

Exploring Forecast-based Financing (FbF) and Flood Risk Prediction (FUNES) by Red Cross Red Crescent Climate Centre

Ashley May Barisoro
Asia Pacific College
Makati City, PHL
abbarisoro@student.apc.edu.ph

Gwyneth Cataylo
Asia Pacific College
Makati City, PHL
gmccataylo@student.apc.edu.ph

Ariana May Saromo
Asia Pacific College
Makati City, PHL
afsaromo@student.apc.edu.ph

Abstract— Natural disasters, aggravated by climate change, demand advanced disaster risk reduction strategies. This paper analyzes two algorithmic solutions from the Red Cross Red Crescent Climate Centre that enable anticipatory action: Forecast-based Financing (FbF) and the Flood Risk Prediction (FUNES) algorithm. FbF is an early financing mechanism that automatically releases pre-allocated funds based on climate forecast thresholds. FUNES is a self-learning flood forecasting tool that integrates rainfall and dam data to issue localized, actionable early warnings on a five-point scale. We detail the conditional logic of FbF and the data-driven process of FUNES. To demonstrate their utility, we developed a simplified, terminal-based Python implementation utilizing real-time data to focus on flood-vulnerable communities in the Philippines. Our efficiency analysis determined that both the core FbF and FUNES algorithms operate with linear time and space complexity, $O(n)$. The paper concludes that integrating these algorithmic tools significantly enhances community preparedness and reinforces Sustainable Development Goal 13 (Climate Action).

Keywords—*Forecast-based Financing (FbF), Flood Risk Prediction (FUNES), Disaster Risk Reduction (DRR), Anticipatory Action.*

I. INTRODUCTION

Every year, natural disasters affect millions of people around the world. These events are caused by climate change, which refers to long-term shifts in temperature and weather patterns. Rising sea levels, extreme heat, wildfires, floods, and droughts are some of the most pressing examples. Beyond harming the environment, these disasters place countless lives at risk. With this, efforts have been made to strengthen disaster risk reduction and preparedness strategies. But responding effectively to these crises requires more than immediate humanitarian aid. It needs approaches that can anticipate risks, allocate resources efficiently, and guide timely action. This is where algorithmic solutions come into play. These aid in decision-making and help organizations predict disasters, design preventive measures, and ultimately save lives.

A key figure in disaster preparedness is the Red Cross Red Crescent Climate Centre. RCCC is a reference center that was established in 2002 by the International Federation of Red Cross and Red Crescent Societies (IFRC). It supports the Red Cross and Red Crescent Movement and its partners in minimizing the consequences of climate change and extreme weather events on vulnerable communities by providing science-based knowledge, developing innovative tools, and strengthening decision-making processes for climate risk

management. This paper will focus on two of their solutions: Forecast-based Financing (FbF) and Flood Risk Prediction (FUNES). FbF uses climate forecasts to trigger early humanitarian actions before disasters occur, while FUNES is a self-learning flood forecasting algorithm that integrates rainfall and dam release data to issue early warnings ^[1].

These solutions align with Sustainable Development Goal (SDG) 13: Climate Action, a global goal that aims to combat climate change and its impacts through early action. The main purpose of FUNES and FbF is to provide early-warning and early-action systems that enable communities to prepare for potential disasters ahead of time and reduce casualties and losses—an approach connected to climate action. This is especially relevant for the Philippines, a country ranked among the world's most disaster-prone and highly vulnerable to floods due to its geography and exposure to extreme weather events ^[17]. As disaster risk management tools, these solutions also support the desired outcomes of the National Innovation Agenda and Strategy Document (NIASD), particularly the goal of transforming the Philippines into an innovative country and attaining a future where Filipinos are strongly rooted, comfortable, and secure. In examining these tools, the paper will analyze their design and efficiency and provide a simple Python implementation.

