Understanding Onsets of Rainfall in Southern Africa using Temporal Probabilistic Modelling

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Abstract
Recent studies have developed many approaches to learn onset of rainfall with the help of highly skilled domain experts. This research investigates an alternative approach to automatically evolve the hidden temporal distribution of onset of rainfall directly from multivariate time series (MTS) data in the absence of domain experts. Temporal probabilistic modelling of the emergent situation awareness (ESA) is proposed to reveal hidden variability and dependencies over time for the onset of rainfall. Several weather parameters such as sea surface temperature, 700hPa wind anomalies, and climate indices such as El-Niño/Southern Oscillation (ENSO), etc. are analysed using the ESA technology to evolve model of temporal dependencies among these parameters. The target parameter, *onset* of rainfall is meant to reveal the degrees of beliefs for *false*, *early*, *normal*, *late* or *failed* state. Using rainfall observations from Botswana, this work has shown that *three month lead time of Southern Oscillation Index (SOI)*; *geopotential height anomalies at 500hpa level* and *wind anomalies at 700 hpa* parameters are better indicators for the onset of summer rains in Southern Africa. Our experimental results give promising insights to approaches to sustainable food security, water conservation and early warning systems in Southern Africa.

Keywords: Rainfall, Environment, Food Security, Statistical and Temporal Probabilistic Models

1. Introduction

The economies of most Sub-Saharan African countries are linked to the onset, reliability and performance of seasonal rainfall. Failure of regular seasonal rains may signal food deficits or poor food security. Farmers, water conservationists and government bodies are responsible for food security, and all have an interest in the aspects seasonal rainfall. This includes approximate dates for *start of the season or onsets*, and probabilities for early, *normal or late onset* of rains.

This knowledge enables them make crucial decisions as to the choice of crops, planting dates, management of dams, pasture and hydro-electric dams. Early planting of staple crops such as maize, wheat and sorghum may lead to crop failure, while late planting may also reduce crop yields due to rainfall deficits. For instance, late onset and subsequent rainfall deficits of summer rains in the region lead to drought, depletion of pasture, followed by animal and cattle losses as they happened following the El-Niño induced events of 1982-1984 and 1991-1992 [3].

While some studies on Southern African rainfall variability and onsets have been carried out, we do not know any research conducted to determine onsets of rainfall in the region with the capability of temporal probabilistic models handling such complex problems herein. Some researchers [5] investigated variability of onset of maize growing season over South Africa and Zimbabwe using self-organizing maps (SOM). They showed that late onset of rainfall in Zimbabwe is associated with heavier rainfall over the continent and accompanied by increased frequency of positive 500 hpa geopotential height anomalies to the South East of the sub-continent. Hachingonta, Reason & Tadross [4] studied the onset and cessation dates of summer rainfall in Zambia. They showed that conditions favourable for early (or late) onsets of rain are strong negative (or positive) anomalies in the 500 hpa geopotential height signifying convective developments (subsidence). They also noted that during *early* onsets there were positive anomalies over South Africa and Indian Ocean.

While the summer rainfall season for much of Southern Africa generally lasts from September to April, rains occur in Botswana mainly from November to March [6]. There is very little rainfall during winter months (May – September). Figure 1 shows dominant synoptic features that influence weather patterns and rainfall in Southern Africa. This study aims to determine degres of beliefs and probabilities for *false, early, normal, late* or *failed* onset of rains given *normal* and *anomalies* of weather parameters and climate indices.

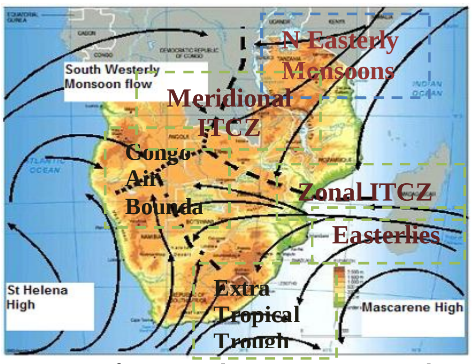


Figure 1: Synoptic features and air-masses over Southern Africa, described by [7]. Background map taken from UNEP/GRID Library [1].

This study takes an in-depth investigation of onset of rainfall in Botswana and atmospheric features that may influence variability of the onsets of rainfall over time. This paper also investigates the emergent situation awareness (ESA) modelling as an alternative technique which reveals the hidden rainfall onsets over time. The ESA technology [2] evolves temporal probabilistic models directly from complex environments captured as multivariate time series (MTS) in the absence of domain experts. It reveals what is currently happening in the meteorological stations by facilitating the relationships of the various climate indices, rainfall and weather parameters. The major contributions in this paper are as follows:

- The application of the temporal probabilistic models to understand the variability of rainfall onset in Southern Africa.
- The evaluation of the model using real life observations captured from Botswana meteorological stations, illustrating to agricultural researchers and practitioners on food sustainability and water conservation.

