An Intelligent Prediction Tool for Infectious Diseases' Outbreaks Using Machine Learning, Climate Data and Indigenous Knowledge

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Abstract. Substantial evidence suggests that climate change significantly contributes to the global rise in infectious disease outbreaks. Advances in Artificial Intelligence (AI) and big climate data have enhanced the accuracy of medical and climate analysis, supporting accurate prediction of climate-related diseases. Conversely, Indigenous Knowledge (IK) has proven its worth in strengthening community resilience to the effects of climate change. When integrated with AI and climate data, IK has the potential to contribute to solutions for combating outbreaks of infectious diseases. Even though AI has already been conjoined with IK to tackle one of the complex problems brought by climate change, drought, this amalgamation has not been explored in predicting infectious diseases. Consequently, this paper proposes a model that integrates IK and machine learning to predict the outbreak of infectious diseases using climate data and malaria historical outbreaks. The resulting model is evaluated using an early warning system prototype to equip key stakeholders with a decision support tool. Implemented using data from Vhembe District in South Africa, the study demonstrates that this approach offers high predictive accuracy (up to 93%) and is culturally relevant, illustrating how coupling IK with modern science can lead to relevant and effective prediction systems for the local people that such systems are intended to serve.

Keywords: Infectious disease prediction, Machine learning, Climate change, Indigenous Knowledge (IK), Early warning system, Climate data.

1. Introduction

The increasing incidences of infectious diseases like malaria, attributed to climate change, pose a major challenge in regions like Sub-Saharan Africa (SSA), where surveillance systems are limited [1]. Predicting infectious disease outbreaks is inherently complex, especially when incorporating climate data due to the dynamic nature of climatic systems [2]. Most existing tools follow a modern scientific approach, focusing on broader scales while neglecting local coping mechanisms and other

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knowledge systems like indigenous knowledge systems (IKSs), which have shown resilience to climate-related shocks [2], [3].

This study proposes an intelligent early warning system (EWS) that integrates machine learning (ML), climate variables, hydrological drought indices, and indigenous knowledge (IK) to predict infectious disease outbreaks. It uses malaria as a representative case. Malaria remains a leading cause of morbidity and mortality in SSA [1] , highlighting the need for predictive tools that are both scientifically robust and contextually relevant. The study advances conventional EWS approaches by incorporating IK as a complementary predictive component alongside ML-based climate models and by introducing hydrological drought indices as indicators of vector conduciveness. Through this integration, the proposed framework extends existing EWS architectures beyond system implementation to a community-centred prediction paradigm. Given technological and literacy constraints in many rural SSA settings [4], bottom-up design is adopted to enhance relevance, interpretability, and uptake of outbreak alerts. Conceptually, the framework positions IK as a localized, context-specific input that augments ML-based predictions, creating a synergistic model in which scientific and IK jointly improve outbreak prediction accuracy and promote community adoption of alerts.

2. Literature review

2.1 Climate Data and AI in Infectious Disease Prediction

Advancements in Information and Communication Technology (ICT) and AI have enhanced the prediction of climate-sensitive infectious diseases [5]. ICT facilitates timely data collection, storage, processing and dissemination, enabling proactive outbreak responses [6], [7]. AI techniques, including ML algorithms, can successfully model climate-sensitive diseases, identify risk factors and generate alerts [8].

The integration of climate data, such as long-term rainfall records, temperature and humidity trends provides critical environmental insights for malaria prediction [9]. Despite their proven success in forecasting droughts events, hydrological drought indices such as the Available Water Resource Index (AWRI) and the Effective Drought Index (EDI) remain underexplored in malaria prediction [10]. AWRI and EDI quantify water availability and drought intensity [11], both of which are linked to malaria vector breeding [10]. Incorporating such indices into predictive models could improve EWSs. On the other hand, cloud platforms and distributed computing frameworks enable real-time processing of large climate datasets for predictive modelling [12]. The combination of these computational tools with predictive algorithms forms the basis of climate-sensitive effective EWSs.

