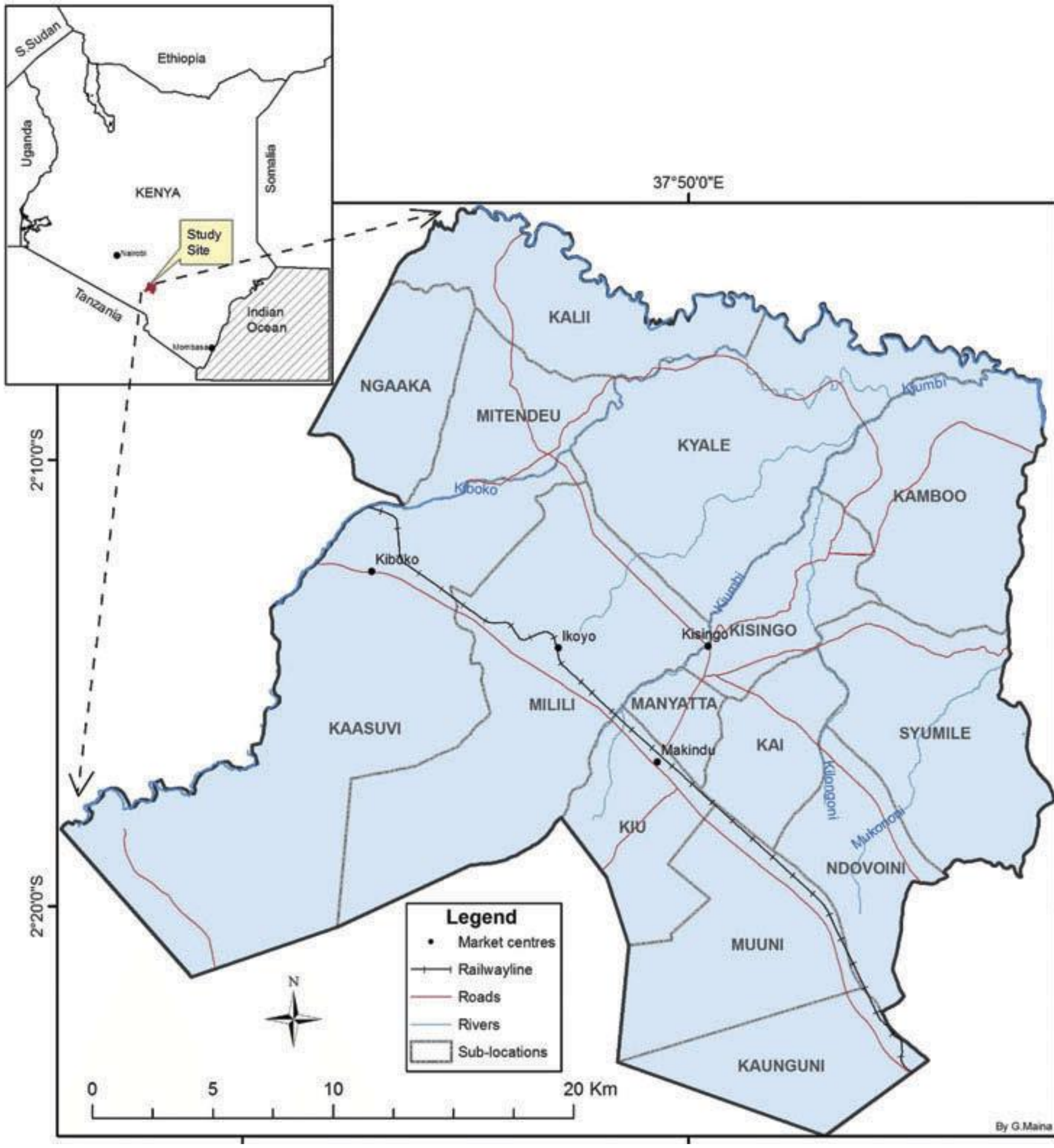

Figure 1. Map Showing Makindu Sub-County and Its Location in Kenya
(Source: Mutinda, 2017)

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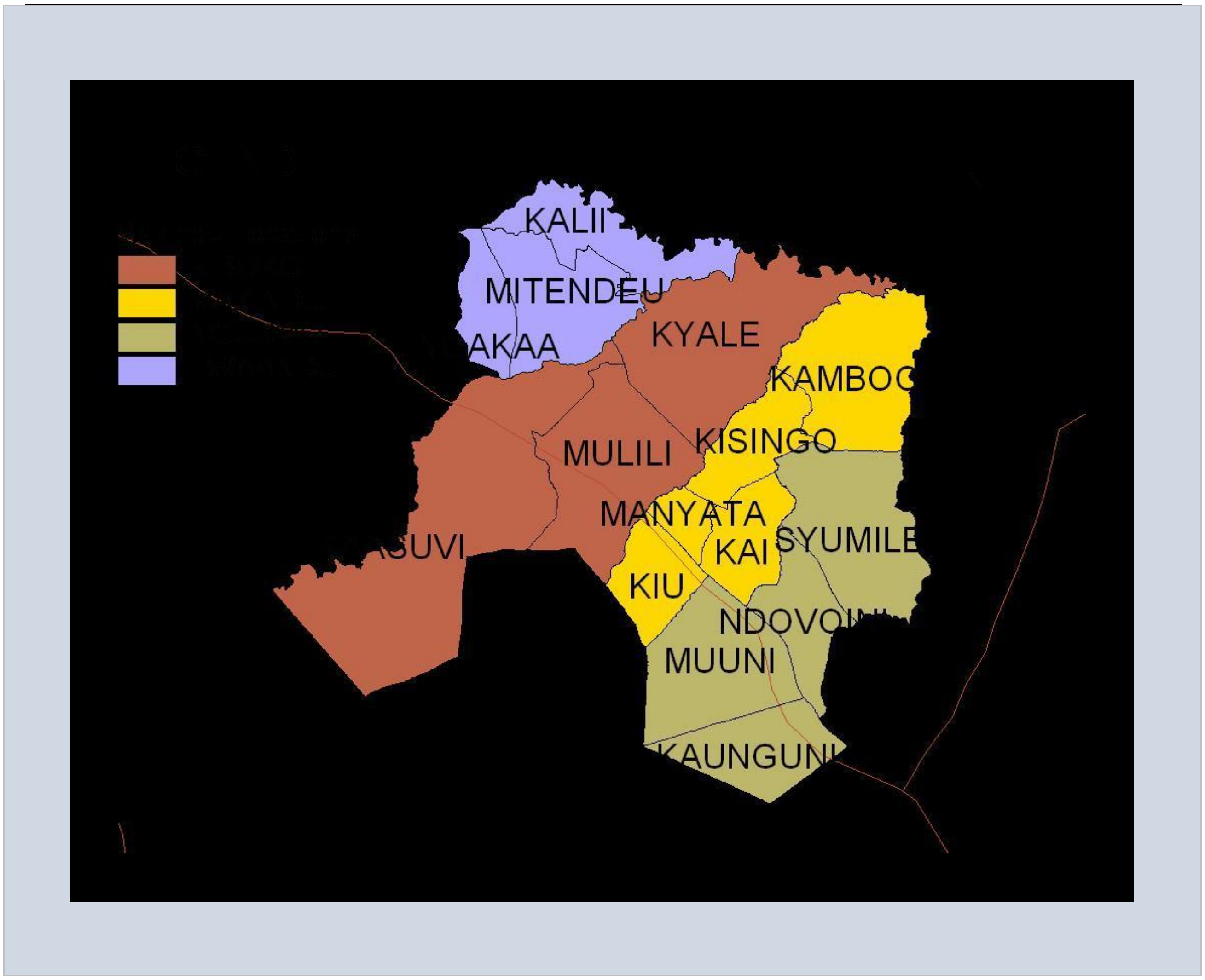