The rest of this paper is arranged as follows: in section 2, we describe dominant synoptic features (weather patterns) that influence rainfall in Southern Africa; in section 3, we describe a proposed methodology for understanding the onset of rainfall. Experimental evaluations of statistical and temporal probabilistic modeling of the ESA are presented in section 4. In section 5, we discuss experimental results and conclude the paper in section 6.

2. Theoretical Backgrounds

2.1 Synoptic Weather Patterns

There are a number of distinct large scale atmospheric weather patterns and synoptic systems that influence rainfall and onset of rainfall in Southern Africa; They are (i) El-Nino/La-Nina; (ii) Sea surface temperatures (SSTs); (iii) The Inter-Tropical Convergence Zone (ITCZ) - It is generally a zone of convergence of North-Easterly and South-Easterly trade winds, and is characterized by convective activities: thunderstorms, precipitation and clouds, Nicholson (2009); (iv) Botswana Upper high - It is a mid-tropospheric or medium-level (850 hPa - 600 hPa) anticyclone found in Southern Africa. It is characterized by marked subsidence and consequently suppression of convection, resulting in clear skies and prolonged dry spells, [7]; and (v) The Angola Heat Low - is a heat low pressure system that exists below 700hpa level in the summer half of the year over south-eastern Angola and north-eastern Namibia [9].

Some of the patterns are illustrated in Figure 1. Each of these systems has an influence on rainfall and the onset dates of rainfall in the region in varying degrees.

2.2 The Theory of Temporal Probabilistic Modelling of the ESA

The simplest form of a temporal probabilistic model or Dynamic Bayesian Network (DBN) is a Hidden Markov Model with V as state variables and E as evidence variables repeated in say, three time steps. DBNs are temporal probabilistic models which are often referred to as an extension of the Bayesian Network (BN) models in artificial intelligence [2]. A Bayesian belief network is formally defined as a directed acyclic graph (DAG) represented as G = {V(G), A(G)}, where V(G) = $\{V1,\ldots,Vn\}$, vertices (or variables) of the graph G and $A(G) \subseteq V(G) \times V(G)$, is the set of arcs of G. Every variable V with a combination of parent(s) values on the graph G captures probabilistic knowledge (distribution) as a conditional probability table (CPT). However, the inability of the BNs to capture time as temporal dependencies facilitated the developments of various ways of modelling the Dynamic Bayesian networks. More information can be found in [2].

3. The Proposed Methodology

3.1 Data Analysis

Daily and monthly rainfall datasets used in this work were obtained from Botswana Meteorological Services. The data covered 29 stations and years 1971 – 2004. Daily rainfall data was arranged with *day 1* being July 1st and the last day (*day 366*), June 30th the following year. For the purpose of labeling, each year in Botswana was determined if it was *normal, wet, or dry* using the formula in equation (1):

$$X_t = \frac{1}{m} \sum_{j=1}^{m} \frac{100 \ X_{tj}}{\overline{X}_j} , \tag{1}$$

where m is the total number of stations used, X_t is the time-dependent rainfall index as a percentage of the mean and averaged over the whole country.

The ***wet*** years had large values of the index (X_t >75%) while ***dry*** years had low values (X_t <=75%). ***Normal*** years had values of this index between -75% and + 75%. Rainfall was normalised to ensure that the mean is zero and the standard deviation was unit. Figure 2 is a standardised anomalies of annual rainfall over Botswana. We obtained monthly sea level pressure (SLP) anomalies, sea surface temperature (SST) anomalies, and other parameters from National Centre for Environmental Prediction (NCEP) and National Centre for Atmospheric Research (NCAR) (1948 – Present) [10].

3.2 Determination of the Start-Of-Season

Since Botswana has a semi-arid climate with large annual rainfall variability, subjective criteria was used to determine the Start of Season (SOS) for each station. In this work, the following definition was used: *the day after 1st October when cumulative rainfall exceeded 20 mm, and that no dry spell exceeding 20 days occurs in the next 30 days.* This definition was adopted and modified from that used by Famine Early Warning System (FEWS) for Southern African countries.

Using a statistical package, a summary was done for each year for each station to determine the mean onset date, standard deviation, minimum and maximum onset dates. Types of onset were determined for each year and categorized as *False (0), Early (1), Normal (2), Late (3), and Failed (4) Onsets.*

3.3 Theory of Correlation Analysis

A correlation technique was used to examine lagged relationship between seasonal rainfall and grid SST values, [11]. The correlation coefficient (r_k) between the seasonal rainfall (y_t) and any lagged SSTs at time lag k, (x_{t-k}) may be expressed as

$$r_k = \frac{\sum_{i=1}^{m} x_{t-k}\, y_t}{\left[\sum y_t^2 \sum x_{t-k}^2\right]^{1/2}} \qquad (2)$$

Where $x_t = X_t - \overline{X}_t$, $y_t = Y_t - \overline{Y}_t$, and $-1 \le r_k \le 1$.

