Drought analysis in Tanzania using Markov chains

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ABSTRACT

The Usambara Mountains are a region in Tanzania with a high population density, low soil fertility and high rainfall variability. The persistence of drought occurrence and the influence of the Indian Ocean Dipole (IOD) driven sea surface temperature (SST) anomalies on drought occurrence in the Usambara Mountains was analyzed. A Markov analysis was used to calculate the rainfall probabilities and drought occurrence. The October-December rainfall season showed a higher rainfall variability than the March-May rainfall season, a higher probability for drought occurrence, is therefore unreliable for the cultivation of crops and is correlated with the IOD.

Keywords

Drought, Tanzania, Markov, Climate Change, Rainfall, Sea Surface Temperature (SST), Indian Ocean Dipole (IOD).

INTRODUCTION

East Africa experienced drought and famine in the last century. This century the food security of the region is threatened by an ever changing climate. Higher temperatures and a decreasing amount of rainfall are detrimental to agriculture and food production, as over 95 percent of Africa's crop production is rain fed (Van Aalst et al., 2007). Agriculture also forms a large part of their economies. In multiple countries variability in rainfall seems to force GDP changes (Barrios et al., 2010). The 2011 drought is a crushing example. The failure of the October-December rains in 2010 and the subsequent March-May rains caused a humanitarian crisis. Over 13 million people were affected and in the beginning only a fraction received food aid (IFRC, 2011).

Like the rest of East Africa, Tanzania suffers increasing occurrence of returning dry spells (Kabanda & Jury, 1999). The people of the Usambara Mountains in Tanzania in particular were and are still greatly affected by these dry spells (Liwenga et al., 2012). The region has one of the highest population densities of Tanzania, 300-480 capita per km^2 with annual growth rates up to 3.5 percent and as a consequence a lot of poverty (NBS, 2012). Yearly rainfall has declined from an average of 1400 mm/y in the 1930's to 800 mm/y on average in the early 2000's. A survey among villagers shows that the October-December rainfall period has become very unreliable and has almost disappeared (Liwenga et al., 2012). The soils have low fertility and are strongly acidic with nutrients only available in the top soil. Moreover, the region has one of the highest erosion rates of Africa (Reyes, 2008).

These facts make it harder for people to make a living, as above 90 percent of the land use is agriculture and forests (NBS, 2012). If crops fail, farmers need other activities to cope and most resort to deforestation to sell wood, which will only lead to more degradation (Liwenga et al., 2012). Also the practice of thinning forest canopy needed for growing cash crops, such as Cardamom, is widespread (Reyes, 2008). Knowledge of drought occurrence and rainfall beforehand will be beneficial for the local farmers for the successful cultivation of crops.

The research to the influence of sea surface temperatures (SST) other than the El Niño Southern Oscillation (ENSO) has started in recent years, which shows a larger role for the Indian Ocean Dipole (IOD) in East Africa weather, which we do not fully understand. Marchant et al. (2006) state that there is more and more evidence that the IOD is a distinct phenomenon separated from the ENSO in contrast to the previous consensus and is partly responsible for the climate on the surrounding landmasses. Black et al. (2003) conclude that large rainfall amounts in East Africa are associated with the sea surface temperature of the Pacific and Indian Ocean. Mutai et al. (1998) suggest there is a significant relationship between the OND rainfall season and SST anomalies. Quantitative knowledge of the relation between the IOD and drought will be needed to predict the nature of future rainfall seasons.

The objectives of this study were; To analyze persistence of drought occurrence in the Usambara Mountains; To analyze the influence of IOD driven SST anomalies on drought occurrence in the Usambara Mountains.

MATERIAL AND METHODS

The rainfall data for this study was obtained from the Sakarina Mission School located in the western Usambara Mountains. The Usambara Mountains are a mountain range located in North-east Tanzania, with a NW-SE orientation and spans about 3600 square kilometers, consists of two blocks and is part of the Eastern Arc Mountains (Murless, 2013). The Usambara Mountains experiences two rainy seasons each year from March to May (MAM) and from October to December (OND), mainly under influence of monsoons, the Intertropical Convergence Zone, subtropical anticyclones, African jet streams, and wave perturbations (Kabanda & Jury, 1999). The dataset comprises the daily rainfall amounts from 1 September 1991 to 31 August 2005.

