USING FUZZY COGNITIVE MAPS IN MODELLING AND REPRESENTING WEATHER LORE FOR SEASONAL WEATHER FORECASTING OVER EAST AND SOUTHERN AFRICA

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ABSTRACT

The creation of scientific weather forecasts is troubled by many technological challenges while their utilization is dismal. Consequently, the majority of small-scale farmers in Africa continue to consult weather lore to reach various cropping decisions. Weather lore is a body of informal folklore associated with the prediction of the weather based on indigenous knowledge and human observation of the environment. As such, it tends to be more holistic and more localized to the farmers' context. However, weather lore has limitations such as inability to offer forecasts beyond a season. Different types of weather lore exist and utilize almost all available human senses (feel, smell, sight and hear). Out of all the types of weather lore in existence, it is the visual or observed weather lore that is mostly used by indigenous societies to come up with weather predictions. Further, meteorologists continue to treat weather lore knowledge as superstition partly because there is no means to scientifically evaluate and validate it. The visualization and characterization of visual sky objects (such as moon, clouds, stars, rainbow, etc) in forecasting weather is a significant subject of research. In order to realize the integration of visual weather lore knowledge in modern weather forecasting systems, there is a need to represent and scientifically substantiate weather lore. This article is aimed at coming up with a method of organizing the weather lore from the visual perspective of humans. To achieve this objective, we used fuzzy cognitive mapping to model and represent causal relationships between weather lore concepts and weather outcomes. The results demonstrated that FCMs are efficient for matrix representation of selected weather outcome scenarios caused visual weather lore concepts. Based on these results the recommendation of this study is to use this approach as a preliminary processing task towards verifying weather lore.

Keywords: Weather lore, indigenous knowledge, drought forecasting, fuzzy logic, cognitive mapping.

INTRODUCTION

In the olden lifestyles, the scientific (especially Seasonal Climate Forecasts (SCFs)) weather forecasting methodologies in use today were not available; people observed (Risiro, Mashoko, Tshuma and Rurinda, 2012) their environment to determine weather patterns. Clues to future weather patterns were realized by looking at the skies, using the behavior of animals, birds, as well as plants (Baliscan, 2001; Dube and Musi, 2002); it was also based on beliefs and myths (Pasztor, 2010; Warren, 1998). Among the observed indicators, it is the observation of the sky (Mountaineering Council of Scotland, 1998) that played the greatest role as a weather prediction method. For instance, a red sky at sunset indicated dry weather condition while red sky at sunrise meant rain was expected. It has been demonstrated that cloud patterns can be used as accurate weather predictors (Mountaineering Council of Scotland, 1998). The rainbow has also been an indicator of weather as it refracts the light and breaks it down into colors (Zuma-netshiukhwi, Stigter and Walker, 2013); for instance, a rainbow in the morning to the west usually indicated approaching rains.

We can define weather lore as the body of informal folklore associated with the prediction of the weather based on indigenous knowledge (IK) and human observation of the environment (Chiwanza, Musingafi and Mupa, 2013). In order to investigate relationships in weather lore concepts, a considerable collection of weather lore is required so that it can be prepared for comparison and possible validation (Anandaraja and Rathakrishnan, 2008). One of the problems in testing the confidence of weather lore on predicting weather is that there are wide varieties of weather lore which are found in the details of indigenous sayings exhibiting region and pattern variations (United-Nations, 2004). Most of the weather lore is identified by the communities using it to support their livelihoods and is not globally available for comparison and validation (Zuma-netshiukhwi, Stigter and Walker, 2013). Sufficient process of gathering IK on weather lore would be the first step towards representing weather lore in order to produce some useful information. Since forecasting weather accurately is a challenge even with today's supercomputers (Lynch, 2008), represented weather lore can be processed further and incorporated into modern weather prediction systems.

A number of researchers have been directing efforts towards promoting weather lore especially on disaster management (Enock, 2013; Johansson and Achola, 2013; Okonya and Kroschel, 2013) and how to integrate them to the SCFs (Chagonda *et al.*, 2015). This is driven by the realisation that SCFs and weather lore complement each other (Abdulrashid, 2013; Masinde, Bagula and Muthama, 2013) and that the rich weather lore could help in making the forecasts more relevant to the local people’s context. Though having generated promising results, such integration initiatives still face many challenges (Chiwanza, Musingafi and Mupa, 2013; Johansson and Achola, 2013; Khalala, Makitla, Botha and Alberts, 2014; Msuya and Programme, 2007). They for instance tend to take the approach of using the weather lore to enrich the SCFs and hence losing most of the weather lore’s richness especially the more sustainable indigenous drought mitigation strategies (Masinde and Bagula, 2012). Weather lore is holistic (Acharya, 2011; Chinlampianga, 2011); it describes the effects of the forecast on the people’s way of life. It gives the details of the rain season in terms of onset, cessation, general distribution (are there dry spells in between), and its suitability for different crops, among others. The forecast further gives decision support information such as when to start and stop planting, how many times planting should be done, what to plant, how to plant and even where to plant (Masinde and Bagula, 2012). Weather lore is so dynamic, in the short-term (up to 24 hours) for example, it gives very accurate information on rainfall timings, including the nature (hails) and direction of the rain. Trying to represent these aspects using conventional system (Shoko, 2012) would yield an incomprehensible complex system (Fajman, 2011). On the other hand, fuzzy cognitive mapping (FCM) can model imprecise data and nonlinear functions of arbitrary complexity and that it is based on natural language (Singh, H., Singh, G. and Bhatia, 2013); this makes it an appropriate vessel for modelling weather lore for use in forecasting sub-Saharan droughts systems.

Knowledge in systems that are characterized by uncertainty (Nakashima and McLean, 2012; Pappenberger *et al.*, 2005) and complex processes can be represented using fuzzy cognitive mapping (a combination of fuzzy logic and cognitive mapping) (Hossein, Zarandi, Khademian and Minaei-bidgoli, 2012). Fuzzy logic is derived from fuzzy set theory (Stylios and Groumpos, 2004) dealing with reasoning that is approximate rather than precisely deducible from classical predicate logic. A cognitive map is a representation and reasoning model on causal knowledge (Kanagasabhapathy and Kumaravel, 2014) in the form of directed, labelled and cyclic graph whose nodes represent causes or effects and whose arcs represent causal relations between these nodes. Cognitive maps represent beliefs (knowledge) which are laid out about a given domain of interest and are useful as a means of decision support. Fuzzy cognitive mapping has proven efficient for solving problems in which a number of decisions and uncontrollable variables are causally interrelated. FCM is a powerful tool in decision making which aims at capturing the functioning of a complex system based on human understanding. FCMs are made up of signed diagraphs (Dissanayake and AbouRizk, 2007; Maitra and Banerjee, 2014) with feedback that describes the causal links between concepts. To come up with common FCM, knowledge from different experts can be accumulated through combining several FCMs into a big FCM by merging same concepts (Jones, 2010).