2.2 Indigenous Knowledge in Infectious Disease Outbreak Prediction

IK encompasses informal and unique knowledge systems acquired over time by a group of people indigenous to a particular geographic area [13]. Local communities use IK to interpret environmental indicators such as animal and plants behavior, to guide survival and decision-making in response to environmental changes [14], [15]. Despite criticisms regarding its lack of precision [16], several researchers maintain that IK is effective to a reasonable extent [14], [17].

While many studies have focused on using IK to predict climatic events like droughts and rainfall [17], [18], only a few have explored its use in disease prediction [19]. In Zimbabwe, for instance, communities linked rainfall patterns with malaria outbreaks, using indicators such as plant phenology and animal behavior to predict the occurrence and intensity of malaria [19]. However, since these observations are mostly informal and individually interpreted, they remain unintegrated into formal health systems, limiting their utility [16]. Despite climate change impacting the reliability of some indicators, the continued use of IK for rainfall predictions [18], [20] suggests that IK still holds predictive value.

The comparison and integration of IK with modern science for prediction purposes highlight strengths and limitations of each [21]. Despite the challenges posed by methodological differences, such as subjective versus objective reasoning and undocumented versus evidence-based approaches, these knowledge systems can complement each other [15]. As climate change increasingly threatens public health, integrating IK and modern science remains an underexplored yet promising frontier for building robust and culturally relevant disease EWSs.

2.3 Early Warning Systems

Globally, EWSs monitor environmental degradation and predict hazards, aiming to reduce their impacts [22]. EWSs comprise four components: risk knowledge, monitoring and prediction, communication, and response [23]. While many EWSs have been developed for infectious diseases such as dengue and malaria [24], most rely solely on modern science and rarely reflect the African context [25], thereby overlooking the value of IKSs. In Africa, IKS-based EWSs have mainly focused on agricultural rainfall and drought prediction [18], [26], with only one known example for infectious diseases [27]. Although effective, it lacked integration with modern science, suggesting combining both approaches could produce more robust systems. People-centred EWSs that engage local communities enhance effectiveness, sustainability, and ownership [28].

Based on the gap highlighted in the literature review, this research study aims to develop an intelligent EWS for infectious disease outbreaks using selected IK, climate data and historical outbreaks of selected infectious diseases in Southern Africa.

1. To guide this study, the following research objectives were formulated
2. To analyse climatic variations and their effects on outbreaks of infectious diseases.

3. To design a framework for an infectious disease early warning system that incorporates machine learning prediction algorithms that model correlations between the selected infectious disease, indigenous knowledge and climatic variations.

To build, test and evaluate the effectiveness of a system prototype that implements the infectious disease early warning system for malaria outbreaks in Limpopo province of South Africa.

3. Methods

3.1 Research Approaches

This study employed a mixed methods approach to capitalise on the complementary strengths of using qualitative and quantitative data [29]. A case study of malaria outbreaks in Vhembe district in Limpopo province in South Africa was selected based on the pronounced incidences of malaria in this district and data availability and reliability.

The following research designs were applied 1) An experimental design was used to assess the effectiveness of supervised ML algorithms in mapping climate variations to malaria outbreaks. It also served to evaluate the suitability of fuzzy logic in capturing and representing the holistic nature of IK for malaria outbreak prediction. 2) A case study design was used to evaluate the malaria outbreak EWS (MOEWS) prototype. 3) A framework development approach was employed to build the MOEWS framework. 4) A prototype was used to develop the various MOEWS sub-systems.

Data collection. This research study used heterogeneous data from three distinct domains. 1) Unstructured indigenous knowledge indicators (IKIs) for malaria outbreaks were collected from the local people in Vhembe District. 2) structured historical weather data from South African Weather Service (SAWS) and 3) structured historical malaria incidences from the Limpopo Department of Health through SAWS. This study adhered to institutional research ethics and data governance requirements for secondary and primary data collection. Weather and malaria data from SAWS was collected in accordance with formal ethical procedures. Malaria records were anonymised ensuring that no personally identifiable information was accessed. IK data was collected through ethically approved, community-engaged processes and informed participation. All datasets were securely stored and used exclusively for research purposes in line with data protection and confidentiality principles. The data was collected in two stages.

