Predicting Malaria Outbreak Using Indigenous Knowledge and Fuzzy Cognitive Maps: A Case Study of Vhembe District in South Africa

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Abstract. Malaria, a vector-borne disease, remains a major public health problem in many countries, particularly in Sub-Saharan Africa, where health resources are limited. Early warning of malaria outbreaks is crucial for effective control and mitigation of the devastating impacts of malaria. Tapping into the vital role indigenous knowledge (IK) plays in combating infectious diseases and the success of an artificial intelligence technique called fuzzy cognitive map (FCM) in modelling infectious diseases, this paper aims to predict malaria outbreaks using IK and FCM. The concepts used to develop the FCM were the IK indicators participants in Vhembe in South Africa used to ṇpredict malaria outbreaks. These IK indicators were collected through unstructured interviews. The developed malaria outbreak prediction FCM model was used to conduct simulations and make predictions of malaria outbreaks. As an initial stride for constructing such a tool, this paper demonstrates how the artificial intelligence technique, FCM, can represent IK indicators and predict malaria outbreaks. This promotes the recognition of IK in the effort to control and mitigate malaria outbreaks. Modelling IK using artificial intelligence opens the opportunity to incorporate IK with modern prediction models to develop robust early warning systems based on multiple knowledge systems.

Keywords: Fuzzy cognitive maps · malaria outbreak prediction · indigenous knowledge · malaria indigenous knowledge indicators · Vhembe district · South Africa

1 Introduction

Malaria remains a significant public health concern in many parts of the world, particularly in sub-Saharan Africa [1]. The global tally of malaria cases reached 247 million in 2021 compared to 245 million in 2020 and 232 million in 2019 [1]. On the other hand, Africa, with an estimated 234 million cases in 2021, accounted for 95% of global cases and 96% of malaria deaths, of which 80% were children under 5 years. Even though there

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are preventive and treatment initiatives to combat malaria, such as RTS, S/AS01 (RTS, S) malaria vaccine, and medicine that includes chemoprophylaxis, malaria continues to claim many people's lives [1].

Various techniques, spanning from machine learning to statistical approaches, have been employed to forecast the occurrence of malaria outbreaks [2–7]. Several studies that have crafted forecasts for malaria prediction and other infectious diseases such as dengue have relied exclusively on modern science approaches [5, 8–10]. However, these approaches have predominately not been in the context of Africa. Even though most have high prediction accuracy, they do not incorporate local knowledge in the prediction. Smylie et al. (2004) [11] argue that early warning systems are more effective if they are relevant and understandable to their intended communities.

A unique approach rooted in Indigenous Knowledge (IK) and Fuzzy Cognitive Map (FCM) methodologies holds promise for enhancing malaria prediction capabilities [12]. Using IK, we tap into the wisdom of local communities, promoting community engagement and ownership in disease surveillance efforts. This article explores a case study conducted in the Vhembe district of South Africa, where the integration of IK and FCM has demonstrated its potential for predicting malaria outbreaks.

2 Related Literature

2.1 Malaria Outbreaks

Malaria is a vector-borne disease spread by the bite of the infected female Anopheles mosquito [13]. Transmission is more intense in places where the mosquito lifespan is longer and where it bites humans rather than other animals [1]. The African vector species' long lifespan and strong human-biting habit are the main reasons most of the world's malaria cases are in Africa [14]. Transmission of malaria also depends on climatic conditions such as temperature and rainfall [15]. Climatic conditions create a conducive environment for malaria to thrive because climate changes impact disease agents' survival, reproduction, or distribution and the means of their transmission environment [16, 17]. Socio-economic factors also affect the severity of malaria and its transmission, including construction activities, education, population intensity and human migration [18, 19]. Indeed, malaria transmission is influenced by a combination of factors contributing to the prevalence and distribution of this vector-borne disease.

In South Africa, Vhembe is one of Limpopo districts prone to malaria outbreaks. Of 129 682 malaria incidences reported in Limpopo province from January 1998 to June 2019, 60% of these incidences were from Vhembe. Vhembe experienced the highest and lowest malaria incidences in 2017 and 2016, respectively, see Fig. 1 below. High incidences of malaria continue to be reported in Vhembe district [20]. On the other hand, Fig. 2 shows malaria incidences in Vhembe according to different months of the year. It can be observed that from 1998 to 2019, June, July, and August were the months with the least number of malaria incidences. The months that recorded high malaria incidences were January, February, March, and April. It can be noted that Vhembe experienced the highest malaria incidences in summer and autumn. The consistent pattern of high malaria incidences in the Vhembe district, particularly during the summer and autumn months, highlights the ongoing need for effective malaria prevention and control measures in this region.

