

Ubuntu Flood AI: A Community-Centered Framework for Integrating Traditional Knowledge and Machine Learning in Flood Early Warning Systems

Sintayehu Adefires Abebe¹, Tade Mule Asrade¹

¹Hydraulic and Water Resources Engineering Department, Debre Markos University, Ethiopia,
sintayehu_adefires@dmu.edu.et, tadie_muluie@dmu.edu.et

Corresponding Author: sintayehu_adefires@dmu.edu.et

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Abstract

Flood early warning systems (EWS) in data-scarce regions like Ethiopia often face significant challenges, including limited sensor coverage, model transferability issues, and low community trust. This paper presents UbuntuFlood AI, a novel, integrative flood monitoring and prediction framework designed for the Ribb River watershed in the Amhara Region. The system addresses these challenges by fusing multi-source satellite data (water indices, precipitation) with locallysourced Traditional Knowledge (TK), including seasonal calendars, animal behavior indicators, and river observation protocols. UbuntuFlood AI features a modular software architecture built with Streamlit, which includes a data processing engine, a machine learning-based flood predictor, and a TK integration module. The model calculates a dynamic, weighted flood risk score by combining real-time water and vegetation indices such as the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Vegetation Index (NDVI) values, rainfall patterns, seasonal baselines, and community-based assessments. A detailed case study of the July 2025 flood event demonstrates the system's capability to provide community alerts. By embedding cultural context and community participation into its core, UbuntuFlood AI enhances not only predictive accuracy but also fosters local ownership, trust, and resilience, offering a scalable and sustainable model for communitycentered disaster risk reduction.

Keywords: *Flood Early Warning, Traditional Knowledge, Machine Learning, Data Integration*

Introduction

The Challenge of Flood Forecasting in Data-Scarce Regions

Floods are among the most devastating and recurrent natural hazards, with impacts projected to intensify under climate change (IPCC, 2023). In the Global South, and particularly in Ethiopia, communities are highly vulnerable due to a confluence of factors: reliance on rain-fed agriculture, dense settlement in fertile floodplains, and limited resources for large-scale hydrological infrastructure and monitoring (Abeje et al., 2019; Bedo et al., 2024). Conventional early warning systems (EWS) in these regions often rely on sparse ground-based sensor networks or global satellite models that may lack the spatial resolution or local context necessary for timely and actionable community-level warnings (Alfieri et al., 2018). This gap in warning dissemination and community response remains a critical failure point.

Furthermore, purely technocratic solutions often suffer from low community trust and adoption. Warnings that are not perceived as culturally relevant or understandable are frequently ignored (Ding, 2020; Ogie et al., 2018). This highlights the need for a paradigm shift towards more inclusive and participatory EWS.

The Untapped Potential of Traditional Knowledge

For generations, communities in watersheds like the Ribb have developed sophisticated, placebased knowledge systems for predicting and responding to environmental changes. This Traditional Knowledge (TK) encompasses observations of animal behavior, changes in river color and sound, plant phenology, and intricate seasonal calendars (e.g., Kiremt, Belg, Bega). While empirically robust and culturally embedded, this knowledge is often oral, localized, and vulnerable to being lost, making it difficult to integrate with modern scientific approaches (Berkes, 2018). However, the integration of TK with scientific data can lead to more holistic, accurate, and trusted environmental monitoring systems (Johnson et al., 2016).

The UbuntuFlood AI Approach

This paper introduces UbuntuFlood AI, a conceptual and software framework named after the African philosophy of "Ubuntu" ("I am because we are"), which emphasizes interconnectedness and community. The system is designed to bridge the gap between modern geospatial data science and community-based knowledge. Its primary innovations are:

- A flexible, watershed-specific configuration that allows the model to be adapted to different geographical and cultural contexts.
- A dynamic risk algorithm that quantitatively integrates satellite-derived indices such as Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Vegetation Index (NDVI), rainfall data, and TK indicators into a single, interpretable flood risk score.
- A community-centered dashboard that presents risk information in both scientific and culturally relevant terms (including local languages), facilitating two-way communication and community reporting.

In this paper, we present the system's architecture, the methodology for data integration and risk calculation, and a validation case study tailored to the Ribb watershed, Ethiopia.

System Overview and Architecture

The UbuntuFlood AI system is implemented as a modular Python application, facilitating separation of concerns, maintainability, and adaptability to other watersheds. The overall system architecture is depicted in Fig. 1.

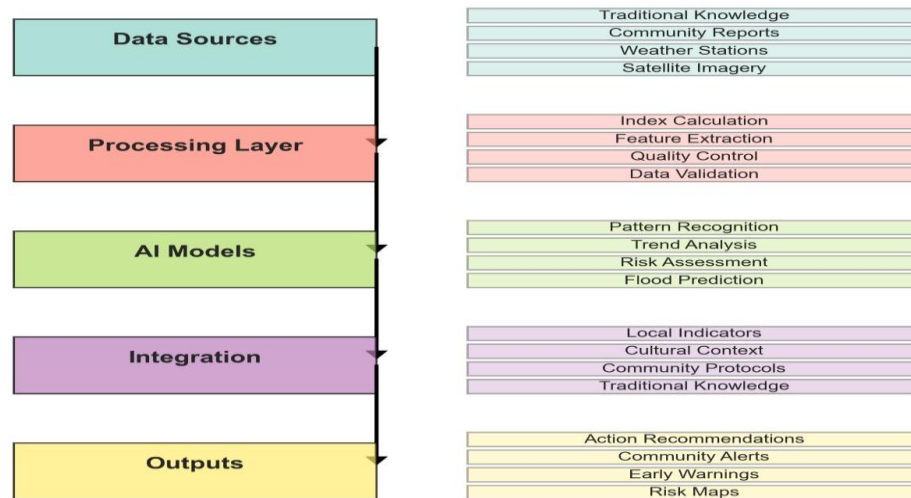


Fig. 1: UbuntuFlood AI System Architecture.