First Phase. In the first phase, the data was collected to create predictive models for malaria outbreaks. Monthly historical weather data and malaria incidences were secondary data from SAWS and the Limpopo Department of Health, respectively, as stated above. These datasets were used to train and test machine learning models for monthly malaria outbreak predictions. The weather data included monthly average precipitation, humidity, and temperature for a period of 21 years (1998 to 2018) from Vhembe District. These variables were selected due to their significant impact on mosquito life cycles and malaria transmission dynamics, making them essential for accurate malaria outbreak predictions [24], [30]. Monthly drought indices, AWRI and EDI, were calculated from precipitation. The use of drought indices introduces a novel perspective in malaria outbreak prediction. On the other hand, malaria data comprised monthly malaria incidences recorded in Vhembe District from 1998 to 2018.

On the other hand, IKIs that participants in Vhembe use to predict malaria outbreaks were collected between October 1, 2020, and July 30, 2021, using a semi-structured questionnaire, which yielded 146 responses. The aim was to assess participants' use of IK, their confidence in the reliability of IKIs, and the feasibility and suitability of a mobile phone–based intelligent tool for malaria prediction in the Vhembe District. Subsequently, the IKIs for malaria outbreaks prediction in Vhembe were collected, documented and stored in a database to build a predictive model.

Second phase. The second phase of the data collection was done from April, May and June 2023 to evaluate MOEWS in Vhembe District. To evaluate the IK predictive model, participants from Vhembe who reflected rich knowledge and use of IK in the first data collection phase were tasked with reporting observed IKIs. The observed IKIs were collected in real time using a mobile application and stored on a cloud platform, facilitating near real-time analysis. For evaluating the ML predictive model of MOEWS, monthly malaria incidences were sourced from the Limpopo Department of Health, while weather parameters (precipitation, humidity and temperature) were retrieved from the online published weather reports and thereafter, AWRI and EDI were computed.

Data Analysis. IK data collected using a questionnaire was analysed using SPSS [31]. Results indicate that the participants from the Vhembe district possessed a rich reservoir of IK for general use and infectious disease prediction (including malaria). Furthermore, they expressed high confidence in the reliability of using IK for both general applications and infectious disease forecasting. The results also reflect high mobile phone penetration among the Vhembe community, encouraging the exploration of mobile phones to collect IKIs and disseminate malaria outbreak alerts.

These IKIs were processed and used to develop FCM models for malaria prediction for the four seasons of the year [32]. The findings from the IKSs analysis highlight that in Autumn, heavy rainfalls and dirty water in containers or small pools are major predictors of malaria outbreaks. In contrast, summer heavy rainfalls, dirty water in containers, and summer temperature are key indicators in summer. On the other hand, the main predictors of malaria in winter are fig Muhuyu trees not shedding leaves and the sight of insects or locusts, while spring rainfalls and 'Mofafa' grass having many ticks were found to be important for malaria prediction in spring [32].

Conversely, weather data (precipitation, temperature, humidity and the hydrological drought indices) was analysed independently of the IK data using the Python programming language and ML in Jupyter Notebook. Preliminary analysis confirmed that Vhembe is generally characterised by wet and warm conditions, as evidenced by rainfall, temperature, AWRI, and EDI, factors conducive to mosquito proliferation [33].

Data pre-processing was essential for integrating heterogeneous sources and ensuring model readiness. This pre-processing involved aligning time series, interpolating missing values, data normalisation and handling outliers and class imbalances. To identify the most relevant predictors of malaria outbreaks, mutual information (MI) analysis was conducted to assess the relationship between malaria incidence and independent variables; weather parameters and drought indices. All variables showed strong associations with malaria incidences. AWRI showed the highest MI, highlighting its potential as a measure of vector conduciveness for malaria transmission [10]. However, optimal MI was achieved at different time lags for the different variables. For AWRI, EDI, and temperature, the highest MI scores were observed at a one-month lag, while rainfall and humidity had the highest MI at a two-month lag.