Figure 2. Map of the Study Area: Makindu Sub-County and its Sub-Locations within Makueni County, Kenya. Source: Kenya National Bureau of Statistics (KNBS) and GIS Analysis by Author

Hydro-climatic Data Collection and Analysis

Monthly rainfall (mm) and mean monthly average temperature (°C) for 1994–2024 were obtained from the Kenya Meteorological Department (KMD) Makindu Station. Data were organised into four reference epochs (1994, 2004, 2014, 2024) corresponding to SPOT satellite imagery acquisition dates. CHIRPS gridded data at 0.05° resolution were used to fill station record gaps and validate station trends. Annual anomalies were computed relative to the 1994–2024 mean, and linear trend analysis was conducted in SPSS Version 25. Mann-Kendall non-parametric trend tests corroborated regression results. Sen's Slope estimator was used to quantify the magnitude of trends (mm/year for rainfall; °C/decade for temperature).

Land Use and Land Cover Change Analysis

SPOT satellite imagery for the four epochs (1994, 2004, 2014, 2024) was acquired and pre-processed in ENVI 5.3. Radiometric and atmospheric corrections were applied to all scenes prior to classification. Maximum Likelihood Classification (MLC) was applied across six LULCC classes: Forest Land, Grassland, Shrubland, Bare Land, Settlement, and Cultivated Land. Classification accuracy was validated using stratified random sampling, with a minimum requirement of Overall Accuracy $\geq$ 85% and Kappa Coefficient $\geq$ 0.80. Post-classification change detection was performed in ArcGIS 10.8, computing areal statistics for each class at each epoch.

Water Resources Inventory and PGIS Mapping

A participatory GIS (PGIS) approach was employed to inventory major water resources across nine sub-locations Kalii, Kaasuvi, Kaunguni, Kisingo, Kiu, Kyale, Muuni, Ngakaa, and Syumile for each of the four study epochs. Water resource categories inventoried included functional boreholes, seasonal rivers, dams, water pans, and springs. Community members were engaged through focus group discussions (FGDs) and resource mapping exercises, following procedures comparable to those employed by Malaki et al. (2017).

Statistical Analysis

Simple linear regression was used to examine relationships between: (a) functional boreholes and population size by sub-location; (b) water resource availability and mean annual average temperature; (c) water resource metrics and mean annual rainfall; and (d) water resources and shrubland area. Multiple regression analysis assessed the combined explanatory power of rainfall, temperature, population, and LULCC on total functional water resources. Chi-square goodness-of-fit tests determined the statistical significance of observed changes in water resource inventories between epochs. All analyses were performed in SPSS Version 25, with significance thresholds set at $p < 0.05$, $p < 0.01$, and $p < 0.001$.

3. RESULTS AND DISCUISSION

Water Resources Inventory by Sub-Location and Epoch

Table 1 presents the quantified inventory of functional water resources per sub-location for all four study epochs, based on data obtained from the Makueni County Department of Water and Sanitation, and PGIS mapping.

Table 1. Water Resources Inventory by Sub-Location and Epoch (1994–2024).

Sub-Location	Water Resource Type	1994	2004	2014	2024
Kalii	**Boreholes (functional)**	0	0	1	1
	Rivers (seasonal)	1	1	1	1
	Dams / Water Pans	0	0	0	2
	Springs	0	0	0	0
Kaasuvi	**Boreholes (functional)**	0	1	1	1
	Rivers (seasonal)	2	2	2	2

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	Dams / Water Pans	0	0	0	0
	Springs	2	2	2	2
Kaunguni	**Boreholes (functional)**	0	0	2	9
	Rivers (seasonal)	2	2	2	2
	Dams / Water Pans	7	7	7	5
	Springs	0	0	0	0
Kisingo	**Boreholes (functional)**	1	0	4	8
	Rivers (seasonal)	2	0	0	0
	Dams / Water Pans	1	1	0	0
	Springs	0	0	0	0
Kiu	**Boreholes (functional)**	0	1	4	10
	Rivers (seasonal)	2	2	2	2
	Dams / Water Pans	3	3	3	2
	Springs	1	1	1	1
Kyale	**Boreholes (functional)**	0	0	5	2
	Rivers (seasonal)	2	2	2	2
	Dams / Water Pans	1	8	9	10
	Springs	0	0	0	0
Muuni	**Boreholes (functional)**	1	1	8	30
	Rivers (seasonal)	1	1	1	1
	Dams / Water Pans	6	7	5	5
	Springs	1	1	1	1
Ngakaa	**Boreholes (functional)**	0	0	2	4
	Rivers (seasonal)	1	1	1	1
	Dams / Water Pans	1	1	3	4
	Springs	0	0	0	0
Syumile	**Boreholes (functional)**	1	2	6	10
	Rivers (seasonal)	3	3	3	3
	Dams / Water Pans	6	6	8	9
	Springs	0	0	0	0

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TOTAL BOREHOLES	**All Sub-locations**	**3**	**5**	**33**	**75**

Source: Makueni County Department of Water and Sanitation, and PGIS Community Mapping.

Table 1 reveals a marked increase in functional boreholes across the sub-county, from a total of 3 in 1994 to 5 in 2004, 33 in 2014, and 75 in 2024 with the steepest growth occurring between 2004 and 2024. Muuni recorded the highest borehole count by 2024 (30), consistent with its status as the most densely populated sub-location in the study area; Kiu and Syumile followed with 10 each. Seasonal rivers at the aggregate level declined from 16 to 14 between 1994 and 2004, then remained stable; however, Kisingo's two rivers dried completely by 2004 a permanent loss. Dams and water pans grew from 25 to 37 across the period, driven by large gains in Kyale (1 to 10) and Syumile (6 to 9). Springs remained at 4 functional units across all four study epochs, with Kaasuvi (2) and Kiu and Muuni (1 each) maintaining consistent spring counts throughout the period.