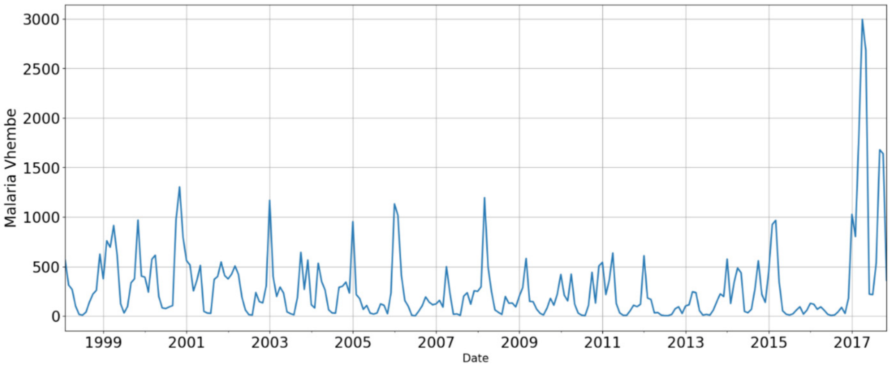

Fig. 1. Malaria incidence trajectories from the year 1998 to 2019 in Vhembe district.

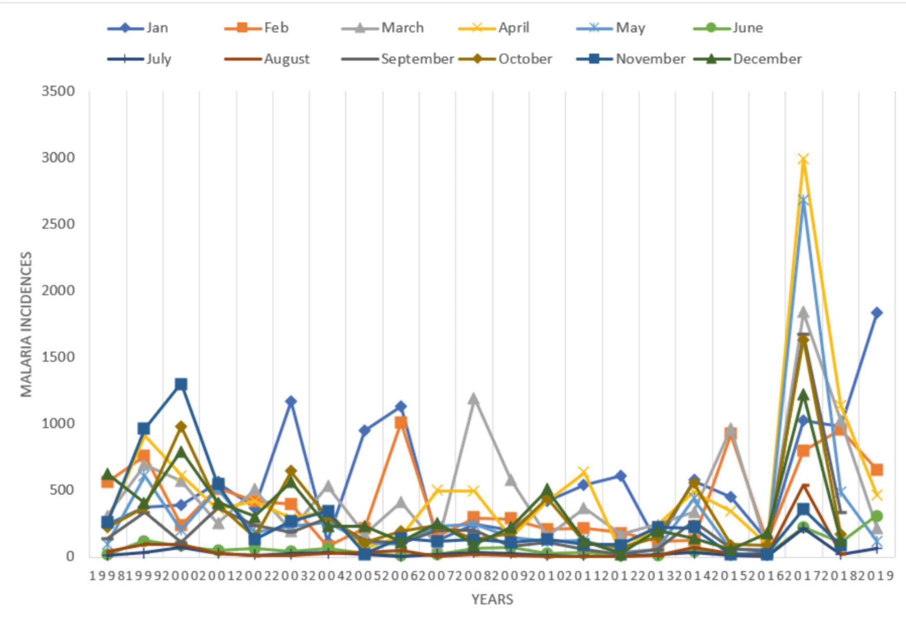

Fig. 2. Malaria incidences in Vhembe district grouped by months.

2.2 Overview of Indigenous Knowledge and Malaria Prediction in African Communities

There is substantial literature on the use of IK to predict weather variations such as drought, rainfall, and floods [21–26] very few studies focusing on the use of IK to predict disease outbreaks [4]. Nevertheless, the same methods can be used to predict weather variations to predict infectious diseases. If the community can relate weather variations to the occurrence of diseases, such a community can predict weather-related disease occurrences [4]. Moreover, local communities use local indicators such as the behaviour of plants, birds, and animals to forecast disease outbreaks such as malaria. Therefore, it is evident that local knowledge can be used in predicting weather-related disease outbreaks, especially if the local communities can predict weather conditions using IK.

In Zimbabwe, IK was used to predict malaria outbreaks. Communities utilized mainly rainfall predictions to predict malaria outbreaks. Plant phenology, insect behaviour, and indicators linked to ancestral spirits were also utilized [27]. For instance, the abundant flowering and fruits were considered to indicate heavy rainfalls and increased malaria risk. The "roaring of mountains" and specific behaviours of ostriches are also considered malaria outbreak indicators. Plant phenology was the most used indicator, predicting malaria occurrence and intensity. However, the informal nature of observations and lack of integration into the health system diminishes the importance and effectiveness of local knowledge [4]. Climate change and variations may impact indicator accuracy [28, 29]. Nevertheless, researchers' consistent interpretation of IK indicators for rainfall predictions suggests potential accuracy [30, 31].