Positive and negative values of r_k are indicative of positive/negative relationship.

The weather parameters, the climate indices, and the result from statistical analysis for onsets are organised, as listed in Table 1. This serves as input for the ESA.

Table 1: Required Attributes for probabilistic modelling

a.	***Station#; Year; Month*** – Station Number, Year, Month
b.	***MTLY_RR*** - Monthly Rainfall (in mm)
c.	***Ind_SST_Anom*** -Indian Ocean Sea Surface Temperature Anomalies (^{0}C)
d.	***Atl_SST_Anom*** - Atlantic Ocean Sea Surface Temperature Anomalies (^{0}C)
e.	***SOI*** - Southern Oscillation Index (Indicator for El-Niño/La-Niña) .
f.	***(T- 3)SOI*** - Three months lag in SOI
g.	***Atl_SLP_Anom*** - Atlantic Ocean Sea Level Pressure Anomalies (hPa/mb)
h.	***SInd_SLP_Anom*** – Southern Indian Ocean (Mascarene area) Sea Level Pressure Anomalies (hPa/mb). Domain :34^{0}S-38^{0}S, 34^{o}E-46^{0}E
i.	***CInd_SLP_Anom*** – Centra Indian Ocean (North of Malagasy area) Sea Level Pressure Anomalies (hPa/mb). Domain: 7^{0}S-14^{0}S, 56^{o}E-64^{0}E
j.	***500Hpa_Anoms*** – 500 hPa level anomalies (in meters)
k.	***700Hpa_U*** - 700 Hpa level zonal winds (meters per second)
l.	***700Hpa_V*** - 700 Hpa level meridional winds (meters per second).
m.	***Onset*** - Onset type in Botswana for particular year, (False (0), Early (1), Normal (2), Late (3), and Failed (4) Onsets)

3.4 The ESA Modelling

The system model of the ESA comprises three essential components which are; learning algorithms, probabilistic distributions, and the trend analysis [2]. The first two components collectively discover system knowledge of rainfall distribution, which are integrated into the third component called the interface (or projection) knowledge. The analysts use this knowledge as a platform to understand the onsets of rainfall over time.

The learning algorithms dynamically evolve temporal models from the weather parameters embedded in the multivariate time series (MTS). The MTS serves as input to the ESA technology. The algorithms emerge interlink temporal models from *frames 0* to *n*. Let V_i^t represent variables of the ESA at time *t*; the temporal dependency relation between the time frames is shown in equation (3).

$$pr(V_1^1, V_2^1 ..., V_n^1) \overset{\Delta}{\equiv} pr(V_1^2, V_2^2 ..., V_n^2) \overset{\Delta}{\equiv} pr(V_1^t, V_2^t ..., V_n^t) \qquad (3)$$

$\overset{\Delta}{\equiv}$ implies that equivalence is *not* true generally.

From equation (3), the relationships embedded among variables *V* at time step 1 may or may not be equivalent to the variables' relationships at time step 2, and for subsequent time steps t. This is as a result of the changes in environmental patterns, which affect the relationships of the model variables over time. An optimized genetic algorithm (GA) is upgraded to evolve over time and is used as a proof of concept in this system model. The algorithm uses information theoretic measures (e.g. Minimum Description Length) and mathematical components (e.g. PowerSet in set theory) as genetic operators and as a means of balancing between efficiency and decomposability.

The other functionality of the probabilistic distribution of the system model is a Bayesian inference of the variable elimination algorithm, which is used to reason over time. This reasoning algorithm is based on Bayes' theorem, expressed as posterior probability in equation (4) for some random variables *Vs* and *Ve*. The *Vs* implies state variable of the model while *Ve* implies evidence variable.

$$\Pr(V_S \mid V_e) = \frac{\Pr(V_e \mid V_S) * \Pr(V_S)}{\Pr(V_e)} \qquad (4)$$

4. Experimental Evaluations

This section brings our theory to practice from statistical analysis and temporal probabilistic modelling.

4.1 Experiment 1: Understanding the Onsets Using the Statistical Methods

4.1.1. Wet and dry years

Figure 2 below is a time series plot of standardized anomalies of rainfall over Botswana. The plot captures wet, dry and normal years over the country.