The ML models, regression and classification, were trained and tested using the pre-processed dataset, which consisted of 21 years of historical weather, malaria data and drought indices. Drought indices derived from daily precipitation data, added a novel dimension to the modelling process. While regression models underperformed, classification algorithms such as MultiLayer Perceptron (MLP), Support Vector Machine, and K-Nearest Neighbour achieved high performance. MLP, as seen in Fig. 1, outperformed the models, achieving an F1 score of 96%, precision of 95%, recall of 100%, and accuracy of 93%, and was, therefore, selected for deployment. Model performance was statistically validated using an 80/20 train–test split implemented in Python (Jupyter Notebook). Performance metrics, accuracy, recall, precision and F1-score, were computed from the test-set confusion matrix for a robust and unbiased evaluation.

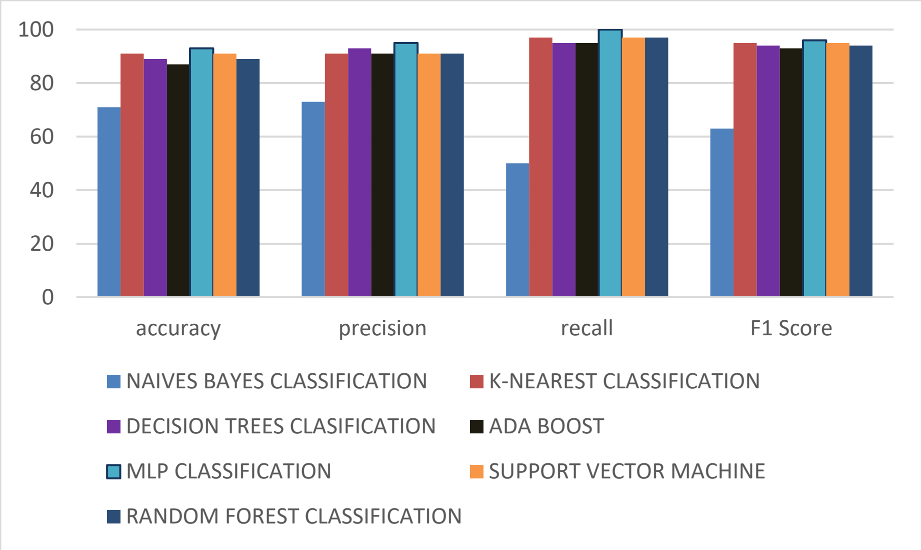

Fig.1. *Performance of the classification models.*

3.2 MOEWS Framework Development

This research study was guided by the Malaria Outbreak EWS (MOEWS) framework, depicted in Fig. 2, which is based on key elements of EWS [23]. MOEWS consists of (1) malaria outbreak risk knowledge, (2) malaria outbreak prediction, and (3) malaria outbreak communication and dissemination. It consists of multiple sub-systems, which are integrated to form a three-layer EWS.