II. LITERATURE REVIEW

A. Forecast-based Financing (FbF)

The study conducted by Red Cross Red Crescent Climate Centre (RCCC), together with the International Federation of Red Cross and Red Crescent Societies (IFRC) and the School of Geography and the Environment at Oxford University ^[2], focuses on the finance mechanism, FbF to support humanitarian action and reduce the impact of disaster displacement. In reducing the humanitarian impacts of disaster displacement, stocktaking of context-specific factors and identifying people at risk are important. The phrases of disaster displacement are the risk of disaster displacement, arbitrary displacement, preparedness and response to disaster displacement, and durable solutions for displaced communities.

Action to support durable solutions should be taken prior to displacement occurring and barriers can be early identified in the process of risk analysis. Examples given are typhoons

in the Philippines where the early humanitarian actions supported by FbF include strengthening and protecting shelters, housing, livelihoods, and consider cash-for-work initiatives. Another example is the severe winters in Mongolia such as protecting vulnerable livelihoods by reducing livestock mortality, distribute livestock nutrition kits, and unconditional cash transfers.

FbF supports several anticipatory humanitarian actions, but more can be done. It is stated that many initiatives to protect against arbitrary displacement, long-term resilience building, disaster risk reduction measures and climate change adaptation are outside the scope of FbF. Anticipatory action or acting prior to the predictable hazards supported by FbF can be integrated to existing disaster preparedness to minimize the humanitarian impacts of disaster displacement.

B. Flood Risk Prediction (FUNES)

FuNES system is a flood forecasting model mainly used at Nangbeto Dam, Togo to predict inflows and outflows. This aims to provide early warnings for flood risk in downstream communities. The system supports dam operators in managing reservoir releases to minimize downstream flood impacts and hydropower production losses. FUNES is used by local personnel with limited technical expertise and continues to be improved for greater forecasting accuracy for a better system and enhancing early action guidelines for vulnerable communities. It integrates with forecast-based financing approaches, lowering the danger of floods by connecting forecasts to early warning systems, evacuation plans, and medical interventions.

A study from Hagan et al. [3] FuNES is a component of an operational, threefold flood forecasting system for Nangbeto Dam that has been evaluated in scientific studies. It uses an ensemble weather forecast with a lead time of up to ten days and focusses on inflow predictions. It employs subjective probabilities for flood extents and reclassifies flood risk into five classes – Very Low risk, Low risk, Medium Risk, Elevated Risk, and Very Elevated Risk, to trigger preparedness of funds and actions.

C. Other Similar Solutions

Aside from the Red Cross's FUNES and Forecast-based Financing (FbF) systems, there exists other algorithmic solutions that provide early warning and support decision-making in the context of natural disasters. These systems play a role in protecting communities by collecting and analysing hydrometeorological and geospatial data, generating forecasts, and coordinating with partner agencies to ensure timely dissemination of information. Through these, they help identify optimal preventive actions that can be taken before a disaster occurs, which in turn minimizes humanitarian impacts and enhances preparedness at local and national levels.

GloFAS - Global Flood Awareness System^[5] the global flood service of the European Commission's Copernicus Emergency Management Service (CEMS). It became fully operational in 2018 after years of pre-operational testing and development by the Joint Research Centre (JRC), the European Centre for Medium-Range Weather Forecasts (ECMWF), and the University of Reading. GloFAS provides global coverage for flood monitoring and forecasting, supporting more than 6,000 registered users, including national and international water authorities, hydropower companies, civil protection agencies, humanitarian

organizations and many more. The system generates daily probabilistic flood forecasts up to 30 days ahead and monthly seasonal streamflow outlooks extending to 16 weeks, which help identify potential flood risks in advance. While GloFAS is not intended to replace local hydrological forecasting systems, it still helps regions where no such systems exist, offering complementary information for transboundary river basins and upstream monitoring. Recent system upgrades have enhanced its accessibility and reliability by providing open access to both real-time and reforecast datasets, allowing researchers and agencies to evaluate forecast skill and integrate GloFAS data into other applications, such as hydropower planning and impact-based early warning systems.