Using IK in early warning systems developed in Africa has focused on rainfall forecast, monitoring air pollution, or drought prediction for agricultural purposes [12, 22, 25]. The possibility of developing a community-centred early warning system for infectious diseases has not been explored despite most infectious diseases being weather-related. To our knowledge, only one early warning system based on local knowledge was developed to predict infectious diseases [27]. The system was based on the indicators formally observed by the community to make predictions. Therefore, IK is one of the underutilized resources in modern decision-making systems when predicting infectious disease outbreaks. Additionally, integrating the IK with other knowledge systems, such as artificial intelligence, can build a more robust knowledge system for malaria outbreaks.

2.3 Fuzzy Cognitive Maps

A fuzzy cognitive map is a knowledge-based recurrent neural network representing and analysing complex systems using fuzzy logic and cognitive mapping [32]. Kosko [33] introduced the FCM as a dynamic and semi-quantitative method for structuring expert knowledge. Its origins can be traced back to cognitive mapping, as Axelrod pioneered in 1976 [34]. FCM, a method based on graph knowledge, functions similarly to traditional cognitive maps. Both consist of concepts and their causal relationships. However, FCM distinguishes itself by representing concepts as fuzzy sets and defining relationships through fuzzy connections [35]. Including fuzzy feedback within FCM enables the extraction and modelling of causal knowledge [36]. By utilizing FCMs, individuals' perceptions can be transformed into conceptual representations and integrated into the system. The FCMs facilitate the creation of a broader perspective by incorporating the collective knowledge and insights of the community [37].

A FCM model is represented as a fuzzy directed graph where the nodes (denoted by C) representing concepts or neurons are interconnected to each other by signed, weighted links representing causal effects [38]. The causal effects are crucial in the systems as they indicate which concept influences the other and to what degree (positive, negative or zero causality). The causal effect is represented as the numeric weight in the range of [–1, 1] and is commonly depicted as an adjacency matrix [38, 39]. On the other hand, each concept is characterised by the fuzzy value P (activation value), which represents the probability of the concept occurrence [32]. The bigger the value of P, the greater its impact on the FCM. The activation value is restricted to P ∈ [0, 1] (Orang et al., 2022). Zero indicates full absence, an increase from zero to 1 indicates an increase in presence, while 1 indicates full presence, as illustrated by Eq. 1 [39].

$$C(p) = \begin{cases} 1, full\_presence & \\ \quad . & \\ \quad . & increasing\_presence \\ \quad . & \\ 0, full\_absence & \end{cases} \tag{1}$$

The value of each concept, C(P), is influenced by the values of the other connected concepts with their corresponding causal weights and their previous value [39]. An initial activation state of a concept is denoted with C0. A new activation vector of concepts is computed at each step t of the simulation by successive multiplications of the state vector by the weight matrix [40], as depicted in Eq. 2 below.

$$C_i^{(t+1)} = f(C_i^t + \sum\nolimits_{\substack{i \neq j \\ j=1}}^{N} C_j^t W_{ij} \tag{2}$$

where C_i^t and C_i^{t+1} are the values of the concept Ci at simulation step t and step t + 1, respectively. C_j^t is the value of the concept j at simulation step t. W_{ij} is the weight of the interconnection from concept Ci to concept *Cj*. The inference procedure calculates new concept values during the simulation and continues until the system reaches either a steady state (equilibrium state), limited cycle or chaotic behaviour [39]. The FCM is said to have converged if it reached equilibrium [39]. On the other hand, function F acts as a threshold, transfer, or activation function to clamp the activation value in the interval [0,1]. The activation functions most extensively used include [38, 39, 41]:

$$\text{bivalent function} : f(x) = \begin{cases} 1, x > 0 \\ 0, x \leq 0 \end{cases} \tag{3}$$

$$\text{saturation function} : f(x) = \begin{cases} 0, & x < 0 \\ x, 0 < x < 1 & \\ 1, & x \geq 1 \end{cases} \tag{4}$$

$$\text{The trivalent function}: f(x) = \begin{cases} -1, & x < 0 \\ 0, & x = 0 \\ 1, & x > 1 \end{cases} \quad (5)$$

$$\text{The hyperbolic function}: f(x) = \frac{e^{2x} - 1}{e^{2x} - 1} \quad (6)$$

$$\text{The sigmoid function}: f(x) = \frac{1}{1 + e^{\lambda(x-h)}} \quad (7)$$

FCMs have been widely employed in diverse domains to construct monitoring and prediction models [32, 37, 42]. Notably, FCMs have demonstrated their efficacy in predicting infectious diseases such as COVID-19 [38] and pulmonary infections [32], as well as forecasting drought occurrences [12, 43]. Moreover, [37] employed FCMs to monitor levels of environmental pollution from the mines. Furthermore, there has been a growing trend in applying FCMs for modelling IK in recent years. Indeed, IK has the potential to tackle challenges such as malaria outbreaks. The primary goal of constructing an FCM model for a problem is to predict the outcome by interacting with relevant concepts.