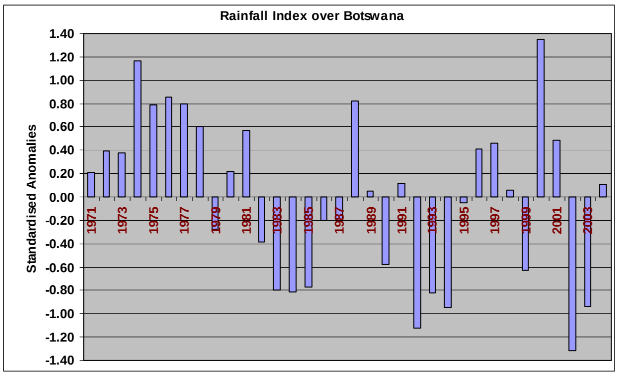


Figure 2: Standardized anomalies of annual rainfall over Botswana.

From the above plot and as noted before, the years 1974 – 1977, 1988, and 2000 were wet years in Southern Africa, [12], while the years 1982-85; 1991-94 and 2002 were dry years in Botswana, mainly influenced by El-Nino phenomenon, [3].

4.1.2 Start-of-Season

Figure 3 is a plot of average onset dates (number of days from 1st July) for Botswana.

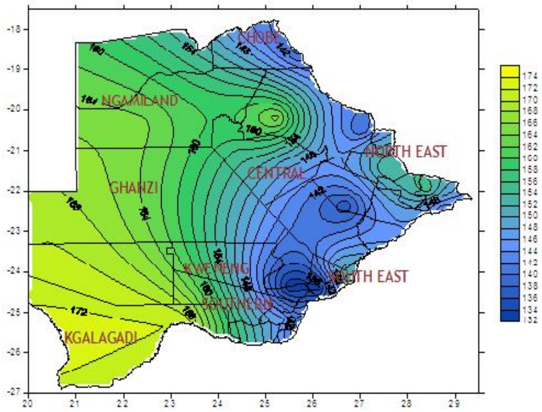


Figure 3: Spatial distribution of onset of rainfall in Botswana. Figures represent days after July 1st.

The earliest *onset date* is 1st October around the hilly areas in South East District, while the latest is 23rd March in dry areas of Kgalagadi District. The arid extreme south-west (Kgalagadi District) represented by stations Ncojane and Werda are the last to receive rains on 17th and 19th December respectively.

Figure 4 below is a resulting time series plot of onset of rainfall and categories of onsets for Botswana. Results from the analysis show that the mean onset date of rainfall in Botswana is 25th November (day 148). *Normal, early, late and failed onset* dates are shown. The average variability (standard deviation) of start of rains in Botswana is 38 days. The largest variability, 55 days, is in the arid Kgalagadi District, while the lowest being in the North-East and the Southern District (20 days).

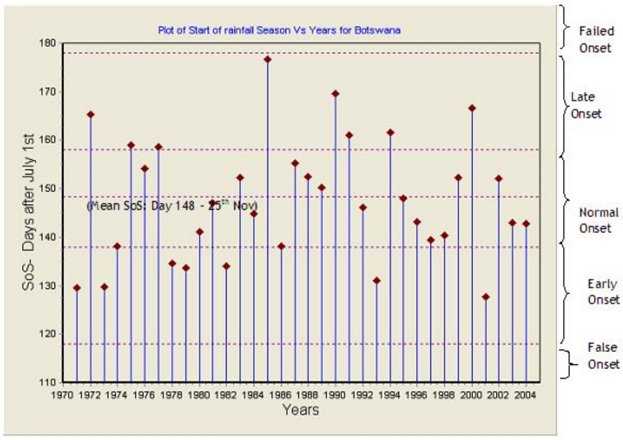


Figure 4: Time series plot of rainfall onset in Botswana

4.1.3 Correlation Analysis

The significant SST modes (Pacific, Atlantic and Indian Oceans) of July, August, September (JAS) months were correlated with October, November, December (OND) rainfall over each of the different regions in Botswana. The following are some of the results obtained:

a. Atlantic Ocean
- Region: 0^0N -8^0N, 39^0W-48^0W correlated positively with stations in Kgalagadi (Ncojane and Werda).
- Region 45^0S -50^0S, 50^0W-56^0W correlated negatively with stations in Northern areas of Botswana.

b. Indian Ocean
- Regions: 7^0S-14^0S, 56^oE-64^0E and 34^0S-38^0S, 34^oE-46^0E, were correlated negatively with Central and South Eastern Stations.

The two domains in the Central and Southern Indian Ocean correspond to regions of dominant synoptic systems, where SLP data were extracted and their anomalies determined. The resulting parameters are *CInd_SLP_Anom and SInd_SLP_Anom*.