Hydrological and meteorological modeling - Essential technologies used in modern flood forecasting systems. These models simulate how rainfall, temperature, and other weather conditions interact with land surfaces and river basins to predict how water will move through the environment. A study titled "The Impact of Spatiotemporal Hydrological Model Resolution on Global Flood Forecasting Skill"^[8] explored how the level of model detail, or resolution, affects the accuracy of flood predictions. Using the Global Flood Awareness System (GloFAS) as a test platform, the researchers adjusted the model's spatial and temporal resolution to see how different settings influenced forecast skill across various river basins worldwide.

The results showed that higher model resolution does not always lead to better forecasts. In some cases, extremely fine detail made the model more sensitive to small data errors, while moderate resolutions achieved more stable and accurate results. The study also found that the importance of temporal resolution, how often model data is updated, varies by region. Fast-responding rivers, which flood quickly after rainfall, benefited more from frequent updates, while larger river systems performed well even with coarser time steps. Overall, the research emphasized that finding the right balance in model resolution is key to improving both the accuracy and efficiency of global flood forecasting systems.

Ensemble forecasting and reforecasting. - Widely used to improve the accuracy and reliability of hydrological and meteorological predictions. Instead of relying on a single forecast, ensemble forecasting produces multiple simulations with slightly different initial conditions to represent a range of possible outcomes. This method helps capture uncertainty in weather patterns and provides probabilistic forecasts that are more informative for decision-making. Harrigan et al.^[7] highlight the use of these techniques in the Global Flood Awareness System (GloFAS), where ensemble forecasts of river discharge are generated daily for up to thirty days ahead. To assess forecast performance, a 20-year reforecast dataset (1999–2018) was developed, allowing comparisons between historical forecasts and observed river data. Their findings show that ensemble and reforecasting methods can achieve high predictive skill, particularly for larger river basins, while smaller or data-scarce regions remain more challenging. The open access to both real-time and reforecast datasets through the Copernicus Climate Data Store further supports transparency and enables other institutions to evaluate and adapt these methods for local use. Overall, ensemble forecasting and reforecasting play a vital role in enhancing the reliability of flood early warning systems and guiding disaster preparedness across different forecasting platforms.

Deep Convolutional Neural Networks - Convolutional Neural Network (CNN) is an artificial intelligence that received strong attention because of its ability to process raw data in image format and utilize spatial information. Maximum water depth predictions are being generated by using CNN as an image-to-image translation task from elevation and hyetograph inputs. CNN for flood prediction requires large input sizes and a large dataset, thus resulting in difficulties in the training of the model. The study by Guo et al. [9] stated that compared to other data-driven techniques, the algorithm's main advantage is its ability to utilize spatial information and handle inputs of large areas without facing exponential growth of model parameters. They have conducted validation tests that showed that the model is accurate when provided with unfamiliar inputs and has a linear time increase for computational time.

The challenges faced by the CNN model include its incapability to be applied across different catchment areas meaning a limit to broader usability, lack of large flood datasets due to the long computational time for simulations and difficulty for deploying sensors for observational data, problems when it comes to the quality of input data, and lastly, input hyetograph vectors having fixed length. It is suggested that the model can still be enhanced by incorporating additional flood-related factors, oversampling, data augmentation, random noise training, and recurrent neural networks.

Project NOAH (Nationwide Operational Assessment of Hazards) - An integrated disaster prevention and mitigation program in the Philippines by the Department of Science and technology and was established in March 2017 at the University of the Philippines as the UP NOAH Center^[10]. As the country is constantly under threat of natural hazards, Project Noah developed tools and systems to provide accurate hazard information through early warning systems and hazard maps accessible through a web portal, mobile apps, and mirror sites. The innovation gives real-time weather data, flood and landslide hazard maps, storm surge inundation maps, and identifies critical facilities.

The system uses advanced technologies such as doppler radars for weather monitoring, 4-hour ClimateX forecast system, hazard mapping technologies, etc. A specific algorithm used is the ForTraCC (Forecast and Tracking the Evolution of Cloud Clusters), which predicts cloud trajectory using image processing techniques. The algorithm tracks and forecasts cloud clusters using satellite infrared imagery and calculating the Percent Chance of Rain using infrared and water vapor satellite image data and Doppler data obtained at near-real-time, combined with statistical evaluation of historical rainfall.