The daily rainfall data was used to perform a zero-order and first-order Markov Chain analysis, which is a stochastic process, to analyze rainfall probability and the difference in length of dry spells (Stern & Coe, 1984). The software INSTAT+ version 3.36 was used to perform this analysis with instructions provided by Stern et al. (2006).

A zero-order approach will deliver a probability that is only affected by the day for which it is calculated. A first order approach will calculate the probability that depends on the state of the previous day being wet or dry with a 0.85 mm threshold, for errors in measurements.

The dataset consists of 15 years (x_i) that all contain 366 days (x_j) which can be dry (x_{ij}=0) or wet (x_{ij}=1). 29th February is discarded for any non-leap years. The zero order Markov Chain analysis is defined as;

$$P_j(r) = \frac{\sum_{i=1}^{i=15} x_{i,j} = 1}{15} \quad [1]$$

There the number of years with a wet state for any given day is counted and then divided by the number of years in the dataset to get the probability for every date in the year. The first order Markov chains are shown in equation 2 and 3. In equation 2 the number of wet days that are preceded by a dry day for any given day in the year was divided by the number of days for that date that are preceded by a dry day.

$$P_j(rd) = \frac{\sum_{i=1}^{i=15} x_{i,j} = 1, x_{i,j-1} = 0}{\sum_{i=1}^{i=15} x_{i,j-1} = 0} \quad [2]$$

In equation 3, the number of wet days that are preceded by a wet day are divided by the total number of days preceded by a wet day. So, two different first-order probabilities were calculated, one for a wet day following a dry day ($P(rd)$) and one for a wet day following a wet day ($P(rr)$).

$$P_j(rr) = \frac{\sum_{i=1}^{i=15} x_{i,j} = 1, x_{i,j-1} = 1}{\sum_{i=1}^{i=15} x_{i,j-1} = 1} \quad [3]$$

The 2nd equation was then used to calculate the probabilities for a dry spell, by calculating the probability for a consecutive number of dry days. Sequences of 7, 14, 21 days of drought were chosen. All probabilities were then calculated over an average of 5 days and a curve was fitted with INSTAT+ by adding harmonics to account for the irregularity of daily rainfall as described by Stern et al. (2006).

To determine the influence of IOD anomalies on rainfall probability the Dipole Mode Index (DMI) was used, which portrays the intensity of IOD anomalies. Monthly data was obtained from JAMSTEC (Japan Agency for Marine-Earth Science and Technology) that was averaged for the rainfall seasons. The average DMI value, as independent variable, was then regressed with the cumulative rainfall in the MAM and OND season as dependent variable to quantify the effect of IOD on the variability of the rainfall seasons in the Usambara Mountains. Rainfall probabilities were separately calculated for years that have a significant positive value (1994, 1997 and 2002) and a significant negative value (1992, 1996 and 1998) to show the effect of the IOD on rainfall probability and drought occurrence. Again also probabilities of sequences of dry days were calculated for these years.

RESULTS

The MAM rainfall period seems to be longer and is observed to have a smaller standard deviation than the OND rainfall period and is therefore a guarantee for rain in the time period of the dataset. The OND rainfall period has a larger spread and a significant amount of rainfall is not guaranteed.

The estimated probabilities for rainfall in the Usambara Mountains are shown in figure 1. The two rain seasons are clearly visible in the chart with probabilities of rain of 30 to 50 percent. The probability for rain in the October-December season is about 20 percent lower than in the March-May season. There exists a smaller difference in probabilities for the rain seasons given the previous day was dry. Also, the $P(r)$ curve in the OND season is notably closer to the $P(rd)$ curve than in the MAM season, indicating a dryer season. Rain in summer seems to be very unlikely but possible given the previous day received rain. In general, the probability of rain after a wet day is significantly higher than the probability of rain after a dry day. So consistency in dry days is the defining factor.

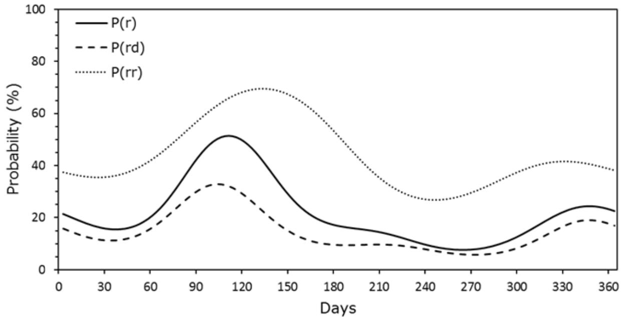

Fig. 1. Probability of daily rainfall for the whole year *P*(*r*), probability of rainfall given previous day was dry *P*(*rd*) and given previous day was wet *P*(*rr*).