The diagram illustrates the end-to-end system architecture of the UbuntuFlood AI framework, which is structured as a sequential, five-layer pipeline. The workflow originates from diverse data sources, including satellite imagery, weather stations, community reports, and traditional knowledge. This raw data flows into

a processing layer responsible for data validation, quality control, feature extraction, and index calculation. The processed features then feed into the AI models layer, which performs flood prediction, risk assessment, trend analysis, and pattern recognition. A dedicated integration layer is a core innovation, where the AI outputs are synthesized with local indicators, cultural context, and community protocols. Finally, the outputs layer delivers actionable intelligence to end-users in the form of early warnings, community alerts, and specific action recommendations.

The architecture underscores the fundamental contribution of this work: the systematic and structural integration of community-based knowledge with modern technological data streams. Unlike conventional systems that treat traditional knowledge as an ancillary input, this model features a dedicated integration layer that actively fuses algorithmic predictions with cultural context and local protocols. This design ensures that the system's outputs are not only scientifically rigorous but also culturally relevant and immediately actionable for the communities at risk. The modular, sequential flow from data to decisions creates a transparent and adaptable framework, demonstrating a scalable blueprint for building equitable, community-centered early warning systems that bridge the gap between satellite technology and ground-level wisdom.

Core Modules

The system is built around four core Python modules that interact to produce actionable flood insights and recommendations:

1. *Configuration Manager (config.py)*: This central module stores all watershed-specific parameters, including geographic coordinates, seasonal calendars, risk thresholds, and file paths for data sources. It allows the entire system to be reconfigured for a new watershed without altering the core logic.
2. *Data Processor (data_processing.py)*: This module is responsible for ingesting, validating, and standardizing all input data. It handles reading comma-separated values (CSV) files for water indices and rainfall, JavaScript Object Notation (JSON) for TK, and GeoJSON for watershed boundaries. It includes methods for handling missing data and calculating preliminary metrics, such as trends and water risk.
3. *Flood Predictor (ml_models.py)*: This module contains the core risk calculation algorithm. It uses the Data Processor module to access real-time data and generates a 7-day flood risk forecast using the Random Forest algorithm. It also synthesizes various risk factors into a final score and classification (Low, Moderate, High, Severe).
4. *TK Integrator (traditional_knowledge.py)*: This module manages the TK database, interprets modern data through a TK lens (e.g., providing interpretations of NDWI values), and combines modern and traditional risk assessments using a configurable weight-based approach.

Figure 2 shows the relative utilization of different data sources and a typical processing pipeline featuring the time required for each stage in the processing pipeline, from data collection to risk prediction.

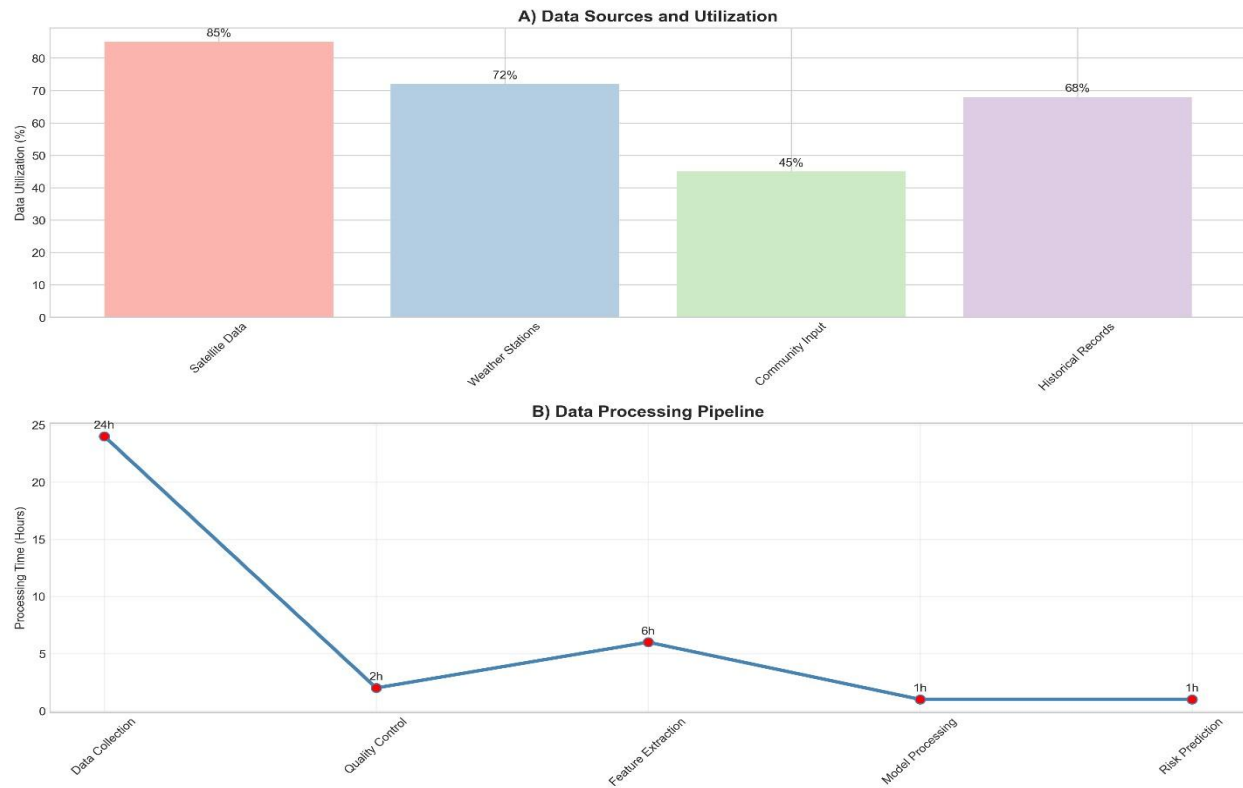


Fig. 2: Data flow and processing pipeline.

