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ASSESSMENT OF TRADITIONAL ENVIRONMENTAL KNOWLEDGE SYSTEMS APPLIED TO RAINFALL FORECASTING IN ROMBO DISTRICT, TANZANIA

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Abstract: *Accurate rainfall forecasting enables rural communities to make informed, timely and effective decisions on their farming activities presumably leading to increased productivity. As such, a more appropriate, accessible and user friendly rainfall forecasting methods and information is needed. This study was conducted to assess efficacy of the traditional environmental knowledge systems applied to rainfall forecasting in Rombo District, Tanzania for sustainable climate change adaptation. Triangulation of data collection methods were used to obtain diverse and detailed information. Out of 611 interviewees, 44.2% could forecast rainfall using environmental indicators (EIs) of whom 75.5% were unable to forecast beyond a week. It was somewhat difficult to judge the reliability of some EIs in forecasting rainfall because the same indicator was rated differently by different respondents, as very reliable, reliable, not reliable and no longer reliable. Although half of the respondents anticipated a decrease in rainfall, forecasting from Global Climate Models revealed the opposite. The study recommends a multidisciplinary approach and sharing of knowledge and information for effective rainfall forecasting.*

Key words: Climate change adaptation, Environmental indicator, Global Climate Model, Rainfall forecast, Traditional environmental knowledge systems

Introduction

Rainfall is an important element of weather that provides water for living organisms. Rainfed agriculture on which most of the third world population depends for their livelihoods is influenced by the timing, quantity and intensity of rainfall. From time immemorial, humans have been using environmental indicators (EIs) to predict timing, quantity and intensity of rainfall. The knowledge developed by people with extended histories of interaction with natural environment is known as Traditional Environmental Knowledge systems (TEK systems)[1,2]. TEK is passed from one generation to the next through cultural transmission, and is stored within people's memories[3]. Methods of applying, retaining and communicating TEK, especially in times of rapid environmental and political change are not reliable, thus, TEK needs to be documented[4]. In this time of global climate change, it is also important to document TEK systems because they provide a new source of climatic data over a spatial-temporal scale of several generations in regions where there is paucity of documented data[5].

One important step in reducing vulnerability to climate hazards is to develop an early warning system for forecasting the timing, quantity and intensity of rainfall[6]. In modern societies, rainfall forecasting is usually done through Global Climate Models (GCMs). Although GCMs can be used to provide rainfall information at local scales through downscaling, such information is limited to end users who have access to it through communication media such as radio, television, newspapers and internet[7]. Delivery vehicles such as time specific programmes through electronic media do not take into account the limited time individuals have, and this may limit their capacity for adaptation[8]. Furthermore, wealthier households benefit more than the poor from the modern rainfall forecasts[9]. This calls for more appropriate, accessible and user friendly rainfall forecasting methods and information.

Studies on rainfall forecasting using EIs are numerous[2, 3, 7, 10, 11, 12, 13, 14]. Indigenous and local people's forecasting methods can offer insights for improving the value of modern scientific forecasting. It is also emphasised that indigenous forecasting practices are needs driven. They focus on the locality, timing of rains and are communicated in local languages by experts well known and entrusted in that particular community[4]. A number of researchers of indigenous knowledge have challenged integration of TEK systems into Modern Environmental Knowledge Systems (MEK systems) to rainfall forecasting by arguing that TEK systems lack benchmarks[12.] However, others have maintained that integration of the two systems of rainfall forecasting will increase overall reliability[3, 7]. Despite these discrepancies, studies which seek to relate TEK and MEK systems as applied to rainfall forecasting in Rombo District are sparse to date. The present study was, therefore, to bridge this gap by assessing the efficacy of TEK systems applied to rainfall forecasting and relating them to MEK systems for sustainable climate change adaptation.

