Information Geography 1 (2025) 100008

Contents lists available at ScienceDirect

Information Geography

journal homepage: www.sciencedirect.com/journal/information-geography

Research Article

National Water Level Forecast (NWLF): An open-source customizable web application for the GEOGLOWS ECMWF global hydrological model

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ARTICLE INFO

Keywords:
GEOGLOWS
ECMWF
Global hydrologic modeling
Discharge-to-water level transformation (DWLT)
Hydrological forecasting
Tethys platform
Early warning systems

ABSTRACT

Water-related disasters, including floods and droughts, require innovative forecasting tools for effective risk management and decision-making. The National Water Level Forecast (NWLF) application addresses this need by integrating global hydrological simulations from the GEOGLOWS ECMWF Global Hydrological Model with locally observed data. Developed using the Tethys platform, NWLF employs a pre-computed backend architecture to deliver reliable water level forecasts, ensuring operational stability and an intuitive user interface. Central to its method is the Discharge-to-Water Level Transformation (DWLT), which uses monthly duration curves to align simulated and observed data through non-exceedance probability, significantly improving forecast accuracy. Case studies across Brazil, Colombia, Ecuador, and Peru demonstrate NWLF's scalability and adaptability in addressing diverse regional hydrological challenges. Enhancements in NWLF architecture, such as pre-computation, enable faster analyses. Opportunities to improve the system include collaborative threshold refinements and enhanced stakeholder engagement, NWLF has the potential to bridge the gap between global models and local applications. This study presents the NWLF application and highlights its potential for advancing hydrological forecasting, contributing to Sustainable Development Goals (SDGs) related to water resource management and disaster risk reduction while paving the way for continuous improvement and broader adoption.

1. Introduction

Water-related disasters such as floods and droughts cause widespread socio-economic impacts, affecting millions globally. As these disasters are exacerbated by climate change, urbanization, and increasing hydrological variability, accurate and efficient forecasting systems are critical to mitigate risks, enhance preparedness, and inform resource management (Acosta-Coll et al., 2018a; Ekeu-wei, 2018). Early warning systems (EWSs) have proven to be effective tools for mitigating these impacts by providing hazard predictions and timely alerts. Hydrological forecasting, particularly water level prediction, is pivotal in EWSs, offering intuitive and actionable information to decision-makers, emergency responders, and vulnerable communities. Unlike discharge data, water level measurements, often called gauge height, are easier to interpret and directly relate to observable impacts, making them indispensable for local decision-making (Acosta-Coll et al., 2018b; Fahlquist and Hopkins, 2021; Moisès and Kunguma, 2023; Perera et al., 2020).

Global hydrological models, such as the GEOGLOWS (Hales et al., 2022) and GloFAS (Alfieri et al., 2013), have revolutionized the hydrological forecasting by providing large-scale, ensemble-based predictions that address data scarcity in many regions. By combining advanced numerical weather predictions with hydrological models, these systems

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https://doi.org/10.1016/j.infgeo.2025.100008
Received 26 January 2025; Received in revised form 21 March 2025; Accepted 24 March 2025
Available online 1 April 2025

deliver streamflow forecasts with a horizon of up to 15 days and retrospective simulations extending back several decades (Alfieri et al., 2013, 2020; Hales et al., 2022; Harrigan et al., 2020; Sanchez Lozano et al., 2021; Sanchez Lozano et al., 2025). These forecasting systems offer valuable insights but face limited scalability, difficulties integrating global and local data, and accessibility constraints. This creates a significant gap between their outputs and practical application at regional levels where disaster impacts are most severe (Ekeu-Wei and Blackburn, 2018).

Recent international efforts, such as the World Meteorological Organization's Early Warnings for All initiative, highlight the urgent need to address global disparities in disaster preparedness (Usamah et al., 2024). One-third of the world's population, primarily in developing countries and small island states, lacks access to multi-hazard early warning systems. This gap leaves millions vulnerable to floods, droughts, and other climate-induced hazards. The initiative emphasizes that EWS is a proven, cost-effective measure, offering a ten times return on investment by reducing damages and saving lives through opportune action. Moreover, it calls for integrated systems that combine hazard monitoring, prediction, communication, and response capabilities (World Meteorological Organization, 2022).

Operational flood forecasting systems have evolved significantly, driven by technological advancements and the increasing demand for actionable disaster management tools in different countries (Adams and Pagano, 2016). However, these systems often face barriers in their global implementation, particularly in developing countries, due to a lack of trained personnel, insufficient financial resources, and fragmented policies (Perera et al., 2020). For instance, a survey revealed that 74% of flood forecasting centers lack experts capable of integrating data and performing forecasts, highlighting the shortage of technical expertise and human resources (Barrett and Tokar, 2018; World Bank, 2018). Additionally, many National Meteorological and Hydrological Services (NMHSs) struggle to secure funding for modernizing services, often relying on post-disaster funding, which leads to fragmented early warning systems that are difficult to operate and maintain (Hallegatte et al., 2018). Efforts to mitigate these issues include competency-based training programs and structured skill development for forecasting.

Sanchez Lozano et al. (2021) developed the Historical Validation Tool (HVT) Web Application on the Tethys Platform (Jones et al., 2014; Swain, 2015), integrating observed and simulated data from multiple sources, including HydroServer Lite (Conner et al., 2013), Hydroshare (Horsburgh et al., 2016), and the GEOGLOWS Model REST API (Hales et al., 2022; Souffront Alcantara et al., 2019). HVT uses the monthly flow duration curve quantile-mapping (MFDC-QM) method (Sanchez Lozano et al., 2025) to bias correct retrospective and forecasted streamflow simulations from the GEOGLOWS Model, providing an accurate and customizable forecast system. In addition, its open-source framework and reliance on freely accessible global services allow agencies with limited resources to adopt HVT at minimal cost. At the same time, the user-friendly interface lowers the technical barriers to staff training and operational use. Consequently, HVT promotes collaboration across institutions, addresses common data-integration challenges, and supports capacity-building efforts aimed at enhancing the global implementation of flood forecasting systems at the local scale. A limitation is that HVT focuses on discharge data, which—despite being crucial for understanding river systems (Depetris, 2021) —requires meeting specific gauge installation conditions that are not always feasible (e.g., stable riverbeds, absence of strong backwater effects, and frequent recalibration) (World Meteorological Organization, 2008, 2010).

To measure river discharge as accurately as possible, the World Meteorological Organization (WMO) recommends selecting gauge sites with stable, uniform conditions—for example, straight reaches, parallel flow velocities, and a regular river bed free from significant backwater effects, flow divisions, and excessive vegetation (World Meteorological Organization, 2008, 2010). In cases where such ideal conditions cannot be guaranteed, the WMO (2010) suggests specific measures to manage rating curves and discharge measurements, including the consistent development of a reliable stage-discharge relationship, routine recalibrations in unstable settings, and the use of auxiliary gauges in environments lying to frequent backwater. However, creating rating curves, usually requires multiple site visits and data-intensive evaluations (Herschy, 1993), which can be difficult for many national hydrological agencies to sustain. Strictly adhering to these guidelines often proves impractical because of financial constraints, limited maintenance capabilities, logistical hurdles, recurring organizational overhauls, on-site safety concerns, outdated data handling systems, and insufficient data collection in numerous countries (Cheng et al., 2019; Haile et al., 2023; Negatu et al., 2022; Rozos et al., 2022; Taye et al., 2023; World Bank, 2018). Moreover, a lack of robust monitoring infrastructure, compounded by various technical, economic, and administrative barriers, exacerbates the uncertainty or absence of discharge values (Bjerklie et al., 2003). As a result, water level emerges as the more reliable measurement in many locations, leading to instances where only water level data can be consistently collected.

Recognizing the challenges in acquiring reliable discharge values—-stemming from logistical, technical, and financial barriers—and the availability of biased discharge simulations through global hydrological models, Rojas Lesmes et al. (2024) developed and tested the Discharge-to-Water Level Transformation (DWLT) methodology. This method transforms simulated discharge values into simulated water level values, addressing the reliance on discharge data in regions where gauging infrastructure is insufficient or unavailable. The DWLT method, based on the MFDC-QM bias correction method (Sanchez Lozano et al., 2025), was validated in more than 7000 gauges globally, showing moderate to good alignment between the transformed GEOGLOWS discharge simulations, expressed as water level time series and gauged water level observations. This demonstrated the reliability of the DWLT method for retrospective simulations and motivated its extension to the GEOGLOWS Model forecast, paving the way for an operational and customizable hydrological forecast system.