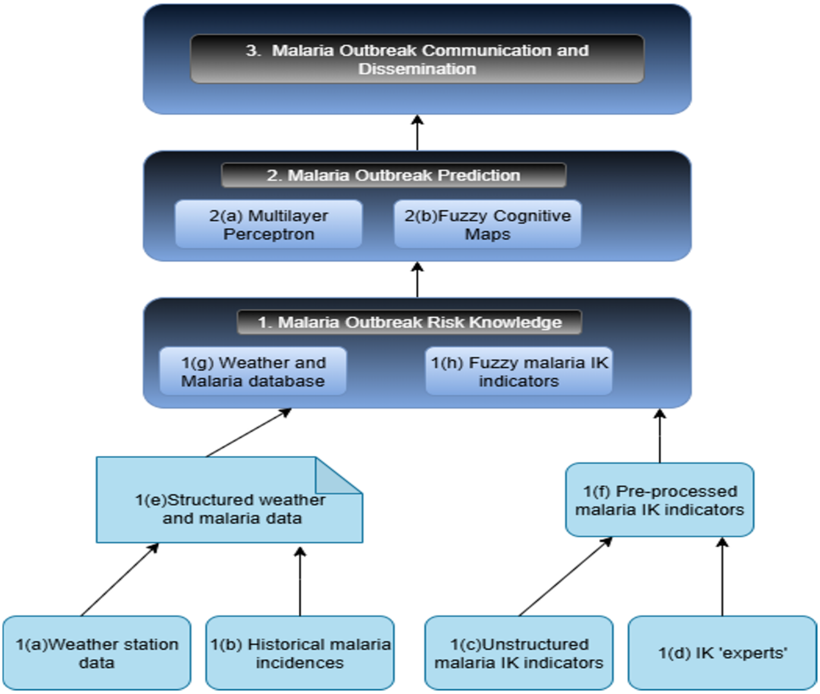

Fig.2. *MOEWS framework.*

The first MOEWS component, Malaria Outbreak Risk Knowledge, focuses on gathering malaria outbreak risk information. 1(a) Weather parameters (precipitation, temperature, humidity) and hydrological drought indices (AWRI and EDI) are computed, pre-processed, and stored as structured data. 1(b) Historical malaria data are similarly pre-processed and stored in the structured database. 1(c) Unstructured IKIs collected during the initial data collection phase are verified and stored in a dedicated repository. 1(d) Real-time IKIs and extreme weather events (e.g., floods) are captured via a mobile application, pre-processed, and stored. 1(e) The structured database stores all structured datasets, while 1(f) fuzzy representations store verified IKIs. The second MOEWS component, Malaria Outbreak Prediction, forecasts outbreaks using two approaches: 2(a) a modern science approach applying an ML model (MLP) to structured dataset, and 2(b) FCMs based on pre-processed, real-time IKIs. All predictions are stored in a central database. **Malaria Outbreaks Communication and Dissemination, which is the** third and final component, disseminates malaria outbreak alerts via a mobile app, web portal, and social media.

4. System Prototype Development and Evaluation

MOEWS comprises several integrated components designed to predict malaria outbreaks. These components include: (1) a **fuzzy cognitive system** for forecasting malaria outbreaks using IKIs; (2) a **MLP model** that utilises weather and drought indices for prediction; (3) a **mobile application** for the input and output of IKIs, extreme weather events, and dissemination of malaria forecast alerts; (4) a **web portal** providing forecasts and system information; and (5) a **Facebook** page for alerts, information sharing, and engagement. In line with MOEWS framework, these modules were implemented across three layers.

4.1 MOEWS layer 1: Malaria Outbreak Risk Knowledge

The data input for malaria outbreak prediction includes observed IKIs, weather parameters (precipitation, humidity, and temperature), and drought indices. Weather data for the Vhembe District is obtained from published reports, as weather forecasting is beyond the scope of this study. Drought indices are subsequently computed from precipitation data, and all data is manually captured in the system database.

Observed malaria IKIs are collected via a mobile application, enabling near real-time reporting by participants. Participants serve as a link between local communities and system administrators. The application includes registration and login features to ensure that only users with IK submit observations, thereby maintaining data validity. Fig. 3 presents the mobile application interface used to report IKIs and extreme weather events.

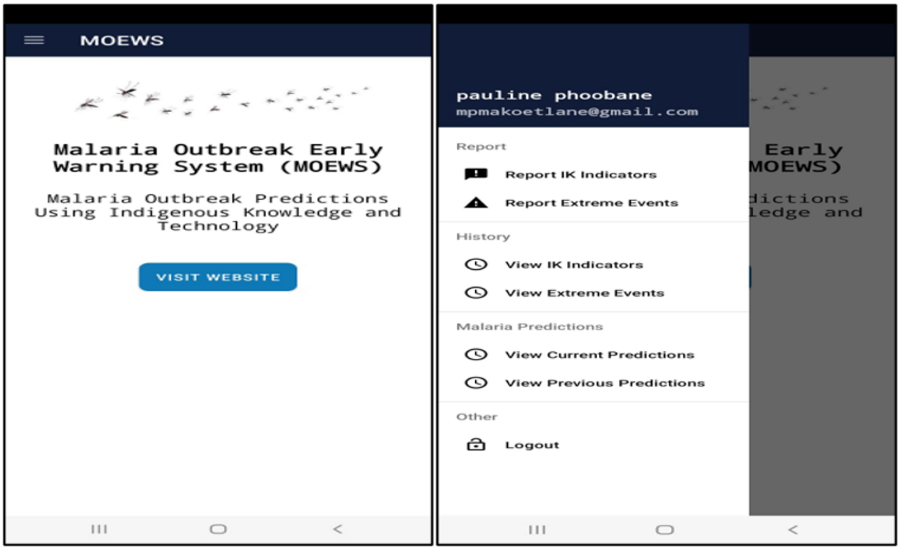

Fig. 3. The mobile application interface for capturing the observed malaria IK indicators.