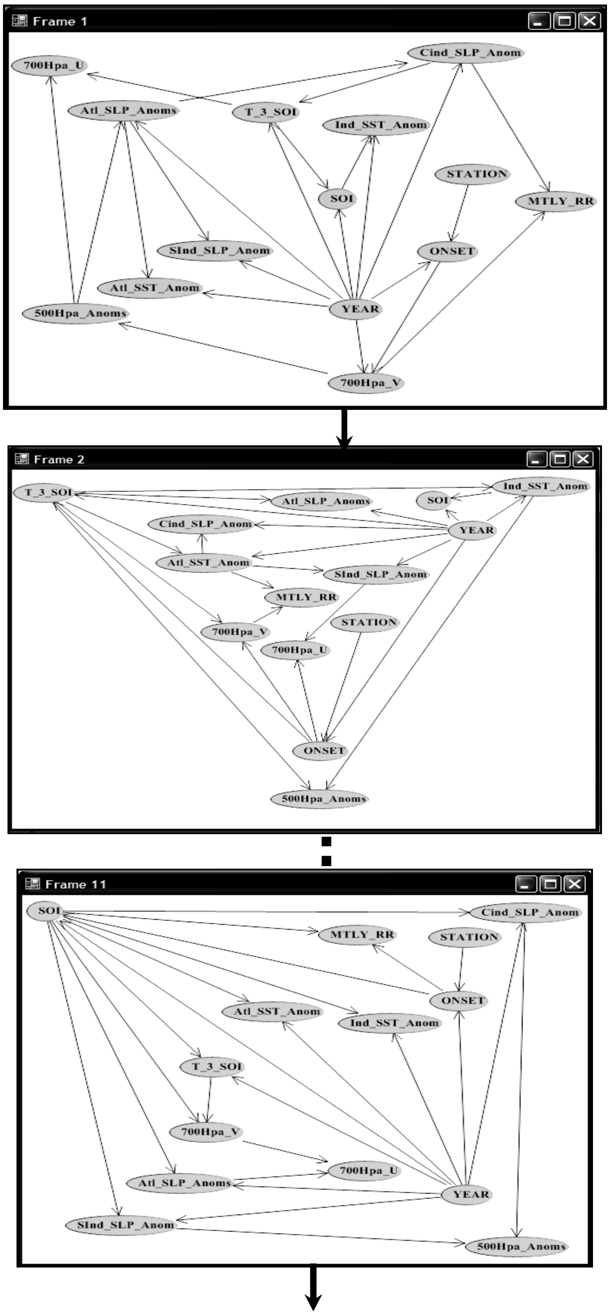
4.2 Experiment 2: Understanding the Onsets Using the Temporal Probabilistic Models

4.2.1 Dynamic Bayesian Network for Botswana Rainfall

Figure 5 shows an evolved DBN model for Botswana rainfall distribution. The Directed Acyclic Graph model reveals temporal dependencies among weather parameters and climate indices over time. The ESA technology learns the model from MTS over the time-steps of *months*. The result was 12 temporal frame model. Frame 1 is equivalent to a Bayesian model for January rainfall situation, while frame 12 corresponds to December. Each Frame reveals hidden relationships among the nodes (or attributes) from the frame data for that particular time step (*month*).

In the four representative frames of the DBN, the *onset* parameter is characteristic to any geographical location (that is *Station* and *Year* parameters). This implies that *Station* and *Year* parameters have direct influence on the o*nset* of rainfall. In Frame 1, the *Onset* of rainfall has direct influence on meridional component of 700 hPa winds *(700 hPa_V)* which has direct influence on monthly rainfall *(MTLY_RR)***.** However in frame 2, the variable *Onset* of rains has direct influence both on meridional and zonal components of winds at 700 hPa level (*700 hPa_U*, *700 hPa_V)*, while in Frame 11, the *Onset* parameter has direct influence on Rainfall (*MTLY_RR*).

In Frame 12, the *Onset* parameter has direct influence on (T-3)*SOI*, the three months lead time of SOI, this implies also that (T-3)*SOI* has direct influence on *Onset* using the principle of "*forward and backward propagation*". Both meridional and zonal components of winds at 700 hPa level (*700 hPa_U*, *700 hPa_V*) have direct influence on monthly rainfall (*MTHLY_RR*), similar to Frame 2.



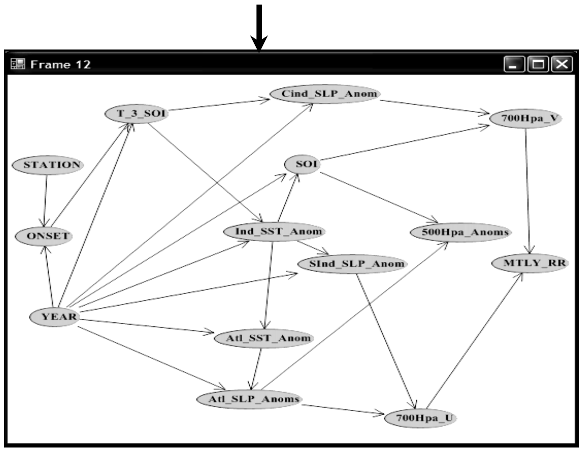


Fig. 5. DBN for Botswana rainfall and associated weather parameters

In frame 11, the Southern Oscillation Index *(SOI)* variable has direct influence the *Onset, while the Onset* has direct influence on monthly rainfall, (*MTLY_RR)***.** In frame 12, the *Onset* parameter has direct influence on *(T-3)SOI***,** the three months lead time of *SOI*. This implies also that *(T-3)SOI* has direct influence on *Onset* with conditional dependencies of BNs.