The UbuntuFlood AI system employs a multi-source data integration framework where satellite imagery constitutes the primary data source (85% utilization), complemented by weather station records (72%), historical data (68%), and community-based inputs (45%), reflecting both data availability and relative reliability weights in the predictive model. The system utilizes a historical flood events database containing dated flood occurrences, intensity metrics, and impact assessments, which serves as critical ground truth for both training the machine learning model and validating prediction accuracy against known past events. The operational pipeline processes data through sequential stages with characteristic time requirements: satellite data collection (24 hours) constitutes the longest phase, followed by quality control (2 hours) and feature extraction (6 hours), while model execution and risk prediction each require approximately 1 hour, resulting in a total processing cycle of approximately 34 hours from data acquisition to actionable flood forecasts.

The Streamlit Dashboard (app.py)

The dashboard serves as the user-facing front end. It leverages the Streamlit framework (<https://streamlit.io/>) to create an interactive web dashboard with five main tabs:

1. *Watershed Map*: A Folium-based interactive map displaying the watershed boundary, monitoring stations, and river network.
2. *Water Indices*: Time-series visualizations of NDWI, MNDWI, and NDVI, with dynamic risk thresholds and AI-powered insights.
3. *Rainfall Data*: Analysis of daily and cumulative precipitation, including seasonal breakdowns.
4. *Traditional Knowledge*: A dedicated space displaying seasonal patterns, animal and river indicators, and community reports.

5. *Flood Prediction*: The main prediction interface, showing the current risk, a 7-day forecast, risk factor breakdown, and integrated assessments with recommended actions.

This modular architecture ensures that the system is not a monolithic application but a suite of interoperable components, making it robust and adaptable.

Methodology and Algorithms

Data preprocessing

The system is designed to be agnostic to specific data providers, relying on a standardized CSV/JSON input structure defined in a configuration file.

1. *Satellite Water Indices*: The primary inputs are the NDWI, MNDWI, and NDVI, derived from satellite imagery (e.g., Sentinel-2, Landsat). NDWI (McFEETERS, 1996) highlights open water features, while MNDWI (Xu, 2006) is more effective in distinguishing water from built-up areas. The data is expected in a CSV file with columns for date and index values. The Data Processor standardizes the date format, handles missing values, and adds seasonal metadata.
2. *Rainfall Data*: Daily precipitation data (in mm) is ingested from weather stations and/or satellite precipitation products. The processor aggregates this into cumulative rainfall and assigns a season based on the national/cultural calendar (e.g., Ethiopian calendar).
3. *Traditional Knowledge*: TK is stored in a JSON file, structured to include animal indicators (species, behavior, interpretation), river indicators, community protocols, and demographic information (e.g., ethnic groups, language). This digitization is a crucial step for making traditional knowledge computable.
4. *Ancillary Data*: Supporting data includes a GeoJSON of the watershed boundary and a CSV of monitoring station locations (ID, name, coordinates, type).

The data preprocessing workflow ensures that all time-series data are synchronized, gap-filled, and ready for analysis.

Dynamic Flood Risk Calculation Algorithm

The core of the UbuntuFlood AI prediction model is a weighted linear combination of multiple risk factors. The algorithm, implemented in the flood prediction module, computes a score between 0 and 1.

The overall risk score R is calculated as: $R = \omega_w \cdot R_w + \omega_p \cdot R_p + \omega_s \cdot R_s$

Where:

- R_w : is water index risk. It measures the proportion of recent days where NDWI and MNDWI values exceed their 'moderate' risk thresholds, weighted by their respective importance.
- R_p : is precipitation risk. It's derived from recent rainfall data, calculating the frequency of exceedance above 'high' and 'severe' thresholds.
- R_s : is the seasonal baseline risk. It's a predefined base risk level for the current season (e.g., 0.6 for Kiremt, 0.3 for Belg, 0.1 for Bega), acknowledging the inherently higher flood probability during the main rainy season.

The weights ω_w , ω_p , ω_s are configurable weights allowing the model to be tuned for specific watershed behaviors.

Integration of Traditional Knowledge

The TK integration is not merely a display feature but a quantitative component of the risk assessment. The integration module performs a data fusion:

$$R_{integrated} = \omega_m \cdot R_{modern} + \omega_t \cdot R_{traditional}$$

Where:

R_{modern} : A risk score derived from the modern algorithm

$R_{traditional}$: A risk score derived from TK. It starts from the seasonal baseline R_s and is increased based on the presence of modern indicators that align with TK, such as heavy rain or sustained high water levels (high MNDWI).

ω_m and ω_t are weights for modern and traditional data. This balance can be adjusted based on the perceived reliability of TK in a given context.

This integration yields a "confidence" level (High, Medium, Low) based on the agreement between the modern and traditional assessments, providing a crucial measure of uncertainty to the user.

Forecast Generation

The forecast generation in UbuntuFlood AI employs a Random Forest classifier that utilizes features derived from historical data, including statistical properties of water and vegetation indices (NDWI, MNDWI and NDVI), rainfall patterns (cumulative precipitation, intensity, heavy rain days), and environmental trends. The model generates probabilistic flood forecasts with a 7day horizon, which are seamlessly integrated with traditional knowledge assessments through a weighted combination approach. This hybrid method provides both data-driven probabilistic predictions and culturally relevant risk assessments, complete with confidence metrics based on model training status and agreement between modern and traditional indicators, offering a significant advancement over simple threshold-based methods while maintaining operational robustness through automated training.

