Effect of Mobile Phone Utilization in Predicting Drought Progression in Arid and Semi-Arid Lands: A Case of Kinna Ward in Isiolo County, Kenya.

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Abstract- In the event of natural disaster occurrences such as hurricanes, earthquakes, floods, pandemic and epidemic diseases, phone utilization aspects such as calls, SMS, airtime, and mobile money transaction have been widely used to monitor behavioral change and prevalence trend of the affected population. However, little is known on the ability of the meta data produced by network operators if could be utilized to monitor and predict drought progression in arid and semi-arid areas in Kenya. The gap necessitated the conveyance of this evaluation to give more insight on the possibility of utilizing the phone generated records in monitoring drought progression. The study was a panel data conducted on January, 2020, June, 2020 and November, 2020 on 233 phone users sampled from a population of 4345 phone owners in Kinna ward, Isiolo County, Kenya. The three drought phases: normal, emergency, and recovery were developed and projected based on the area standard precipitation index derived from 2009-2019 precipitation values recorded by the Kenya meteorological department. Daily information on calls made and received, SMSs send and received, airtime purchased, and money send and received through mobile money as well as villages visited during the three phases were recorded accordingly. The study used fixed effects panel regression model to reveal the fixed effect of phone utilization aspects on drought progression phases and found out that the phone utilization aspects: received calls, call length, money transaction records and locations significantly influenced drought progression from normal, to emergency to recovery. The study concludes that telecommunication data which can be cheaply obtained has a potential to be employed in drought monitoring in regions with restricted ability to gather information like in ASALs regions of Kenya.

Keywords**-** drought phases, phone utilization aspects, disaster, data

1.0 Introduction

Kenya's arid and semi-arid lands (ASAL) covers over 75% of her land, with 29 counties out of 47 categorized under ASAL region. The ASAL face unique challenges that affect peoples' socio-economic development and environmental sustainability [1]. These challenges include climate change, insecurity, communal conflicts, low capital investment, poverty prevalence, and food insecurity which require a multidisciplinary approach in search of sustainable solutions. The ASAL is characterized by low and erratic precipitation and sporadic drought occurrences. The droughts can vary in severity, but the region is no stranger to these catastrophes. Between 1900 and 2010, more than 18 severe drought periods were experienced in the region's history [1]. According to Stockholm Environment Institute (2009) report on the economies climate change Kenya, the financial loss of the 1998-2000 drought that affected Kenya was documented at $2.8 billion. More significantly, the assessment undertaken after the 2008-2011 drought estimated that $12.1 billion were lost in countries' national economy. Such huge losses were evidenced due to cases of local market distortions, reliance on relief aid, the dilemma of severe drought followed by heavy rains that causes floods in the regions and destruction of resourceful infrastructure [2]. The drought and flooding tragedies occurrence further distorted the economic activities as it was experienced in 2018 drought and floods which destroyed road infrastructure, food supplies for the residents due to flooded road network making them impassable. While humanitarian assistance can save lives, long-term strategies should be put in place to build communities resilience in order to manage drought crisis in real time and help them prevent future destruction [2].

According to Kenya's national 2019 census statistics, approximately 20 million individuals own a mobile phone. Whereas 22.6% of persons aged above 3 years have access to internet [3]. During the pre-event(normal) phase of drought classification, the situation is characterized by community preparedness actions where cell phones and other media networking instruments like radio and TV can give data about the changing behavior in terms of phone utilization variation and other communication information toward risk and tips to promptly plan for its effect. During the reaction(emergency) and recuperation(recovery) stages, the general media always considered on giving evaluation information of damages and misfortunes caused by these climatic disasters. Because of the far-reaching acknowledgment of the expanding multifaceted nature with respect to disaster mitigation, there has been enthusiasm for developing resilience plans for drought monitoring for ASAL. This calls for extended financing from relevant actors and the incorporation of proactive drought management as a center planning component across all sectors. The ASAL region therefore remain a sole proof for developing enthusiasm in drought monitoring and management [4]. While the underlying diversion in drought assessment tools is a cause of concern, there is a growing anxiety to achieve an effective drought monitoring approach that can resolve all ASALs climate changes effects due to its catastrophe recurrent happenings. As resilience centered investments keep on being made in ASALs, the requirement for better understanding and monitoring continue to increase. In this manner, the pointers for drought progression and how dynamic would that prediction be, is the main concern to government agencies, humanitarian organizations, and environmental researchers [4].