4.2.2 Relationships of rainfall onsets to various parameters

4.2.2.1 Normal, Wet and Dry Years

Normal Year

We take a normal rainfall year 1998 in Botswana that had a *normal* onset from statistical analysis. Figure 6 below shows a graph of probabilistic reasoning over time followed by a user's interaction. The model reveals the probability as a *normal (2) onset* given that monthly rainfall was at most 56.2 mm but more than 26.6mm. It can be seen that probability for a *normal* onset for November *Month* is very high (90%). November to March reveal high probability of onset of rainfall (above 82%), January to March (100%). However, we have lower degrees of belief for *normal* onset for April to October (less than 70%).

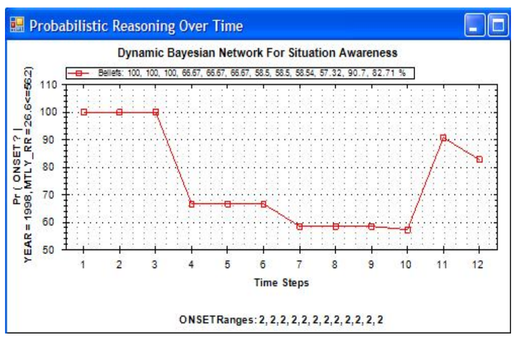


Figure 6a: Emergent Situation of ***onset*** in **1998** when monthly rainfall (*MTLY_RR*) was within '**26.6** <= **56.2**'. The ***onset*** was *normal* (2).

Dry Year

A similar experiment was done for a dry year, 1985, which showed that the probability for *failed (4)* onset for November and December months were 65% and 55% respectively.

El-Nino years

The figure below is an example of a well marked El-Niño episode, ***(T-3)SOI*** <= -13.9. There is some marked probabilities for a *late* (3) onset in November (40%), December (47%) and March (55%).

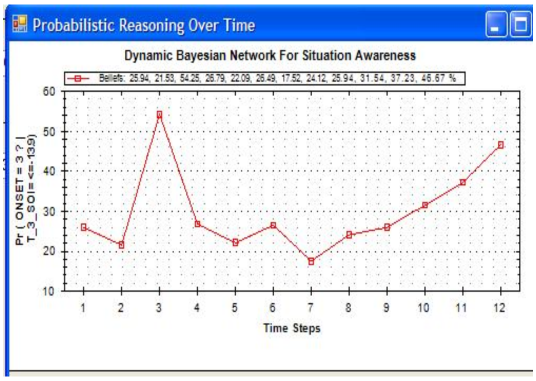


Fig 6b: Emergent Situation of **late onset** when ***(T-3) SOI*** is **small** (<= - 13.9). (A well marked El-Nino situation).

4.2.2.2 Sea level pressure

From Figure 7 below, the probability for *normal* onset given the negative SLP anomalies in the South Indian Ocean (Mascarene region) (*SInd_SLP_Anom <= -1.082*) are: (i) October (30%), (ii) November (90%), and (iii) December (50%). However given positive pressure anomalies (*SInd_SLP_Anom 0.4<= 1.25*), the probabilities for *normal* onset are lower for November (62%), but higher for October (50%), and December (70%).

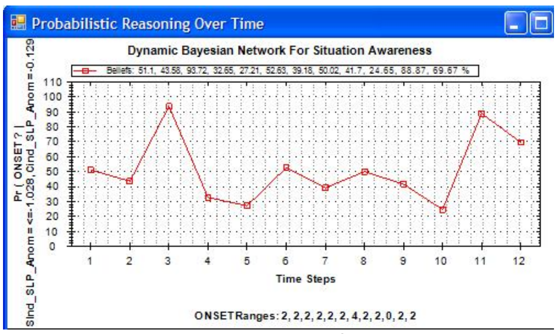


Figure 7: Emergent Situation of ***Onset*** when *Sind_slp_Annom* <= '**-1.082**',and *Cind_slp_Annom* falls within '**-0.129<=2.47**'

4.2.2.3 Sea Surface Temperature

Figure 8 below reveals high probabilities for normal onset for November – December month given anomalous warming in Indian Ocean. This agrees with arguments advanced by [9],[3]. The probabilities are reduced for lower SST values.