To address these challenges, we developed the National Water Level Forecast (NWLF) application, presented herein as a scalable, open-source tool to integrate global hydrological models with local decision-making needs. By integrating the GEOGLOWS ECMWF Global Hydrological Model with observed water level data and applying the DWLT methodology (Rojas Lesmes et al., 2024), NWLF transforms global forecasts into actionable simulated values for local applications. Its design overcomes the limitations of discharge-based systems by using water level measurements, ensuring accessibility, and promoting ease of use. This paper presents the development, implementation, and evaluation of NWLF as a solution to enhance flood and drought risk management, align with global initiatives, and build resilience in vulnerable regions.

The remainder of this paper is organized as follows: Section 2 presents the data and methods used for the NWLF development; Section 3 presents the NWLF software implementation, and results of four applied study cases, and additional achievements of the applications; Section 4 provides a brief discussion of the methods; and Section 5 presents the conclusions of the study.

2. Methods

2.1. Requirements

The NWLF application requires spatial data to represent stream networks and gauging stations and connections to observed data to analyze temporal changes in water levels. The NWLF was developed using the Tethys Platform, a web development framework designed to support hydrological applications by handling spatial and temporal data (Jones et al., 2014; Swain, 2015; Swain et al., 2015, 2016). This framework has been widely used to create web applications focused on water resources (Ashby et al., 2021; Romero Bustamante et al., 2021; Dolder et al., 2021; Evans et al., 2020; Jones et al., 2023; Krewson, 2019; Magoffin et al., 2025; McStraw et al., 2022; Nelson et al., 2019; Sanchez Lozano et al., 2021; Snow et al., 2016). As with many hydrological computational tools, significant effort is dedicated to data preparation and pre-processing to ensure the information is in the appropriate format for analysis and communication. To streamline these processes, the NWLF integrates data acquisition and pre-processing functionalities, enabling efficient validation of the GEOGLOWS Model (Hales et al., 2022) using locally observed data.

In the framework of the NASA SERVIR-Amazonia project, the NWLF application was customized for four specific countries—Brazil, Colombia, Ecuador, and Peru—as part of case studies that demonstrate its ability to facilitate the use of global hydrological data by local end-users. The analyzed regions exhibit a variety of climatic conditions. While much of the area is dominated by tropical climates, southern Brazil has a temperate climate, the east coast of Brazil and the west coast of Peru experience arid conditions, and the Andes Mountains feature a temperate climate, according to the Köppen climate classification (Köppen, 1936).

Each study case study highlights the shared functionalities of the NWLF application across the regions, with Colombia featuring an additional customization for low-water-level warnings. We met with national hydrological agencies during the design phase to identify their key requirements. We integrated these into a standardized set of features applied to all app versions. Besides differences in maps, station networks, and Colombia's unique customization, the apps maintain consistent design and capabilities across the case studies.

Although the NWLF was customized for each region, the computational methods and data pre- and post-processing tools remained consistent across cases. App customization involved shaping the sources and types of spatial and temporal data to reflect the unique characteristics of each region. The selected data sources were used to implement the DWLT using monthly duration curves (Rojas Lesmes et al., 2024) methodology and produce a local Water Level Forecast System based on the GEOGLOWS Model and locally observed data.

2.2. GEOGLOWS ECMWF hydrological model

The GEOGLOWS ECMWF Hydrological Model (Ashby et al., 2021; Hales et al., 2022; Qiao et al., 2019; Snow, 2015; Snow et al., 2016; Souffront Alcantara et al., 2019), also referred to as the Streamflow Prediction Tool (Bhandari et al., 2023), GloFAS-SPT (Tsering et al., 2022), and GEOGLOWS ECMWF Streamflow Services (GESS) (Sanchez Lozano et al., 2021), serves as a global streamflow forecasting platform aimed at delivering hydrological information that is both accessible and actionable. The model relies on total runoff outputs produced by ECMWF's ECLand land surface model (Boussetta et al., 2021), capturing both surface and subsurface hydrological processes. These runoff estimates, provided in gridded format, are transformed into river reach-specific flow volumes through an area-weighted grid-to-reach mapping technique. Subsequently, the model employs Muskingum routing — implemented with the RAPID modeling framework (David et al., 2011) — to simulate the movement of water through the global river network.

Historical simulations within GEOGLOWS are generated using the ERA5 reanalysis dataset (Hersbach et al., 2020), covering approximately one million stream reaches (Hales et al., 2022). In addition to historical data, the system provides ensemble-based streamflow forecasts with lead times of up to 15 days, leveraging meteorological forecasts from the ECMWF Integrated Forecast System (IFS) (ECMWF, 2024). GEOGLOWS also supports statistical hydrological analysis by offering tools such as return periods, flow duration curves, and other indicators that help inform flood risk assessments and water resource planning.

Complementing the model computations, the GEOGLOWS platform includes a robust cyberinfrastructure for data storage, visualization, and dissemination. Through web-based tools and API access, users at the national, basin, and local levels can retrieve and utilize model outputs for flood forecasting, water management decision-making, and infrastructure planning (Deval et al., 2024; Hales et al., 2022; Sanchez Lozano et al., 2021; Souffront Alcantara et al., 2019). This ecosystem facilitates the integration of global-scale hydrological forecasts into operational and research applications worldwide.

2.3. Data

The NWLF application requires geographical information data, including at least two shapefiles, to load the necessary spatial data. The first shapefile is derived from the GEOGLOWS Model's system of watersheds and streams (Ashby, 2020), containing river reaches within the domain of each study case country. The second shapefile represents the locations of gauging stations with observed water level data in the country of interest. In addition to these baseline requirements, the customization process included incorporating national political divisions obtained from the GADM website (GADM, 2023) and hydrological divisions provided directly by the respective National Hydrological Services. These additional layers ensure that the application aligns with the specific geographic and administrative contexts of each country.

To perform the DWLT method to the GEOGLOWS Model, historical observed water level data was required at a daily time scale also obtained from the national hydrological services. The data were retrieved through web services in Colombia and Brazil, while they were provided directly by the Hydrometeorological Information Direction and the Hydrology Direction in Ecuador and Peru, respectively. The collected datasets included 1708 gauging stations in Brazil, 1242 in Colombia, 298 in Ecuador, and 210 in Peru.

The simulated streamflow data used in the NWLF were accessed through the GEOGLOWS Model REST API using the concept of Hydrologic Modeling as a Service (HMaaS) (Souffront Alcantara et al., 2019). These data included both retrospective simulations and forecasts covering the case study regions.

2.4. Spatial data pre-processing

The GEOGLOWS Model generates retrospective streamflow simulations and forecasts for approximately one million streams worldwide, divided into 13 regions (Hales et al., 2022). For this study, a customized NWLF application was developed for four countries—Brazil, Colombia, Ecuador, and Peru—focusing on streams within the **south_america-geoglows** region. We used publicly available shapefiles from HydroShare (Ashby, 2020) to define the areas of interest representing the GEOGLOWS stream network. The shapefile corresponding to the **south_america-geoglows** region covers a significantly larger area than the countries included in the case studies. Therefore, it was clipped to the boundaries of each country in the case studies. The processed shapefiles were then uploaded to a GeoServer for visualization and interaction.

A critical step in the customization process involved pairing each gauging station with its corresponding reach ID from the GEOGLOWS Model. This assignment ensures that observed and simulated data represent the same watershed, enabling accurate analysis and transformation of water levels. To achieve this, we used the assignations calculated by Rojas Lesmes et al. (2024), who employed a GIS spatial join operation to match stations with reach IDs. The process accounted for key challenges, including imprecise station locations and discrepancies between gauging station basins and modeled basins. Stations that could not be connected to a reach ID in the GEOGLOWS Model were excluded. This exclusion affected approximately 11.9% of stations in Brazil (203 out of 1708), 0.6% in Colombia (8 out of 1242), 7.0% in Ecuador (21 out of 298), and none in Peru (0 out of 210).