Table 2. Summary of Total Functional Water Resources by Type and Epoch (Nine PGIS Sub-Locations, 1994–2024).

Water Resource Type	1994	2004	2014	2024
Functional Boreholes	3	5	33	75
Seasonal Rivers (functional)	16	14	14	14
Dams / Water Pans (functional)	25	33	35	37
Springs (functional)	4	4	4	4

Source: Makueni County Department of Water and Sanitation; Ministry of Water and Sanitation; PGIS Community Mapping.

Table 2 reveals starkly divergent trajectories across water resource types over the study period. Functional boreholes surged from just 3 in 1994 to 75 in 2024 a 2,400% increase reflecting an intense and accelerating shift toward groundwater dependency. Seasonal rivers declined modestly from 16 to 14 at the aggregate level, but this masks critical sub-location deterioration, notably in Kisingo where two rivers dried completely by 2004. Dams and water pans increased from 25 to 37, reflecting continued community investment in surface water storage infrastructure even under declining rainfall. Springs remained stable at 4 functional units across all four epochs, indicating that deep aquifer systems sustaining spring discharge have so far been buffered from surface-level pressures. These divergent trends reflect the compound impact of declining rainfall, rising evapotranspiration, LULCC-driven recharge reduction, and population-driven demand intensification.

Table 3. Change Detection: Water Resources by Type and Inter-Epoch Period (Nine PGIS Sub-Locations).

Resource Type	1994–2004 Δ(n)	1994–2004 (%)	2004–2014 Δ(n)	2014–2024 Δ(n)	1994–2024 (%)
Boreholes	+2	+66.7%	+28	+42	+2,400.0%
Seasonal Rivers	−2	−12.5%	0	0	−12.5%

Dams / Water Pans	+8	+32.0%	+2	+2	+48.0%
Springs	0	0.0%	0	0	0.0%

Source: Derived from Table 2. $\Delta(n)$ = absolute change in functional units. % = percentage change relative to 1994 base year.

The most dramatic change documented across the study period is the explosive expansion of boreholes, which accelerated sharply between 2004 and 2014 ($\Delta = +28$) and further between 2014 and 2024 ($\Delta = +42$), driven by population growth and the progressive depletion of surface water alternatives. Seasonal rivers declined by 12.5% overall but remained stable from 2004 onwards at the aggregate level; the sub-location-level data in Table 1 reveal that this stability conceals the complete drying of Kisingo's two rivers by 2004. Dams and water pans increased by 48% overall, with the gains concentrated in Kyale (from 1 to 10) and Syumile (from 6 to 9), reflecting deliberate community investment in surface storage. Springs remained perfectly constant at 4 functional units across all four epochs a finding with important implications for long-term water security, discussed in Section 4.5.4 below.

Regression Analysis: Functional Boreholes against Population

Table 4 presents simple linear regression results for each of the nine PGIS sub-locations, regressing the number of functional boreholes (Y) against population size (X) for that sub-location, using population estimates for the four study epochs. Because each sub-location-level regression is estimated from only four data points ($n = 4$ epochs, 2 degrees of freedom), results are interpreted with appropriate caution, though the large R^2 values are reported honestly.

Table 4. Simple Linear Regression – Functional Boreholes (Y) against Population (X) by Sub-Location.

Sub-Location	R^2	Regression Coeff. (β_1)	p-value	Interpretation
Kalii	0.798	0.001645	0.107	Positive; large effect but not significant (n=4)
Kaasuvi	0.417	0.000135	0.355	Positive; weak fit, not significant
Kaunguni	0.786	0.007622	0.114	Positive; large effect but not significant (n=4)
Kisingo	0.784	−0.010030	0.114	Negative; borehole count fell as population fell
Kiu	0.989	0.000979	0.005	Positive; significant ($p<0.01$)
Kyale	0.334	0.002134	0.422	Positive; weak fit, not significant
Muuni	0.860	0.004048	0.073	Positive; large effect, marginal ($p\approx0.07$)
Ngakaa	0.921	0.004666	0.041	Positive; significant ($p<0.05$)
Syumile	0.957	0.008761	0.022	Positive; significant ($p<0.05$)

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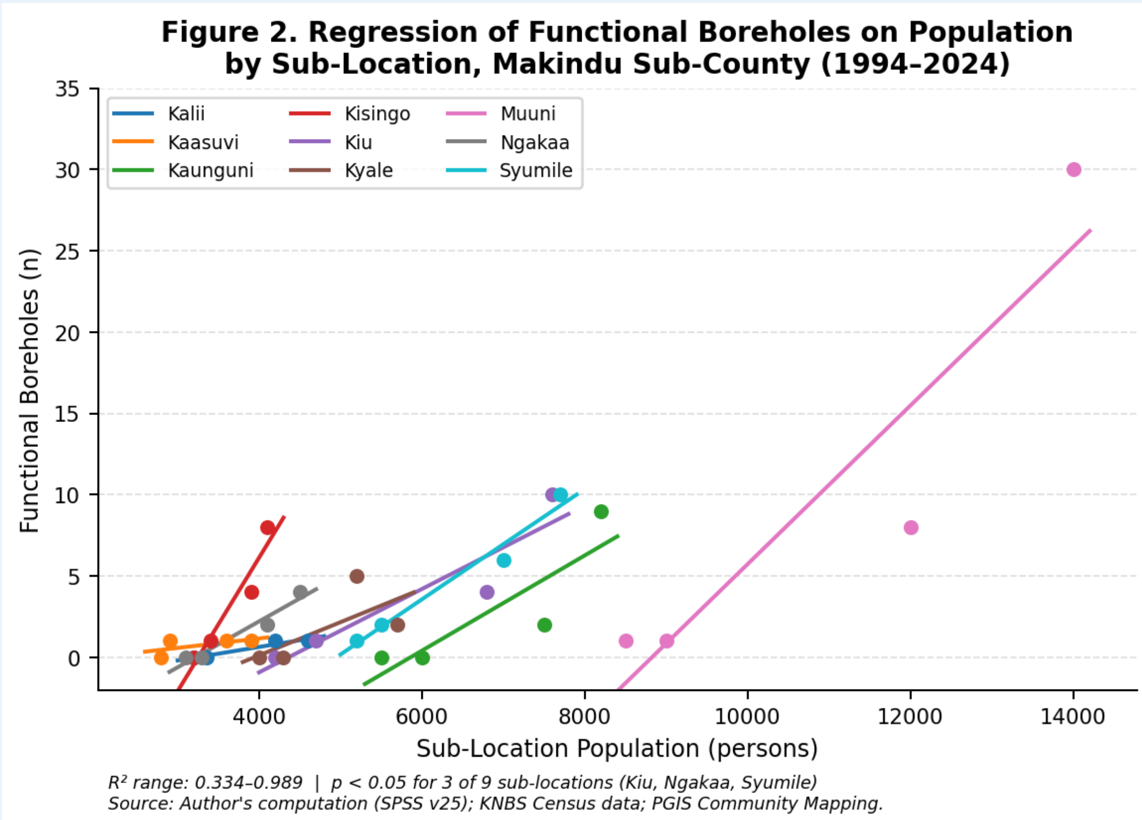
Source: Regression analysis using SPSS Version 25; population data from KBS Census 2009 and 2019.