Since the IKIs are grouped by the four seasons of the year, summer, autumn, winter and spring (see Fig. 4), the participant selects the season for which to report the observed IKIs.

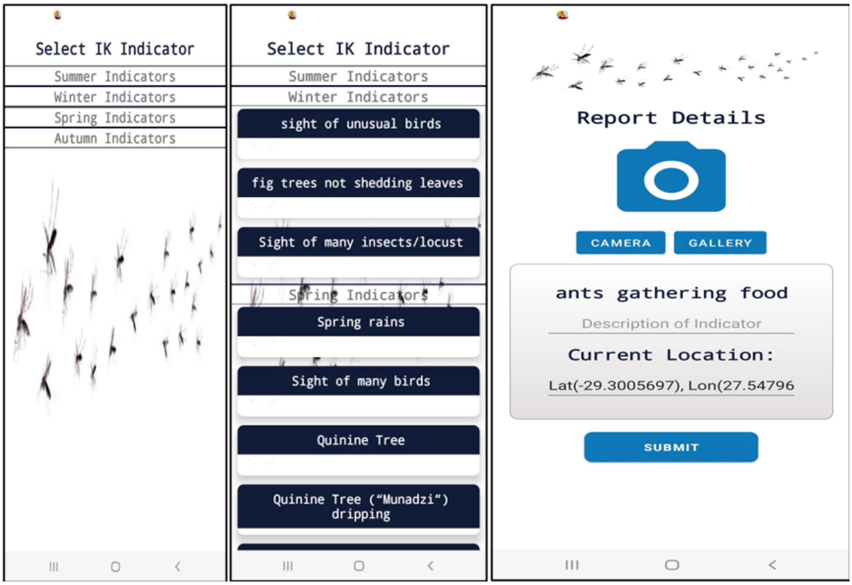

Fig. 4. *Mobile app screens showing preloaded IK indicators grouped by seasons.*

All known IKIs identified during the first data collection phase are preloaded into the database to ensure consistency and minimise errors. For each observation, participants upload an image and provide a brief description while the app automatically captures participants' global position system (GPS) coordinates. To address limited internet connectivity, Firebase Realtime Database supports offline data storage, automatically synchronising observations and extreme weather events once connectivity is restored. Given the link between weather variability and malaria outbreaks, the application also allows reporting of extreme events in Vhembe. All reported data are stored in the Firebase database for use in the second-layer prediction component. While only authorised participants can submit reports, all registered users can view the reported malaria IKIs and extreme weather events.

4.2 MOEWS layer 2: Malaria Prediction

The collected data, stored in the database, is used in two ways. 1) Weather data and drought indices are used to predict monthly malaria incidences using the MLP, which was identified as the best-performing classification model and selected for the prototype. One-month lags are applied to AWRI, EDI, and temperature, and two-month lags to humidity and precipitation. 2) The FCM system predicts malaria outbreaks using observed IKIs, with predictions made per season [31]. Predictions from both subsystems are stored in the database for dissemination.

4.3 MOEWS layer 3: Malaria Forecast Communication and Dissemination

Malaria outbreak predictions from MOEWS are disseminated through three channels: (1) a mobile app for Android that sends alerts and updates on extreme weather to registered users, (2) a web portal presenting alerts and contributing weather and IKIs in text and graphical formats, and (3) a Facebook page to extend reach, provide real-time updates, and enable community engagement.

4.4 System Evaluation

MOEWS was tested with respect to its input, processing and output components. The real time data was used for evaluating the system. For input, observed IKIs were reported via the mobile application in the near real time, while weather data were entered manually. Fig. 5 below shows some of the reported IKIs.