III. DESIGN ANALYSIS

The Red Cross Red Crescent Climate Centre developed and presented the Forecast-based Financing (FbF) during the 2017 World Hydropower Congress to predict and prepare for flood risks []. It is a machine learning algorithm that analyses climate forecasts and flood risk data to communicate to the communities at risk by triggering pre-allocated funding and early preparedness actions before predictable disasters in a clear and timely manner.

FUNES is a self-learning algorithm for flood risk forecasting that helps predict flood risk levels of selected areas by integrating daily flow data entered by the dam to forecast risk levels by locality [1]. The system uses data from rainfall forecasts and flood hazard maps to make predictions that will serve as a scientific basis for early action protocols. Being linked to the forecast-based financing (FbF) mechanism, when a specific flood risk level is forecasted, it triggers specific preparedness actions and releases pre-allocated contingency funds to Red Cross for rapid risk reduction.

FbF has three components: trigger, early actions, and financing mechanism. The allocation of funds and assistance will be provided based on the trigger or the specific threshold values based on the weather and climate forecast. Its algorithm type is conditional which uses the if-then logic. Experts analyze relevant natural hazards, assess the impacts of previous disasters, and vulnerabilities.

When the trigger gets activated, early actions are initiated. Predefined measures aim to minimize impacts of extreme weather events and save lives. And lastly setting up the Forecast-based Action, which is the financing mechanism that automatically allocates resources when a trigger is activated, and early actions are needed. The fund is available to all Red Cross and Red Crescent societies, which successfully developed an early action protocol. The algorithm design is essential if the forecast value is greater than or equal to the threshold value, then the trigger activates, releases funds, and initiates early actions.

FUNES hydrometeorological flood prediction tool daily posts two-day forecast risk level. Each level of FUNES-forecasted risk triggers a specific set of actions, standard operating procedures (SOPs), and triggers authorization to release funds necessary to carry out the SOP, from a designated contingency fund.

FUNES gives dams the ability to anticipate inflows and recent outflows. With that information, FUNES will calculate the level of expected flood risk in downstream communities. It also estimates anticipated inflows, enabling dam operators to plan releases to minimize impacts. For the algorithm to work, it requires daily hydrological and meteorological observer data with post-flood impact data. Togo Red Cross was able to enhance their community-based early warning systems by installing rainfall gauges in schools and limnimeters on river poles. FUNES determine risk levels based on elevation with a 5-point danger level scale: Very low risk, low risk, medium risk, elevated risk, and very elevated risk.