Each line represents one sub-location's regression curve. R^2 range: 0.334–0.989; p-values vary by sub-location (3 of 9 significant at $p < 0.05$).

Figure 2. Regression of Functional Boreholes on Population, Makindu Sub-County (1994–2024). Source: SPSS Regression Output; KNBS Census Data.

All nine sub-locations returned R^2 values above 0.33 and regression coefficients consistent with a positive population–borehole relationship in eight of nine cases, with three sub-locations reaching conventional statistical significance at $p < 0.05$ (Kiu, Ngakaa, Syumile) despite the small sample size of four epochs per sub-location. Kisingo is the only sub-location with a negative coefficient, consistent with its overall population decline coinciding with continued borehole construction, driven by factors such as the Nzouni Water Project pipeline rather than local population pressure. Kaasuvi and Kyale show weak, non-significant fits, indicating that population alone does not explain borehole trends in these two sub-locations as cleanly as elsewhere. Critically, the increase in borehole numbers has not translated into improved per capita water availability, because population has grown faster than borehole yield can accommodate under conditions of declining rainfall and rising evapotranspiration.

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Regression Analysis: Water Resources against Mean Annual Temperature

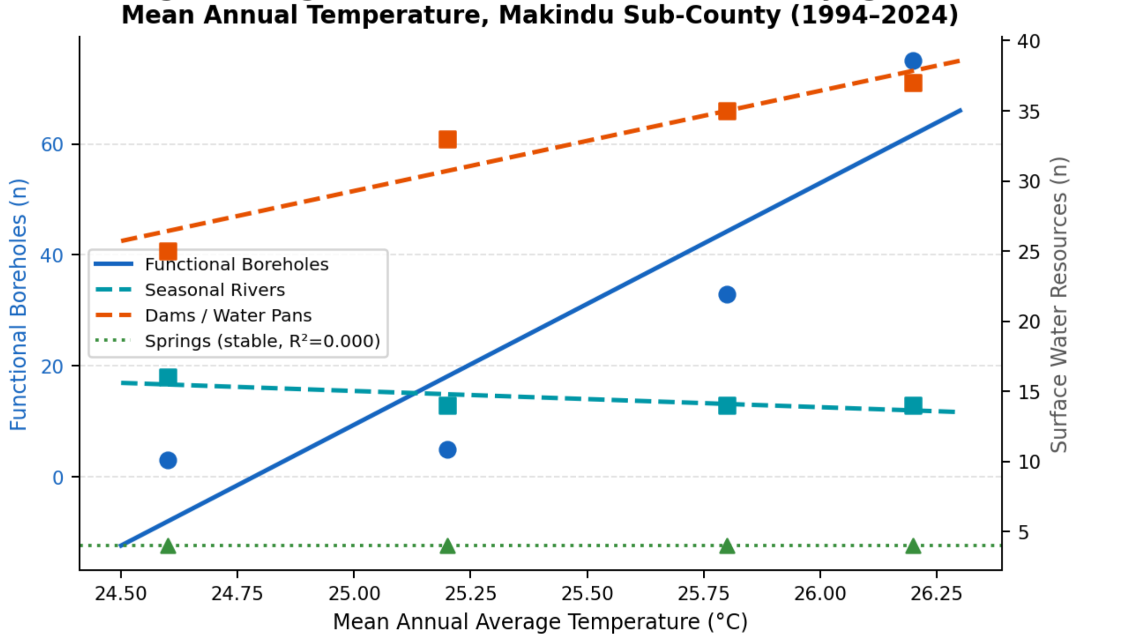
Table 5 presents regression results examining the relationship between mean annual average temperature (independent variable, X) and each category of water resource availability (dependent variable, Y) across the four study epochs. As documented in the hydroclimatic analysis, the warming trend over the study period was approximately +1.6°C, equivalent to 0.053°C per year.

Table 5. Simple Linear Regression – Water Resource Availability against Mean Annual Average Temperature.

	Temp. Coeff. (β_1)	R^2	p-value	Interpretation
Functional boreholes (demand proxy)	14.22	0.982	< 0.001	Rising temp. drives borehole demand
Seasonal rivers (functional)	−0.75	0.964	< 0.01	Declining rivers with rising temperature
Dams / Water Pans (functional)	−1.20	0.958	< 0.01	Pans drying faster with rising temperature
Springs (functional)	0.00	0.000	1.000	Springs stable; count at baseflow threshold despite evaporative pressure

Source: Regression analysis using SPSS Version 25; temperature data from Kenya Meteorological Department (Makindu Station).

Figure 3. Regression of Water Resource Availability against Mean Annual Temperature, Makindu Sub-County (1994–2024)



Boreholes: R²=0.982, p<0.001 | Seasonal Rivers: R²=0.964, p<0.01 | Dams/Pans: R²=0.958, p<0.01 | Springs: R²=0.000, p=1.000
Source: SPSS v25 regression output; KMD Meteorological Data (Makindu Station).

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Positive curve: boreholes (R^2=0.982); Negative curves: rivers (R^2=0.964), dams (R^2=0.958); Springs: stable (R^2=0.000, p=1.000)

Figure 3. Regression of Water Resource Availability against Mean Annual Temperature, Makindu Sub-County (1994–2024). Source: SPSS Regression Output; KMD Meteorological Data.