THEORETICAL FRAMEWORK

Fuzzy cognitive maps can be used to represent the causal knowledge and experience, which have been accumulated over a certain period on a complex phenomenon; this makes them a good candidate for modelling and representing weather lore. In modelling weather lore, an FCM is developed using human IK experts (Msuya and Programme, 2007) that know the operation of the system and its behaviour in different circumstances. Weather lore is hardly documented; it is orally (Chiwanza, Musingafi and Mupa, 2013; Msuya and Programme, 2007; Suter, 2013) passed on from one generation to the next. In the face of events such as industrialisation and modernisation, a significant proportion of weather lore has been lost (Owiny and Maretzki, 2014; United-Nations, 2004). The ability of FCMs to work efficiently with missing data in modelling systems with nonlinearities and surrounding uncertainty (Carvalho, 2010) will help re-dress this. This (ability of FCMs) is facilitated by the use of artificial neural networks (Rahul and Khurana, 2012) techniques that incorporate ideas from fuzzy logic, to create decision support systems (Singh, H., Singh, G. and Bhatia, 2013).

Modelling of Fuzzy cognitive maps

In modelling FCMs, cognitive maps are used to represent causal relationships among concepts that could be assigned values (Calais, 2008). Causal relationships between two concepts can be of types – positive, negative or neutral (Kanagasabhapathy and Kumaravel, 2014). Increase in the value of one concept yields a corresponding positive or negative increase in the concepts connected to the concept. FCMs consist of factor-concepts (inputs) and decision-concepts (outputs). The relationship between two concepts in FCMs can take a value in an interval called weight (Praveena *et al.*, 2012).

An FCM (Figure 1) is represented as a directed graph (Carvalho, 2010) where each node represents a concept (representation of a characteristic of the system such as events, actions, goals, values and trends being modelled by the FCM). Each arc (E_i) is directed as well as weighted, and represents a causal link between concepts, showing how concept C_i causes concept C_j.

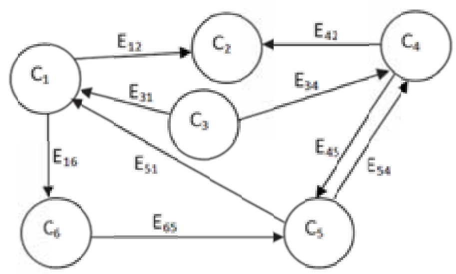

Figure 1: A sample FCM.

In FCMs the directed edge E_{ij} from causal concept C_i to concept C_j measures how much C_i causes C_j. The edges E_{ij} take values in a fuzzy causal interval [0,1] or [-1,1] according to system specifics. $E_{ij} = 0$ indicates no causality, $E_{ij} > 0$ indicates causal increase C_j increases as C_i increases (or C_j decreases as C_i decreases). $E_{ij} < 0$ indicates causal decrease or negative causality. C_j decreases as C_i increases (and or C_j increases as C_i decreases). In an FCM, the state of a node C_i is determined by the sum of its inputs modified by causal link weights, and a non-linear transfer function S (Equation 1).

$$c_i(t+1) = S(\sum_{j=0}^{n-1} c_j(t) \bullet w_{ij})$$

Equation 1: Where t=concept t; t+1=next concept after concept t; w=causal weight; S= sum.

Updating the states of an FCM includes feeding the FCM with a stimulus state vector until it converges to one of the three possibilities (Karagiannis and Groumpos, 2013) i.e. state vector remains unchanged; a sequence of state vectors keep repeating or the state vector keeps changing indefinitely. The evolved states of an FCM can be useful in decision support. FCMs can be used in problem domain analysis by: (a) determining how significant a concept is; (b) determining the degree of influence of a concept on other concepts; (c) determining the impact of a change in a concept on other concepts and; (d) determination of the evolution of a system with time, given a set of values for all concepts at a point in time (Carvalho, 2010). When the nodes of the FCM are fuzzy sets, then they are called as fuzzy nodes. FCMs with edge weights or causalities from the set {.1, 0, 1} are called simple FCMs. An FCM with cycles is said to have a feedback and as such, the FCM is called a dynamical system.

Finite number of FCMs can be combined together to produce the joint effect of all the FCMs. Let E_1, E_2, . , E_p be the adjacency matrices of the FCMs with nodes C_1, C_2, ., C_n then the combined FCM is computed by adding all the adjacency matrices E_1, E_2, ., E_p . The combined FCM adjacency matrix is denoted by $E = E_1 + E_2 + ...+ E_p$

Fuzzy cognitive maps application domains

To predict or forecast (Sperry and Jetter, 2012), the concept of fuzzy logic can be combined with fuzzy cognitive maps (FCM) to determine the relationship between various input factors. Modelling and controlling (Elpiniki, 2011) of complex problems qualitatively uses FCMs as a tool for answering what if questions during the solution planning stage. To facilitate reasoning in complex systems fuzzy logic and FCMs can model complex social problems and the dynamic causal relationships of the context variables in a virtual world where the variables update their states with respect to different update times. FCMs are simple graphical representation, and as such, they can be used to make knowledge widely available through computer systems. FCMs are able to incorporate experts' knowledge and represent (Papageorgiou, 2008) knowledge in a symbolic manner to relate states, processes, policies, events, values and inputs. FCMs have been used effectively in medical fields (Guerram, Maamri and Sahnoun, 2010) for decision making, diagnosis and predictive classification, with the experience of many experts and knowledge from historical data combined to form the FCMs.

DESIGNING FUZZY COGNITIVE MAPS

FCMs constructed by experts using prior knowledge do not acquire the implicit knowledge from the data of systems directly as this may distort the dynamical behaviour of the system (Aguilar, 2005) in which knowledge representation and reasoning are based on FCMs. A prediction and control model based on fuzzy cognitive maps can be developed followed by constructing a genetic algorithm (Dissanayake and AbouRizk, 2007) for finding the connection matrix of the FCM. Fuzzy cognitive map models can be tested dynamically though simulations (Xirogiannis and Glykas, 2004) where scenarios are introduced and predictions made by viewing dynamically the consequences of the corresponding actions. To get complex personal knowledge concerning concepts, a controlled interview can be used and information transcription from recorded interview to the concept map formalized (Sperry and Jetter, 2012). Fuzzy cognitive maps are recorded in the form of matrices of relations between concepts (Din and Cretan, 2014). A learning method that can improve the speed of learning process and the quality of learning FCMs with more nodes (Chrysafiadi and Virvou, 2013; Stach, Kurgan and Pedrycz, 2007), was proposed to construct causal graph based on historical data and by using Tabu Search (Pang, 2013) (a metaheuristic search method employing local search methods used for mathematical optimization). FCMs can be constructed using a systematic approach where concepts are gathered from survey respondents followed by taking into account the expert judgment in causal relationships between the concepts. A prediction algorithm can be constructed using fuzzy cognitive map and fuzzy c-means clustering algorithm was where a genetic algorithm is applied to learn weights of the FCM (Rangarajan *et al.*, 2012). This way, a fully learned fuzzy cognitive map can be used to represent, store fuzzy logic relationships of fuzzy time series and realize prediction (Singh, H., Singh, G. and Bhatia, 2013). Fuzzy cognitive maps can be designed using crisp decision trees (Elpiniki, 2011; Jones, 2010) (well known intelligent techniques that extract rules from both symbolic and numeric data) that have been fuzzified. Fuzzy rules can be combined and used to express non-monotonic causality in fuzzy cognitive maps along with aggregation operators for combining multiple causal influences. In situations where domain experts are not able to express the causal relationships data driven methods for learning FCMs can be used (Stach, Kurgan and Pedrycz, 2007). Heuristically, FCM learning, an FCM construction can be accomplished in the following steps: (a) identification of concepts and its interconnections determining the nature (positive, negative or null) of the causal relationships between concepts; (b) initial data acquisition by the expert opinions and/or by an equation analysis when the mathematical system model is known; (c) submitting the data from the expert opinions to a fuzzy system which output represents the weights of the FCM; (d) weight adaptation and optimization of the initially proposed FCM, adjusting its response to the desired output; and (e) validation of the adjusted FCM. The process of gathering and integrating knowledge from experts in form of fuzzy cognitive maps can be enhanced with choices of graph-based learning methods in order to improve the effectiveness of the final digraphs.