For each study case, the metadata for the selected stations — including station code, name, latitude, longitude, and warning levels, among others—were compiled into a CSV file. The NWLF backend updates warning levels in the file, which are displayed on the map panel as geoJSON markers. Marker colors reflect the calculated warning levels, providing users with an intuitive interface to monitor hydrological conditions.

2.5. Discharge to water level transformation

The Discharge-to-Water Level Transformation (DWLT) method leverages key hydrological concepts, such as flow duration curves and water-level duration curves, to transform discharge simulations into water level predictions. A flow duration curve represents the relationship between the magnitude and frequency of streamflow for a river, indicating the percentage of time a given discharge value is not exceeded (i.e., the non-exceedance probability). Similarly, a water-level duration curve illustrates the percentage of time that water levels are not exceeded (Law, 2002; Vogel and Fennessey, 1994, 1995). The non-exceedance probability associated with a discharge or water level value expresses the proportion of observations that are less than or equal to that value in the historical record.

The DWLT method applies these concepts to align simulated discharge values from the GEOGLOWS ECMWF Global Hydrological Model with observed water level data. The process involves determining the non-exceedance probability of each simulated discharge value based on the simulated flow duration curve. The corresponding observed water level value, having the same non-exceedance probability in the observed water level duration curve, is then used to replace the simulated discharge value (Fig. 1). Return period thresholds are recalculated using the resulting simulated water levels by applying the Gumbel Distribution.

Similar to the extension of the MFDC-QM method to the GEOGLOWS forecasts by Sanchez Lozano et al. (2021), the DWLT methodology has been adapted for use with the GEOGLOWS forecast. For this application, each simulated discharge value from all forecast ensembles is assigned a non-exceedance probability derived from the retrospective simulation flow duration curve for the specific month of the forecast launch. This probability is then matched to the observed water level values with the same probability in that month's observed water level duration curve, replacing the simulated values with the equivalent observed values (Fig. 2). This approach assumes consistency between the flow duration curves of the GEOGLOWS forecast and the retrospective simulation.

2.6. Web application design

The NWLF web application design is divided into two primary components: the backend and the frontend. This architecture ensures robust processing capabilities and a user-friendly interface, optimizing performance and accessibility.

2.6.1. Backend

The backend is the core data processing component for storage, updates, transformations, and warning evaluations. Its implementation includes the following elements:

i. Database Architecture:

The backend uses a PostgreSQL database, partitioned into distinct sections for efficient data management:

- **Observed Data:** Updated with measurements provided by the National Hydrological Services of each country.
- **Retrospective Simulated Data:** Obtained using the GEOGLOWS Model REST API.
- **Forecast Data:** Retrieved daily from the GEOGLOWS Model REST API.
- **Transformed Historical Simulated Data:** Generated by applying the DWLT methodology to the historical simulation data.
- **Transformed Forecast Data:** Created by applying the DWLT methodology to the forecast data.

ii. Data Update Processes:

Python scripts, scheduled to run as crontab jobs on the server, ensure regular and automated database updates. The scripts perform the following tasks:

- **Observed Data Updates:** updates in these cases occur manually and on-demand when the entire dataset is refreshed. In Ecuador and Peru, there is a lack of web services for accessing the observed

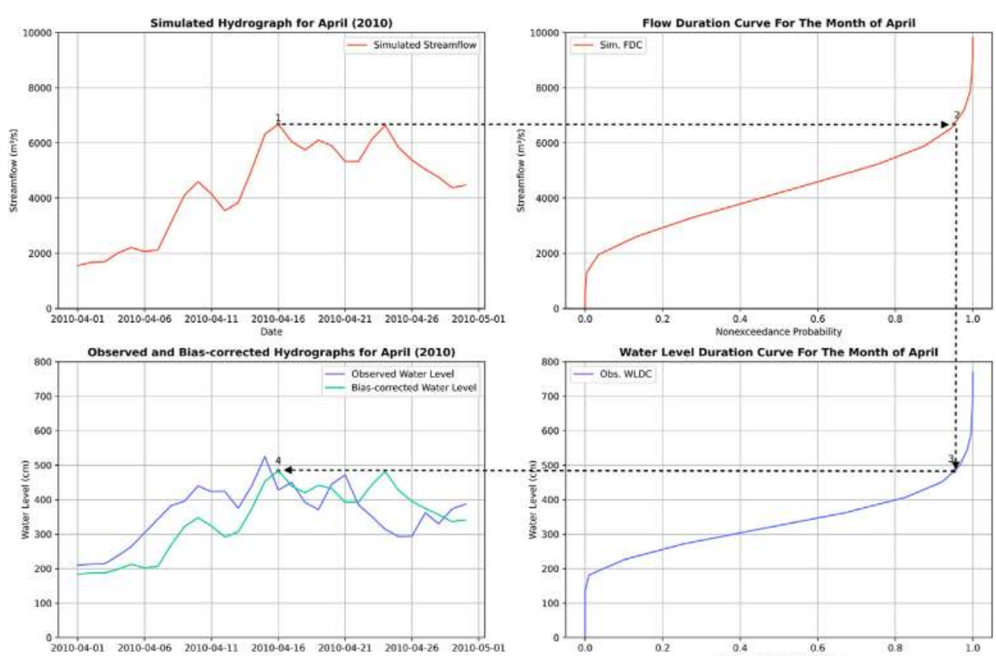

Fig. 1. The Discharge-to-Water Level Transformation (DWLT) using monthly duration curves proposed by Rojas Lesmes et al. (2024).

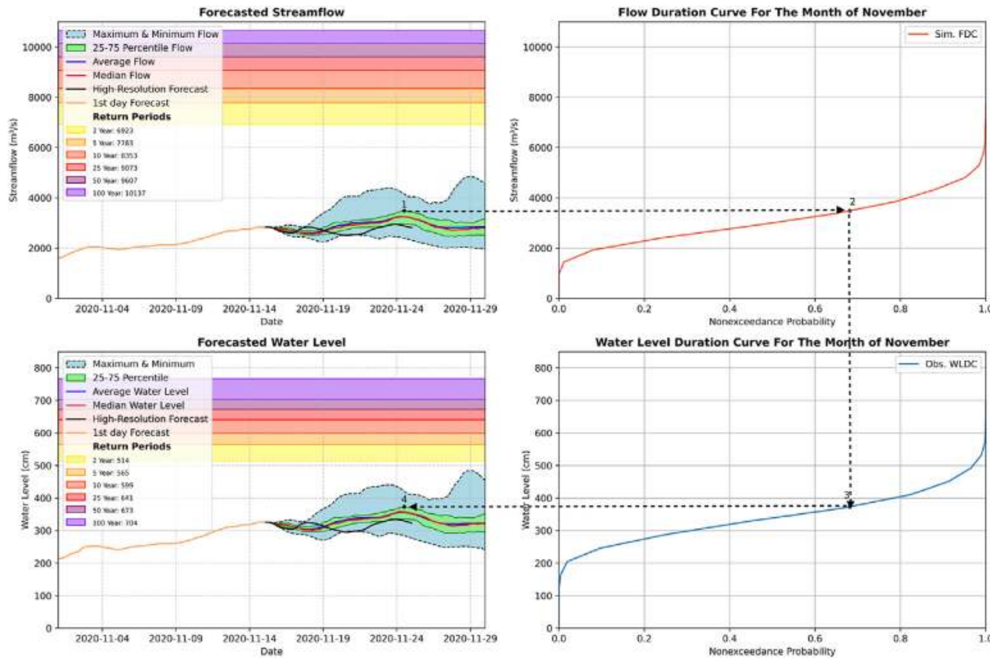

Fig. 2. The Discharge-to-Water Level Transformation (DWLT) using monthly duration curves extended to the GEOGLOWS forecast.

hydrological data. In Colombia and Brazil, there are web services for getting observed data; unfortunately, they present challenges for automation.