3 Methodology of Fuzzy Cognitive Map for Prediction of Malaria Outbreak

3.1 Data Collection

A cohort of 134 participants, purposively and snow sampled and possessing indigenous knowledge, participated in questionnaires to identify the indigenous knowledge indicators utilized in predicting malaria outbreaks. The participants hailed from various villages in the Vhembe district of South Africa. Moreover, these participants provided insights into their perceptions regarding the influence of one indicator on another.

3.2 Identification and Analysis of Concepts for Malaria Prediction

The IK indicators for malaria outbreak prediction were restructured to form the FCM concepts. The concepts were classified into Astronomical and meteorological, Behaviours of Birds, Behaviours of Trees/Plants, Insect behaviour, Myth, Religious Beliefs and others and knowledge of the seasons. The interpretation of IK indicators is also based on the year's four seasons of South Africa.

As illustrated in Table 1 below, there were 35 concepts in total: 20, 5, 3, and 7 for summer, autumn, winter, and spring, respectively. The concepts grouped by seasons and labelled from C1 to Cn where n is the total number of concepts in each season.

Table 1. Concepts for malaria prediction according to seasons.

	Concepts			
	Summer	Autumn	Winter	Spring
Astronomical and meteorological	C1: summer floods C2: summer heavy rainfalls C3: Tilted moon C4: Moon surrounded by clouds C5: Sun surrounded by the clouds C6: Clustered stars along the horizon C7: Moon surrounded by a ring of stars	C1: Autumn lots of rainfalls		C1: Spring rains
Behaviours of Birds	C8: Many birds C9: swallows		C1: sight of unusual birds (less/no malaria)	C2: Sight of many birds
Behaviours of Trees/Plants	C10: Black spots on mangos C11: many mangoes/jackals/marula falling from the tree C12: Tree leaves turning yellow (no malaria)		C2: Fig trees not shedding leaves (no/less malaria)	C3: heavy mangos flowering C4: Quinine Tree ("Munadzi") dripping C5: "mofafa grass" having many ticks
Insect behaviour	C13: Ants gathering food C14: the sight of butterflies, crows/millipedes	C2: Ants gathering food/store them underground C3: cattle frequently running with tails raised up	C3: the sight of many insects/locusts (no/less malaria)	C6: Ants gathering food
Animal Behaviour	C15: the sight of many sardines in dams C16: Croaking frogs C17: Cattle running with tails raised up			C7: many cattle Egrets around cattle

(*continued*)

Table 1. (*continued*)

	Concepts			
	Summer	Autumn	Winter	Spring
Myth, Religious Beliefs and others	C18: Severe malaria outbreak after a period of 5 – 7 years C19: Dirty water in containers/small pools	C4: Dirty water in tins/small pools		
Knowledge of Seasons	C20: Summer high temperature	C5: Autumn high temperature		

4 Results

4.1 Representing the Concepts and Finding the Causal Effects of Concepts

FCM served as the instrument for gathering, confirming, and authenticating IK indicators used for malaria outbreak predictions in the Vhembe district. The concepts (IK indicators and malaria incidence) identified during the understanding and analysis of IK indicators for malaria prediction were uniquely structured by their respective position n state vector (C1, C2, …Cn). Each indicator represents a concept or node in an FCM.

The causal effects were represented statistically to determine the weights among the concepts. The participants individually stated their perceptions of the causal effects of IK indicators on malaria outbreak and IK indicators to other IK indicators. Tables 2, 3, 4 and 5 below show the statistics representation of the responses in terms of the percentage, mode and mean for each interacting concept for summer, autumn, winter and spring concepts, respectively. The mode and the mean of the responses under each concept were used to aggregate the participants' perceptions. The concepts were categorised according to the four seasons. The weights between concepts and malaria outbreak were declared as values in a range interval $[-1, 1]$. The following linguistic variables were used to express the causal effect $\{1 \leq$ Strong positive $< 0.5, 0.5 \leq$ Positive $< 0, 0 =$ None, $0 \leq$ negative $< -0.5, -0.5 \leq$ strong negative $< -1\}$.