Research hypothesis

FCMs can be used efficiently for modelling and representing weather lore as used in traditional communities for seasonal weather forecasting.

METHODOLOGY

Structured interviews (Duan and Hoagwood, 2013; Preist, Massung and Coyle, 2014) were done in the South African community of KwaZulu-Natal and Kenya (Taita-Taveta County). During the interview sample astronomical and meteorological images were exposed to informants for identification and description of associated weather. In each of the case study locations private venues were arranged for interview sessions. The research population was the community members of the study communities. The systematic purposive sampling method (Risiro, Mashoko, Tshuma and Rurinda, 2012) was used to select 50 respondents (perceived knowledgeable persons) comprising of both traditional farmers and herdsmen and local residents.

Data was collected with the help of research assistants (selected students on vacation and volunteers) from the communities.

The research assistants were trained with regard to interpretation of the questionnaire, interviewing guidelines and research ethics. An introductory letter from the university was used to introduce the researchers. The collected data was digitized for storing in a computer and for transferring to the main researcher. A spreadsheet was used for easy storage and retrieval of data. For safety and recovery of information backup copies of the data were made and stored separately.

Structured interviews (Stern and Easterling, 1999) using questionnaires proved satisfactory to gather qualitative information. The data collection method permitted the respondents enough time and capacity to question their opinions on the visual weather lore domain. The focus points of the interviews were decided by the main researcher since there were aspects in the weather lore domain the research was interested in exploring (visual astronomical and meteorological). The main objective of using structured interviews was to understand the respondent(s) point of view so that individual opinions about the visual weather lore could be analyzed.

Qualitative research (Duan and Hoagwood, 2013) was used to describe the causal links between visual weather lore and weather outcomes. Quantitative methods were used to establish statistically significant conclusions about the populations in the case study locations by analyzing the gathered data from the representative sample of the population.

The research used purposive sampling (Meier, 2011) to target a particular category of respondents. The study targeted respondents in the rural communities of KwaZulu-Natal (South Africa) and Taita-Taveta (Kenya) where farmers and people who rely on weather for their activities were located. The major drawback was that the research incorporated other categories of people such as teachers since most farmers and herdsmen are difficult to get during daytime working hours. A general category of respondents who were residents in the case study locations were considered.

The data analysis involved identifying key indicators of causal effects between visual weather lore and weather outcomes (also referred to as concepts in this research). These indicators were were recorded by scales of magnitudes of effects between the concepts (strong negative, negative, none, positive and strong positive).

The collected data was set up in an SPSS codebook with some scales of semi-informal transformations. In order to derive common knowledge the data was analyzed using both quantitative (such as percentage or number of respondents) and descriptive statistics (mode and mean of categorical responses). The analyzed data was represented as group knowledge (on visual astronomical and meteorological weather concepts and the causal effects on short term weather) using statistical summaries.

The responses for all the respondents in case study locations were collated, analyzed, and summarized to answer the research questions. The analysis was categorized in terms of the following sections which provided answers to specific research objectives.

(a) Study area and demographic information of the respondents – the interest at this point was to understand the way of life and economic activities of the people. This was also reflected in the experience and length of stay in the communities.

(b) Impact of weather on daily activities of the respondents – the interest of this was to determine if weather affects the daily activities of the people in the communities. The answer to this section provided a clue whether or not the communities relied on weather and therefore they use some means to predict weather.

(c) Means of forecasting weather as used by respondents – the interest at this point was to determine the frequently used methods of predicting weather outcomes. Since some communities in rural areas do not rely on modern technology, answers to this provided a clue if the people relied on traditional visual weather indictors.

(d) Respondent(s) knowledge of visual (meteorological and astronomical) weather indicators – the interest in this was to determine if the people had knowledge on visual (astronomical or meteorological) weather indicators. The knowledge of this indicator provided a clue whether or not they used visual weather lore to predict weather outcomes.

(e) Causal links and effects between the visual weather indicators and weather outcomes – the interest of this was to determine if people could link between visual weather indicators and weather outcomes. The analysis results of this section gave a clue on whether links exist between visual weather indicators and weather outcomes.

(f) Identification of weather seasons characteristics – the interest at this point was to determine the pattern in weather seasons between the case studies and to come up with a general trend in the weather seasons.

SEASONAL WEATHER KNOWLEDGE REPRESENTATION

A fuzzy cognitive mapping (FCM) based prediction scenario process consisting of six steps, was used. This process has been used by previous researchers to come up with fuzzy cognitive maps based scenario prediction systems (Jetter, 2011).

The first FCM step was the clarification of information requirements (Jones, 2010). This step was achieved by using literature review together with preliminary studies that were aimed at understanding the visual weather lore domain. In this step the scope of the visual weather lore domain to be investigated was defined. The second step was to define a plan for gathering relevant weather lore related information. This step allowed the identification of the sources of visual weather lore knowledge as well as selection of appropriate methods for gathering visual weather lore knowledge. The third step involved gathering of knowledge that was achieved through two case studies. In this step the final output was data that was organized with causal relations between visual weather lore and weather outcomes. In the fourth step conceptual seasonal fuzzy cognitive maps were designed. The fifth step was the design of detailed fuzzy cognitive maps that had represented weather lore causal effects between the combined case studies. In this step the selection of input variables and functions for fuzzy cognitive maps were designated. The final step involved testing the fuzzy cognitive maps, interpretation of resulting predicted weather outcomes (outputs).

RESULTS

Range of visual weather lore knowledge

The study considered visual weather lore aspects from the world perspective; for this, literature was reviewed to gain insights on the global perceptions of weather lore. A wide variety of visual astronomical and meteorological weather indicators were identified from literature (Mwagha and Masinde, 2015) and considered for further investigation (Table 1).