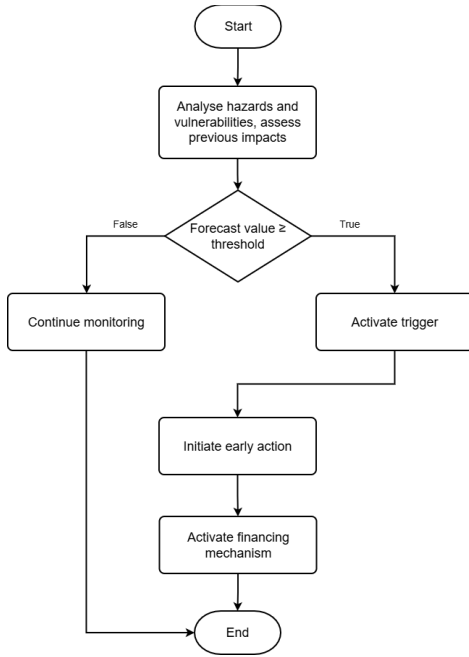


Fig. 1. FbF Flowcart

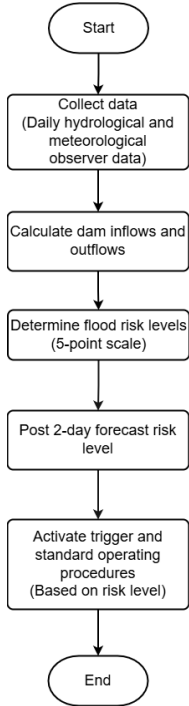


Fig. 2. FUNES Flowchart

IV. EFFICIENCY ANALYSIS

The FbF algorithm has a linear time and space complexity. For all operations having a time complexity of $O(1)$ except for the analysis of hazards, vulnerabilities, and previous impacts as iterates n historical record being the dominant term $O(n)$. The FUNES algorithm also takes a linear time and space complexity such as collecting data, calculating the inflows and outflows, and determining the flood risk level takes a complexity of $O(n)$ where n being the number of days of observation data. While the rest of the operations take constant time and space complexity $O(1)$. Both algorithms have the

linear time and space complexity $O(n)$. Meaning the speed of the operations is directly proportional to the data size.

Since the original FbF and FUNES source codes are not publicly accessible, only the theoretical computational efficiency can be evaluated.

V. IMPLEMENTATION

The mini app version of Forecast-based Financing (FbF) and FUNES was built in Python as a terminal-based application. It forecasts flood risk levels for today and the next two days and shows the corresponding early action measures to reduce flood-related loss and damage. Each risk level—VERY LOW, LOW, MEDIUM, HIGH, or VERY HIGH—has a corresponding FbF plan that includes recommended actions, target areas, the number of personnel needed, and estimated costs. The program only uses data from two sources:

- **Dam Data:** Users manually input current water levels of Angat Dam and Ipo Dam, obtained from the official PAGASA website.
- **Rainfall Data:** Real-time rainfall information is retrieved through the OpenWeather API.

Dam levels and rainfall intensity are classified using thresholds derived from PAGASA standards. The app focuses on Angat Dam and Ipo Dam and two downstream localities, San Rafael and Norzagaray, Bulacan, which are most at risk of flooding during overflows or high releases of reservoir. Based on the combination of dam levels and rainfall, it calculates an overall flood risk level and shows the appropriate response plan for each level.

The mini app has some limitations. It only covers two dams and two localities, and dam levels must be entered manually, which can introduce errors or delays. Unlike the original FUNES and FbF systems, which use river flow data entered by dam operators as input, this mini app uses dam water levels instead. This is because there is no publicly available source that provides the latest river flow data for these dams, and PAGASA does not offer a way to automatically retrieve such data, either through an exportable file or an API. Rainfall forecasts rely solely on OpenWeather API data and use 24-hour windows, which may miss sudden changes or extreme events. Thresholds are fixed and do not adjust for seasonal or local differences. On top of that, the app does not include maps, integration with local authorities, or a graphical interface, which can make it less user-friendly.

VI. RESULTS AND DISCUSSION

In terms of Big-O notation, Both the original FbF and FUNES algorithms, as well as the mini app have a linear time and space complexity of $O(n)$. The mini app was executed 30

times to estimate the average performance. Using the built-in timeit module ^[14], the average execution time of the whole program takes 0.2987 seconds.

Throughput is calculated using the formula:

$$\text{Throughput} = \frac{\text{No. of operations}}{\text{Execution time}}$$

Derived from its original definition: number of units produced divided by the time periods [13]. The app has an estimate of 201 operations and 673.01 ops/sec throughput as a result.

VII. CONCLUSION

The integration of algorithmic solutions such as FbF and FUNES helps the community by improving information dissemination, early action protocols, and decision-making for flood preparedness and response. It emphasizes the importance to disaster risk reduction and reinforces the relevance to SDG 13 (Climate Action) and the Philippines.

As suggestions for future research, improvements could include automated retrieval of dam levels and river flow data, integration with real-time mapping and local authorities, dynamic adjustment of thresholds based on seasonal or local variations, and the incorporation of self-learning algorithms like the original FUNES to improve prediction accuracy over time. Using more comprehensive datasets, such as upstream rainfall, river flow measurements, and local hydrological observations, can help more accurately determine flood risk levels for different localities. Expanding the app's coverage to include more dams and vulnerable communities and developing a user-friendly graphical interface can also enhance its usability and operational relevance for disaster preparedness. The system could also be enhanced to automatically authorize the release of funds in accordance with the assessed risk level and pre-approved FbF plan.