- **GEOGLOWS Historical Simulated Data Updates:** Scheduled monthly.
- **Transformed Historical Data Updates:** Updated whenever observed or historical simulated data are modified. The return periods (2, 5, 10, 25, 50, and 100 years) are recalculated after each update to maintain accurate warning thresholds.
- **Transformed Historical Simulated Data:** Generated by applying the DWLT methodology to the historical simulation data.
- **GEOGLOWS Forecast Data Updates:** Automatically retrieved daily from the ECMWF REST API. This process begins at 08:00 UTC and typically completes by 11:00 UTC. If the API is unavailable, retries are scheduled at 14:00 UTC and 23:00 UTC, ensuring data reliability.
- **Transformed Forecast Data Updates:** Executed immediately after the forecast data retrieval. Warnings for each station are then calculated based on the forecast ensembles.

iii. Warning Evaluation:

The backend identifies potential flood events by determining when a defined percentage of the transformed forecast ensemble exceeds return periods of 2, 5, 10, 25, 50, or 100 years. The threshold percentage is specified by each country's national hydrological service, ensuring the warnings are regionally relevant. In addition to the flood warning, as a particular customization for the Colombia study case, the backend processes identify low warnings, determined by the number of days where the median forecast falls below the 7Q10 threshold. The 7Q10 statistic traditionally represents the lowest 7-day consecutive average streamflow expected to occur once every 10 years, commonly used in hydrology for assessing low-flow conditions and regulatory water quality thresholds (Ames, 2006). In the context of the NWLF, this metric has been adapted to use water level values instead of discharge, aligning the analysis with observed and transformed water level data to provide relevant low-level warnings for decision-making. For durations lasting from 3 to 7 days, the warning level is classified as 'low possibility of a dry period.' For durations spanning from 7 to 10 days, it's labeled as a 'medium possibility of a dry period,' and for durations surpassing 10 days, it's deemed a 'high possibility of a dry period.'

2.6.2. Frontend

The frontend of the NWLF web application is designed to provide an intuitive and user-friendly interface for accessing and visualizing observed water level values and transforming them into water level GEOGLOWS simulations, including the retrospective simulation and the hydrological forecast. It is the interactive layer between users and the backend, ensuring effective data delivery. The frontend is composed of three primary panels, each one offering different functions:

i. Map Panel:
   - The map panel allows users to identify high and/or low warning levels based on the color of the markers displayed at gauging station locations.
   - The icon's color corresponds to the return period exceeded and/or the possibility of a dry period in the forecast data, providing visual indications for flood or low-level warnings.
   - Users can navigate the map to explore stations in different regions and basins and zoom into specific areas for localized analysis.

ii. Search and Legend Panel:
   - The search and legend panel includes a legend explaining the color-coded warning levels displayed on the map and a search tool.
   - The search functionality allows users to locate specific stations by department, province, state, or any political division used in the country and hydrological regions, such as basins or sub-basins defined by the national hydrological services.
   - Additionally, users can search for stations by their code, name, or associated river, facilitating efficient navigation.

iii. Station Data Panel:
   - Displayed when a user selects a station, this panel provides detailed station information, including station name, station code, river name, and geographical coordinates (latitude and longitude).
   - It contains historical data, visual comparative analyses between observed water level values and transformed to water level simulated values, and statistical metrics to assess data accuracy and reliability. It offers insights into the precision of the hydrological simulations and the water level forecast.

The frontend is designed to be responsive and accessible from various devices, enabling decision-makers, researchers, and hydrological managers to access and interpret data effectively from anywhere. Its modular and intuitive layout ensures that users can navigate between spatial visualizations, search tools, and station-specific analyses, making the NWLF a valuable tool for flood and drought risk management.

3. Results

This section highlights both the implementation of the software and the hydrological results derived from four case studies. The NWLF is an open-source, web-based platform accessible globally and enables users to compute and retrieve transformed water level forecasts. To deliver region-specific forecasts, the NWLF requires customization to address the unique needs of each area, leveraging the GEOGLOWS model. The source code for the application is publicly available on GitHub (SERVIR-Amazonia, 2023/2023a, 2023/2023b, 2023/2023c, 2023/2024), allowing others to download, adapt, and use it for their purposes.

3.1. Web application design

The NWLF application provides:

- Visualizations for observed and transformed historical streamflow data.
- Tools for analyzing daily and monthly seasonality and scatter plots in both normal and logarithmic scales.
- Users can navigate the map to explore stations in different regions and basins and zoom into specific areas for localized analysis.
- Statistical validation metrics comparing observed and transformed simulated data.
- Visualization and access to transformed forecasts, supporting local hydrological managers in decision-making

The NWLF integrates these functionalities, eliminating the need for users to directly interact with or modify the original GEOGLOWS Model to produce simulated water level values. Users are not required to coordinate with the model developers for adjustments, as the NWLF handles the discharge-to-water level transformation for specific sites or regions using only local observed data.

The NWLF main page (Fig. 3) displays streams and stations for the country, watershed, or region of interest. For instance, Fig. 3 presents the main page of the HVT customized for Colombia. Stations are marked in green when no flood warnings are active, while markers ranging from yellow to purple indicate return periods from 2 to 100 years being exceeded. Additionally, in the case of Colombia, markers in light green, gray, or black signify a low, medium, or high likelihood of dry periods within the next 15 days.

Users can click on a gauge station on the main page to open a pop-up window displaying details about the selected station. This window includes four tabs: historical simulation (Fig. 4), statistical visual analysis (Fig. 5), statistical metrics report (Fig. 6), and water level forecast (Fig. 7). Each of these tabs is described in greater detail in the following sections.

3.1.1. User interface: historical data

The first tab in the pop-up window is labeled 'Historical Simulation.' Fig. 4 shows this tab displays two hydrographs: one for observed historical water level data and another for transformed simulated historical data converted using the DWLT methodology. Fig. 4 illustrates data from the Vinces en Vinces-DCP [H0348] station on the Vinces River in Ecuador. The plots highlight the alignment between the transformed water level data (blue) and the observed water level data (orange). Users can toggle the visibility of each hydrograph to enhance their understanding and confidence in the results. The transformed data can also be downloaded for further analysis or external use. However, downloading observed values is only available in countries with open data access policies.

3.1.2. User interface: visual analysis

The second tab in the pop-up window is labeled 'Visual Analysis.' As shown in Fig. 5, this tab provides visualizations of daily and monthly seasonality patterns and scatter plots for the Contamana [251102] Station on the Ucayali River in Peru. The daily and monthly seasonality plots illustrate the alignment between the average observed water levels and the historical simulated data transformed using the DWLT methodology, with peak values observed in March and the lowest in September. The scatter plots confirm the relationship between simulated and observed values, with points generally following the 45-degree line ($y = x$) and showing some dispersion around it.

3.1.3. User interface: metrics report

The third tab in the pop-up window is labeled 'Metrics Report.' Fig. 6 illustrates the metrics report for the Pedras Negras [15150000] station on

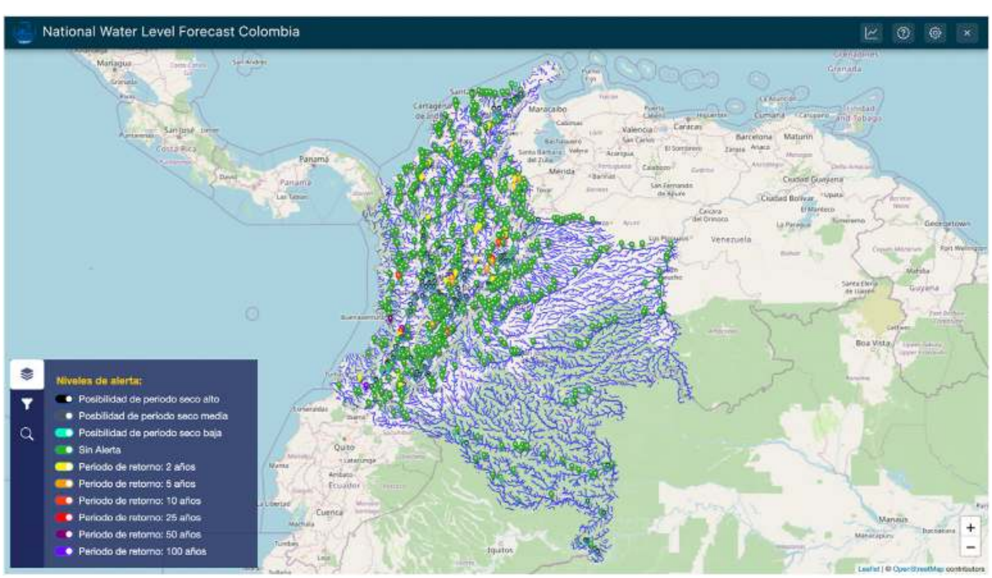

Fig. 3. Main page for the national water level forecast app for Colombia.