Reduction of the identified visual weather concepts

Based on clouds patterns, colour and shape characteristics, the following clouds characteristics were linked to specific cloud types: cirrus, cirrostratus, cirrocumulus, high clouds, low clouds, medium clouds, blue clouds, brown clouds, cauliflower clouds, feathery clouds, filaments clouds, grey clouds, layered clouds, nimbus, red clouds, rippled clouds, tower clouds, uniform clouds and white clouds.

Using knowledge on associations and characteristics of clouds, the clouds concepts were re-grouped according to levels. For instance, high clouds consisted of cirrus, cirrostratus and cirrocumulus clouds which were characterized by being white and taking the shapes of feathers, filaments or hair. The high clouds appeared yellow or red at sunset (Table 2).

Table 1: Initial weather indicators.

Object	Indicators							
Cloud color	White	Grey						
Cloud types	Altocumulus	Altostratus	Cirrocumulus	Cirrostratus	Cirrus	Cumulonimbus	Stratocumulus	Stratus
Cloud shape	Cauliflower	Towers						
Cloud patterns	Feathery	Layered	Rippled	Uniform		Filaments		
Cloud levels	Low	Medium	High					
Sun	Hallo around							
Stars	Dull	Twinkle						
Stars	Filled	Few						
Moon phase	New	Full	Dark	Transition	Hallo around			
Night sky	Clear	Dark	Red					
Lightning	High	Low						
Rainbow	Morning	Evening						

Table 2: Grouping of clouds by levels.

Cloud Group	Cloud Type	Characteristics
High clouds	Cirrus	Feathery, white, filaments, hair like, yellow/red at sunset/rise
	Cirrostratus	Creates halo around sun/moon, white, can cover all sky, hair like, smooth smooth
	Cirrocumulus	Clusters of small round white patches, ripples/grains
Middle clouds	Altostratus	Grey/bluish cloud sheets, thin can reveal sun
	Altocumulus	White/grey patches, rounded masses or rolls
Low and vertical clouds	Stratus	A fog not far from ground, gray cloud layer, a uniform base
	Stratocumulus	Layered, Gray or whitish patch, honeycomb appearance, rounded masses or rolls
	Nimbostratus	Dark rain clouds, covers sky, blocks sun, grey, continuous rain cloud, results from thickening altostratus
	Cumulus	Fair weather, cauliflower, detached, rising mounds, domes or towers
	Cumulonimbus	Brings and goes with rain, thunderstorm cloud, mountain or huge tower

Using knowledge on concept associations, the initial concepts were condensed by clustering similar and restating opposing concepts leading to a fewer number of concepts. The notion of condensing the concepts was necessitated by fuzziness in the occurrence of concepts meaning that some concepts could overlap and inherit characteristics of other concepts. The clouds concepts were reduced to high, medium and low level clouds respectively. The dark and clear sky were considered to be opposing each other hence by identifying one concept, the other could be determined as the converse. Twinkling and many stars were combined to represent one concept, while dull and few stars were combined to come up with a new concept. The twinkling/many and dull/few stars were determined as opposing hence by identifying one, the other is determined as the converse. The rainbows occurring at any time of the day were reduced to represent a single concept. The concepts relating to lightning (much and less) were taken to represent a single concept. Due to the fact that changes in weather outcomes occur mostly between the full/visible to dark moon transitions, the concepts dark moon, full moon, decreasing moon, increasing moon and new moon were condensed to two concepts – full/visible moon and partial/dark moon. The weather outcomes were reduced to only four concepts (rain, hot, cold and dry) which proved significant to the daily activities of humans. The concepts, cloudy and clear skies were considered redundant while the concepts of windy and calm were considered having non visual characteristics. The final list of interacting concepts were determined as: high clouds; low clouds; medium clouds; clear sky; many stars; rainbow; lightning; partial/dark moon; full/visible moon; rain; dry; hot and cold

CASE STUDY OF KWAZULU-NATAL PROVINCE OF SOUTH AFRICA

Description of the study area

KwaZulu-Natal (Figures 1 and 2) is South Africa's third smallest province with a total area of 94,361 square kilometers and taking up 7.7% of South Africa's land area. The province has the second largest population in South Africa (10.3 million people in 2015). Climate in the coastal areas of KwaZulu-Natal is subtropical with summer temperatures rising to over 30º celsius. KwaZulu-Natal gets the most rain (over 1 000mm a year) in South Africa, which occurs between the months of October and April and mostly during the summer months of December to February in which thunderstorms can occur almost every afternoon. During winter seasons, the temperatures are usually mild to warm (average are over 20º celsius) and the probability of rain is low. KwaZulu-Natal has fertile soils making agriculture the major economic activity.

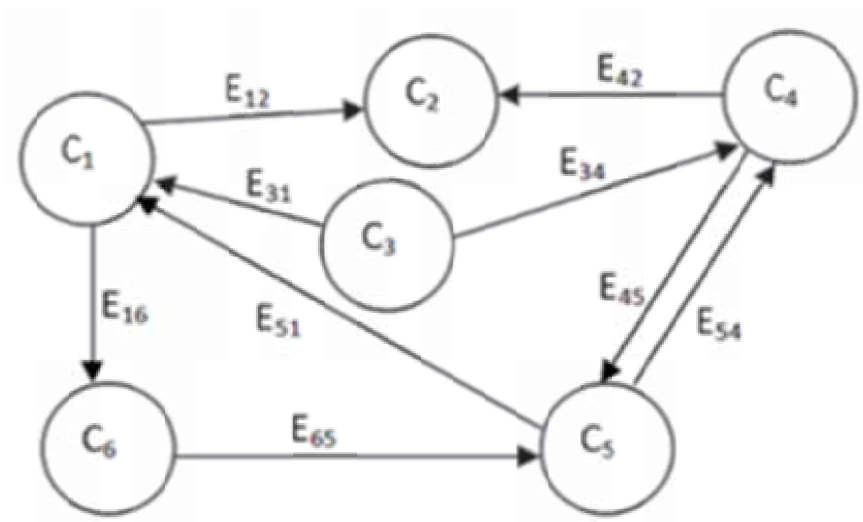

Figure 1:

Figure 2: Map of KwaZulu-Natal.

Case Two: Taita-Taveta county of Kenya

Description of the study area

Taita-Taveta (Figures 3 and 4) is an arid and semi arid (ASAL) county in Kenya covering an area of 17,083.9 km2. The County lies between 2° 46’ north to 4° 10’ north and longitudes 37° 36’ east to 30°14’ east. The altitude of Taita-Taveta varies between 481m above sea level in the lowlands to 2,200m above sea level for highlands, giving two distinct climatic characteristics, with the hills experiencing lower temperatures (as low as 18.2˚C) compared to the lower zones with an average temperature of 24.6°C. The average temperature in the county is 23˚C. The county is divided into highlands zone, dry lowlands zone and some volcanic foothills. The highlands receive high rainfall and are suitable for horticultural farming. The county experiences two rain seasons the long rains between the months of March and May and the short rains between November and December. The rainfall distribution is uneven in the county, with the highlands receiving higher rainfall than the lowland areas. The highlands have cooler temperatures while the lowland areas experience higher temperatures. The major economic activities in the county include ranching and farming (such as maize and sisal). (Taita-Taveta County Government Profile, 2015).