Community Engagement and Usability

The UbuntuFlood AI dashboard (Fig. 3) is designed not just as a monitoring tool but as a platform for dialogue. The "Watershed Map" and "Water Indices" tabs feature watershed physiography and satellite-based indices, respectively. The "Rainfall Data" tab shows the daily, seasonal, and cumulative rainfall analysis for the watershed. The "Traditional Knowledge" tab serves to digitally preserve and integrate local knowledge, making it accessible to younger generations. The "Flood Prediction" tab features flood risk forecasts and recommended actions.

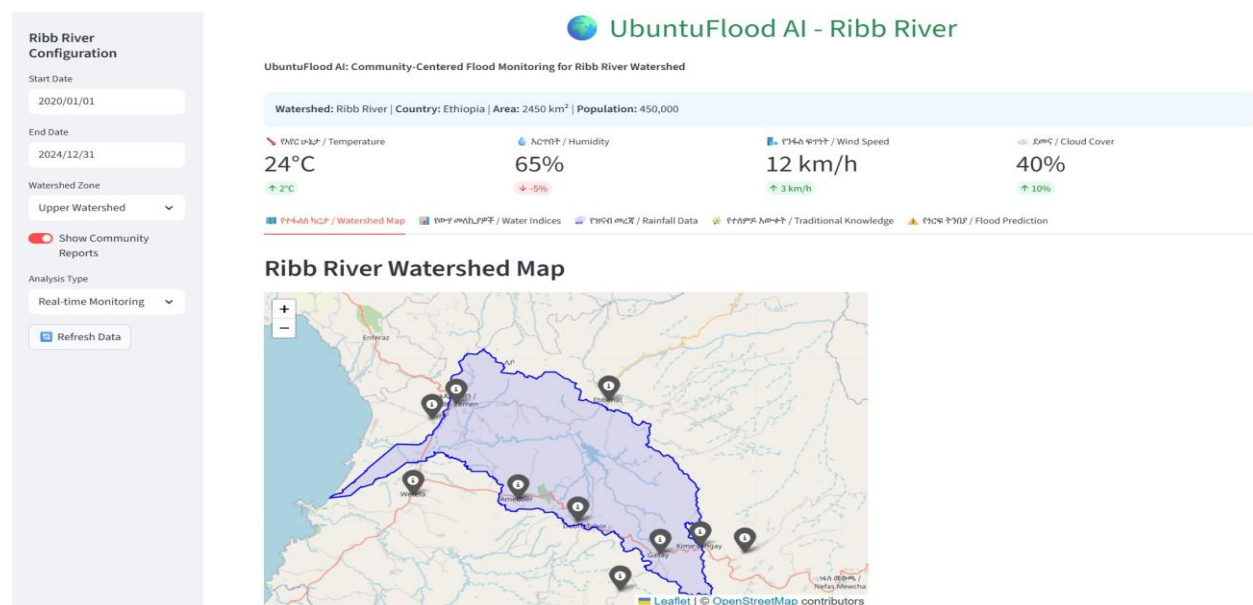


Fig. 3: UbuntuFlood AI Dashboard Overview.

The inclusion of local language text and culturally familiar concepts (e.g., local month names, interpretations of animal behavior) lowers the barrier to understanding and fosters a sense of ownership. The "Generate Community Alert" button under the "Flood Prediction" tab creates a plain-text, actionable message that can be disseminated via SMS or community loudspeakers, directly linking the digital system to on-the-ground response.

Sustainability and Scalability

The system's design, with its configuration-first approach, makes it inherently scalable. Adapting UbuntuFlood AI to a new watershed primarily involves updating geographic parameters, seasonal calendars, risk thresholds, and the TK database, rather than rewriting code. The use of open-source libraries and the Streamlit framework minimizes software costs and technical barriers to deployment.

The most significant challenge for scalability is the initial effort required to digitize and structure the local TK for a new community. This process must be conducted ethically and collaboratively, ensuring that communities are partners in the process and retain ownership of their knowledge.

Case Study: The July 2025 Flood Event

To validate the UbuntuFlood AI framework, we conducted a case study analysis of a flood event that occurred in the Ribb watershed on July 24, 2025. The case study period spans from May 1 to September 23, 2025, capturing the flood's buildup, peak, and recession. Figure 4 shows the geographic location of the Ribb River watershed.