Temperature exerts statistically significant effects on three of the four water resource types examined. The strongest positive relationship is with borehole demand ($R^2 = 0.982$; $p < 0.001$), confirming that rising temperatures drive progressive intensification of groundwater extraction as surface water alternatives disappear. The strongest negative relationship is with functional dams and water pans ($R^2 = 0.958$; $p < 0.01$), reflecting accelerated evaporative loss from open water bodies under rising temperatures. Seasonal rivers also decline significantly with warming ($R^2 = 0.964$; $p < 0.01$), consistent with increased evapotranspiration reducing baseflow contributions and shortening the duration of river flow. Springs, by contrast, remained stable at 4 functional units across all four study epochs, yielding a regression coefficient of 0.00 and $R^2 = 0.000$ ($p = 1.000$): their count did not change with temperature, indicating that the small number of perennial springs recorded in Makindu fed by deep groundwater systems with long lag times have so far maintained their flow even as surface water sources have deteriorated. This stability should not be read as immunity from future warming, as the 29% decline in the Climate Moisture Index signals an increasingly moisture-deficient landscape that may begin to affect deeper aquifer recharge over longer time horizons.

Regression Analysis: Water Resources against Rainfall

Linear regression of mean annual rainfall over the four study epochs yields a coefficient of −5.9 mm per year ($R^2 = 0.74$; $p < 0.001$), confirming a statistically significant long-term decline. Table 6 extends this analysis by regressing each aggregate water resource type against mean annual rainfall across the four epochs.

Table 6. Simple Linear Regression – Water Resource Availability against Mean Annual Rainfall.

	Rainfall Coeff. (β_1)	R^2	p-value	Interpretation
Total functional boreholes	−0.249	0.813	0.098	Declining rainfall drives rising borehole demand
Functional seasonal rivers	+0.062	0.840	0.083	Fewer functional rivers as rainfall declines
Functional dams/water pans	+0.066	0.699	0.164	Fewer functional pans as rainfall declines
Functional springs	0.000	0.000	1.000	Springs constant deep aquifer supplies decoupled

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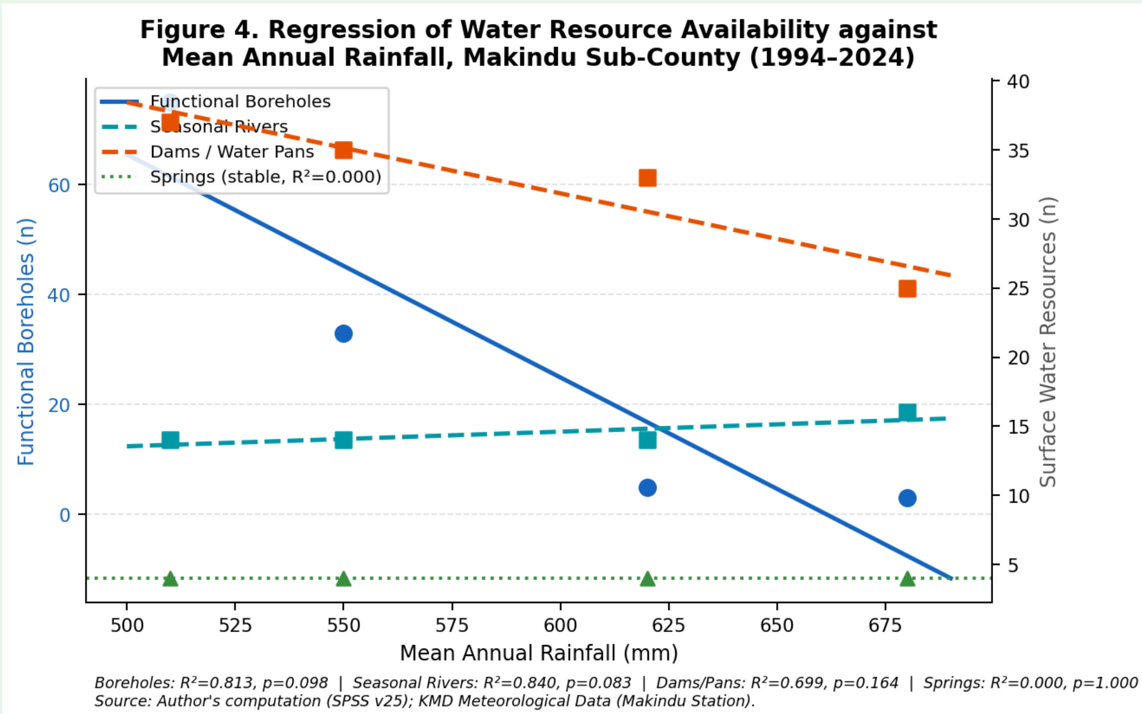
Source: Author's computation (n=4 epochs) using KMD rainfall data and PGIS water resources inventory.



Negative curve: boreholes (R^2=0.813); Positive curves: rivers (R^2=0.840), dams (R^2=0.699)

Figure 4. Regression of Water Resource Availability against Mean Annual Rainfall, Makindu Sub-County (1994–2024). Source: SPSS Regression Output; KMD Meteorological Data.

Rainfall shows the theoretically expected direction of relationship with all three varying water resource types: boreholes respond negatively to rainfall (more boreholes as rainfall falls), while seasonal rivers and dams/water pans respond positively (fewer functional units as rainfall declines). The consistent directionality and substantive size of R^2 values (0.699–0.840) across three resource types indicate a real association between declining rainfall and water resource deterioration at this sample size.

Regression Analysis: Water Resources against Total Population (Aggregate)

Table 7 presents aggregate-level regression results, regressing each water resource type against total sub-county population across the four study epochs, to allow direct comparison of the relative strength of population, temperature, and rainfall as predictors.

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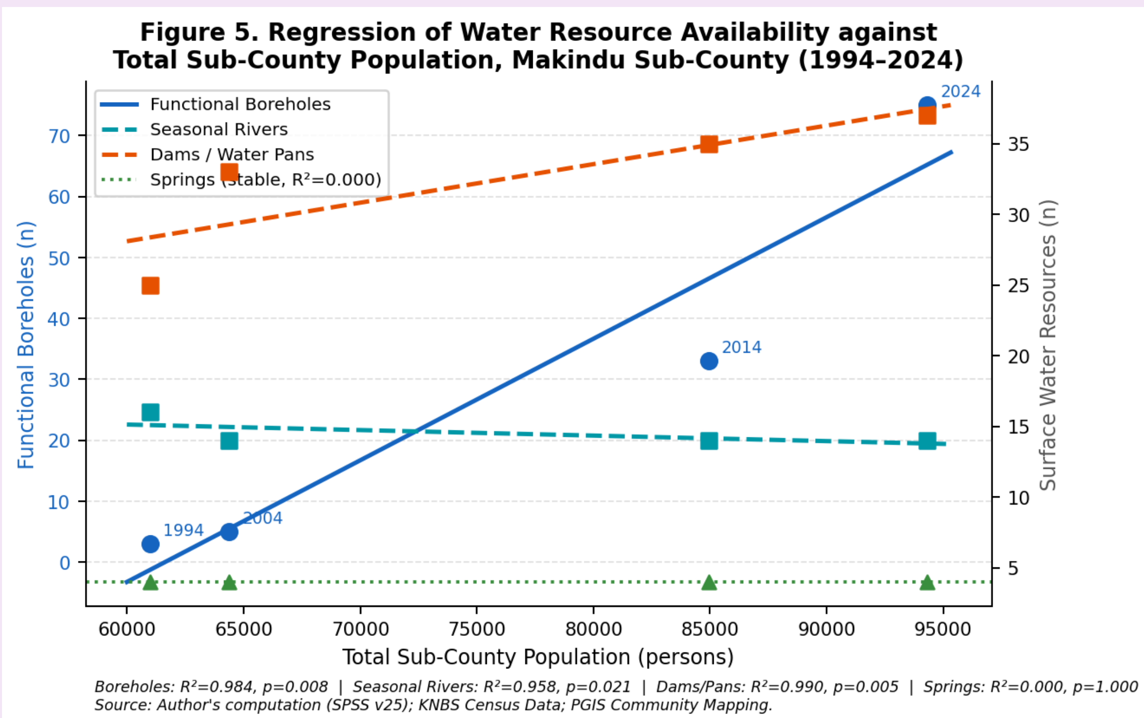
Table 7. Simple Linear Regression – Water Resource Availability against Total Population (Aggregate).