Figure 3: Data points at KwaZulu-Natal.

Figure 4: Map of Taita-Taveta.

Significance of weather on daily activities and knowledge of visual weather indicators

The analysis of the two case studies depict that weather is significant on human activities (Figure 5). This is depicted by the statistics that majority of humans (58% in South Africa and 71% in Kenya) stating that sometimes weather affects their daily activities. Majority (above 50%) of the respondents in both case studies stated that they often check for weather forecasts. On the knowledge of visual weather indicators most of the respondents in both case studies stated that they knew (over 50%) some visual indicators and that the visual indicators help (over 50%) them to predict weather.

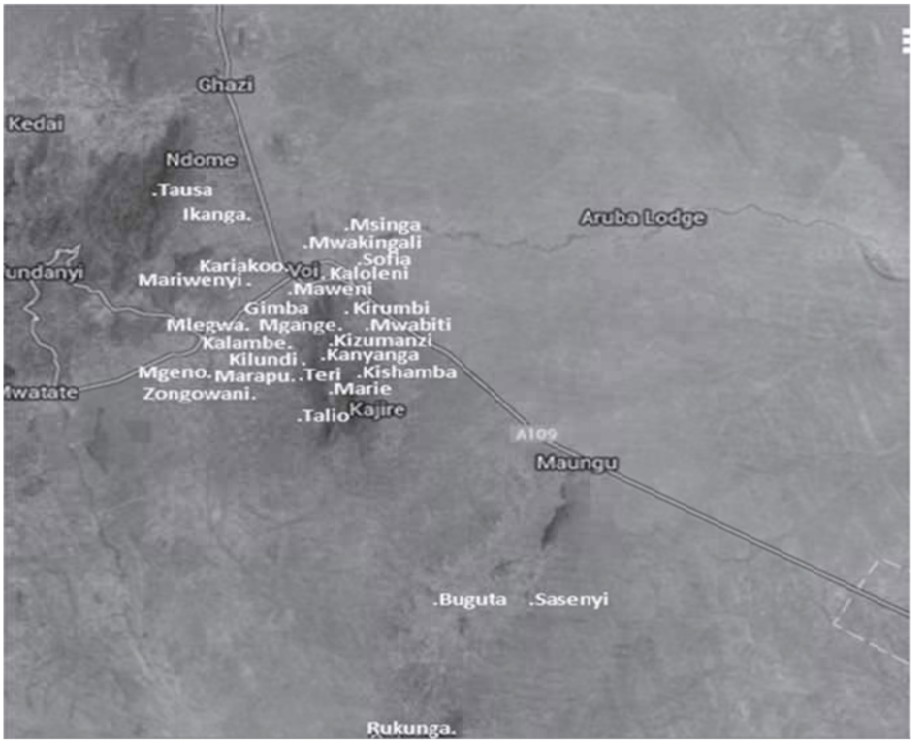

Figure 5: Data points in Taita-Taveta.

Causal effects between astronomical and meteorological concepts: Kenya vs South Africa

The mode (preferred since it is the most repeated) and mean knowledge (separately for Kenya and South Africa) were determined for each set of interacting concepts. The analysis (Table 3) showed that weather season's patterns in Kenya and South Africa correspond but the extremes (between high and low values) vary significantly.

Table 3: Relation between concepts (Kenya vs South Africa).

Concept to Concept	Causal Effect (mode Values)		Causal Effect (mean Values)	
	Kenya	South Africa	Kenya	South Africa
High clouds to low clouds	.0	.0	-.1	-.2
High clouds to medium clouds	.0	.0	-.1	-.3
High clouds to clear sky	.5	.5	.5	.5
High clouds to many stars	.0	.0	-.1	-.1
High clouds to rainbow	.0	.0	-.1	.0
High clouds to lightining	-1.0	-1.0	-.8	-.9
High clouds to partial/dark moon	.0	.0	.0	.0
High clouds to full/visible moon	.0	.0	.1	.1
Medium clouds to low clouds	.0	.0	.0	.0
Medium clouds to clear sky	-.5	-.5	-.5	-.5
Medium clouds to many stars	.0	.0	-.2	-.2
Medium clouds to rainbow	.0	-1.0	-.3	-.5
Medium clouds to lightining	.0	.0	.1	.1
Medium clouds to partial/dark moon	.0	.0	.1	.1
Medium clouds to full/visible moon	.0	-1.0	-.2	-.5
Low clouds to clear sky	-1.0	-1.0	-.8	-.9
Low clouds to many stars	.0	.0	-.1	-.1
Low clouds to rainbow	.0	.0	-.1	.0
Low clouds to lighining	.0	.0	.1	.0
Low clouds to partial/dark moon	.0	.0	.1	.0
Low clouds to full/visible moon	.0	.0	-.2	-.1
Clear sky to many stars	.0	.0	.2	.1
Clear sky to rainbow	.0	.0	.1	.1
Clear sky to lightining	-1.0	-1.0	-.8	-.8
Clear sky to partial/dark moon	.0	.0	-.2	-.5
Clear sky to full/visible moon	.0	.0	.2	.2
Many stars to rainbow	.0	.0	.2	.1
Many stars to lightining	.0	.0	-.2	-.1
Many stars to partial/dark moon	.0	-.5	-.2	-.3
Many stars to full/visible moon	.0	.0	.3	.3
Rainbow to lightining	.0	.0	-.3	-.2
Rainbow to partial/dark moon	.0	.0	.0	.0
Rainbow to full/visible moon	.0	.0	.1	.1
Lightining to partial/dark moon	.0	.0	.2	.1
Lightining to full/visible moon	.0	.0	-.2	-.1
Partial/dark moon to full/visible moon	.0	.0	-.2	-.1

Table 4: Summary of causal effects.