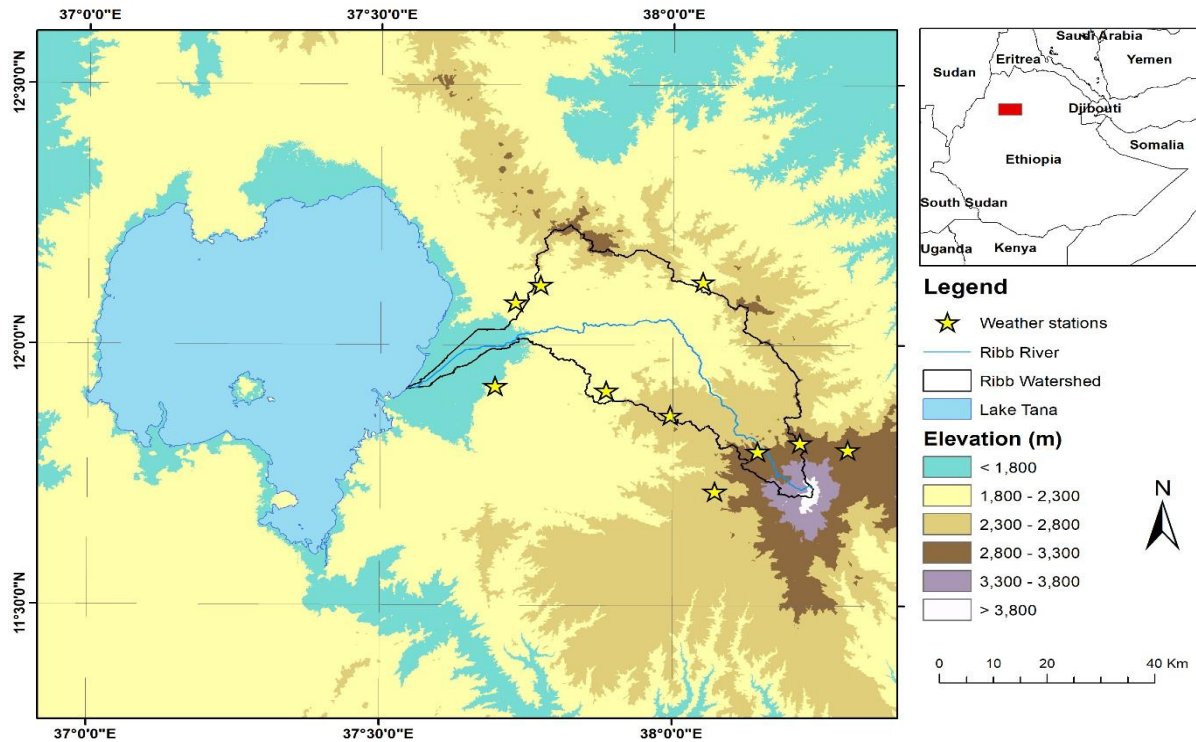


Fig. 4: Study area map showing elevation of the Ribb watershed and flood plains near Lake Tana.

The Ribb Watershed, located in the Amhara Region of northwestern Ethiopia, drains an area of approximately 1562 km² before joining Lake Tana. Characterized by a rugged topography with elevations ranging from 1,784 to 3,811 meters, the watershed exhibits a pronounced seasonal hydrologic regime heavily influenced by the Kiremt rainy season (June-September). Intensive rainfall during this period,

coupled with steep slopes and widespread agricultural land use on vulnerable floodplains, renders the area highly susceptible to recurrent and destructive flooding. These events consistently impact a population of over 450,000, primarily agrarian communities, by damaging vital crops, infrastructure, and livelihoods, making the watershed a critical and representative case for developing integrated flood early warning systems in data-scarce, agrarian-based regions.

Data and Setup

We utilized the flood information from the Ethiopia Disaster Risk Management Commission (EDRMC) early warning and response analysis (<https://edrmc.gov.et/>). According to the report, the July 24, 2025, flood affected 1325 households in Fogera and Dera districts of Amhara region, Ethiopia. Furthermore, the flood resulted in crop damage to 913 hectares of agricultural land.

To analyze the behaviour of the flood, the study utilized multi-source satellite and ground-based data to develop an integrated flood monitoring system. Satellite-derived water indices—including NDVI, NDWI, and MNDWI were computed from Sentinel-2 imagery using Google Earth Engine to monitor vegetation dynamics, surface water extent, and flood-prone areas. Precipitation data were sourced from a combination of in-situ meteorological stations and the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, providing high-resolution rainfall estimates.

Historical flood events were compiled from global and regional databases, including the Global Flood Database (GFD), the international disaster database EM-DAT, and national government disaster reports, to validate and train the predictive model.

To complement remote sensing and hydrological data, traditional ecological knowledge was systematically collected from community elders and residents in the Ribb Watershed. This included documentation of seasonal flood indicators, such as animal behavior, river condition changes, and vegetation responses, as well as community-based response protocols. These qualitative data were digitized, categorized, and integrated into the flood risk algorithm, assigning reliability scores based on consistency and historical accuracy. This hybrid approach ensured the model incorporated locally relevant, time-tested indicators while maintaining scientific rigor, enhancing both the predictive accuracy and cultural relevance of the flood early warning system.

Temporal analysis of input data

Figure 5 presents a seasonal analysis of the key hydrological and knowledge-based drivers of flood risk in the Ribb Watershed. Panel (A) quantifies the seasonal signal in surface water extent, showing the mean MNDWI is highest during the Kiremt season, indicating expanded water bodies and saturated land. This is directly driven by the precipitation regime shown in Panel (B), where the Kiremt season accounts for the dominant share (82.8%) of annual rainfall, with Belg and Bega seasons contributing 9.8% and 7.4%, respectively. This climatological forcing is formalized into a base flood risk score in Panel (C), which assigns the highest inherent risk to Kiremt (0.6), followed by Belg (0.3) and Bega (0.1). Finally, Panel (D) validates the integration of local ecological knowledge, demonstrating that traditional animal indicators—specifically sheep behavior (0.8) and bird activity (0.7)—are considered reliable predictors by local

communities.