Table 2. Causal Effects of **IK indicators** (concepts) **to malaria outbreak** in **summer**.

IK indicators to malaria outbreak	Causal Effects for Summer Concepts						
	Strong positive	Positive	None	Negative	Strong negative	mode -1 to 1	Mean -1 to 1
Summer floods	64%	36%				1	0.8
Summer Heavy rainfalls	64%	36%				1	0.8
Summer tilted moon		64%	36%			0.5	0.3
Summer moon surrounded by clouds	36%	64%				0.5	0.7
Summer sun surrounded by the clouds	18%	64%	18%			0.5	0.5
Summer clustered stars along the horizon		64%	36%			0.5	0.3
Summer moon surrounded by a ring of stars		64%	36%			0	0.3
Summer many birds		64%	36%			0.5	0.3
Summer many swallows	9%	73%	18%			0.5	0.5
Black spots on mangos	27	55%	18%			0	0.5
Too many mangoes/jackals/marula falling from the tree	18%	64%	18%			0.5	0.5
Summer yellow tree leaves			36%	64%		-0.5	−0.3
Ants gathering food		45%	55%			0	0.2
The sight of butterflies/crows/millipedes	18%	64%	18%			0.5	0.5
Croaking frogs	9%	64%	27%			0.5	0.4
The sight of many sardines in dams	27%	55%	18%			0.5	0.5
Cattle frequently running with tails raised up		55%	45%			0.5	0.3
Severe malaria outbreak after 5 –7 years		45%	55%			0	0.2
Dirty water in containers/small pools	64%	36%				0.5	0.8
Summer high temperature	36%	55%	9%			0.5	0.6

Table 3. Causal Effects of **IK indicators** (concepts) to **malaria outbreak** in **autumn**.

IK indicators to malaria outbreak	Causal effects in autumn						
	Strong positive	Positive	None (0)	Negative	Strong negative	mode -1 to 1	Mean -1 to 1
Autumn heavy rains	45%	55%				1	0.7
Ants gathering food		45%	55%			0	0.2
Cattle frequently running with tails raised up		45%	55%			0	0.2
Dirty water in containers/small pools	64%	36%				0.5	0.8
Autumn high temperature	36%	55%	9%			0.5	0.6

Table 4. Causal Effects of **IK indicators** (concepts) on **malaria outbreak** in **winter**.

IK indicators to malaria outbreak	Causal effects in winter						
	Strong Positive (1)	Positive (0.5)	none	Negative (−0.5)	Strong negative (−1)	Mode −1 to1	Mean −1 to 1
The sight of unusual birds				100%		−0.5	−0.5
The fig “Muhuyu” trees not shedding leaves				82%	18%	−0.5	−0.6
The sight of many insects/locusts				73%	27%	−0.5	−0.6

4.2 Constructing Adjacency Matrices and Developing a Fuzzy Cognitive Map

The representation of the aggregated responses of participants using the mean over mode depicted a good aggregate of causal effects; hence, the mean aggregate was preferred as the best statistic to represent the causal effects for the concepts. The causal effects of other concepts to each other (IK indicators to other IK indicators except malaria incidences) were created in the same fashion as done above for causal effects of IK indicators to malaria incidences.

Table 5. Causal Effects of **IK indicators** (concepts) on **malaria outbreak** in **spring**.

IK indicators to malaria outbreak	Causal effects in spring						
	Strong Positive (1)	Positive (0.5)	None (0)	Negative (−0.5)	Strong negative (−1)	Mode (−1 to1)	Mean (−1 to 1)
Spring rains	36%	45%	18%			1	0.6
The sight of many birds	9%	55%	36%			0.5	0.3
Heavy mangos flowering		82%	18%			0.5	0.4
Quinine Tree dripping		55%	45%			0.5	0.2
The “mofafa grass” having many ticks	18%	55%	27%			0.5	0.4
Ants gathering food		27%	73%			0	0.1
Many cattle Egrets around cattle	9%	55%	36%			0.5	0.3

The FCM was modelled using a software called FCM Expert [39]. The weighted n x n adjacency matrices, denoted by W, were created to statistically represent the causal effects among the concepts and malaria outbreak distinguished by the four weather seasons. Table 5 above illustrates a 6 X 6 weighted matrix for autumn.