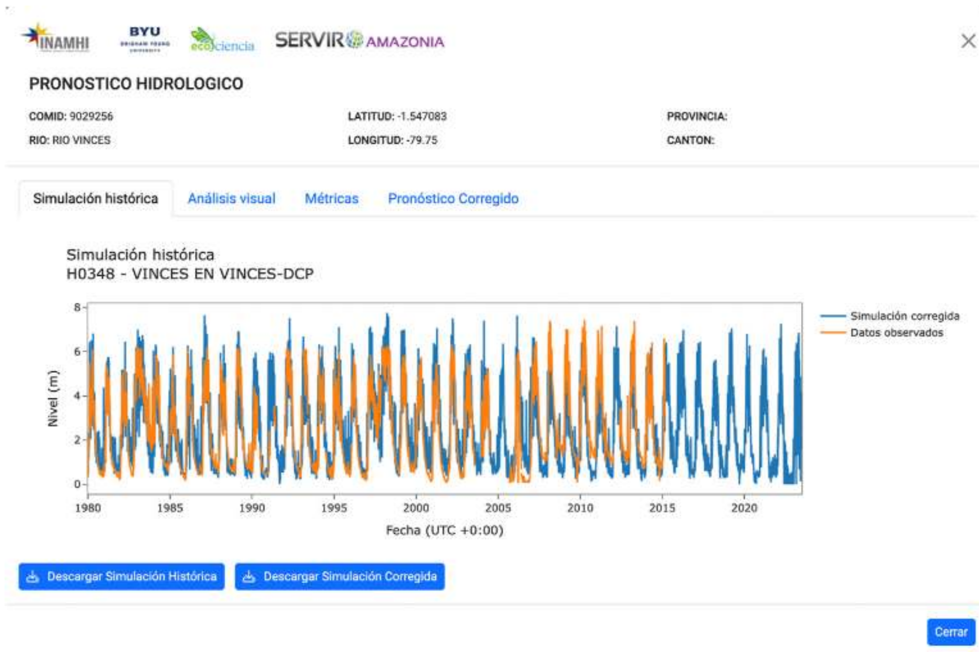

Fig. 4. Hydrographs tab for the Vinces en Vinces-DCP [H0348] station in the national water level forecast app for Ecuador.

the Guapore River in Brazil. This report includes a list of predefined metrics, allowing users to add metrics from those available in the HydroStats package (Roberts et al., 2018) through a selection menu. The metrics provide error calculations that evaluate the performance and alignment between the transformed retrospective simulation data generated using the DWLT method and the observed water level data. Fig. 6 shows how several metrics are displayed in the app, including Mean Error (ME) (Sammut and Webb, 2010), Root Mean Square Error (RMSE) (Dawson et al., 2007), Normalized Root Mean Squared Error (NRMSE) (Jain and Srinivasulu, 2006), Nash–Sutcliffe model efficiency coefficient (NSE) (Nash and Sutcliffe, 1970), the Kling–Gupta efficiency (2009) (KGE, 2009) (Gupta et al., 2009), the Kling–Gupta efficiency (2012) (KGE, 2012) (Kling et al., 2012), Pearson Correlation (R Pearson) (Kirch, 2008), Spearman's rank correlation coefficient (R Spearman) (Dodge, 2008b), and the coefficient of determination (r^2) (Dodge, 2008a). In this case, the last six metrics exhibit values above 0.9, indicating a strong agreement between the observed and simulated data.

3.1.4. User interface: Forecast Visualization

The fourth tab in the pop-up window is titled 'Forecast Visualization.' Fig. 7 displays the Puerto Inca [231101] station forecast on the Pachitea River in Peru. This tab presents the GEOGLOWS forecast transformed into water level predictions using the DWLT method. The upper plot features the forecast hydrograph, including ensemble statistics, the mean, 25th percentile, 75th percentile, minimum, and maximum values, and the 24-h average forecast from the previous week. It also provides return period thresholds derived from the transformed historical simulation. The lower section contains a table that specifies the percentage of ensemble members exceeding each return period threshold for each forecast day. In this specific case, none of the ensemble members exceed any threshold.

3.1.5. User interface: zoom to geographic regions

The NWLF application includes a zoom feature that lets users focus on specific geographic areas. This function has been customized to align with each country's political and hydrological boundaries. For example, Fig. 8 illustrates the zoom feature applied to the Amazonas department in Colombia. Additionally, NWLF provides a station search tool that allows users to locate stations based on attributes such as station code, name, or stream name. This feature simplifies the process of finding relevant stations. Fig. 9 displays the results of a search for stations along the Amazon River in Brazil.

3.2. Study case results

Four countries were selected to perform study cases, viz., Brazil, Colombia, Ecuador, and Peru, to evaluate the NWLF through country-wide analyses. Each case used a version of the NWLF application customized to the region of interest, incorporating access to the observed data relevant to that area. The customizations mainly involved adapting the PostgreSQL database with the observed water level data and the GEOGLOWS simulations for the country stream network and configuring the geographical information for the zoom functionality to meet the specific needs of each country. Additionally, variations were made in the designation of the parameter that defines the percentage of ensemble members required to exceed a return period threshold for issuing a flood warning on the main page. The respective National Hydrological Services are currently performing this definition. An additional distinction is the inclusion of low-level warnings implemented exclusively in the Colombia case study. The observed water level data for the NWLF applications were collected as follows:

- **Brazil**: data for 1505 gauging stations were retrieved via the National Water and Sanitation Agency (ANA) web interface. On average, these time series span 26 years (1992–2019), with approximately 11% missing data.
- **Ecuador**: data for 262 gauging stations were obtained through the SERVIR-Amazonia project by directly requesting it from the Hydrometeorological Information Division of the Ecuadorian National Institute of Meteorology and Hydrology (INAMHI). The time series span an average of 33 years (1976–2009), with around 29% missing data.
- **Colombia**: data for 864 gauging stations were accessed using the Hydrological and Meteorological Data (DHIME) system of the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM). These time series cover an average of 33 years (1982–2014), with approximately 15% missing data.

Fig. 5. Visual analysis for the Contamana [251102] station in the national water level forecast app for Peru.

- **Peru**: data for 210 gauging stations were acquired through the SERVIR-Amazonia project by requesting it directly from the Hydrology Division of the Peruvian National Meteorology and Hydrology Service (SENAMHI). The time series span an average of 14 years (2008–2022), with approximately 15% missing data.

The performance of the DWLT method was evaluated using the Kling–Gupta Efficiency coefficient (KGE) (Kling et al., 2012). As shown in Fig. 10, results across all four case studies indicate generally strong performance, particularly within the Amazon watershed. Moderate performance was observed in the Andes regions and southern Brazil, while lower performance is evident along Brazil's eastern coast. This spatial variability arises from several factors. First, as highlighted by Rojas Lesmes et al. (2024), certain regions—including the Brazilian east coast—pose challenges for the GEOGLOWS model due to the difficulty of accurately representing small, highly dynamic river systems and localized hydrometeorological events. Second, limitations in the observed water level data, such as digitization errors, sudden changes in station zero levels, or anomalous spikes in recorded data, distort duration curves and reduce transformation accuracy. Finally, timing discrepancies between modeled discharge peaks and observed events can also impact performance. Despite these challenges, the findings are encouraging and demonstrate the potential of the DWLT method and the NWLF platform to improve forecast accuracy and hydrological risk assessment.

3.3. Applications of NWLF

The NWLF application has been applied in various regions to support decision-making processes. This section highlights practical case studies from Brazil and Colombia, demonstrating the tool's effectiveness in addressing specific hydrological challenges. These examples showcase how the NWLF facilitates real-time monitoring with accurate forecasts and provides actionable insights for managing water levels and flood risks. These case studies demonstrate the application's versatility and potential for broader regional adoption by customizing the application to local needs.