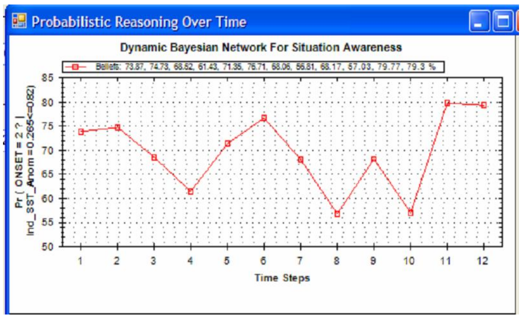


Figure 8: Emergent Situation of **normal onset** when ***Ind_SST_Anom*** is **high** (0.265<=0.82).

4.2.2.4 The 500 hPa geopotential height anomalies

Result from the ESA showed that when there are positive geopotential height anomalies in 500 hPa level, there were reduced degree of beliefs, compared to that of negative anomalies (***500HPa_Anoms <= -7.974***) as shown in Figure 9. The probabilities of onset for the negative anomalies of 500 hPa geopotential heights are: (i) November (80%), and (ii) December (55%). This agrees with reasons presented by [5]. Figure 10 is a NCEP/NCAR reanalysis for 500 hPa height anomalies over the region confirm that during a wet year (2000) there were marked negative height anomalies.

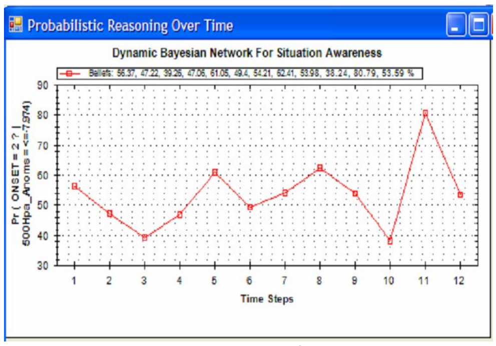


Figure 9: Emergent Situation of **normal onset**, when **500HPa_Anoms <= -7.974**

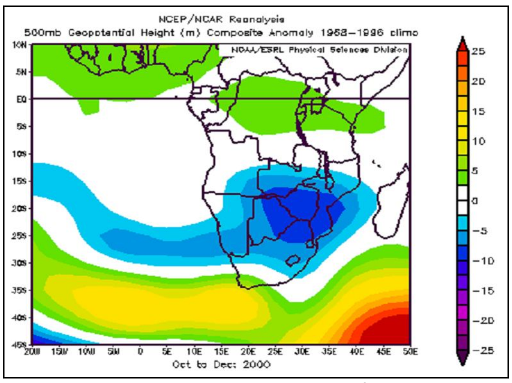


Fig. 10: NCEP/NCAR reanalysis for 500 hPa geopotential height anomalies for wet year – 2000.

4.2.2.5 Winds at 700 hPa level

In a case where there are weak southerly winds at 700hPa level, the degrees of belief for normal onset were higher in November (65%) and December (75%), figure 11. A 700 hPa NCEP/NCAR reanalysis for wet year (2000) showed marked southerly meridional components of winds as shown in Figure 12. A similar analysis for a dry year (1985) showed that there was marked northerly meridional flow.

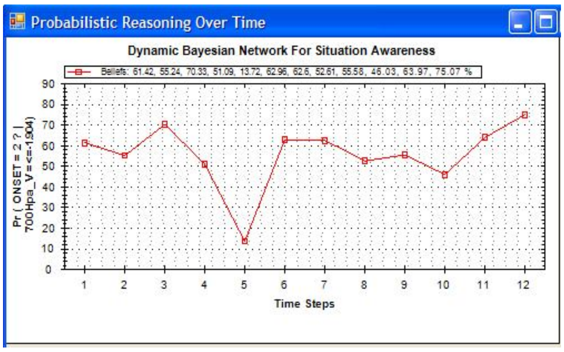


Figure 11: Emergent Situation of **normal onset**, when **700HPa_V<= -1.904**

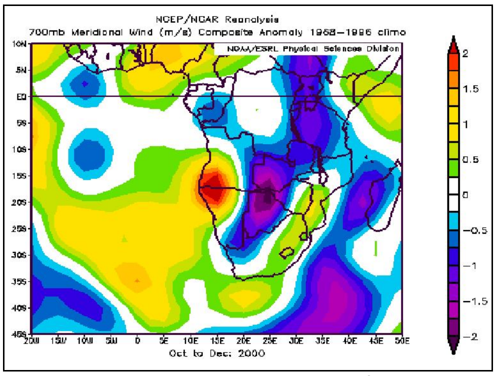


Figure 12: NCEP/NCAR reanalysis for 700 hPa meridional wind anomalies for year 2000.