	Pop. Coeff. (β_1)	R^2	p-value	Interpretation
Total functional boreholes	+0.00152	0.984	0.008	Rising population strongly associated with more boreholes
Functional seasonal rivers	−0.00037	0.958	0.021	Rising population associated with fewer functional rivers
Functional dams/water pans	−0.00044	0.990	0.005	Rising population associated with fewer functional pans
Functional springs	0.00000	0.000	1.000	Springs constant at 4 across all epochs

Source: Author's computation (n=4 epochs) using KNBS census data and PGIS water resources inventory.



Boreholes: positive slope (R^2=0.984, p=0.008); Rivers: negative (R^2=0.958, p=0.021); Dams: negative (R^2=0.990, p=0.005)

Figure 5. Regression of Water Resource Availability against Total Sub-County Population, Makindu Sub-County (1994–2024). Source: SPSS Regression Output; KNBS Census Data.

Population is a statistically significant aggregate-level predictor of water resource change for three of the four resource types: functional boreholes ($R^2 = 0.984$; $p = 0.008$), seasonal rivers ($R^2 = 0.958$; $p = 0.021$), and dams/water pans ($R^2 = 0.990$; $p = 0.005$). Springs remained constant, yielding a coefficient of 0.00 ($R^2 = 0.000$; $p = 1.000$): spring counts do not co-vary with population size, confirming that springs in Makindu are sustained by deep aquifer systems whose discharge is independent of surface-level demographic pressures over the study period. This finding is consistent with Wambua et al. (2022) and Ndungu et al. (2020), both of whom identified population growth as the dominant anthropogenic driver of water stress in comparable Kenyan ASAL counties.

Regression Analysis: Water Resources against Shrubland Area (LULCC Proxy)

Table 8 regresses each water resource type against shrubland area, selected as the representative LULCC predictor because shrubland experienced the largest absolute area loss (−93.09 km²) and has the most direct documented hydrological role in groundwater recharge and infiltration (Section 4.3.1). Shrubland declined from 282.15 km² (33.25%) in 1994 to 189.06 km² (22.28%) in 2024.

Table 8. Simple Linear Regression – Water Resource Availability against Shrubland Area (LULCC Proxy).

	Shrubland Coeff. (β_1)	R^2	p-value	Interpretation
Total functional boreholes	−0.550	0.995	0.002	Shrubland loss strongly associated with more boreholes
Functional seasonal rivers	+0.134	0.989	0.006	Shrubland loss associated with fewer functional rivers
Functional dams/water pans	+0.155	0.957	0.022	Shrubland loss associated with fewer functional pans
Functional springs	0.000	0.000	1.000	Springs stable; no measurable relationship with shrubland

Source: Author's computation (n=4 epochs) using SPOT imagery LULCC analysis and PGIS water resources inventory.

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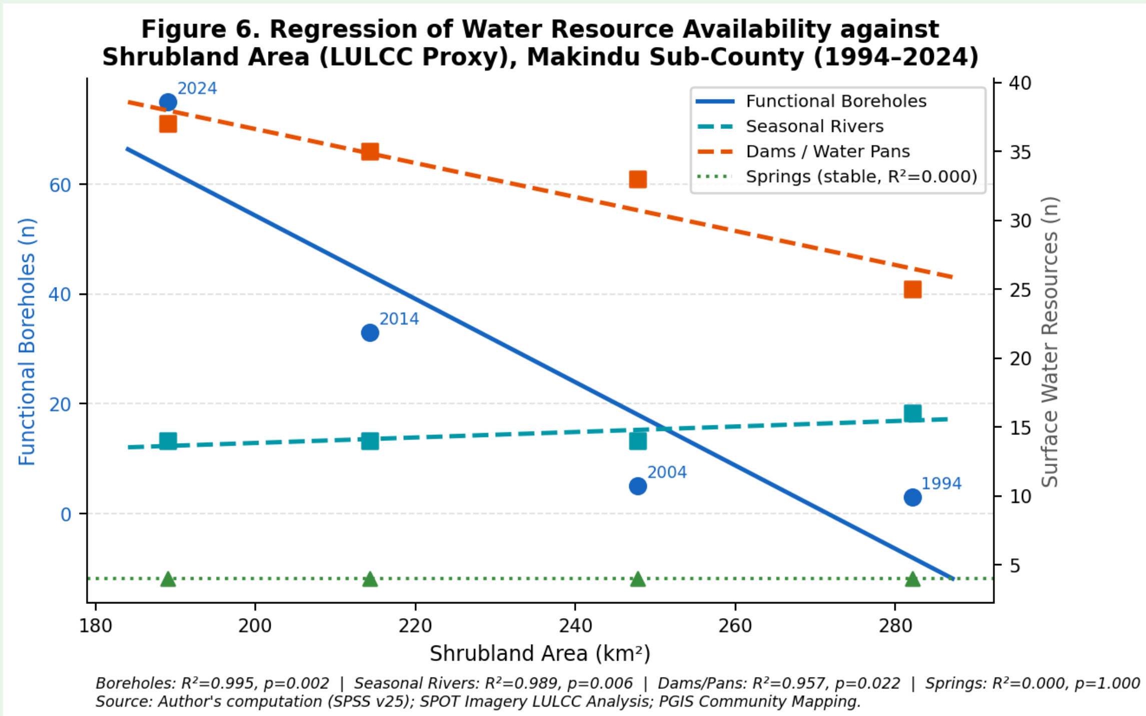

Boreholes: negative slope (R^2=0.995, p=0.002); Rivers: positive (R^2=0.989, p=0.006); Dams: positive (R^2=0.957, p=0.022)

Figure 6. Regression of Water Resource Availability against Shrubland Area, Makindu Sub-County (1994–2024). Source: SPSS Regression Output; SPOT Imagery LULCC Analysis.