REFERENCES

- [1] "Deutsches Rotes Kreuz HELP." Available: <https://www.forecast-based-financing.org/wp-content/uploads/2019/01/Brochure-vertical-Cruz-Roja-Togo-Ingles-con-foto.pdf>
- [2] L. Thalheimer, E. Jjemba, and E. Simperingham, "The role of forecast-based financing," *Forced Migration Review*, no. 69, pp. 36–39, Feb. 2022, <https://www.fmreview.org/climate-crisis/thalheimer-jjemba-simperingham>
- [3] J. S. Hagen, A. Cutler, P. Trambauer, A. Weerts, P. Suarez, and D. Solomatine, "Development and evaluation of flood forecasting models for forecast-based financing using a novel model suitability matrix," *Progress in Disaster Science*, vol. 6, p. 100076, Apr. 2020, doi: <https://doi.org/10.1016/j.pdisas.2020.100076>.
- [4] "PAGASA," www.pagasa.dost.gov.ph. <https://www.pagasa.dost.gov.ph/flood>
- [5] Joint, "Global Flood Awareness System," *Copernicus.eu*, 2020. <https://global-flood.emergency.copernicus.eu/general-information/about-glofas/>
- [6] G. Map, "The Copernicus Global Flood Awareness Systems (GloFAS) Overview and service evolution With contributions from the GloFAS team at ECMWF, at the JRC and also at the University of Reading." https://globalfloodpartnership.org/sites/default/files/2019-06/gfp2020/session2/02_Zsoter_ECMWF.pdf
- [7] S. Harrigan, E. Zsoter, H. Cloke, P. Salamon, and C. Prudhomme, "Daily ensemble river discharge reforecasts and real-time forecasts from the operational Global Flood Awareness System," *Hydrology and Earth System Sciences*, vol. 27, no. 1, pp. 1–19, Jan. 2023, doi: <https://doi.org/10.5194/hess-27-1-2023>.
- [8] Q. Zhu, X. Qin, D. Zhou, T. Yang, and X. Song, "Impacts of spatiotemporal resolutions of precipitation on flood event simulation based on multimodel structures – a case study over the Xiang River basin in China," *Hydrology and earth system sciences*, vol. 28, no. 7, pp. 1665–1686, Apr. 2024, doi: <https://doi.org/10.5194/hess-28-1665-2024>.
- [9] Z. Guo, J. P. Leitão, N. E. Simões, and V. Moosavi, "Data-driven flood emulation: Speeding up urban flood predictions by deep convolutional neural networks," *Journal of Flood Risk Management*, Dec. 2020, doi: <https://doi.org/10.1111/jfr3.12684>.
- [10] Development Academy of the Philippines, "Project NOAH (Nationwide Operational Assessment of Hazards)," *Development Academy of the Philippines*, Oct. 02, 2020. <https://coe-psp.dap.edu.ph/compendium-innovation/project-noah-nationwide-operational-assessment-of-hazards-2/>
- [11] United Nations, "What is Climate Change?," *United Nations*, 2025. <https://www.un.org/en/climatechange/what-is-climate-change>
- [12] GeeksforGeeks, "How to measure time taken by a program," *GeeksforGeeks*, Feb. 12, 2025. <https://www.geeksforgeeks.org/blogs/how-to-measure-time-taken-by-a-program/>
- [13] GeeksforGeeks, "Latency and Throughput in System Design," *GeeksforGeeks*, Sep. 14, 2023. <https://www.geeksforgeeks.org/system-design/latency-in-system-design/>
- [14] GeeksforGeeks, "Measure time taken by program to execute in Python," *GeeksforGeeks*, May 15, 2020. <https://www.geeksforgeeks.org/python/python-measure-time-taken-by-program-to-execute/>
- [15] "Step-by-Step Guide: Calculating Big-O Notation | Blog Algorithm Examples," *Algorithm Examples*, Feb. 06, 2024. <https://blog.algorithmexamples.com/big-o-notation/step-by-step-guide-calculating-big-o-notation/>
- [16] B. Anushka, M. Amey, P. Aakash, S. Saniya, and H. Mrunmayee, "FLOOD FORECASTING SYSTEM USING MACHINE LEARNING," *International Journal of Creative Research Thoughts*, vol. 12, no. 2320–2882, pp. 2320–2882, 2024, <https://ijcrt.org/papers/IJCRT24A3133.pdf>
- [17] W. B. Group, "Project Highlights: Metro Manila Flood Management," *World Bank*, Dec. 11, 2017. https://www.worldbank.org/en/country/philippines/brief/project-highlights-metro-manila-flood-management?utm_source=chatgpt.com