Methodology

This study was conducted in Rombo District (Figure 1). The study area has a mountainous climate with two distinctive rainfall regimes: a short rainy season occurring from October to December and a long rainy season from March to May[15]. The dominant economic activity in the region is subsistence agriculture, which involves cultivation of rainfed crops including coffee, bananas, maize and beans, cassava, millet, sorghum, sweet potatoes, sunflower, yams, and various fruits and vegetables. Coffee and bananas are the main cash crops. Zero grazing livestock is another economic activity that involves keeping of cattle, goats, sheep, pigs and poultry. Micro-businesses such as small shops and local brew bars, and micro-industries such as carpentry and bicycle repairs are also practised to sustain family livelihoods with few individuals earning income from wage employment in both private and public sectors.

Questionnaires were administered to 611 respondents identified through random sampling in eight villages, in three agroecological zones (AEZ) (Figure 1) to collect information on the socio-economic characteristics of respondents, knowledge on using EIs to forecast rainfall and the perceptions of future rainfall characteristics. Three focus group discussions were also used to collect narrative information on the subject matter from 21 participants who were purposively selected from the three AEZs of the study area. In-depth interviews were conducted with three Agricultural Extension Officers (AEOs) and the District Agricultural and Livestock Development Officer (DALDO) selected purposively from the study area to determine official support for rainfall forecasting. Field observations were also employed to collect none verbal information. Recorded and climate model rainfall data were obtained from

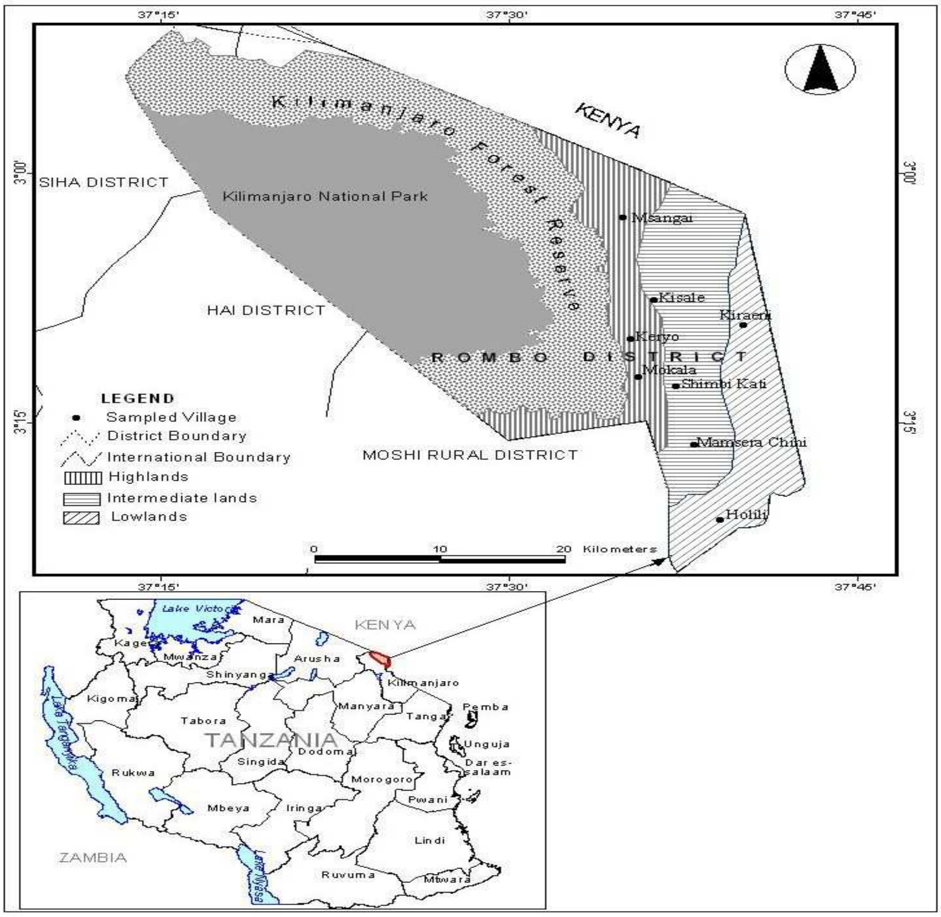
Tanzania Meteorological Agency (TMA) at Ubungo Plaza and the Intergovernmental Panel on Climate Change (IPCC) Data Distribution centre respectively. Quantitative data were analysed with a Statistical Package for Social Sciences Software (SPSS, version 16) and Word Excel, while qualitative data from interviews and focus group discussions were thematically analysed and presented in frequency tables, figures and narrations.