The probabilities for drought exceeding 7, 14 and 21 days are shown in figure 2. A noticeable dip in probabilities for the sequences exceeding 7 days can be seen in the MAM season and dips in the sequences exceeding 14 days in the OND season. This means the MAM season is almost a guarantee for the occurrence of rainfall needed for the successful cultivation of crops but the OND season is highly variable. The OND season has a more than 90 percent probability for a drought exceeding 7 days and even occurrence of droughts exceeding 21 days, while the MAM season has a 50 percent probability of a dry spell exceeding 7 days and only a very small probability of a dry spell exceeding 14 days. In summer there is a 60 percent probability for a drought exceeding 21 days.

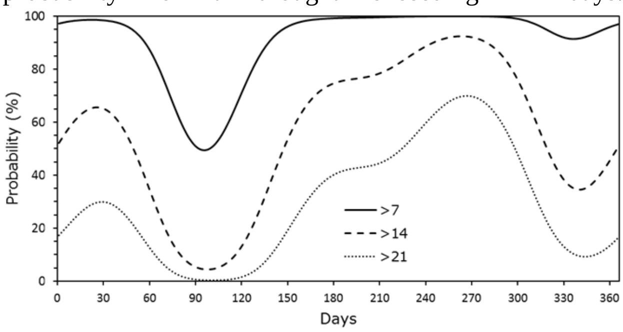

Fig. 2. Probabilities of drought occurrence of length exceeding 7, 14 and 21 days.

A regression was run between average DMI and cumulative rainfall for the MAM and the OND season to quantify the relationship between IOD and rainfall probability. It showed that there is no significant relationship between the MAM cumulative rainfall and DMI in the same months as a correlation coefficient of 0.20

($p \approx 0.5$) was calculated. A better fit is there between average OND DMI and cumulative rainfall for the same period with a correlation coefficient of 0.73 ($p \approx 0.00$). At least in part the IOD driven SST anomalies are responsible for variability of rainfall in the OND period. So for only the OND period the rainfall probabilities and drought occurrence will be calculated for years with positive and negative IOD separately.

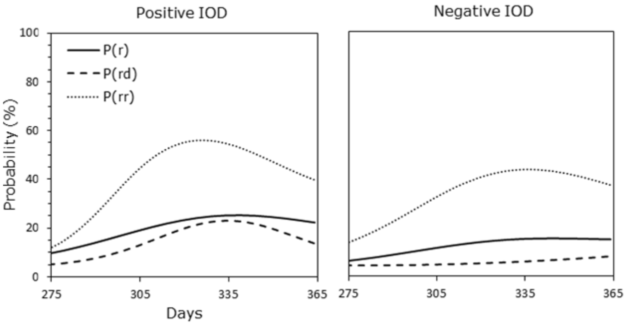

Fig. 3. Probabilities of daily rainfall (OND) for positive and negative IOD conditions.

The results of the separate analysis of rainfall probabilities of the OND season for years with a high IOD and low IOD separately can be found in figure 3. A difference of about 10 percent can be seen between the rainfall probabilities. The largest difference can be seen in the probability of rain given the previous day was dry. In the positive IOD scenario the probability has a convex shape over the length of the OND season while in the negative IOD scenario a concave shape is shown, as a result the difference in probability is up to 15 percent. This will have consequences for the length of a sequence of dry days. Dry spells will be longer and more frequent.

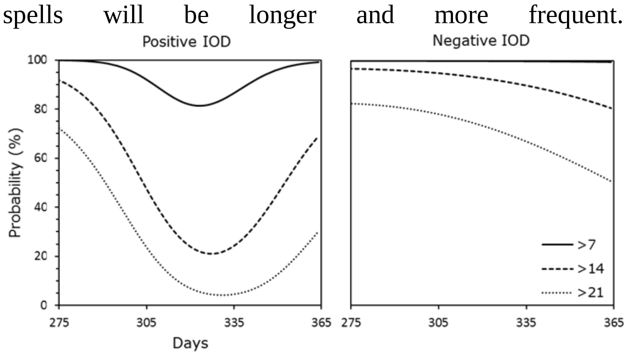

Fig. 4. Probabilities of drought (OND) for positive and negative IOD conditions.