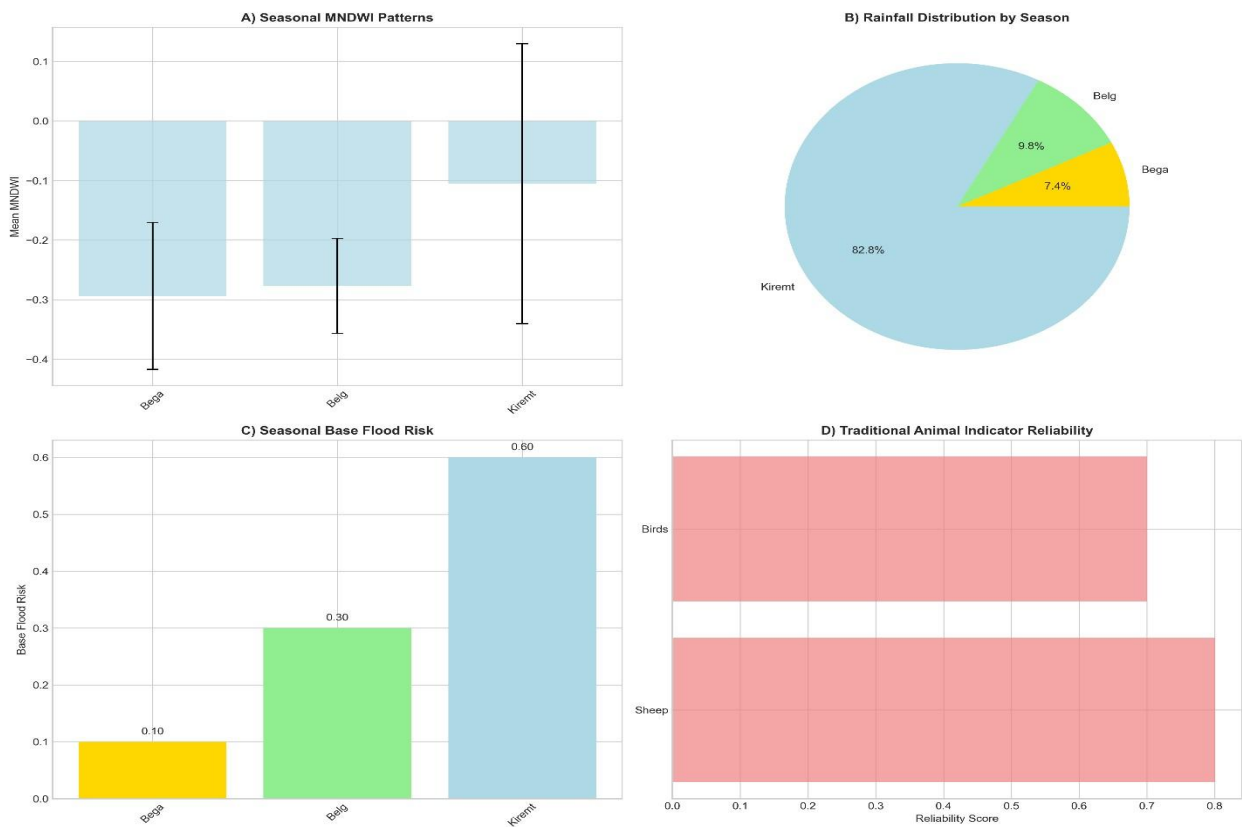


Fig. 5: Seasonal analysis of datasets

The integrated analysis confirms that the high flood risk during the Kiremt season is a function of a powerful synergy between peak rainfall and consequent rises in surface water extent. The lower base risk during the Belg season, despite its precipitation, suggests that antecedent conditions and rainfall intensity are critical differentiating factors. Crucially, the reliability of traditional animal indicators aligns with this seasonal framework; the high reliability score for sheep behavior (0.75), which involves moving to high ground before heavy rain, provides a ground-truth, early warning signal that effectively complements the satellite-observed rise in MNDWI. This synergy between quantifiable seasonal risk and validated indigenous knowledge forms a robust foundation for a culturally resonant and temporally precise early warning system.

Figure 6 provides a comprehensive temporal analysis of satellite-derived water indices for the Ribb Watershed from 2019 to 2025. Panel (A) illustrates the raw time series of NDWI, MNDWI, and NDVI, revealing distinct seasonal oscillations and notable peaks corresponding to flood events. Panel (B) decomposes the MNDWI signal using a 30-day moving average, effectively isolating the strong seasonal trend from short-term noise. The distribution of MNDWI values is presented in Panel (C), showing a mean value of -0.259 and a spread that captures the dynamic range between dry and saturated land conditions. Panel (D) displays the correlation matrix between the indices, indicating a very strong negative correlation between NDWI and NDVI (-0.94), while MNDWI exhibits a weak negative correlation with both NDVI.