Concept to Outcome	Seasonal causal effects (modal Values)							
	Winter		Summer		Autumn		Spring	
	Kenya	South Africa	Kenya	South Africa	Kenya	South Africa	Kenya	South Africa
High clouds to rain	-1.0	.0	-1.0	-1.0	-1.0	-.5	-1.0	-.5
Low clouds to rain	.5	.5	.0	1.0	1.0	1.0	.5	.5
Medium clouds to rain	.0	.5	.5	.5	.5	.5	-.5	.5
Clear sky to rain	-1.0	.0	-1.0	-.5	-1.0	-1.0	-1.0	-.5
Many stars to rain	-1.0	.0	-.5	-1.0	-1.0	-1.0	-1.0	-1.0
Rainbow to rain	-.5	-.5	-.5	-.5	-.5	-1.0	-.5	-.5
Lightning to rain	.5	.5	.0	1.0	1.0	.5	1.0	1.0
Partial/dark moon to rain	.5	.0	.5	.5	.5	.5	.5	.5
Full/visible moon to rain	.0	.0	-.5	-1.0	-.5	-.5	-.5	-1.0
High clouds to dry	1.0	1.0	1.0	1.0	1.0	.5	1.0	.5
Low clouds to dry	.5	1.0	-1.0	-1.0	-1.0	-1.0	-.5	.5
Medium clouds to dry	-.5	1.0	-.5	-.5	-.5	-1.0	.5	-.5
Clear sky to dry	1.0	1.0	1.0	1.0	1.0	.5	1.0	.5
Many stars to dry	.5	1.0	1.0	1.0	1.0	-1.0	1.0	.5
Rainbow to dry	.0	1.0	.5	.5	.5	.5	.5	-.5
Lightning to dry	-.5	-1.0	-1.0	-1.0	-1.0	-.5	-1.0	-1.0
Partial/dark moon to dry	-.5	-.5	-.5	-1.0	-.5	-.5	-.5	-1.0
Full/visible moon to dry	.5	.5	1.0	1.0	.5	.5	.5	-1.0
High clouds to hot	.5	-.5	1.0	1.0	.5	.5	1.0	.5
Low clouds to hot	-1.0	-.5	-1.0	-1.0	-.5	-.5	-.5	-.5
Medium clouds to hot	-.5	-.5	-.5	1.0	.5	-1.0	.5	-.5
Clear sky to hot	.5	.5	1.0	1.0	1.0	.5	1.0	1.0
Many stars to hot	.5	.5	1.0	1.0	1.0	-1.0	1.0	.5
Rainbow to hot	.5	.5	1.0	.5	.5	.5	.5	.5
Lightning to hot	-.5	-1.0	-1.0	-.5	-.5	-.5	-1.0	-.5
Partial/dark moon to hot	-.5	.0	-.5	-1.0	-.5	-.5	-.5	-.5
Full/visible moon to hot	.5	.5	1.0	1.0	1.0	.5	.5	1.0
High clouds to cold	-.5	1.0	-1.0	-1.0	-1.0	.5	-1.0	-1.0
Low clouds to cold	1.0	1.0	.5	.5	.5	.5	.5	.5
Medium clouds to cold	.5	1.0	.5	-1.0	.5	.5	.5	.5
Clear sky to cold	-.5	.5	-1.0	-1.0	-1.0	.5	-1.0	-1.0
Many stars to cold	-.5	.5	-.5	-1.0	-.5	.5	-1.0	-1.0
Rainbow to cold	-.5	.5	-.5	-1.0	-.5	.5	.5	-.5
Lightning to cold	.5	1.0	.5	.5	1.0	.5	1.0	.5
Partial/dark moon to cold	.5	1.0	-.5	.5	.5	.5	.5	.5
Full/visible moon to cold	-.5	1.0	-1.0	-1.0	-.5	.5	-.5	-1.0

Aggregation of seasonal knowledge from case studies

To represent common knowledge for the two case studies, joint statistics mode values were determined for:

- between the visual astronomical and meteorological concepts (Table 5) and
- between the astronomical and meteorological concepts to weather outcomes in the various seasons (Table 6).

Table 5: Aggregated causal effect (Kenya and South Africa).

Concept to concept	Value
High clouds to low clouds	0
High clouds to medium clouds	0
High clouds to clear sky	0.5
High clouds to many stars	0
High clouds to rainbow	0
High clouds to lightining	-1
High clouds to partial/dark moon	0
High clouds to full/visible moon	0
Medium clouds to low clouds	0
Medium clouds to clear sky	-0.5
Medium clouds to many stars	0
Medium clouds to rainbow	-0.5
Medium clouds to lightining	0
Medium clouds to partial/dark moon	0
Medium clouds to full/visible moon	-0.5
Low clouds to clear sky	-1
Low clouds to many stars	0
Low clouds to rainbow	0

Concept to concept	Value
Low clouds to lighining	0
Low clouds to partial/dark moon	0
Low clouds to full/visible moon	0
Clear sky to many stars	0
Clear sky to rainbow	0
Clear sky to lightining	-1
Clear sky to partial/dark moon	0
Clear sky to full/visible moon	0
Many stars to rainbow	0
Many stars to lightining	0
Many stars to partial/dark moon	-0.25
Many stars to full/visible moon	0
Rainbow to lightining	0
Rainbow to partial/dark moon	0
Rainbow to full/visible moon	0
Lightining to partial/dark moon	0
Lightining to full/visible moon	0
Partial/dark moon to full/visible moon	0

Table 6: Kenya and South Africa aggregated seasonal causal effects.

Concept to outcome	Winter	Summer	Autumn	Spring
High clouds to rain	-0.5	-1	-0.75	-0.75
Low clouds to rain	0.5	0.5	1	0.5
Medium clouds to rain	0.25	0.5	0.5	0
Clear sky to rain	-0.5	-0.75	-1	-0.75
Many stars to rain	-0.5	-0.75	-1	-1
Rainbow to rain	-0.5	-0.5	-0.75	-0.5
Lightning to rain	0.5	0.5	0.75	1
Partial/dark moon to rain	0.25	0.5	0.5	0.5
Full/visible moon to rain	0	-0.75	-0.5	-0.75
High clouds to dry	1	1	0.75	0.75
Low clouds to dry	0.75	-1	-1	0
Medium clouds to dry	0.25	-0.5	-0.75	0
Clear sky to dry	1	1	0.75	0.75
Many stars to dry	0.75	1	0	0.75
Rainbow to dry	0.5	0.5	0.5	0
Lightning to dry	-0.75	-1	-0.75	-1
Partial/dark moon to dry	-0.5	-0.75	-0.5	-0.75
Full/visible moon to dry	0.5	1	0.5	-0.25
High clouds to hot	0	1	0.5	0.75
Low clouds to hot	-0.75	-1	-0.5	-0.5
Medium clouds to hot	-0.5	0.25	-0.25	0
Clear sky to hot	0.5	1	0.75	1
Many stars to hot	0.5	1	0	0.75
Rainbow to hot	0.5	0.75	0.5	0.5
Lightning to hot	-0.75	-0.75	-0.5	-0.75
Partial/dark moon to hot	-0.25	-0.75	-0.5	-0.5
Full/visible moon to hot	0.5	1	0.75	0.75
High clouds to cold	0.25	-1	-0.25	-1
Low clouds to cold	1	0.5	0.5	0.5
Medium clouds to cold	0.75	-0.25	0.5	0.5
Clear sky to cold	0	-1	-0.25	-1
Many stars to cold	0	-0.75	0	-1
Rainbow to cold	0	-0.75	0	0
Lightning to cold	0.75	0.5	0.75	0.75
Partial/dark moon to cold	0.75	0	0.5	0.5
Full/visible moon to cold	0.25	-1	0	-0.75

Aggregated mode values for the four weather seasons were summarized to depict the trends in the aggregated causal effects for the winter, summer, autumn and spring seasons.