In the weighted matrices, the names of all the concepts were written as row headings and concept symbols like C1, C2, …., Cn., were written as column headings where each cell contains a value, i.e., weight (Wij). The value of Wij indicates how strongly concept Ci (row i) influences concept Cj (column j). The sign of Wij indicates whether the relationship between concepts Ci and Cj is direct or inverse (Hoyos, Aguilar and Toro, 2022). The positive sign (+) was used to indicate a positive causality between concepts, whereas the negative sign (- sign) indicated a negative causality (Napoles et al., 2028). For example, from the matrix representing autumn knowledge (Table 7), w1,6 has a positive value (+0.7), and it, therefore, means the increase in autumn rains (C1) results in an increase in malaria incidences (C6).

Table 6. Summary of mode and mean of concepts (IK indicators) casual effects to malaria for different seasons.

Summer			Autumn			winter			spring		
concept	mode	mean	Concept	mode	mean	Concept	mode	mean	concept	mode	mean
Summer floods	1	0.8	Autumn heavy rains	1	0.7	The sight of unusual birds	−0.5	−0.5	Spring rains	1	0.6
Summer heavy rainfalls	1	0.8	Ants gathering food	0	0.2	The fig "Muhuyu" trees not shedding leaves	−0.5	−0.6	The sight of many birds	0.5	0.3
Summer tilted moon	0.5	0.3	Cattle frequently running with tails raised up	0	0.2	The sight of many insects/locusts	−0.5	−0.6	Heavy mangos flowering	0.5	0.4
Summer moon surrounded by clouds	0.5	0.7	Dirty water in containers/small pools	0.5	0.8				Quinine Tree ("Munadzi") dripping	0.5	0.2
Summer sun surrounded by the clouds	0.5	0.5	Autumn high temperature	0.5	0.6				The "mofafa grass" having many ticks	1	0.4
Summer clustered stars along the horizon	0.5	0.3							Ants gathering food	0	0.1
Summer moon surrounded by a ring of stars	0	0.3							Many cattle Egrets around cattle	0.5	0.3
Summer many birds	0.5	0.3									
Summer many swallows	0.5	0.5									

(*continued*)

Table 6. (*continued*)

Summer			Autumn			winter			spring		
Black spots on mangos	0	0.5									
Too many mangoes/jackals/marula falling from the tree	0.5	0.5									
Summer yellow tree leaves	-0.5	-0.3									
Ants gathering food	0	0.2									
the sight of butterflies/crows/millipedes	0.5	0.5									
Croaking frogs	0.5	0.4									
sight of many sardines in dams	0.5	0.5									
Cattle frequently running with tails raised up	0.5	0.3									
Severe malaria outbreak after 5–7 years	0	0.2									
Dirty water in containers/small pools	0.5	0.8									
Summer high temperature	0.5	0.6									

Table 7. Adjacency matrix for autumn.

Concepts	symbol	C1	C2	C3	C4	C5	C6
Autumn rains	C1	0	0	0	0.8	0	0.7
Ants gathering food	C2	0.3	0	0	0	0	0.2
cattle frequently running with tails raised up	C3	0.3	0	0	0	0	0.2
Dirty water in containers/small pools	C4	0	0	0	0	0	0.8
Autumn high temperature	C5	0	0	0	-0.2	0	0.6
Malaria outbreak (no to low, low to moderate, moderate to high, high to extreme, extremely high)	C6	0	0	0	0	0	0

Table 8. Analysis of the importance of nodes/concepts in the FCM for autumn.

Concepts	Concept type	Indegree	Outdegree	Centrality
Autumn heavy rainfalls	ordinary	0.6	1.5	2.1
Ants gathering food	driver	0	0.5	0.5
Cattle running with their tails raised up	driver	0	0.5	0.5
Dirty water in the containers/small pools	ordinary	0.8	0.8	1.6
Autumn high temperature	driver	0	0.4	
Malaria outbreak (severe, moderate, low, none)	receiver	1.9	0	1.9

On the other hand, W12,21 (–0.3) is a negative value indicating an inverse relationship; an increase in the yellow tree leaves (C12) results in a decrease in malaria incidences (C3). Yellow tree leaves in summer mean drought, hence less malaria incidences. The diagonal of the matrix is zero since it is assumed that the concept does not have a causal effect on itself, and thus, Wii = 0. The concepts with no relationship were also given the value of zero.

From the autumn concepts in Table 1, the relationships were graphically represented as shown in Fig. 3.