Rainfall prediction for the overall region was done using 22 GCMs downloaded from the IPCC Data Distribution Centre website. The downloaded GCMs were characteristically sensitive to 21st Century Scenarios which considered the atmosphere to have elevated concentration of carbon dioxide as compared to preindustrial era. Since the GCMs' coordinates (i.e. latitudes and longitudes) were not always the same as those of the study area, decisions were made based on the enclosure of the GCM coordinates in relation to the study area. The accuracy and precision of the GCM data were maintained by selecting the upper latitudes and longitudes (centroids) for each model. The generated data were used to predict future rainfall changes of the study area.

After downloading the historical precipitation data for each model, skill score tests were performed by summing the minimum relative frequencies (rf) of either observed (recorded) data or GCM data [i.e. *Skill Score* $= \sum_{i}^{n} \min(rfObserve, rfGCM)$]. Due to differences in skill score results, models with greater than 50% and which are in scenario A2 family were chosen for predicting future rainfall changes (*DeltaChange*). The GCMs in scenario A2 family assumes that the world is characterised by independently operating, self-reliant nations with continuously increasing population and regionally oriented economic development[16]. Based on these criteria, three GCMs; ncar_ccsm3_3, ipsl_cm4 and gfdl_cm2.0 were selected to determine future rainfall changes in which changes in GCM historical rainfall data were subtracted from the forecasted rainfall and divided by changes in GCM historical rainfall data (i.e. $DeltaChange = \frac{DeltaGCMHistorical - DeltaGCMForecasted}{DeltaGCMHistorical}$).

Since each model showed variations in rainfall (i.e. increase or decrease), multi-model means were determined and used to plot rainfall changes (%) against time (year) to minimize individual model bias. The 1961-1990 rainfall data were taken as the baseline from which the 2011-2030 and 2046-2065 rainfall changes were referred.

Figure 1: Study area



Findings and Discussion

Socio-economic characteristics of respondents

Out of 611 respondents contacted for direct questionnaire, 85.3% were males and 14.7% females. Of these, 90% were married, with 10.7% having attained no formal education. All of the respondents engaged in subsistence crop production. Maize and beans are grown in all agroecological zones (AEZs) of the study area, while bananas and coffee are mostly grown in the highland and intermediate AEZs. About 99.2% mentioned to practise zero grazing livestock keeping in which 92.2% keep goats, 80% poultry, 61.5% cattle and 29.9% pigs. Livestock are mainly kept for manure. Sixty percents of respondents mentioned to involve in off-farm activities such as entrepreneurship, casual labour and formal employment. About 92.7% of the respondents possessed at least one type of communication facility, with a majority (56.6%) possessing radios and mobile phones.

TEK systems applied to rainfall forecasting

Findings revealed that out of 611 respondents contacted for a direct questionnaire, 270 (44.2%) used environmental indicators (EIs) to forecast rainfall (44% of all males and 45.7% of all females). These findings suggest that females are slightly more conversant with EIs in forecasting rainfall than males because of the farming and family responsibilities females are obliged to. It is reported that African females in Africa are more involved in cultivation than males[8, 17], and are often denied access to climate information due to limited participation in gatherings[18] and engagement in family chores[15].

It was, further, found that the time at which an individual is exposed to the environment contributed to the acquisition of TEK relevant to rainfall forecasting. This is because no respondents in the age group 15-24 mentioned use of EIs to forecast rainfall. These findings concur with the study conducted in Burkina Faso, in which seniority was found to be a mark of authority because elders were believed to have accumulated a great deal of experience[14]. The study, further, revealed that respondents with post secondary education (76.9%) use more EIs to forecast rainfall than those without this level of education. This contradicts with the report that people who are trained in western education rely more heavily on modern methods of forecasting rainfall because they perceive TEK systems as outdated[7].