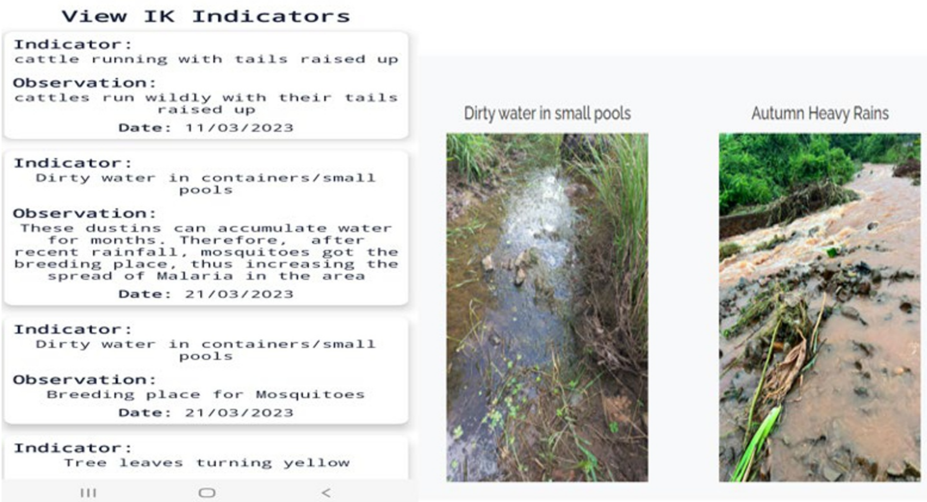

Fig. 5. Examples of real-time textual and graphical IK indicators reported by participants.

MOEWS's predictive performance was evaluated for autumn 2023 using both its IK–based and weather-based components, and the predictions are shown in Fig. 6.

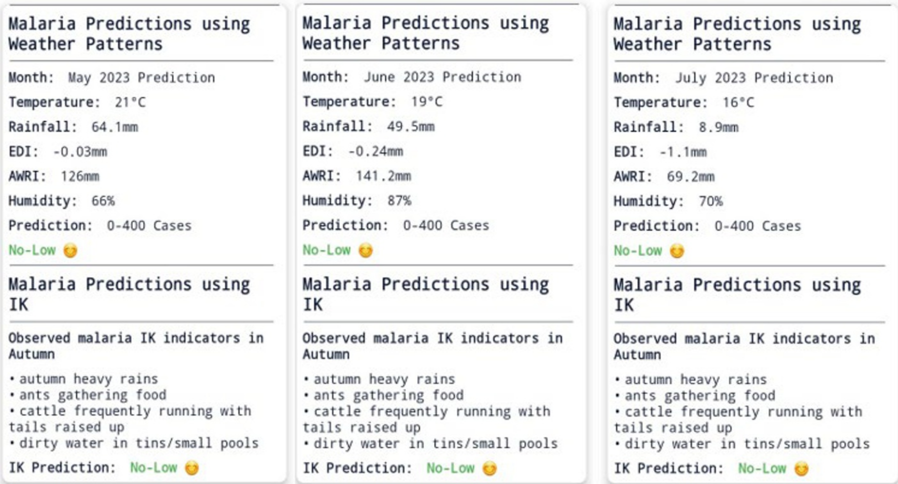

Fig.6*. MOEWS weather-based and IK-based predictions for Autumn 2023.*

The FCM predicted 0–600 malaria cases for the autumn season, while the MLP forecasted Category 1 cases (0–400 malaria cased) for each month, May, June and July 2023. Comparison with Limpopo Department of Health data (95, 7, and 9 cases), MOEWS showed 100% prediction accuracy for both models, based on alignment with observed malaria categories rather than exact counts. Since predictions fell entirely within observed ranges, both models are considered fully accurate in this categorical, range-based evaluation.

The system output was evaluated using malaria forecasts from both IK-based and scientific approaches, with predictions accessible via the mobile app, web portal, and Facebook. Table 1 summarises user feedback on MOEWS, rated from 1 (strongly disagree) to 5 (strongly agree).

Table *1*. The importance of MOEWS according to users.