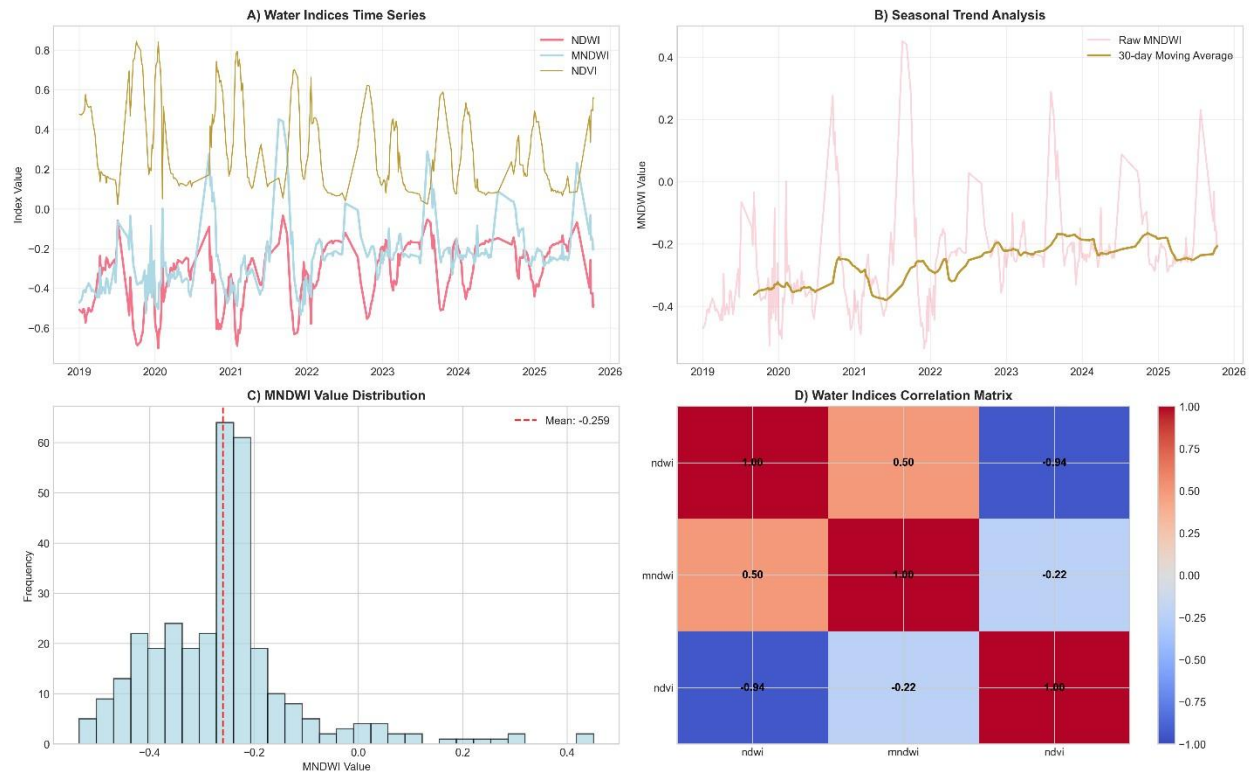


Fig. 6: Time series analysis of water indices

The multi-year time series confirms the robustness of MNDWI as the primary indicator for surface water monitoring in this region, effectively capturing the watershed's pronounced seasonal hydrology and extreme flood events. The inverse relationship between NDVI and the water indices is critical; it demonstrates that periods of peak surface water inundation (high MNDWI) consistently coincide with reduced vegetation activity (low NDVI), likely due to flood-induced submergence or waterlogging stress on crops. This analysis establishes that these indices provide a coherent and reliable signal for tracking hydrological dynamics, forming a foundational data layer for the flood prediction model.

Timeline of Events and System Performance

Figure 7 presents a detailed timeline of the July 2025 flood event in the Ribb Watershed, comparing the lead-up and system response across multiple data streams. Panel (A) shows a sharp increase in both NDWI and MNDWI values coinciding with the flood date, indicating a rapid expansion of surface water, while NDVI displays a corresponding dip, signaling vegetation stress. Panel (B) reveals the triggering mechanism: spikes in daily rainfall, exceeding 20mm, preceding the flood. The system's predictive capability is demonstrated in Panel (C), where the AI-generated flood risk score escalated through predefined thresholds, crossing into the "High" risk bracket days before the event. Panel (D) tracks the traditional knowledge assessment, which also showed a rising risk trend with the flood.