The findings also revealed that the possession of communication facilities reduces the use of EIs to forecast rainfall. Seventy five percent of respondents who owned radio and/or television did not mention the use of EIs to forecast rainfall. Earlier studies reported that wealthy households, who owned and use communication facilities, benefit more from weather forecasting using modern methods than the poor[7, 9].

The study found that the EIs used by the respondents to forecast rainfall can be categorised into meteorological, biological, astronomical and others (Appendix 1). The EIs identified in this study are similar to those mentioned elsewhere by other researchers of TEK related to rainfall forecasts[3, 7, 10, 11, 12, 14]. The appendix 1 shows that clouds were the most used signs in forecasting rainfall simply because rainfall is antecedent by clouds.

Provision of accurate seasonal climate prediction and early warning of climate events requires the availability of reliable predictors, with sufficient lead time[19]. In this study, it was also established that the time respondents could predict rainfall in advance is of great concern. The findings presented in Appendix 2 indicate that 75.5% of respondents were unable to forecast rainfall beyond a week. These respondents benefit less from knowing the expected characteristics of rainfall because a week is too short for anticipatory adaptation and, hence, reactive adaptation. Reactive adaptation lead into unsustainable use of resources, and it always leaves the affected community poorer and less able to recover from the climate shock[20]. About 10.1% of the respondents are expected to be better prepared for the outcome by being able to forecast rainfall beyond a month in advance. Being able to predict rainfall a month ahead or more may facilitate anticipatory adaptation in which today's resources may be used to prevent possible crises in the future or to reap the benefits of expected rainfall characteristics[20].

However, the study also found that most of the EIs people used to forecast rainfall beyond a month using a traditional calendar or vegetation characteristics were generally claimed to be unreliable (Appendix 3). The appendix shows that insects were rated by our interviewees to be very reliable and reliable despite the fact that behaviour of biological indicators is expected to be altered by climate change. Changes in climatic variables can lead to changes in physiology of living organisms as a way of adapting to new ecological conditions[4]. Similarly, characteristics of winds are usually influenced by global warming and, therefore, winds are expected to alter direction, frequency and force rendering them less reliable in forecasting rainfall.

It was, however, difficult to judge on the reliability of some EIs in forecasting rainfall because the same indicator was rated differently by different respondents, as very reliable, reliable, not reliable or no longer reliable (Appendix 3). The EIs rated not reliable and no longer reliable were once reliable, but increasingly inconsistent especially in recent years. Similarly, the study conducted in Burkina Faso revealed a reduced use of local forecasting knowledge because there was an inconsistency between the usual indicators and their effectiveness in the current trends of the increased climate change[11]. Similar findings were also reported in the Sahel Africa[6]. However, studies conducted in the Nigerian Savannah concluded that farmers are no longer able to predict rain or to know precisely when to plant their crops[21]. The 89.6% of respondents noted that to use forecasted information for farming activities is full of ambiguities. This is because in-depth interviews with the District Agricultural and Livestock Development Officer and Agricultural Extension Officers suggested that most of the farmers in the study area plant crops based on traditions, and that they do not predetermine planting of crop types based on forecasted rainfall characteristics in any case. Therefore, the forecasted rainfall characteristics may not be necessarily a triggering factor for a certain agricultural practice such as when and which type of crop to plant.

Findings revealed that respondents have lost confidence over EIs because all mentioned to complement their own knowledge of forecasting rainfall with other sources: 68.3% depend on Tanzania Meteorological Agency (TMA) through radio, television and formal meetings; 7.7% on friends; and 23.9% depend on both TMA and friends. During FGD held in the highland AEZ, it was noted that peasants were interested in forecasted information from Kenya Meteorological Department because the forecasted information were found to be more accurate and reliable than those of the TMA. As for this study, alternative sources of rainfall prediction were considered important to farmers who had lost confidence in their ability to predict rainfall[11].