The resulting drought occurrence from the $P(rd)$ from figure 3 can be seen in figure 4 where the drought occurrence with lengths exceeding 7, 14 and 21 days is plotted for a positive and negative IOD separately. A considerable dip in probability for a drought exceeding 14 days was calculated for the middle of the OND season with a positive IOD. This would be beneficial for agriculture. No such dip can be found in the graph for the negative IOD where there is a 100 percent probability for a period of drought exceeding 7 days during the whole season. Also a very high probability can be seen from 50 to 80 percent probability for a drought exceeding 21 days. In a negative IOD scenario the successful cultivation of crop seems very unlikely with these conditions.

To determine if the IOD conditions for the OND season is predictable a regression was run between the DMI of September and the DMI from October to December. A very good fit was found between these two values. A correlation coefficient of 0.98 ($p \approx 0.00$) suggests a very strong correlation and a very high significance. This means that the DMI of October to December can be predicted with certainty in September. This would be sufficient time for farmers to prepare for the coming season.

DISCUSSION

The Usambara Mountains rainfall probabilities show a higher probability of rain in the MAM season than in the OND season. There is a difference of about 20 percent in the annual rainfall probability and probability given the previous day was wet and less so given the previous day was dry. Barron et al. (2003) studied rainfall probabilities in Tanzania and Kenya. The data, originating from Tanzania, shows the same trend, only with a smaller probability difference of 15 percent. The data from Kenya shows an OND season that has a higher probability than the MAM season by about 10 percent. However other research from Kenya shows a stronger MAM season with a 20 to 25 percent higher probability of rain in the center of the season (Ochola & Kerkides, 2003). This might be due to differences in latitude of the locations in Kenya.

Drought occurrence in the region show the same thing. While the probability for dry spells exceeding 21 days for both season is almost zero, probabilities for dry spells exceeding 7 and 14 days show a 40 and 30 percent difference in probability respectively between rainfall seasons. In the research of Barron et al. (2003) there only exists an approximately 10 percent difference in probability of the dry spells of the same length. A much larger difference in dry spell occurrence was found in Kenya where the probability of a dry spell exceeding 14 or 21 days in the OND season was about 60 percent higher than in the MAM season (Sharma, 1993).

The results of the high rainfall variability for the people in the Usambara Mountains was discussed by Liwenga et al. (2012). The people are very vulnerable to rainfall variability as their livelihood most depends on agriculture. To cope with these challenges farmers will often resort to other activities. The long dry spells in the OND season make it impossible to use traditional irrigation, due to availability of water, and will make the keeping of livestock and the cultivation of crops almost impossible. The conditions force migration as one of the main factors. Multiple years of drought will threaten food security as farmers will find another way to make a living.

One of the main causes of the rainfall variability in the OND season was measured to be IOD anomalies, with a correlation coefficient of 0.73. In particular, the IOD anomalies have an effect on the length of dry spells. This is in line with other research. Black (2005) calculated that the September-November seasonal rainfall in equatorial coastal East Africa is consistently higher in years with positive IOD. Mutai et al. (1998) found significant correlations between East African rainfall from 1949-1988 and sea surface temperature of the tropical Pacific and Indian Oceans. Saji et al. (1999) argue that some experiments demonstrate the important effect of the Indian Ocean SST changes on East African rainfall variability. Ummenhofer et al. (2009) conclude that increased amounts of East African rainfall in the OND season are primarily driven by positive SST anomalies in the western Indian Ocean.

The accuracy of the results was sufficient due to daily rainfall that spans 15 years (Stern et al, 2006). There are problems with the accuracy of the negative and positive IOD scenarios as they are both only based on three years of data. Daily rainfall data for the last decade will hugely increase the accuracy of these scenarios and will give more insight in the influence of IOD on drought occurrence.