Implementation of the fuzzy cognitive maps models for weather lore

In this research the membership functions for the terms of the causal effect were classified to signify strength of cause based on values in the range [-1, 1] as follows:

$$0.5 < strong\_positive \leq 1$$
$$0 < positive \leq 0.5$$
$$0 = none$$
$$-0.5 < negativee < 0$$
$$-1 \leq strong\_negative < -0.5$$

Equation 2: Representation of concepts relations using fuzzy cognitive maps.

The relations between the concepts were represented by a statistically weighted *n x n* adjacency matrix *W*, which mapped the causal weights at the intersection of concepts pair's (see Equation 3).

$$W = \begin{bmatrix} w_{11} & \dots & w_{1j} \\ . & & \\ w_{i1} & & w_{ij} \end{bmatrix}$$

Equation 3: The value *n* represents the number of interacting concepts that falls in the range $1 \leq (i, j) \leq n$

The general rule of fuzzy cognitive maps (Din and Cretan, 2014; Najafi and Afrazeh, 2008) was applied i.e. for any concept c_i, the causal effect of concept c_i on another concept c_i is w_{ij}

The final (Kenya and South Africa) fuzzy cognitive maps were formulated as *n x n* matrices *W*, using the results of statistical analysis. The adjacency matrices were filled with values w_{ij} indicating the strength of the relationship between interacting concepts at position c_{ij}. A positive sign (+ or no sign) was used before the value to indicate an enhancing effect while a negative sign (-) was used to indicate a depressing effect. The value of zero (0) was used to mean that concept c_i has no causal effect to an adjacent concept c_j

Table 7: Final fuzzy cognitive map for winter season.

Concepts	High clouds	Low clouds	Medium clouds	Clear sky	Many stars	Rainbow	lighting	Partial/dark moon	Full/visible moon	Rain	Dry	Hot	Cold
High clouds	0.00	0.00	0.00	0.50	0.00	0.00	-1.00	0.00	0.00	-0.50	1.00	0.00	0.25
Low clouds	0.00	0.00	0.00	-1.00	0.00	0.00	0.00	0.00	0.00	0.50	0.75	-0.75	1.00
Medium clouds	0.00	0.00	0.00	-0.50	0.00	0.00	0.00	0.00	-0.50	0.25	0.25	-0.50	0.75
Clear sky	0.00	0.00	0.00	0.00	0.00	0.00	-1.00	0.00	0.00	-0.50	1.00	0.50	0.00
Many stars	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.75	0.50	0.00
Rainbow	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.50	0.50	0.00
Lightning	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	-0.75	-0.75	0.75
Partial/dark moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	-0.50	-0.25	0.75
Full/visible moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.25
Rain	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Dry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hot	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cold	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 8: Final fuzzy cognitive map for summer season.

Concepts	High clouds	Low clouds	Medium clouds	Clear sky	Many stars	Rainbow	Lightning	Partial/dark moon	Full/visible moon	Rain	Dry	Hot	Cold
High clouds	0.00	0.00	0.00	0.50	0.00	0.00	-1.00	0.00	0.00	-1.00	1.00	1.00	-1.00
Low clouds	0.00	0.00	0.00	-1.00	0.00	0.00	0.00	0.00	0.00	0.50	-1.00	-1.00	0.50
Medium clouds	0.00	0.00	0.00	-0.50	0.00	0.00	0.00	0.00	-0.50	0.50	-0.50	0.25	-0.25
Clear sky	0.00	0.00	0.00	0.00	0.00	0.00	-1.00	0.00	0.00	-0.75	1.00	1.00	-1.00
Many stars	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.75	1.00	1.00	-0.75
Rainbow	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.50	0.75	-0.75
Lightning	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	-1.00	-0.75	0.50
Partial/dark moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	-0.75	-0.75	0.00
Full/visible moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.75	1.00	1.00	-1.00
Rain	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Dry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hot	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cold	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 9: Final fuzzy cognitive map for autumn season.

Concepts	High clouds	Low clouds	Medium clouds	Clear sky	Many stars	Rainbow	Lightning	Partial/dark moon	Full/visible moon	Rain	Dry	Hot	Cold
High clouds	0.00	0.00	0.00	0.50	0.00	0.00	-1.00	0.00	0.00	-0.75	0.75	0.50	-0.25
Low clouds	0.00	0.00	0.00	-1.00	0.00	0.00	0.00	0.00	0.00	1.00	-1.00	-0.50	0.50
Medium clouds	0.00	0.00	0.00	-0.50	0.00	0.00	0.00	0.00	-0.50	0.50	-0.75	-0.25	0.50
Clear sky	0.00	0.00	0.00	0.00	0.00	0.00	-1.00	0.00	0.00	-1.00	0.75	0.75	-0.25
Many stars	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.00	0.00	0.00	0.00
Rainbow	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.75	0.50	0.50	0.00
Lightning	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	-0.75	-0.50	0.75
Partial/dark moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	-0.50	-0.50	0.50
Full/visible moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.50	0.75	0.00
Rain	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Dry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hot	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cold	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 10: Final fuzzy cognitive map for spring season.

Concepts	High clouds	Low clouds	Medium clouds	Clear sky	Many stars	Rainbow	Lightning	Partial/dark moon	Full/visible moon	Rain	Dry	Hot	Cold
High clouds	0.00	0.00	0.00	0.50	0.00	0.00	-1.00	0.00	0.00	-0.75	0.75	0.75	-1.00
Low clouds	0.00	0.00	0.00	-1.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	-0.50	0.50
Medium clouds	0.00	0.00	0.00	-0.50	0.00	0.00	0.00	0.00	-0.50	0.00	0.00	0.00	0.50
Clear sky	0.00	0.00	0.00	0.00	0.00	0.00	-1.00	0.00	0.00	-0.75	0.75	1.00	-1.00
Many stars	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.00	0.75	0.75	-1.00
Rainbow	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.50	0.00	0.50	0.00
Lightning	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	-1.00	-0.75	0.75
Partial/dark moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	-0.75	-0.50	0.50
Full/visible moon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.75	-0.25	0.75	-0.75
Rain	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Dry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hot	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cold	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The final fuzzy cognitive maps connection matrices consisted of collective knowledge from both Kenya and South Africa (Tables 7, 8, 9 and 10). An FCM network for the spring season is depicted in figure 6.

The significance of the visual weather concepts were analyzed and presented in Table .

Table 11: Analysis of the importance of nodes (concepts) for spring season.