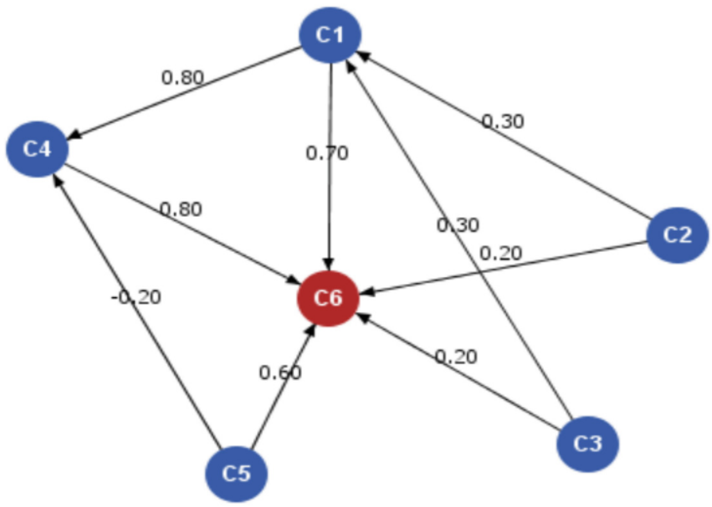

Fig. 3. FCM for autumn (Key: C1 = Autumn heavy rainfalls, C2 = Ants gathering food, C3 = Cattle frequently running with their tails raised up, C4 = Dirty water in the containers/small pools, C5 = Autumn high temperature C6 = Malaria outbreak (none-low, low-moderate, moderate-high, high-extreme).

The FCM indices such as significance of in-degree (sum of weights of the incoming links to a concept), outdegree (sum of weights of outgoing links from a concept) and centrality of the concepts (sum of weights of the outgoing and ingoing links) [44] were calculated using the mental modeler software. Table 6 illustrates the FCM indices for autumn concepts.

The high centrality of the concept indicates that the weights and connections are higher; thus, the concept is more central to the system [40]. Concept centrality emphasizes the importance of the concepts in the FCM [36]. Centrality is computed as the sum of the corresponding indegree and outdegree causal weight [44]. The concepts with high centrality for autumn are heavy rainfalls and dirty water in the containers/small pools. These IK indicators are crucial for malaria outbreak prediction in autumn in Vhembe (Table 7).

5 Applying Malaria Outbreak Prediction FCM for Scenario Analysis

For simulation, the IK experts were asked to report the IK indicators observed in the autumn. The observed IK indicators were captured using a mobile app. The autumn seasonal adjacency matrix was chosen for simulation. In each scenario, there is an initial vector Vi, representing the values of the observed IK indicators in autumn. If a certain IK indicator is not observed, it takes a value of zero in the initial vector; otherwise, it takes a value between 0 and 1. The final vector, Vf, represents the last state achieved through the inference procedure. This research study used the fixed-point attractor of

0.001 (default) as the steady state. This means when the difference between the values of the concepts in the current and previous iteration is 0.001 or less, it indicates that the values of the concepts do not evolve anymore, and therefore, the system has converged.

For a scenario run in autumn, these were the initial values of the vector created as per the following IK indicators observed by the IK experts during this season (heavy autumn rainfalls (0.3), ants gathering food (0.4), cattle frequently running with their tails raised up (0.0), dirty water in the containers/small pools (0.1), autumn high temperature (0.1)):

Vi = {0.3, 0.4, 0.0, 0.1, 0.1,0.0}.

The table and the graph below show the values of concepts at different iterations. The equilibrium was reached at iteration 11 with the final vector having the following values: Vf = {0,499, 0.5, 0.4998,0,4959, 0.4998, 0.4837} (Figs. 4 and 5).

Step	C1	C2	C3	C4	C5	C6
0	0.3	0.4	0.0	0.1	0.1	0.0
1	0.3186	0.4502	0.2689	0.2769	0.31	0.0666
2	0.3702	0.4751	0.3865	0.3406	0.4061	0.1397
3	0.4152	0.4876	0.4435	0.3802	0.4532	0.2099
4	0.4474	0.4938	0.4718	0.4118	0.4766	0.274
5	0.4686	0.4969	0.4859	0.4375	0.4883	0.3299
6	0.4817	0.4984	0.4929	0.4575	0.4942	0.3764
7	0.4896	0.4992	0.4965	0.472	0.4971	0.4131
8	0.4941	0.4996	0.4982	0.4821	0.4985	0.4407
9	0.4967	0.4998	0.4991	0.4889	0.4993	0.4606
10	0.4982	0.4999	0.4996	0.4932	0.4996	0.4744
11	0.499	0.5	0.4998	0.4959	0.4998	0.4837

Fig. 4. Inference process showing the number of iterations.

The output of the simulation run provides the predicted value of the output concept, malaria outbreak. This value is in the closet set of [0,1], representing the grade of the expected malaria outbreak. The output concept, malaria outbreak, is extracted from the final vector from the inference process (Table 8).