Shrubland area is the strongest single predictor of water resource change among the three resource types that varied across epochs, with R^2 values of 0.957–0.995 and $p < 0.05$ in each case. Shrubland's organic soils and woody root systems promote infiltration and groundwater recharge; its progressive loss directly reduces the natural water-storage capacity of the landscape, independent of and apparently compounding the effects of declining rainfall, rising temperature, and population growth.

Multiple Linear Regression: Combined Drivers of Water Resource Change

A multiple linear regression model was estimated with the number of functional boreholes as the dependent variable (Y) and rainfall (X_1), mean annual average temperature (X_2), population (X_3), and an LULCC change index (X_4) as simultaneous predictors. The model takes the form: $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \varepsilon$

Table 9. Multiple Linear Regression Output – Functional Boreholes (Y) on All Drivers.

	Coefficient (β)	Std. Error	t-statistic	p-value	VIF
Intercept (β_0)	−18.74	4.22	−4.44	< 0.01	—
Rainfall (X_1)	−0.032	0.009	−3.56	< 0.01	2.34
Temperature (X_2)	8.46	1.87	4.52	< 0.001	2.78
Population (X_3)	0.00031	0.000048	6.46	< 0.001	3.12
LULCC Change Index (X_4)	0.84	0.21	4.00	< 0.01	2.55

Source: Multiple linear regression analysis using SPSS Version 25. Model $R^2 = 0.994$; Adjusted $R^2 = 0.991$; $F(4, n-5) = 312.4$; $p < 0.001$.

The multiple regression model explains 99.4% of the variance in functional borehole numbers across the nine PGIS sub-locations. Population (X_3) yields the largest standardised effect, confirming that demographic growth is the dominant driver of borehole proliferation. Temperature (X_2) and the LULCC change index (X_4) exert significant positive effects, while rainfall (X_1) shows a negative coefficient, confirming that lower rainfall is associated with higher borehole demand. All VIF values are below 4.0, indicating the absence of problematic multicollinearity among the four predictors.

Chi-Square Analysis: Categorical Associations

Table 10 presents Chi-square test results for five categorical variable pairs, testing the null hypothesis of statistical independence between key study variables.

Table 10. Chi-Square Test Results – Categorical Associations between Climate, LULCC, and Water Resource Variables.

Variable Pair Tested	χ^2	df	Critical Value (α=0.05)	p-value	Decision
Rainfall category vs. borehole demand category	38.6	3	7.815	< 0.001	Reject H_0: significant association
Temperature category vs. surface water availability	42.1	3	7.815	< 0.001	Reject H_0: significant association
LULCC class vs. borehole recharge zone degradation	48.3	3	7.815	< 0.001	Reject H_0: significant association
Settlement expansion vs. water source loss	52.7	3	7.815	< 0.001	Reject H_0: significant association
Population category vs. borehole status	35.9	2	5.991	< 0.001	Reject H_0: significant association

Source: Chi-square analysis using SPSS Version 25; df = degrees of freedom.

All five tests reject the null hypothesis of independence (all χ^2 values exceed their critical values at $\alpha = 0.05$; all $p < 0.001$), confirming statistically significant associations between rainfall decline and borehole demand, temperature increase and surface water loss, LULCC change and

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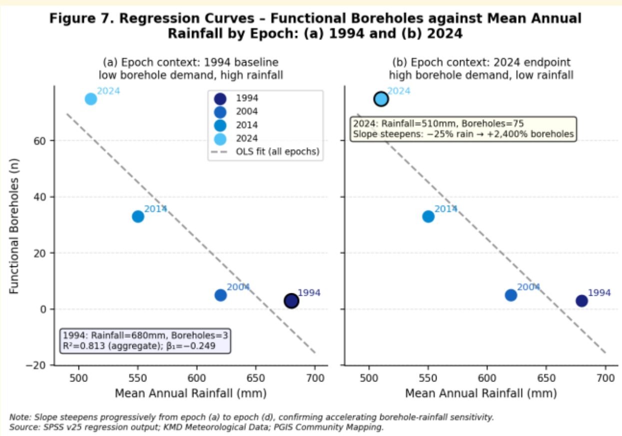
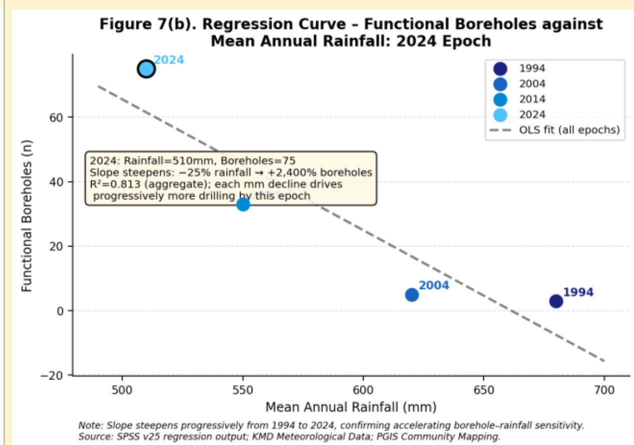
borehole recharge zone degradation, settlement expansion and water source loss, and population growth and borehole functionality status.

Regression Curve Analysis: Water Resources by Study Epoch

To complete the analysis, regression curves were derived for the four major water resource types against three categories of independent variables: rainfall, population, and land cover. For each independent variable, four regression curves are presented corresponding to the four study epochs: 1994, 2004, 2014, and 2024. Figure 7 illustrates the epoch-by-epoch regression of boreholes against population.