Trends of future rainfall

Because of the inability of respondents to use EIs to forecast rainfall beyond a year, questions to determine their perceptions on the trends of future rainfall were formulated. The results show that perceptions of future rainfall trends differ according to the characteristics of our respondents. Respondents predicted a decrease of rainfall over time as it had experienced in the past, and they anticipated this trend to persist mainly due to the continued tree felling, drying of trees and difficulty in raising tree seedlings (see Appendix 4). These findings imply that local people are aware that deforestation induces climate variability and changes including decreasing rainfall similar to modern scientists[23].

Moreover, results presented in Appendix 4 show that 30% of respondents anticipated an increase in rainfall due to the prohibition of tree felling, and tree planting campaigns. Tree felling in the study area was prohibited unless by permit, and, as well, there was a campaign for planting trees in which every household and institution was supposed to plant 5 and 20 trees respectively. The respondents with this opinion expected that prohibiting tree felling, and the tree planting campaign to increase vegetation cover would attract more rainfall. This observation is in line with the IPCC report which emphasises tree planting to offer sinks for carbon dioxide[23].

Appendix 4 also indicates that some respondents perceived trends of rainfall to be unpredictable and didn't know what to expect. These respondents were noted to have had experienced unpredictable rainfall in the past, and expected the same level of unpredictability in the future. Both respondents who considered future rainfall to be unpredictable and those who did not know what the trend might be said it was impossible to predict rainfall because it is controlled by God. Thus, predicting future rainfall characteristics is full of uncertainties because it is based on individuals' perceptions[13].

Based on A2 scenario (Appendix 5), prediction of rainfall changes using three GCMs indicate that there will be variation in both annual and seasonal rainfall. The figure fails to give clear trend of rainfall with all GCMs. When multi-means (averages) are used, the figure indicates that while rainfall for annual and October-December are expected to increase the opposite is expected for June-September. The figure, further, shows that the January-February and March-May are expected to decrease and then increase. It is difficult to argue on the accuracy between the perception of respondents and GCMs because of the divergent results despite the fact that increase in rainfall in areas with bimodal rainfall have been projected[24]. The March-May and October-December rains are very important as they mark two seasons for growing annual crops in the study area. Abnormal characteristics of these rains may have catastrophic impacts to the livelihoods of people in the study area.

Conclusions and recommendations

Based on the findings and discussions, it can be concluded that the efficacy of TEK systems in forecast rainfall in the study area is dwindled because: less than half of the respondents could forecast rainfall using EIs; very few respondents could use EIs to forecast rainfall beyond a month in advance; and the same EIs was rated differently by different respondents based on reliability scale. It is also difficult to integrate TEK and MEK systems in forecasting rainfall because of the divergent results from respondents and GCMs on the future characteristics of rainfall. Still the information obtained seemed meaningful in planning for agricultural and other daily activities. For effective rainfall forecasting, the study recommended that respondents who could forecast rainfall using EIs should share not only the knowledge but also the forecasted information with others; monitoring of the EIs; and careful multidisciplinary approach.

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Appendix 1 Environmental indicators used to forecast rainfall (N=270)