5. Discussion

In this section, the results for the statistical and the DBN are presented.

a. Results from the DBN of the ESA showed that in the years that had *normal* and *above* normal rainfall (wet years), the probability of a *normal* onset was high. The month of November had probability of 90% for a normal onset. This agreed with statistical results that showed that the mean onset date in Botswana is 25th November, and the mean variability (standard deviation) of onset of rains is 38 days.

b. In a dry year the probability for *failed (4)* onset for November and December months were found to be 65% and 55% respectively. Except for Serowe Station in Central District, nearly all stations in Botswana experienced late onset of rains in 1985.

c. During an El-Nino year, there is some probability for *late* (3) onset of rains: 40% in November and 55% in March.

d. While it is an established fact that the strengthening of Mascarene High pressure cell induces moisture influx into the interior of Southern Africa, leading to wetter conditions, [13], this research found that if there are negative sea level pressure (SLPs) anomalies in Mascarene area and near normal SLPs in Central Indian Ocean, the degrees of beliefs are high for normal *onset* in Botswana for the months of November (88%) and December (70%).

e. There are higher degrees of belief for *normal* onset of rains given positive (warming) sea surface temperatures (SSTs) anomalies in Indian Ocean, (November and December - 80%) and Atlantic Ocean (November – 77%, December – 82%). There are reduced degrees of belief for negative (cooler) SSTs. This agrees with reasons advanced by [9].

f. Positive 500 hPa geopotential height anomalies in the interior of the sub-continent, lead to lower degrees of belief for normal onset of rains. Conversely negative 500 hPa geopotential height anomalies lead to higher degrees of belief for *normal* onset for the month of November (80%), but lower for other months (less than 50%).

g. A marked southerly component of wind flow at 700 hPa level lead to higher probabilities for *normal* onset while a northerly flow leads to reduced probabilities for *normal* onset. The results showed that during wet year, 2000, there was marked southerly flow across Botswana, while in a dry year, 1985, there was marked northerly flow over the region.

h. From the DAG that models relationships among the parameters, the monthly rains (***MTLY_RR***) are *caused* by the following parameters: Onset of rains (***Onset***); the Southern Oscillation Index (SOI); winds at 700hPa level (***700hPa_U***, ***700hPa_V***); Atlantic Ocean Sea Surface Temperature anomalies (***Atl_SST_Anom***) and Central Indian Ocean Sea Level Pressure Anomalies (***CInd_SLP_Anom***).

i. From figure 5, the three month lead time in SOI ***((T-3)SOI),*** has direct influence, for the four time slices, on the following parameters:
   - i DBN for January – ***SOI*** and ***700hPa_U***
   - ii. DBN for February – ***500hPa_Anom***, ***Ind_SST_Anom***, ***Atl_SLP_Anom*** and ***Atl_SST_anom***.
   - iii. DBN for November - ***700hPa_V***
   - iv. DBN for December – ***Ind_SST_Anom***, ***CInd_SLP_Anom***.

j. The parameter (T-3SOI), among others, can be used as indicators by planners, farming community and policy makers to make early warning, in case of impending drought or floods; conserve water or put in place contingency measures for food supplies and distribution.

6. Conclusion and Future Work

The methodology and results obtained in this paper are based on the following recent work [14]. From statistical analysis, one can determine *Start-of-*Rains or onset dates, their means and variability, while the temporal probabilistic modelling of the ESA reveals hidden variability of parameters over time. Each of the parameters and climate indices revealed varying degrees of beliefs for *early, normal, late* or *faile*d rainfall onsets in Botswana.

Results from the ESA show that the onset of rains takes place in the month of November. The ESA does not show the actual dates, since the time-step was *month* and not daily. While the two approaches are complementary in understanding and determining the onset of rainfall, the temporal probabilistic modelling of the ESA is better in revealing hidden variability and dependencies of onset of rainfall over time.

This work has shown that the temporal probabilistic model suggests that all the parameters and climate indices positively or negatively influence the onset of rains in Botswana. The differences are the degrees of beliefs. Owing to the complexity of the atmosphere and its processes, weather parameters and climate indices are related and interlinked.

We have shown that the following parameters revealed higher degrees of beliefs for onset of rains in Botswana (i) three month lead time of Southern Oscillation climate index *(T-3SOI), (ii)* geopotential height anomalies at 500 hPa level *(500hPa_Anoms)*, (iii) anomalously warmer SSTs in Indian and Atlantic Oceans and (iv) meridional component of winds at 700 hPa level *(700hPa_V)*. These parameters may be useful to policy makers, farmers as indicators to ensure food security and water conservation.

This work used larger time-step, (the *Month)*. Future work should use shorter time-steps, like 10 day *(dekad)* or 5 day *(pentad)* periods. The results could then be compared with statistical determination of *onset dates.*

Acknowledgements

The authors gratefully acknowledge resources and support from the Kenya Meteorological Department, the Institute for Meteorological Training & Research (IMTR) and the Council for Scientific and Industrial Research (CSIR), South Africa.

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