Where x is the value of the malaria concept from the final vector, Vf. The output value will be between 0 and 1, where 0 indicates that the malaria concept is not present (0%) and 1 (100%) malaria concept is fully present. From 0 to 1 will indicate various grades of malaria concept presences.

From the results obtained in the simulation, the malaria outbreak concept shows a value of 0.4837 from the final vector, and using the above formula, it gives 0% of malaria outbreak severity. This result was further expressed into a human-readable format using linguistic variables: $0 \leq$ no to low malaria $<20\%$, $20\ \% \leq lowtomoderate < 40\%$, $40 \leq$ moderate to high $< 65\%$, $65\% \leq$ high to extreme malaria $\leq 80\%$, $80\% <$ extremely high malaria. From the above simulation, no to low malaria incidences could be expected in Vhembe based on observed IK indicators in autumn.

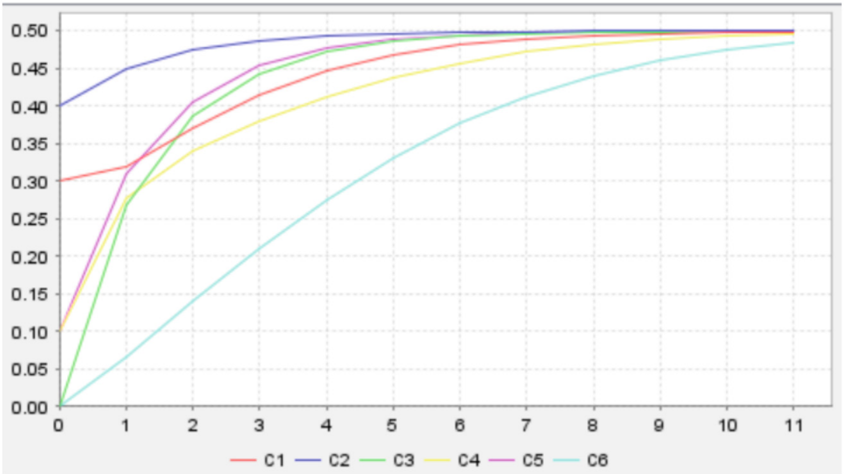

Fig. 5. Inference process for malaria prediction.

6 Conclusion

This research paper uses indigenous knowledge and fuzzy cognitive maps to predict malaria outbreaks. By leveraging the wisdom of local communities and combining it with the power of artificial intelligence through FCMs, the research contributes to developing early warning systems for malaria. The study focuses on the Vhembe district in South Africa and investigates IK indicators used by the community to forecast malaria outbreaks. Through a meticulous data collection, analysis, and modelling process, the paper constructs FCMs that capture the causal relationships between these indicators and malaria outbreaks for different seasons.

The research highlights the significance of community-centered approaches in disease surveillance and prediction. The IK indicators, often rooted in local observations of natural phenomena, offer valuable insights that can enhance the accuracy and relevance of early warning systems. By representing IK indicators as concepts within FCMs, the study establishes a predictive model that integrates traditional knowledge with modern computational methods.

The results of the simulations using FCMs demonstrate how the interconnectedness of these IK indicators can be used to predict the likelihood of malaria outbreaks. The analysis of FCM indices, such as centrality and in/outdegree, emphasizes the importance of specific concepts in influencing the overall system behaviour. This provides a foundation for scenario analysis and prediction under different conditions.

While the paper presents a promising initial stride towards incorporating IK and FCMs for malaria outbreak prediction, it also opens avenues for further research. Using FCMs to model IK can be extended to other regions affected by malaria or other weather-related diseases. Moreover, the paper underscores the potential of combining multiple knowledge systems—traditional and modern—to create robust early warning systems. As the field of AI and disease prediction continues to evolve, embracing local wisdom in tandem with advanced technologies could lead to more effective and contextually relevant disease control and mitigation strategies.

The policymakers should acknowledge and respect indigenous knowledge, fostering collaboration to integrate it into healthcare, particularly in disease-prone regions like malaria. Secondly, investments in research and technology should bridge the gap between indigenous wisdom and modern science, using tools like fuzzy cognitive maps. Furthermore, community engagement in disease surveillance is crucial, empowering locals to contribute knowledge. Lastly, governments and international bodies must allocate resources for initiatives preserving indigenous knowledge through education and cultural exchanges. In essence, the policy would harmonize indigenous knowledge with modern science, improving disease response and preserving cultural heritage.

This work contributes towards building empirical evidence on malaria prediction in Africa domain and broadening the previous research on malaria prediction. These contributions are in support of the efforts to respond to malaria and other infectious diseases under the current global changes.

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