Detailed datasets are available due to the evolution of the transformative and innovative telecommunication transmission industry. Cellphones have reformed the world of correspondence. Mobile phones have picked up a great deal of significance in the lifestyles of most Kenyans. In the region, mobile phone penetration in Kenya stands at 62 percent which is the highest [5]. The penetration has been enhanced by the possibility of individual customers to own multiple SIM cards an attribute motivated by subscribers wanting to gain benefits from low prices offered by competitor telecommunication companies [5]. Through various mobile-based applications, numerous individuals' lives have been transformed [6]. Individuals currently get information, learning and conducting business using their mobile phones. Additionally, there are numerous advancements that are being done on the broad applications that identifies call detail records (CDR) as an indicator could offer one of the best avenues for effective and efficient drought monitoring and management, particularly with the increased mobile utilization in Kenya's disaster-stricken counties [5,6].

In their study [7], revealed that regular drought early warning further guarantees household food safety and nourishment by availing timely data, however, the provision of these early warnings faced the high cost and irregular constrains. Their study recommended an improvement of existing early warning systems which focused primarily on more aggregate indicators mostly around Household Economic Approach (HEAs), which CDRs could have provided as well. An information gap that necessitated the survey.

2.0 EMPIRICAL OVERVIEW

2.1 Mobile Data Utilization in Disaster Management

Numerous studies have dealt with the era of big data application in diminishing tragedies. Relevant literatures are available which have successfully attested use of mobile generated records as an indicator for social interactions [8]. Telecommunication networks extensively collects subscribers' data on calls, calling trend, financial transactions and their location [2,8]. The volume data derived from mobile users can be abused for erroneous intention. However, scientists have an enormous opportunity to utilize the privacy-safe anonymized datasets to discover the configurations and dynamics of mobile users at diverse stages of communal unique behavior with precision [2].

Total elimination of disaster event occurrences is beyond human capability, however, innovative technologies are accredited as approaches that can reduce to some extent the magnitude of tragedy losses. Emergency responders often hears about the crisis occurrences through bystanders' accounts either on TV coverage or callers of the emergency numbers. They provide information which lacks wide range perspective of the actual status of the crisis and therefore might not be reliable and lacks the aspect of actionable data [9]. Managing catastrophe events require actual facts dissemination being utilized by emergency service providers in order to target the real victims at the accurate time. The concern is being focused on available critical information and innovation to avert, alleviate, and manage calamity [8]. Due to technological advancement, real-time data can be captured in various sources such as social networks and mobile devices [2]. Situational analysis using the advance technologies in big data analytics gives accurate information that empower emergency service providers in making informed decision, taking suitable act as well as improved management and response process [8].

The Covid-19 pandemic outbreak has intensified the discussion on usage of mobile phone generated records in epidemic response [10]. The mobile data generated is still being utilized to curb corona virus blowout through informing the response team on human mobility variation, evaluation of intervention as well as identifying hotspots where innovative actions need to be applied [10].

3.0 RESEARCH ELABORATIONS

3.1 Study Design

The survey explored the possibility that variability of phone generated records: calls, SMS, airtime, mobile money transaction and location can be used to estimate the drought progression especially in ASAL regions of Kenya which lacks sufficient alternative drought monitoring information systems. The study relied on monthly precipitation secondary data collected in Isiolo county for the past 10 years by the Kenya Meteorological Department. The precipitation trend was used to develop the standard precipitation index (SPI) that categorized 3 drought progression phases: normal, emergency, and recovery. The secondary data revealed a consistent trend of precipitation since 2013, from January-April the meteorological department recorded high values of precipitation, May-September registered lowest precipitation values mostly zero, whereas October-December documented high precipitation values. The study identified January, June and November 2020, as the three phase panel period, where information on various phone utilization aspects was collected on those three periods on a sample of 233 phone users sampled from a population of 4345 phone owners of Kinna ward, Isiolo county. Various mobile utilization aspects identified were collected form the sample of 233 derived using Yamane sample size determination method [11]. Sample population utilized by the survey was derived using Yamane's (1972) formula of finite population to get the actual sample of the population labelled *n*. The study assumed a 95% confidence level, P = 0.5. sampling error of 6% was assumed in deriving the sample size. As a common rule of thumb, any sampling error below 10% is acceptable. The sample size was derived using Yamane (1972) formula as follows:

$$n = \frac{N}{1 + N(e)^2}$$

where:

$n =$ sample population
$N =$ Target Population
$e =$ Accepted sampling – error (0.06)

$$n = \frac{4345}{1 + 4345(0.06)^2}$$ = 232.9939~ **233 respondents were interviewed**.

3.2 Data Collection

The purpose of the study was to estimate drought progression using the mobile phone usage as some indicator variables as reported by 233 sampled from 4345 residents of Kinna ward, Isiolo County who owns and use phone [11]. In Kenya, ward is the smallest electoral division in Kenya, it is composed of several villages and is represented by a member of county assembly (MCA).

Mobile phone generated recorded variables were captured by an enumerator who conducted a face-to-face interview from the sampled residents on phone utilization aspects such as an average calls made and received per day, length of both calls made and received, SMSs received and send per day, airtime bought per day, an average money send or received per day and the village visited during the three drought progression phases identified: normal, emergency and recovery.

To classify drought progression phases, the survey relied on Kenya meteorological department precipitation data of Isiolo county available since 2008. The SPI was derived from the precipitation values captured. The SPI is a multifaceted probability measure of precipitation discrepancy that relates recorded precipitation to the median of past precipitation over an array of time scales. Based on the precipitation trend over the past 10 years, three phases of precipitation variation were identified and termed: normal from Jan-April, emergency from May-September, and recovery from October to December. The information guided the survey on the ideal period to conduct the panel survey. January 2020, was selected to represent the normal phase, June 2020 to represent the emergency phase, and November, 2020 to represent the recovery period. The panel survey was conducted in January, June and November, 2020 collecting similar mobile phone variables to unveil the variation across the three identified drought progression phases.

3.3 Data analysis

Panel data also referred to as cross-sectional time-series data or longitudinal data is defined as a data whose observations of a particular variable is done on different periods of time on a specific unit such as individual or group. The panel data can be analyzed to reveal the individual/group effect using fixed or random regression models. The study conducted the Hausman specification test $\{ H = \varepsilon[u_{it} / x_{it}] = 0 \}$ to understand which model between fixed effect and random effect is suitable for the survey data. The test results revealed random-effect is not suitable for the data hence adopting Fixed effect model [12]. The study embraced the fixed effect regression model which is casual inference model that tests intercept variation across clusters and time period [12,13]. Benefits of using panel data over cross-section data: large sample form repeated observation thus giving more degree of freedom, variability and information among the variables investigated. It also allows dynamic analysis due to time heterogeneity [14]. The data collected from the survey on drought phases and phone generated records was observed repeatedly over numerous panel surfs. Due to the qualification of the data collected to be declared panel data, fixed effect regression model was therefore preferred over other models that do not reflect on the panel feature of the data. In the fixed effect, the survey nested the time variable within the cross-section. The fixed regression model is deliberated under the assumptions: heterogeneous intercept, homogeneous slope, constant error variant, within effect estimation, and F-test for hypothesis testing.

The survey derived a fixed effect regression formula as follows

$$Dp_{it} = \beta_0 + \beta_1(vv_{it}) + \beta_2(cm_{it}) + \beta_3(cr_{it}) + \beta_4(cl_{it})$$
$$+ \beta_5(sms_{it}) + \beta_6(ap_{it}) + \beta_7 In(ms_{it}) + \beta_8 In(mr_{it}) + v_{it}$$

Where:

$\mathrm{t} = \mathrm{drought\ - phase}(1,2,3)$
$\mathrm{i} = \mathrm{individual\ - respondent}(1-233)$
$\mathrm{Dp} = \mathrm{Drought\ Phases}$
$\mathrm{vv} = \mathrm{Number\ of\ Village\ Visited}$
$\mathrm{cm} = \mathrm{Number\ of\ calls - made}$
$\mathrm{cr} = \mathrm{Number\ of\ calls - received}$
$\mathrm{cl} = \mathrm{call - length}$
$\mathrm{sms} = \mathrm{messages\ send\ \&\ received}$
$\mathrm{ap} = \mathrm{airtime\ purchased}$
$\mathrm{In(ms)} = \mathrm{The\ natural\ Log\ for\ money\ send}$
$\mathrm{In(mr)} = \mathrm{The\ natural\ Log\ for\ money\ received}$
$\mathrm{v} = \mathrm{error\ component\ disturbanc\ es}$
$\beta = \mathrm{marginal\ effect}$

The X_{it} are presumed independent of the v_{it} for all i and t.

The STATA statistical software was used to execute the results of the fixed effects regression where the marginal effect for each exogenous variables was generated for inferences. Drought phases interval were used as depended variable: normal, emergency, and recovery levels. The independent variables recorded as phone utilization aspects, its marginal influence was sought within the three identified drought periods.

4.0 Results

Summary statistics was first done to assess the suitability of the variables to undertake the panel data analysis as shown in Table 1. All the eight independent variables have showed the suitability to proceed with panel data analysis.

Table 1. Summary statistics of the exogenous variables

Variable	phase	Mean	Std. Dev	Min	Max	Obs.
Village visited	Overl Btwn Within	2.18	1.11 .85 .71	0 0 .18	7 5 4.52	N=699 n=233 T=3
Calls made	Overl Btwn Within	6.70	3.55 3.15 1.65	0 1.33 -1.96	25 17.3 14.3	N=699 n=233 T=3
Calls received	Overl Btwn Within	8.93	5.65 5.21 2.22	0 0 .26	28 22.7 18.6	N=699 n=233 T=3
Calls length	Overl Btwn Within	3.84	2.97 2.52 1.59	0 0 -7.33	24.2 15.9 12.5	N=699 n=233 T=3
SMS send & receive	Overl Btwn Within	7.97	6.59 5.96 2.83	0 0 -7.70	40 26 22.3	N=699 n=233 T=3
Airtime purchased	Overl Btwn Within	59.06	34.08 27.17 20.63	10 13.33 2.39	200 133.3 142.4	N=699 n=233 T=3
Log of money send	Overl Btwn Within	8.15	1.61 1.55 .44	0 0 5.85	12.4 12.11 12.75	N=699 n=233 T=3
Log of money receive	Overl Btwn Within	8.14	1.73 1.70 .34	0 0 6.95	12.91 11.98 10.06	N=699 n=233 T=3

Table 2: Hausman specification test

	(b) b_fe	(B) b_re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Village_Vi~d	.1987298	.0885968	.110133	.0366274
Calls Made	.0290178	-.0000928	.0291105	.0193841
Received Calls	-.0514757	-.0095618	-.0419139	.015349
Call Length	.1375364	.0415817	.0959547	.0174575
SMS	.0141232	.0019232	.0122	.0111238
Airtime_pu~d	.0009063	-.0004026	.0013089	.0013026
Money_send	-.5759427	-.0461584	-.5297843	.0732016
Received_M~	-.2508633	-.0086905	-.2421728	.0952837

---- Coefficients ----

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(8) = (b-B)'[(V_b-V_B) ^ (-1)] (b-B) = 125.33

Prob>chi2 = 0.0000

Table 3: Fixed effect (within) regression results

Variable	Coefficient	Std. Dev	t-statistic	probability
Village visited	0.199***	0.052	3.73	0.000
Calls made	0.029	0.025	1.18	0.240
Calls received	-0.0515**	0.019	-2.73	0.007
Calls length	0.1375***	0.0232	5.90	0.000
SMS send & received	0.0141	0.0134	1.05	0.293
Airtime purchased	0.0009	0.0018	0.50	0.615
Log of money send	-0.576***	0.085	-6.78	0.000
Log of money received	-0.251*	0.1079	-2.32	0.021
Constant	7.8751***	0.922	8.54	0.000

$* \, p \le 0.05, \quad ** p \le 0.01 \quad *** \, p \le 0.001$

corr(u_i, Xb) = -0.9489
$R^{-squared}$ within =0.2186
F (8,458) =16.02
Prob<F = 0.000
Number of groups=233

5.0 Discussion

The Tables 3 and 2, gives the functional results of fixed-regression model between phone generated records and the drought levels in a time series. The drought change results into changes in phone utilization levels. The result showed significant correlation effect of phone utilization aspects within the drought progression phases. The behavioral change in terms of phone utilization was evidenced when the drought progresses from normal to emergency to recovery. Thus, the results allow to postulate that there is significant correlation between individual phone utilization behavioral change and the drought levels.