Environmental indicator	**Respondents (%)**	**Indicators of rainfall onset**
1. Meteorological	**41.4**	
Cloud	36.4	-Presence of dark clouds in the north-eastern side (*ndumuha*). -Presence of cap-like clouds (*ngoviri/uviri*) at the top of Mount Kilimanjaro.
Thunder	3.9	-Thunder heard from the north-eastern side (Taita Hill).
Wind	1.1	-North-westerly winds. -Strong wind blows dust and other materials into the sky in a spiral-like (*kititimakwe*).
2. Biological	**23.7**	
Human body	13.6	-Feels overtired with excessive sweating and slumbering (*ronge).* -Dreaming to swim in high water.
Vegetation	5.9	-Flowering in mango trees (*Mangifera indica*), coffee (*Coffea arabica*) and jacaranda (*Jacaranda mimosifolia*). -Formation of new leaves in fig tree (*Ficus benjamina*) and banana plantain (*Musa acuminata*).
Bird	2.5	-Cries of certain birds (*modudu)*. -Migration of pigeons (*mbuku*) in a big flock eastwards and trumpeter hornbill (*Bycanistes bucinator*) westwards.
Insect	1.7	-Termites (*Reticulitermes virginicus*) build a mound with wet soil in the evening. -Tree bugs (*mbalamata*) discharges much water than normal.
3. Astronomical	13.5	
Moon	8.6	-Moon set between Kibo and Mawenzi peaks of Mount Kilimanjaro. -Moon appears bigger than normal when rise at 6 pm (*mweri mlemeni*).
Sun	4.9	-Sun appears more glittered than normal while most of sky covered with dark clouds.
4. Others	**21.4**	
Mt. Kilimanjaro	16	-Cap-like clouds (*ngoviri/uviri*) at the top of Mount Kilimanjaro.
Calendar	3.9	-Traditional agricultural year begins in September after hearing thunder.

Source: Field Data (2012)

Appendix 2 Time in advance for rainfall forecasting

Environmental indicator	**Responses on onset of rainfall (%)**				
	Hour-7days	7–14 days	14-21 days	21-28 days	28+ days
Clouds	80.7	5.2	5.5	1.2	7.3
Mt. Kilimanjaro	70.3	13.3	4.4	1.9	9.2
Vegetation	56.5	6.5	4.8	6.5	25.9
Human body	85.2	7.4	2.5	2.5	2.5
Insects	66.7	19	9.5	4.8	0
Birds	76.5	8.8	2.9	8.8	2.9
Moon	72.9	9.4	1.2	1.2	15.3
Sun	58.2	9.1	10.9	0	21.8
Calendar	54.8	6.5	1.6	1.6	34.5
Wind	78.3	4.3	13	0	4.3
Thunder	72.1	14	4.7	2.3	7
Rainbow	100	0	0	0	0
Total (N=270)	**75.5**	**7.8**	**4.9**	**1.7**	**10.1**

Source: Field Data (2012)

Appendix 3 Reliability of environmental indicators in forecasting rainfall

Environmental Indicator	Responses on reliability (%)			
	Very reliable	Reliable	Not reliable	No longer
Clouds	47.5	43.5	5.3	3.7
Mt. Kilimanjaro	47.4	37.2	9	6.4
Vegetation	58.1	29	8.1	4.8
Human body	45.9	45.1	8.2	0.8
Insects	95.2	4.8	0	0
Birds	70.6	26.5	2.9	0
Moon	51.8	29.4	16.5	2.4
Sun	61.5	21.2	17.3	0
Calendar	63.5	12.7	15.9	7.9
Wind	69.6	30.4	0	0
Thunder	44.2	30.2	20.9	4.7
Rainbow	27.3	36.4	36.4	0
Total (N=270)	**47.9**	**41.3**	**7**	**3.8**

Source: Field Data (2012)

Appendix 4 Perception of future trends of rainfall

Characteristics of respondents	Perception of rainfall trends (%)			
	Increase	Decrease	Unpredictable	Don't know
AEZ				
Highland (n=10)	20	50	30	0
Intermediate (n=10)	60	10	20	10
Lowland (n=10)	10	90	0	0
Sex				
Male (n=22)	27.3	54.5	18.2	0
Female (n=8)	37.5	37.5	12.5	12.5
Age group				
25-34 (n=1)	0	100	0	0
35-44 (n=5)	60	20	20	0
45-54 (n=8)	25	37.5	25	12.5
55-64 (n=11)	36.4	45.5	18.2	0
65+ (n=5)	30	50	16.7	3.3
Education				
Primary (n=26)	30.8	46.2	19.2	3.8
Post Sec. (n=1)	0	100	0	0
No Formal (n=3)	33.3	66.6	0	0
Total (N=30)	**30**	**50**	**16.7**	**3.3**

Source: Field Data (2012)

Appendix 5 Projected rainfall change at Huruma Convent gauging station