Concepts	Outdegree	Indegree	Centrality
High clouds	4.75	0.00	4.75
Low clouds	2.50	0.00	2.50
Medium clouds	1.50	0.00	1.50
Clear sky	4.50	2.00	6.50
Many stars	3.50	0.00	3.50
Rainbow	1.00	0.00	1.00
Lightning	3.50	2.00	5.50
Partial/dark moon	2.25	0.00	2.25
Full/visible moon	2.50	0.50	3.00
Rain	0.00	5.75	5.75
Dry	0.00	4.25	4.25
Hot	0.00	5.50	5.50
Cold	0.00	6.00	6.00

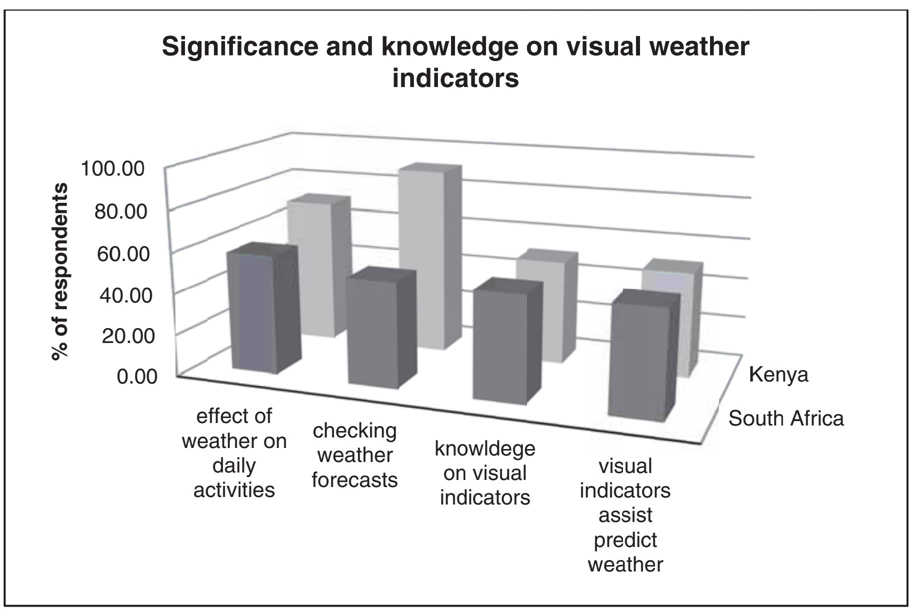

Figure 6: Significance and knowledge on weather indicators.

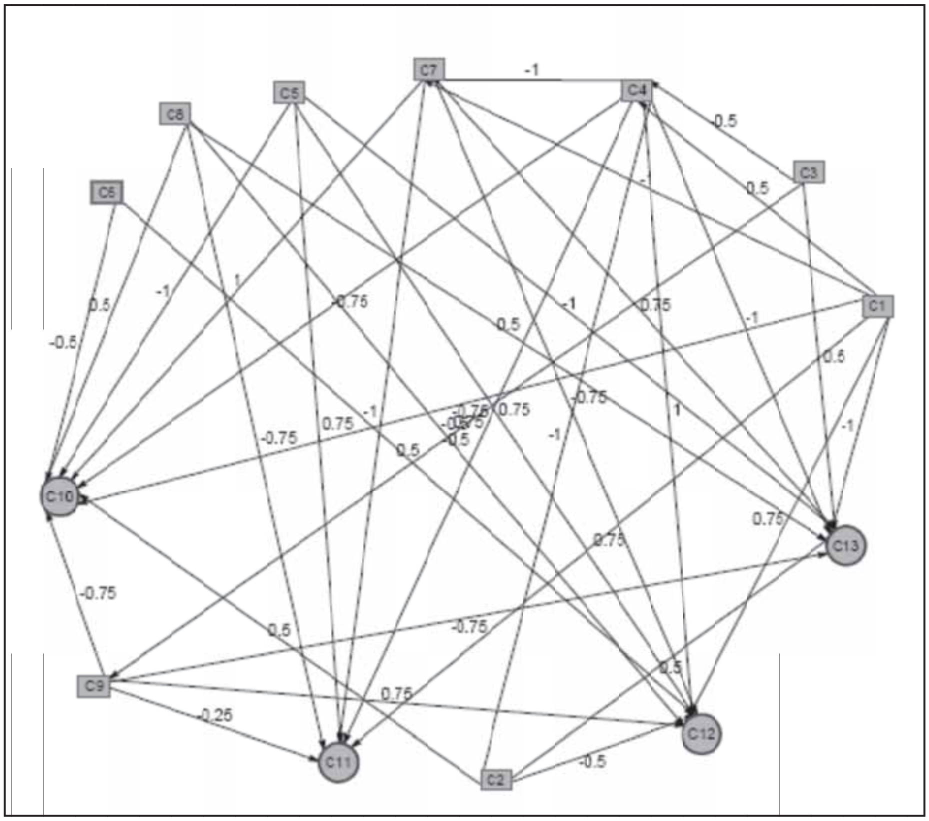

Figure 7: FCM for the spring season; (C1=high clouds; C2=low clouds; C3=medium clouds; C4=clear sky; C5=many stars; C6=rainbow; C7=lightining; C8=partial/dark moon; C9=full/visible moon: C10=rain; C11=dry; C12=hot; C13=cold).

DISCUSSION AND CONCLUSIONS

An investigation was completed on the most influential visual weather concepts that humans exploit in deciding on weather outcomes in the process of planning for their daily activities. The investigation established that traditional knowledge was locality specific, due to the fact that the effects of weather outcomes vary from different categories of people (such as farmers and general rural inhabitants).

The results of analyzing knowledge from the two case studies showed that weather is significant on human activities. This was depicted by the result that majority of human daily activities (58% in South Africa and 71% in Kenya) were sometimes affected by weather. The analysis results also depicted that the majority of respondents in both case studies often check for weather forecasts. The results also showed that most of the respondents in both case studies knew some visual indicators and that the visual indicators help them to predict weather.

Influential sky weather concepts (also referred to as astronomical and meteorological weather concepts) were portrayed through weather lore domain understanding and analysis (high clouds; low clouds; medium clouds; clear sky; many stars; rainbow; lightning; partial/dark moon; full/visible moon; rain; dry; hot; cold).

The seasonal fuzzy cognitive maps were accomplished by analyzing and interpreting the relations between the sky concepts. The analysis results permitted a more understanding concerning the structural properties and dynamics of the seasonal fuzzy cognitive maps. The type and the role of each sky concept within seasonal fuzzy cognitive maps were accomplished by analyzing the density, indegree, outdegree and centrality measures

FCMs are found to be a useful mechanism for representation of interactions in complex systems since they have been used successfully in many different application areas. Collections of important visual weather lore concepts were used to guide in design of the FCM. As a first step only astronomical factors related to cloud physics only were used to come up with a model of the FCM. Causal links between visual weather concepts have been investigated using two case studies in which results were compared and aggregated to build up common knowledge. The results of statistical knowledge were used to formally represent seasonal weather knowledge using fuzzy cognitive maps in the form of connection matrices and network graph.

In further research the FCM can be enhanced by incorporating sub FCMs from other WL aspects such as animals or plants behaviours. With the complexity of incorporation of many concepts from sub FCM models, the FCM outputs after can be demonstrated by machine learning methods.

The applications and preservation of the weather lore need to be recognized by policy bodies. This will assure that research findings are put in economic use as well as advancing research outputs.

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