“Forecast-based Financing A new era for the humanitarian system.” Available: https://www.forecast-based-financing.org/wp-content/uploads/2019/03/DRK_Broschuere_2019_new_era.pdf

AI PROMPTS

Microsoft Copilot:

what can be included in an efficiency analysis excluding big-o notation

Copilot ⓘ

Great question! When performing an efficiency analysis of a program or system—excluding Big-O notation—you can include several practical and performance-related metrics that reflect how well resources are used. Here's a breakdown of what you can include:

✍ 1. Execution Time

- **Definition:** How long the program takes to run.
- **Tools:** `timeit`, `perf_counter`, profiling tools.
- **Use:** Helps identify bottlenecks and optimize slow sections.

📊 2. Throughput

- **Definition:** Number of operations completed per unit of time.
- **Formula:**
$$\text{Throughput} = \frac{\text{Total Operations}}{\text{Execution Time}}$$
- **Use:** Useful for comparing performance across systems or configurations.

💡 3. Resource Utilization

- **CPU Usage:** How much processing power is consumed.
- **Memory Usage:** RAM consumed during execution.

what are performance metrics of a program code

Copilot ⓘ

Performance metrics for program code are measurements that help evaluate how efficiently and effectively a program runs. They typically fall into several categories:

1. Execution Speed

- **Runtime:** How long the program takes to complete.
- **Latency:** Time taken to respond to a single request.
- **Throughput:** Number of operations or requests processed per unit time.

2. Resource Utilization

- **CPU Usage:** Percentage of CPU consumed during execution.
- **Memory Usage:** Amount of RAM used by the program.
- **Disk I/O:** Read/write operations on storage.
- **Network Usage:** Data sent/received over the network.

3. Scalability

- How performance changes as input size or number of users increases.
- Metrics like speedup and efficiency for parallel programs.

4. Reliability & Stability

- **Error Rate:** Frequency of crashes or exceptions.
- **Uptime:** How long the program runs without failure.

5. Maintainability

- **Code Complexity:** Measured by cyclomatic complexity or lines of code.
- **Test Coverage:** Percentage of code covered by automated tests.

6. Energy Efficiency

- Power consumption, especially for embedded systems or mobile apps.

is execution speed the same with execution time??

Copilot ⓘ

Not exactly—they're related but not the same:

- **Execution Time** refers to the **total time taken by a program to run from start to finish**. It's usually measured in seconds or milliseconds.
- **Execution Speed** is more about **how fast the program performs its tasks**, often expressed as operations per second or compared against other implementations. It's a relative measure of performance.

Think of it this way:

- If Program A finishes in 2 seconds and Program B in 4 seconds, Program A has a **shorter execution time** and a **higher execution speed**.
- Speed is often used when benchmarking or comparing efficiency, while time is an absolute metric.


Do you want me to show you: ☒ A formula to calculate execution time and speed?

☒ Or how to measure them in code (e.g., Python)?

Perplexity


can you give me related literature of FuNES FLoofd Risk Prediction

Answer Images Sources 13

- 


sciencedirect
sciencedirect.com/science/articl...

Development and evaluation of flood forecasting models for forecast ...