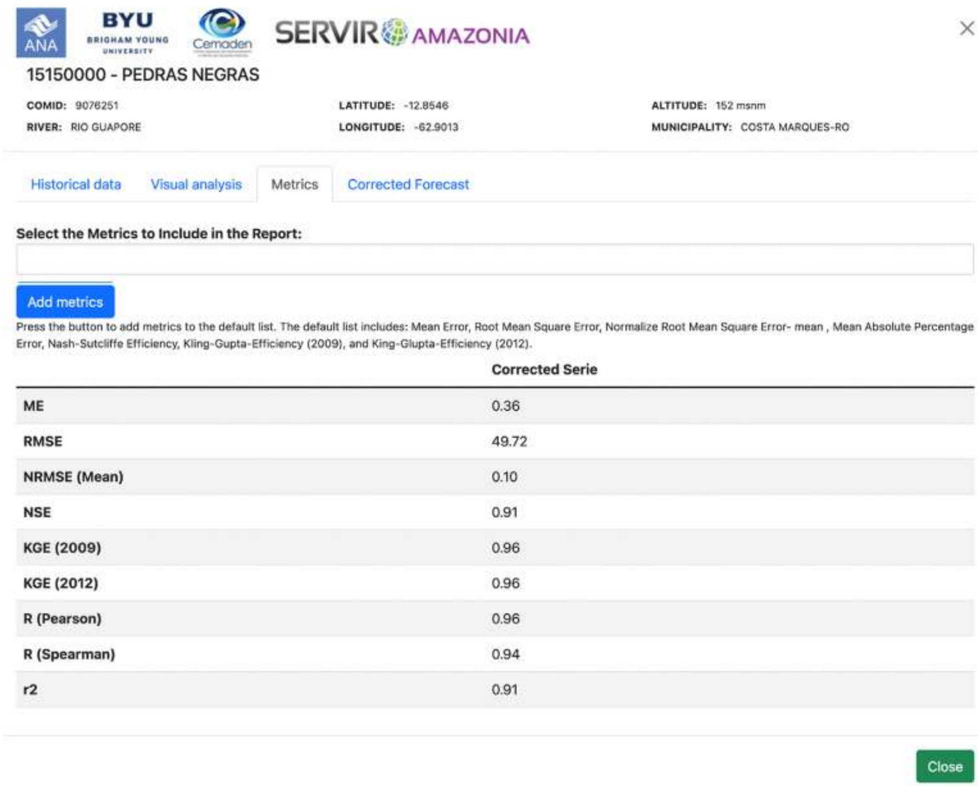

Fig. 6. Metrics report for the Pedras Negras [15150000] station in the national water level forecast app for Brazil.

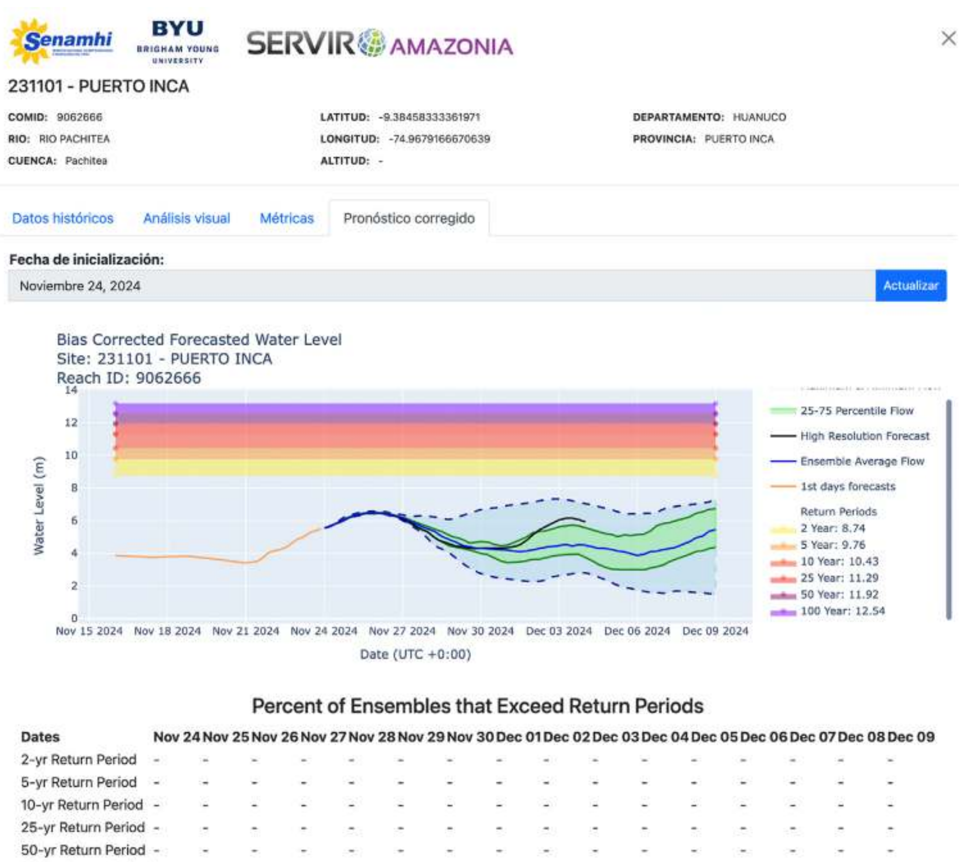

Fig. 7. Forecast for the Puerto Inca [231101] station in the national water level forecast app for Peru.

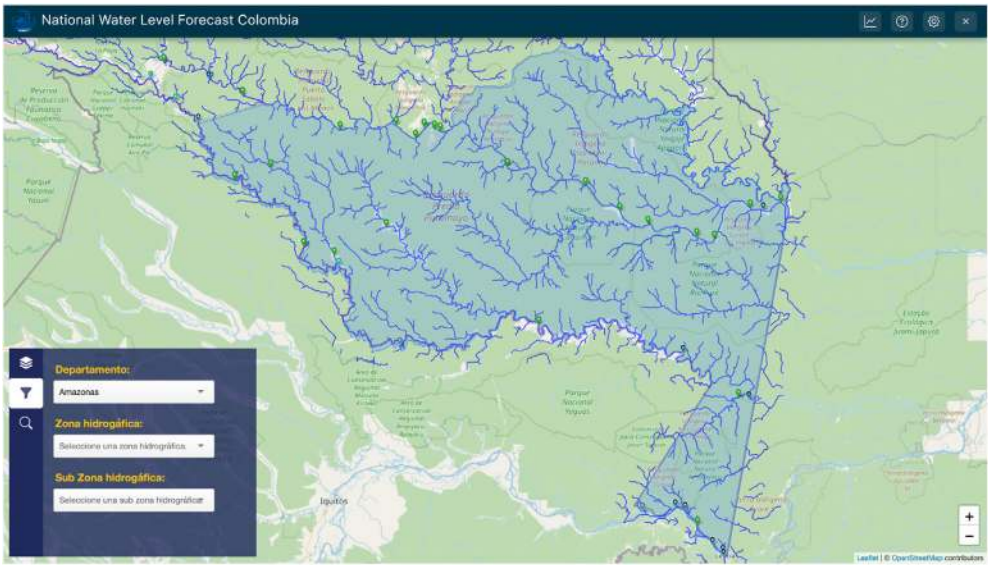

Fig. 8. Forecast for the Puerto Inca [231101] station in the national water level forecast app for Peru.