	1	2	3	4	5
MOEWS app interface is easy to use.	0%	0%	0%	10%	90%
MOEWS app's menus and navigation are clear and intuitive.	0%	0%	0%	15%	85%
I can easily access MOEWS on my smart phone.	0%	0%	0%	5%	95%
The information is presented in a language and format I understand.	0%	5%	30%	50%	15%
I receive alerts through channels that are accessible to me	0%	5%	5%	45%	45%
The alerts are timely and relevant for malaria preparedness.	0%	0%	0%	10%	90%
I trust the alerts provided by MOEWS.	0%	0%	0%	10%	90%
Overall, I am satisfied with the MOEWS system.	0%	0%	0%	10%	90%

Survey results show high satisfaction with MOEWS' relevance, usability, timeliness, trust, and performance, but lower scores for language and format.

4.5 The Limitations of the Study

This study has several limitations. While MOEWS uses extensive meteorological data, adding heterogeneous factors like satellite indicators could improve predictive robustness and generalisability. The dissemination component is limited by the lack of local language support, voice interfaces, and alternative channels. Moreover, integration between IK and ML predictions remains limited, requiring deeper reconciliation to enhance predictive consistency and community relevance.

5. Discussion

The study achieved its objectives through a threefold approach. First, climatic variations were analysed using Mutual Information (MI), revealing strong associations between malaria outbreaks and independent variables: AWRI, EDI, rainfall, humidity, and temperature. Optimal ML scores occurred at different time lags, with AWRI, EDI, and temperature peaking at one month, and rainfall and humidity at two months, confirming AWRI as the strongest indicator of vector conduciveness. While our findings on precipitation, humidity, and temperature align with previous research [34], [35], the identification of drought indices as predictors of malaria contributes novel insights to the prediction of climate-sensitive infectious diseases. Second, this study presents a MOEWS framework that uniquely integrates IK with climatic data and ML, representing a new and significant advancement over conventional malaria prediction approaches. The dual use of FCMs for IKIs and an MLP for climatic data captured both cultural and environmental predictors. Third, the MOEWS prototype was built, tested, and evaluated in Vhembe District, demonstrating robust performance with 93% prediction accuracy for the MLP during testing and 100% seasonal prediction accuracy for the IK-based model and MLP during evaluation. Real-time evaluation in 2023 confirmed alignment between predictions and actual malaria cases, while user feedback highlighted high trust, relevance, and usability, with recommendations for improved communication formats and alert channels.

This study advances malaria EWS research by moving beyond single-source, climate-driven prediction models toward an integrated AI–IK framework. Previous malaria EWSs have largely relied on statistical or ML-based methods to determine relationships between weather parameters and malaria incidences or broader climate-driven frameworks [36], [37], without incorporation of local contextual knowledge. The identification of AWRI and EDI as leading predictors represents methodological advancement in malaria research. These drought indices more effectively capture prolonged moisture stress and vector habitat suitability than rainfall alone, which has shown inconsistent associations with malaria risk in semi-arid settings [38]. While some ML-based malaria models report accuracies exceeding 99% [39], [40] the proposed MOEWS achieved robust predictive performance (93% testing accuracy) while enhancing interpretability and contextual relevance through the formal integration of IK. Unlike prior frameworks that treat IK as anecdotal [41], this study integrates IK as a parallel predictive subsystem, capturing socio-ecological signals beyond climatic data. Real-time evaluation and high user trust further distinguish MOEWS from earlier conceptual or retrospective EWSs, advancing malaria EWSs beyond climate-only and purely data-driven approaches.

6. Conclusion

This study developed a hybrid Malaria Outbreak Early Warning System (MOEWS) that uses IK, ML, and climate data to provide culturally relevant and context-aware predictions of malaria in Vhembe district in South Africa. The novelty lies in using IK, drought indices (AWRI and EDI) and modern prediction algorithms, enabling improved outbreak forecasting. Implemented through a mobile app and web portal, MOEWS facilitates real-time data collection, prediction, and dissemination of alerts, thereby enhancing preparedness and empowering climate-vulnerable communities to take proactive measures. Although focused on malaria in Vhembe, the framework can generalize to other climate-sensitive diseases and regions by retraining models with local data and using relevant IKIs. Integrating IK in malaria EWSs can inform policy-making by guiding timely, targeted, and culturally appropriate malaria interventions, improving resource allocation and strategic planning.

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Disclosure of Interests. The authors have no competing interests.

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