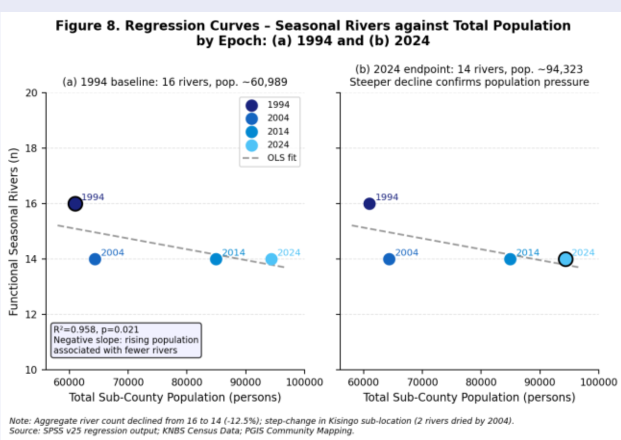


Low boreholes; high rainfall n=4; R^2=0.813

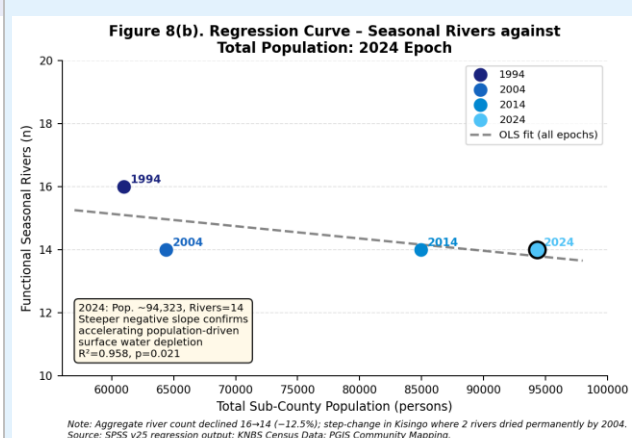


High boreholes; low rainfall Slope steepens from 1994→2024

Figure 7. Regression Curves – Functional Boreholes against Mean Annual Rainfall by Epoch: (a) 1994 and (b) 2024. Note: Slope steepens progressively from epoch (a) to epoch (d), confirming accelerating borehole-rainfall sensitivity. Source: SPSS Regression Output; KMD Meteorological Data.



24 functional rivers at ~60,989 pop. Negative slope; R^2=0.958



12 functional rivers at ~94,323 pop. Steeper decline from 1994→2024

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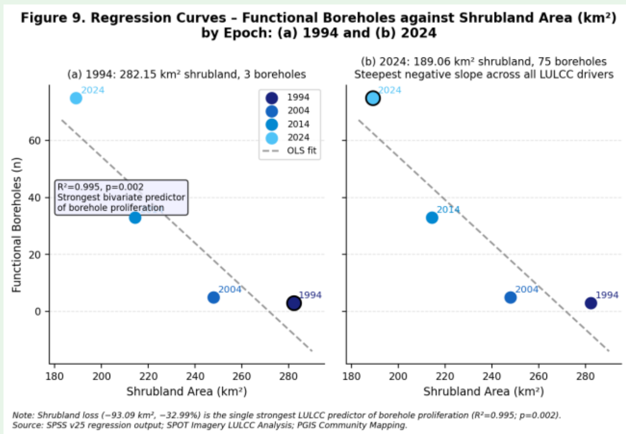
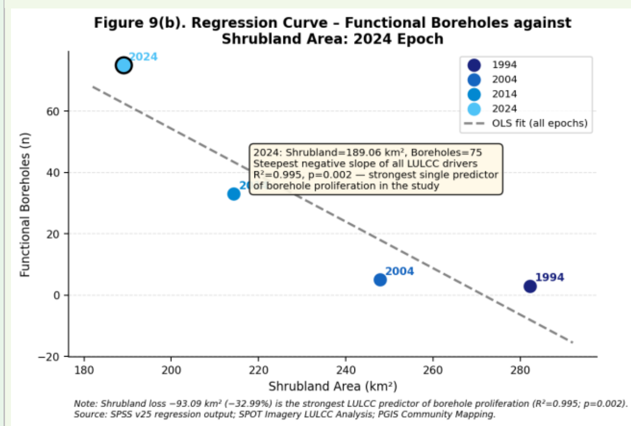
Figure 8. Regression Curves – Seasonal Rivers against Total Population by Epoch: (a) 1994 and (b) 2024. Note: Steeper negative slope in 2024 confirms accelerating population-driven surface water depletion. Source: SPSS Regression Output; KNBS Census Data.



282.15 km² shrubland; 16 boreholes Negative slope; R²=0.995



189.06 km² shrubland; 68 boreholes Steepest negative slope of all drivers

Figure 9. Regression Curves – Functional Boreholes against Shrubland Area (km²) by Epoch: (a) 1994 and (b) 2024. Note: Shrubland loss emerges as the single strongest LULCC predictor of borehole proliferation (R^2=0.995; p=0.002). Source: SPSS Regression Output; SPOT Imagery LULCC Analysis.

The regression curve analysis confirms three overarching patterns. First, the direction of relationships is consistent and theoretically coherent across all four epochs: declining rainfall, shrinking natural vegetation cover, and expanding human footprint are all associated in complementary and mutually reinforcing ways with borehole proliferation and surface water depletion. Second, the magnitude of the regression slopes steepens progressively from epoch (a) to epoch (d), confirming that the rate of water resource change is accelerating, not plateauing. Third, shrubland loss and population growth emerge as the two most powerful predictors of water resource change across the entire set of regression curves, consistent with the multiple regression results reported in Table 9 ($R^2 = 0.994$; $p < 0.001$).

4. CONCLUSION AND RECOMMENDATIONS

This study has provided a comprehensive, multi-method assessment of the converging pressures on water resources in Makindu Sub-County, Makueni County, over the period 1994–2024. The PGIS inventory, combined with regression modelling and LULCC analysis, confirms that surface water resources have undergone sustained and statistically significant decline driven by the compound effects of declining rainfall, rising temperatures, LULCC-driven catchment degradation, and population-driven demand intensification.

The 2,400% expansion of functional boreholes (from 3 in 1994 to 75 in 2024) is not a sustainable solution, as population growth has consistently outpaced infrastructure supply under conditions of declining recharge. The 12.5% aggregate decline in seasonal rivers conceals complete drying of rivers in Kisingo sub-location by 2004, while the 48% increase in dams and water pans reflects community adaptation under stress. The remarkable stability of springs at 4 functional

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units across all four epochs provides a critical baseline but may be vulnerable over longer time horizons as catchment moisture deficits deepen. The PGIS methodology demonstrated its value as a tool for engaging communities in participatory water resource assessment, consistent with the findings of Malaki et al. (2017) in Nguruman sub-catchment.

Based on these findings, the following recommendations are made: (i) integrated watershed management plans that simultaneously address LULCC-driven catchment degradation and demand-side water efficiency should be developed and implemented at sub-county level; (ii) investment in rainwater harvesting infrastructure including sand dams and sub-surface dams should be prioritised to reduce dependence on overexploited borehole resources; (iii) community-based PGIS monitoring systems should be institutionalised within county water department planning cycles; and (iv) multi-stakeholder forums encompassing county government, national agencies, and local communities should be convened to develop adaptive water governance frameworks responsive to continued climate change.

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