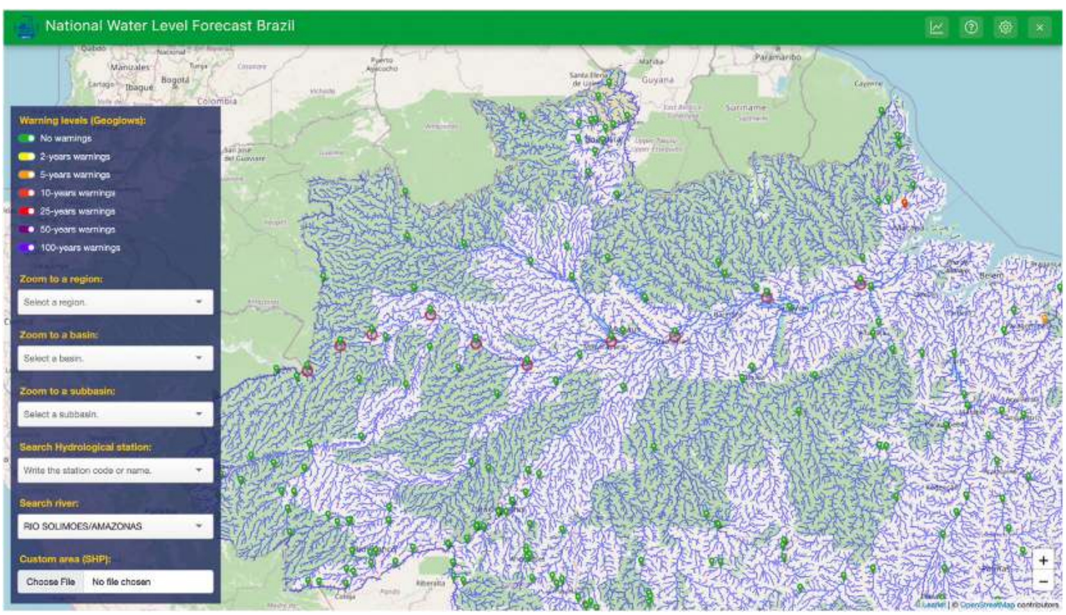

Fig. 9. Forecast for the Puerto Inca [231101] station in the national water level forecast app for Peru.

3.3.1. *Case study: Brazil*

The NWLF application was used during a significant flood event in Rio Grande do Sul, Brazil, between September 11 and 14, 2023 (Célia dos Santos Alvalá et al., 2024). This period was marked by persistent moderate to heavy rainfall, which, combined with prior accumulated precipitation, elevated flooding risks across multiple regions. GEOGLOWS, integrated with the NWLF, provided 15-day forecasts highlighting critical warning levels at specific gauging stations. During this event, the NWLF's spatial forecast warnings worked effectively (Fig. 11). At the Pedro Osório [88641000] station on the Piratini River in Southeast Rio Grande do Sul, forecasts indicated that the mean ensemble member could exceed the 50-year return period threshold. Similarly, at the Quaraí [77500000] station on the Quaraí River in Southwest Rio Grande do Sul, the forecast suggested the potential to surpass the 5-year return period threshold. In contrast, at the Porto Mariante [86895000] station on the Taquari River, located in the Center-East region of Rio Grande do Sul, water levels were predicted to approach the 2-year return period threshold. These forecasts provided critical early warnings, enabling local authorities to prepare for potential hydrological adverse events. The tool's ability to deliver accurate and timely predictions for different return periods proved invaluable for supporting flood risk management and decision-making in Brazil.

3.3.2. *Case study: Colombia*

The NWLF application proved instrumental in analyzing hydrological events in Colombia, ranging from floods to dry periods during the second semester of 2023. A notable example is the flood event in Quetame, Cundinamarca, in July 2023 (Salazar, 2023), where the NWLF application demonstrated its ability to provide early and accurate warnings. The tool issued a 25-year return period warning for the location eight days before the event, escalating to a 100-year return period warning four days before the flood occurred. These opportune forecasts enable local authorities to prepare for potential impacts. The NWLF's ability to detect and escalate warnings based on updated forecasts showcases its value in flood early warning systems (Fig. 12).

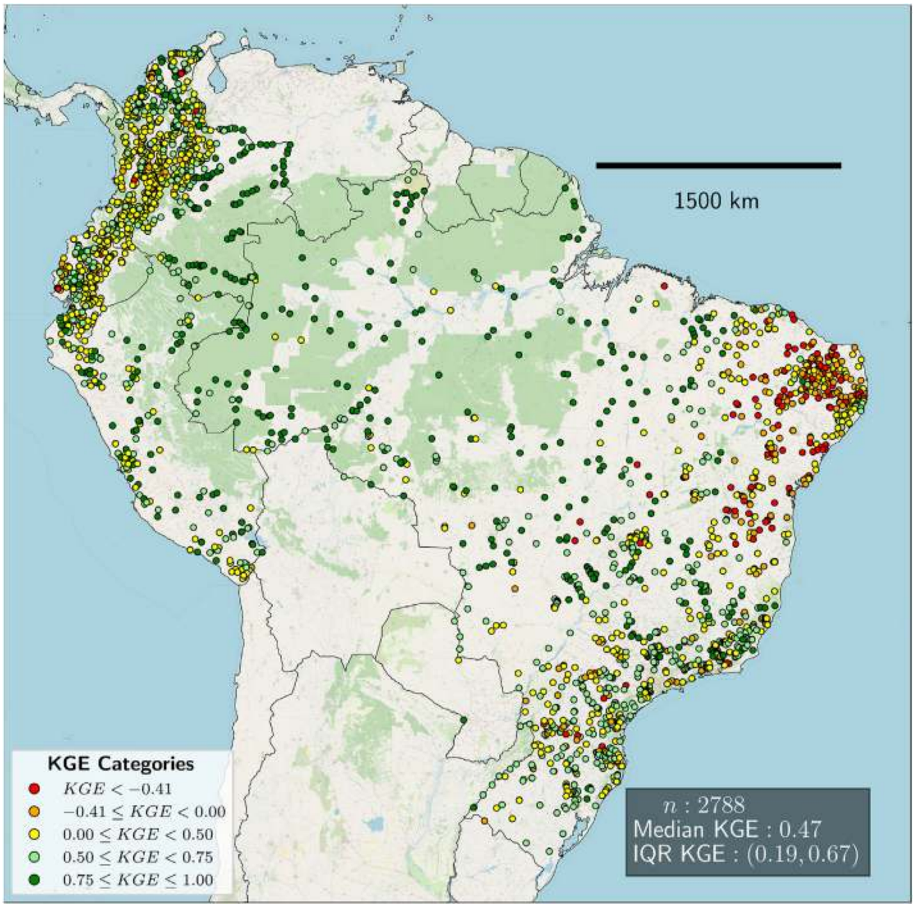

Fig. 10. KGE error metric between the transformed to water level historical simulation and the observed water level data for Brazil, Colombia, Ecuador, and Peru.

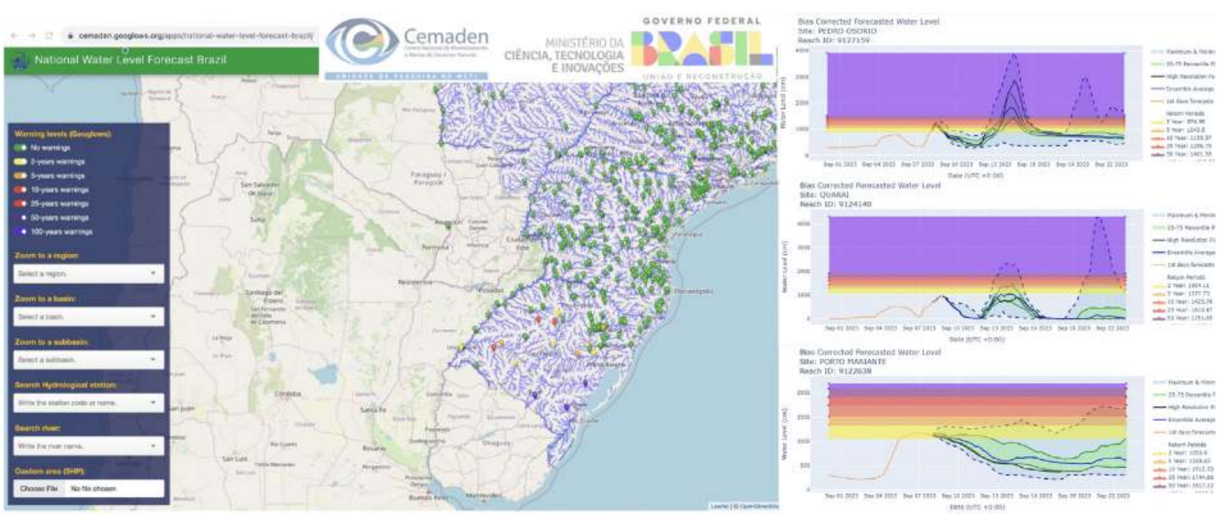

Fig. 11. Composite visualization of the NWLF forecast during the September 2023 flood event in Rio Grande do Sul, Brazil. The spatial map (left) shows the color-coded, based on their respective warning levels, focused on the Rio Grande do Sul region. Hydrographs (right) display forecasted water levels for each station, with marked thresholds for the 50-year, 5-year, and 2-year return periods. The Pedro Osório [88641000] station forecast exceeded the 50-year return period, Quaraí [77500000] station surpassed the 5-year threshold, and Porto Mariante [86895000] station approached the 2-year threshold.