CONCLUSION

The rainfall probabilities calculated with daily rainfall data from the Usambara Mountains in Tanzania show various trends. The OND season is more variable than the MAM season and rainfall probabilities are lower. Also the season suffers from significantly more dry spells that exceed 7 and 14 days and even experiences some dry spells that exceed 21 days while the MAM season does not. Rainfall probability in the OND season is also highly correlated with the IOD in the same period. In the negative IOD scenario the probability of rainfall is at least 10 percent lower than in the positive IOD scenario. Drought occurrence that exceeds 7 days is certain in the negative IOD scenario while dry spells exceeding 21 days is above the 60 percentile. In the positive IOD scenario probability of drought occurrence is generally much lower. The IOD in the OND season is almost totally dependent on the IOD in September, so good predictions can be made before the rainfall season starts for the successful cultivation of crops.

ROLE OF THE STUDENT

The undergraduate student J.H. den Daas performed the research of this report under supervision of dr. ir. G. Sterk. The topic was suggested by the supervisor. The study, the processing of the results as well as formulation of the conclusions and the writing were done by the student.

REFERENCES

Barrios, S., Bertinelli, L., & Strobl, E. (2010). Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy. The Review of Economics and Statistics, 92(2), 350-366.

Barron, J., Rockström, J., Gichuki, F., & Hatibu, N. (2003). Dry spell analysis and maize yields for two semi-arid locations in East Africa. Agricultural and forest meteorology, 117(1), 23-37.

Black, E., Slingo, J., & Sperber, K. R. (2003). An observational study of the relationship between excessively strong short rains in coastal East Africa and Indian Ocean SST. Monthly Weather Review, 131(1), 74-94.

Black, E. (2005). The relationship between Indian Ocean sea–surface temperature and East African rainfall. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 363(1826), 43-47.

International Federation of Red Cross and Red Crescent Societies. (2011). Drought in the Horn of Africa; Preventing the next disaster.

Japan Agency for Marine-Earth Science and Technology. (2014). SST DMI dataset (monthly from 1958 to 2010) derived from HadISST dataset.

Liwenga, E., Kwezi, L. & Afifi, T. (2012). Rainfall, food security and human mobility. Case study: Tanzania. United Nations University report 6.

Kabanda, T. A., & Jury, M. R. (1999). Inter-annual variability of short rains over northern Tanzania. Climate Research, 13(3), 231-241.

Marchant, R., Mumbi, C., Behera, S., & Yamagata, T. (2007). The Indian Ocean dipole–the unsung driver of climatic variability in East Africa. African Journal of Ecology, 45(1), 4-16.

Murless, P. (2013) The Usambara Mountains of Tanzania; A short history, geology and biology.

Mutai, C. C., Ward, M. N., & Colman, A. W. (1998). Towards the prediction of the East Africa short rains based on sea-surface temperature–atmosphere coupling. International Journal of Climatology, 18(9), 975-997.

National Bureau of Statistics. (2012) Population and Housing Census 2012.

Ochola, W. O., & Kerkides, P. (2003). A Markov chain simulation model for predicting critical wet and dry spells in Kenya: analysing rainfall events in the Kano plains. Irrigation and drainage, 52(4), 327-342.

Reyes, T. (2008). Agroforestry systems for sustainable livelihoods and improved land management in the East Usambara Mountains, Tanzania. University of Helsinki Tropical Forestry Reports No, 34.

Saji, N. H., Goswami, B. N., Vinayachandran, P. N., & Yamagata, T. (1999). A dipole mode in the tropical Indian Ocean. Nature, 401(6751), 360-363.

Sharma, T. C. (1996). Simulation of the Kenyan longest dry and wet spells and the largest rain-sums using a Markov model. Journal of Hydrology, 178(1), 55-67.

Stern, R. D., & Coe, R. (1984). A model fitting analysis of daily rainfall data. Journal of the Royal Statistical Society. Series A (General), 1-34.

Stern, R., Rijks, D., Dale, I., & Knock, J. (2006). INSTAT climatic guide. Reading (UK): University of Reading.

Ummenhofer, C. C., Sen Gupta, A., England, M. H., & Reason, C. J. (2009). Contributions of Indian Ocean sea surface temperatures to enhanced East African rainfall. Journal of Climate, 22(4), 993-1013.

Van Aalst, M., Hellmuth, M., and D. Ponzi (2007). Come rain or shine: Integrating climate risk management into African Development Bank operations. Working Paper, No 89. African Development Bank (AfDB).