3/s). As can be seen, only FUNES obtained a forecast hit at first observed exceedance of the forecast threshold in 2016. However, FUNES consistently overestimated inflows throughout the wet season, causing daily false alarms, and is clearly not constrained within the range of ...
- 

tudelft
research.tudelft.nl/files/83622822...

[PDF] Development and evaluation of flood forecasting models for forecast ...

comprises a rudimentary hydraulic model (no measured cross-sections) with subjective probabilities assigned to flood extents in downstream villages. Further reclassification to five risk classes was used to establish triggers for release of pre-allocated funds, secured by the German Red Cross with governmental support. As ...
- 

forecast-based-financing
forecast-based-financing.org/wp-content/upl...

Brochure vertical - Cruz Roja - Togo - Ingles - con foto

Dams control flooding, up to a limit. FUNES gives Nangbéto dam the ability to anticipate inflows as well as outflows 'today' and for 2 days into the future. Once the reservoir has filled, to prevent the dam from giving way, any more water coming down the river must be allowed to overspill. FUNES uses anticipated flow information ...

Ask a follow-up



Can you give me what are the needed objectives for FuNES Forecasting Flood Risk algorithm to recreate it.

Answer Sources 18

- colorado
[PDF] Flood Modelling and Assessments for...
- forecast-based-financi...
Brochure vertical - Cruz Roja - Togo - Ingles - con...
- sciencedirect
Development and evaluation of flood...
- FasterCapital
Forecasting objectives: How to set and achieve...

The needed objectives for recreating the FuNES (Flood Early Notification System) forecasting flood risk algorithm include:

1. **Collect Daily Hydrological and Meteorological Data:** FuNES requires daily rainfall, river level (limnimeters), and post-flood impact data collected by trained volunteers and hydrometeorological services. This data is critical for feeding the model inputs.
2. **Incorporate Self-learning Flood Risk Assessment:** FuNES uses a self-learning approach that improves its flood risk predictions over time by learning from actual flood impacts and geographical data. This embodies a feedback loop where the algorithm constantly refines danger levels.
3. **Define Risk Scenarios and Danger Levels:** FuNES categorizes risk with a 5-point danger level scale — from very low risk to very elevated risk — based on elevation and flood impact scenarios. These risk levels update dynamically as more event data is gathered.
4. **Formulate Early Actions Based on Forecast Triggers:** The algorithm informs early actions (such as evacuation preparations or health advisories) with predefined standard operating procedures (SOPs). Each danger level triggers corresponding measures involving stakeholders like communities, hydropower operators, and Red Cross volunteers.
5. **Enable Community Engagement and Data Collection:** The system relies on community engagement for data collection (e.g., flood impact surveys via mobile phones) and disseminating warnings to improve accuracy and responsiveness.
6. **Integration with Hydropower Management:** FuNES optimizes the timing of controlled water releases from dams to minimize downstream flood impacts, particularly coordinating releases to avoid simultaneous precipitation-induced flooding.
7. **Continuous Monitoring and Improvement:** Continuous monitoring, evaluation, and revision of SOPs and forecasting models to reduce false alarms and increase forecast skill over time.

These objectives enable FuNES to provide timely, localized flood risk warnings that can save

what are the dam level range of Angat Dam

Answer Images Sources 28

- Wikimedia Foundation...
Angat Dam
- Pnagovph
Angat Dam water rises past minimum operating level...
- SunStar Publishing Inc.
Angat Dam water level remains below normal
- SunStar Publishing Inc.
Angat water level below normal

Assistant steps >



The water level range of Angat Dam is as follows:

- The normal high water level (NHWL) is about 210 meters.
- The minimum operating level is generally at 180 meters. Below this, water supply for hydropower and irrigation is stopped, and only raw water supply for Metro Manila is maintained.
- The dam's maximum reservoir water level can reach around 214 meters, which is considered the maximum safe storage capacity.
- Historical low levels have gone down to about 157.76 meters during extreme drought conditions (e.g., El Niño in 2010).

Current operational water levels usually range between 180 meters and 210 meters depending on rainfall and reservoir status. The dam is 131 meters high and critical for water supply to Metro Manila, power generation, and irrigation use.