The results show that out of the eight variables the study projected to have some variation effect on drought, only five variables: village visited, call received, call length, money send and money received, showed significant variation effect on drought progression.

The coefficient on drought progression indicates that as the situation changes from normal to emergency to recovery drought phases, it raises the number village an individual visit in search of pastures and other social amenities by 20%. The progression of drought reduces the number of calls received by an individual experiencing drought by 5.1%. On the other hand, the situation increases the length of calls either made or received by 13.8%. The drought situational change also affects money transactions negatively: money send and received, as drought progresses, money send and received decreases by 57.6% and 25.1% respectively. The coefficient of determination (R^2) represents the measure of goodness-of-fit, the study recorded an R^2 of 21.8% indicating that the eight explanatory variables adopted by the study explains about 21.8% of the variation of drought progression leaving 79.2% unexplained. The coefficient intercept of 7.8752 detailed by the study is significant at 1%.

The survey results were similar to that of [15] findings in their quest to understand whether human social behavior changes upon disaster occurrence as a critical feature in refining disaster organization and preclusion. They developed a framework proposal that can be utilized to analyze human social behavioral variations in the event of tragedy occurrence by means of utilizing Call Detail Records (CDRs) gathered from a telecommunications corporation tower. The framework projected to involve three stages: data pre-processing, behavioral standard calculation and tragedy analytics processes [15]. It's expected to extract human social features from the spatial-temporal data, then compare the captured information with the common behavioral standards that have been used to study social interaction variations happening due to tragedy occurrences. Therefore, the framework can be utilized to manage or monitor the tragedy events occurrence by delivering real time spatial-temporal datasets for any type of tragedy incidence. Their assessment showed the framework is capable of generating valued data both in terms of movements indulgence while appraising communication variations [15].

In their research [10, 16] on COVID-19 mobility behavior, [16] observed day-to-day changes of movement in near-real-time by means of anonymized mobile phone data, they did a behavioral comparison before, during and after a country-wide lockdown imposed by the Austria government as measure to curb COVID-19 spread. Their findings similar to that of drought progression in the survey found out that mobile phone usage data authorizes actual quantification of mobility behavior for the entire country. Their research recommended the need to emphasize on improving the availability anonymized data to improve on quick rejoinder to control the fight against COVID-19 and other pandemics [16].

The survey findings were similar with that of a study conducted in Haiti during the 2010 cholera outbreak by [17] that used mobile phone data in aiding to predict the epidemic spread. In their study [18], on poverty mapping using both satellite and phone data, found out that in an effort to end poverty, it's important to rely on actual information on the real habitation areas of the affected people using the real-time phone data. Such information helps in increasing the knowledge of the components of monitoring poverty rates over time. Also in their study by [19], which revealed similar findings that social human behaviors consideration in terms of movements and communication arrangements during and after tragedies is vital in situational analysis and discerning the geospatial localities that may require immediate actions. These findings provide the shred of evidence that can be relied on by governments and other development partners on resources allocations in the event of tragedy happening.

Conclusion

There is an upsurge of phone mobile users in Kenya even in ASAL where drought occurrence is a frequent phenomenon. Big data on phone utilization is readily available from telecommunication operators if privacy of users is guaranteed The study analysis demonstrates that indeed drought progression can be estimated by the evaluating behavioral change in terms of phone utilization variation of the mobile users' in area where drought occurrence is frequent. The study lays foundation on possibility of focusing on the available real –time mobile phones bulk data to predict the drought situation in prone areas such as ASAL in future. The study reveals the possibility of including observation of behavioral change in terms phone utilization as another form of drought indicators on top of precipitation and vegetation interpretations.

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