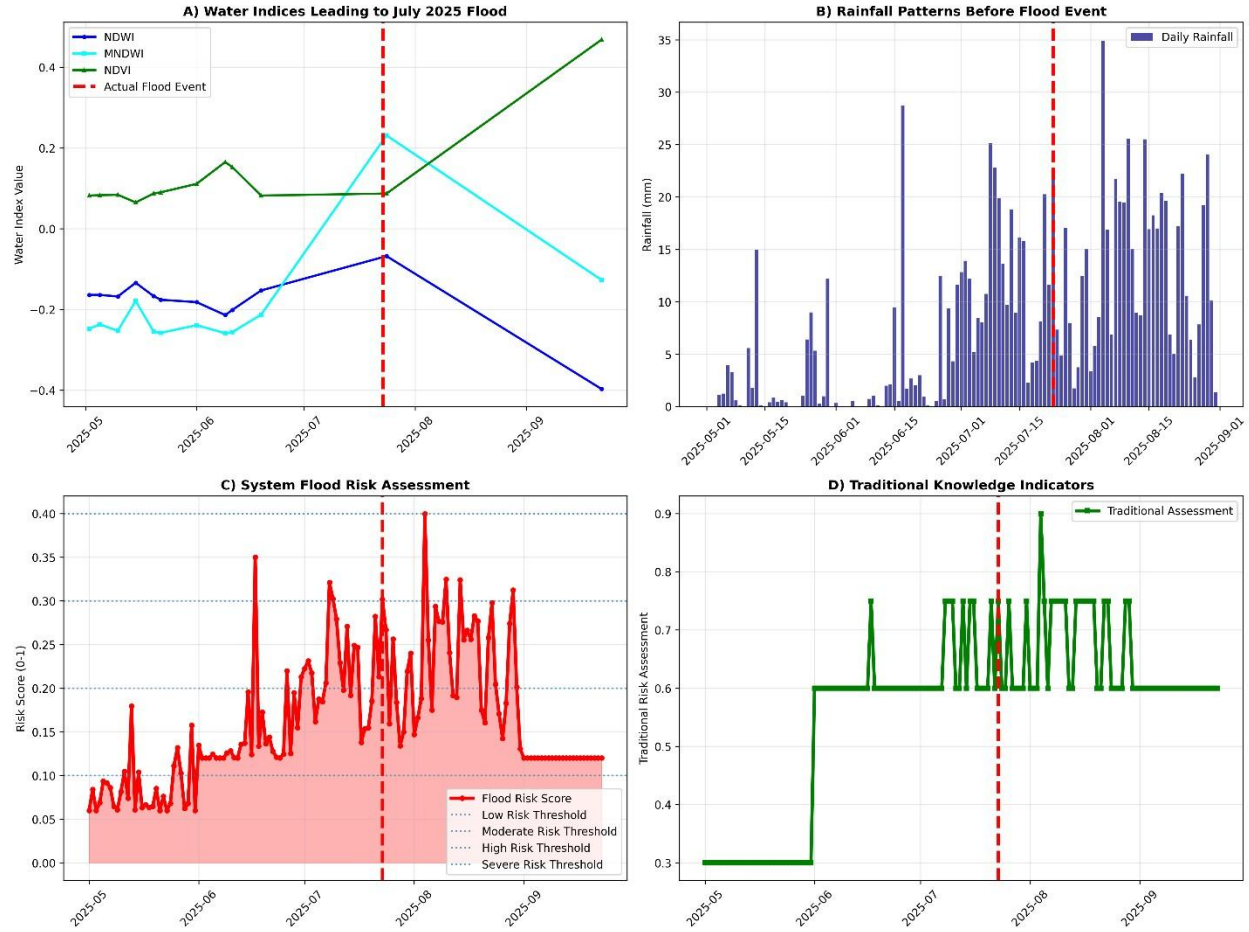


Fig. 7: Timeline of the July 2025 Flood Event.

This case study validates the integrated early warning framework, demonstrating its ability to synthesize satellite, meteorological, and traditional knowledge for effective forecasting. The system provided a crucial lead time by translating the observed rainfall and rising water indices into a quantifiable risk score that surpasses the high-risk threshold before the flood's occurrence. The parallel increase in traditional assessments underscores a key finding: indigenous knowledge systems detected the mounting hazard through environmental cues, aligning temporally with technological indicators. The convergence of these independent data sources—the physical measurements of rainfall and water extent, the algorithmic risk calculation, and the grounded traditional assessment—provides a robust, multi-layered confirmation of the event, highlighting the reliability of the integrated approach.

Conclusions and Future Work

Summary of Contributions

This paper introduced UbuntuFlood AI, a novel software framework for community-centered flood early warning. Its primary contributions are fourfold. First, it establishes a flexible architectural model, with a modular codebase that separates core algorithms from watershed-specific configurations to ensure transferability. Second, it presents a novel data integration algorithm that quantitatively fuses multi-temporal satellite data (NDVI, NDWI, MNDWI, precipitation) with structured traditional knowledge into a single, dynamic flood risk score. Third, validation via the July 2025 Ribb watershed case study demonstrated that this integrated approach yields accurate predictions. Finally, the entire framework serves as a blueprint for participatory modeling, designed from the ground up to facilitate community engagement

through its two-way communication dashboard and the direct incorporation of local knowledge into the predictive model.

Limitations and Future Work

The current system has limitations that guide future research. Its accuracy is contingent on satellite data quality, which can be compromised by cloud cover, and the risk algorithm is a conceptual weighting of factors rather than a full physical hydrological model. Future work will therefore focus on integrating simplified hydrological models and expanding data streams with soil moisture and forecast data. We will also explore advanced deep learning models like Long Short-Term Memory (LSTM) networks for forecasting.

References

- Abeje, M. T., Tsunekawa, A., Haregeweyn, N., Nigussie, Z., Adgo, E., Ayalew, Z., Tsubo, M., Elias, A., Berihun, D., Quandt, A., Berihun, M. L., & Masunaga, T. (2019). Communities' Livelihood Vulnerability to Climate Variability in Ethiopia. *Sustainability*, 11(22), 6302. <https://doi.org/10.3390/su11226302>
- Alfieri, L., Cohen, S., Galantowicz, J., Schumann, G. J.-P., Trigg, M. A., Zsoter, E., Prudhomme, C., Kruczkiewicz, A., Coughlan De Perez, E., Flamig, Z., Rudari, R., Wu, H., Adler, R. F., Brakenridge, R. G., Kettner, A., Weerts, A., Matgen, P., Islam, S. A. K. M., De Groeve, T., & Salamon, P. (2018). A global network for operational flood risk reduction. *Environmental Science & Policy*, 84, 149–158. <https://doi.org/10.1016/j.envsci.2018.03.014>
- Bedo, D., Mekuriaw, A., & Bantider, A. (2024). Vulnerability of household livelihoods to climate variability and change in the central rift valley sub-basin of Ethiopia. *Heliyon*, 10(3), e25108. <https://doi.org/10.1016/j.heliyon.2024.e25108>
- Berkes, F. (2018). *Sacred ecology* (Fourth edition). Routledge, Taylor & Francis Group. <https://doi.org/10.4324/9781315114644>
- Ding, H. (2020). Crowdsourcing, Social Media, and Intercultural Communication About Zika: Use Contextualized Research to Bridge the Digital Divide in Global Health Intervention. *Journal of Technical Writing and Communication*, 50(2), 141–166. <https://doi.org/10.1177/0047281620906127>
- IPCC. (2023). *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (1st ed.). Cambridge University Press. <https://doi.org/10.1017/9781009325844>
- Johnson, J. T., Howitt, R., Cajete, G., Berkes, F., Louis, R. P., & Kliskey, A. (2016). Weaving Indigenous and sustainability sciences to diversify our methods. *Sustainability Science*, 11(1), 1–11. <https://doi.org/10.1007/s11625-015-0349-x>
- McFEETERS, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432. <https://doi.org/10.1080/01431169608948714>
- Ogie, R., Rho, J. C., Clarke, R. J., & Moore, A. (2018). Disaster Risk Communication in Culturally and Linguistically Diverse Communities: The Role of Technology. *UCAmI* 2018, 1256. <https://doi.org/10.3390/proceedings2191256>
- Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27(14), 3025–3033. <https://doi.org/10.1080/01431160600589179>