On the other hand, the NWLF application played a critical role in monitoring low water level events along the Amazon River in Colombia during 2023, particularly for extended dry periods influenced by the El Niño Southern Oscillation (ENSO) (Espinoza et al., 2024; Gutierrez-Villarreal et al., 2024; Marengo et al., 2024). These events, characterized by significant drops in water levels, posed challenges for water resource management, navigation, and ecosystem sustainability. The analysis focused on data from the Leticia - AUT [48017010] station, the only station in the region providing real-time observed data. Two key periods of concern during the year 2023 include one between late June and mid-July, where a sharp and prolonged drop in water levels was observed, falling below historical minimum thresholds, and one between

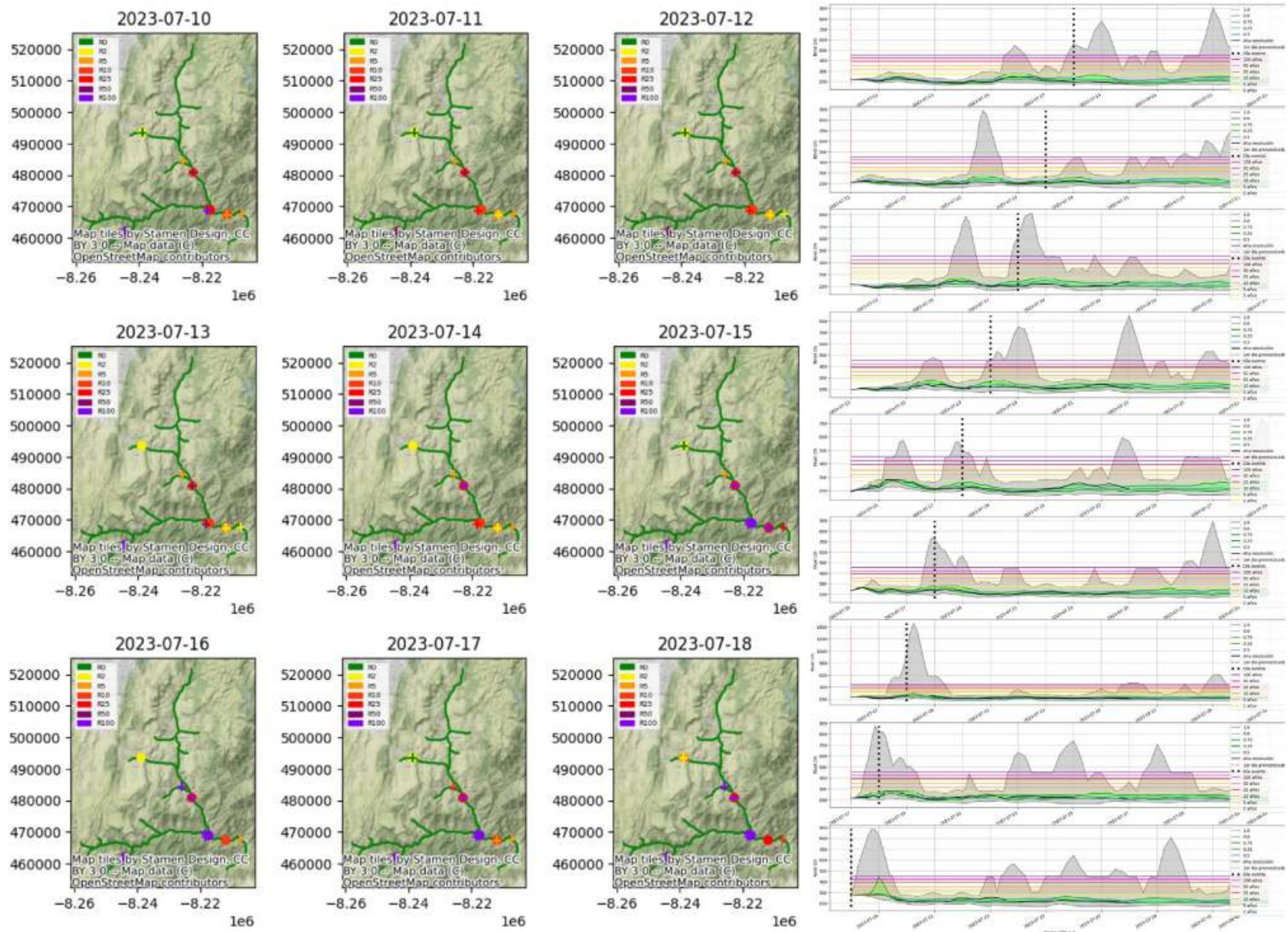

Fig. 12. Composite visualization of the NWLF forecast during the July 2023 flood event in Quetame, Colombia. The spatial maps on the left illustrate the forecast warnings, color-coded by return periods, from July 10 to July 18, showing the progression and intensification of warnings leading up to the event. The hydrographs on the right correspond to the Guacapate [35027190] station, displaying forecasted water levels for each launch date. The hydrographs highlight the alignment between forecast updates and the increasing flood risk, with warnings escalating from the 25-year return period to the 100-year return period.

mid-September and October, during which water levels remained consistently low, coinciding with the region's natural seasonal low flow period.

Fig. 13 illustrates the NWLF's performance in identifying these events. The top panel of the figure presents the NWLF's spatial map for Colombia, with color-coded alerts for low water levels. Stations flagged with low water level warnings are highlighted, and two key clusters of alerts are circled on the map, indicating areas of significant concern during the analysis period. The bottom two panels of the figure show the observed and simulated-corrected hydrographs for the Leticia station. Despite having a short data record in 2023 (middle panel), the observed data clearly display a rapid drop in water levels during the critical periods of mid-June to mid-July (blue box). The simulated-corrected data (bottom panel) closely aligns with the observed trends, confirming the NWLF's capacity to effectively predict and monitor these dry periods. This alignment also captured the drop from mid-June to mid-July (blue box). While this rapid drop could appear as a numerical or modeling error, the observed data from the station confirms it.

The hydrographs also show the daily maximum, minimum, and average water levels and daily percentiles (10th, 25th, and 33rd) calculated from historical records for each calendar day, offering a precise benchmark for interpreting 2023's conditions. Using a secondary axis, the percentile of the observed data (middle panel) and the simulated data (bottom panel) are drawn in a green olive dashed line. Unfortunately, that secondary axis is not aligned with the principal axis. In the observed data plot (middle panel), we can see a notable drop in the percentile of the observed data, from the 40th percentile to the 10th percentile from the beginning of July to the middle of July.

In the simulated data (bottom panel), it is possible to identify three periods of time during 2023 where the simulated water levels were under the 10th percentile as threshold (red boxes), identifying three levels periods: January and March, mid-June to mid-July, and mid-September to October. We only have evidence of the second event in the observed data. However, this alignment demonstrates the DWLT method applied to the GEOGLOWS Model to detect and forecast dry periods.

4. Discussion

The NWLF application represents a significant step forward in leveraging global hydrological data for regional decision-making. While its technical design offers notable improvements over prior tools, such as the HVT, and its development aligns with the collaborative goals of the SERVIR-Amazonia Project, several challenges remain. This discussion focuses on four critical aspects: (i) the technical and operational advancements in NWLF's architecture, (ii) the limitations of return period-based alerts in capturing localized flood risks, (iii) the institutional barriers that have delayed the application's broader adoption, and (iv) the future development directions. Together, these points provide a framework for understanding both the potential and the areas for improvement in deploying NWLF as a decision-support tool.

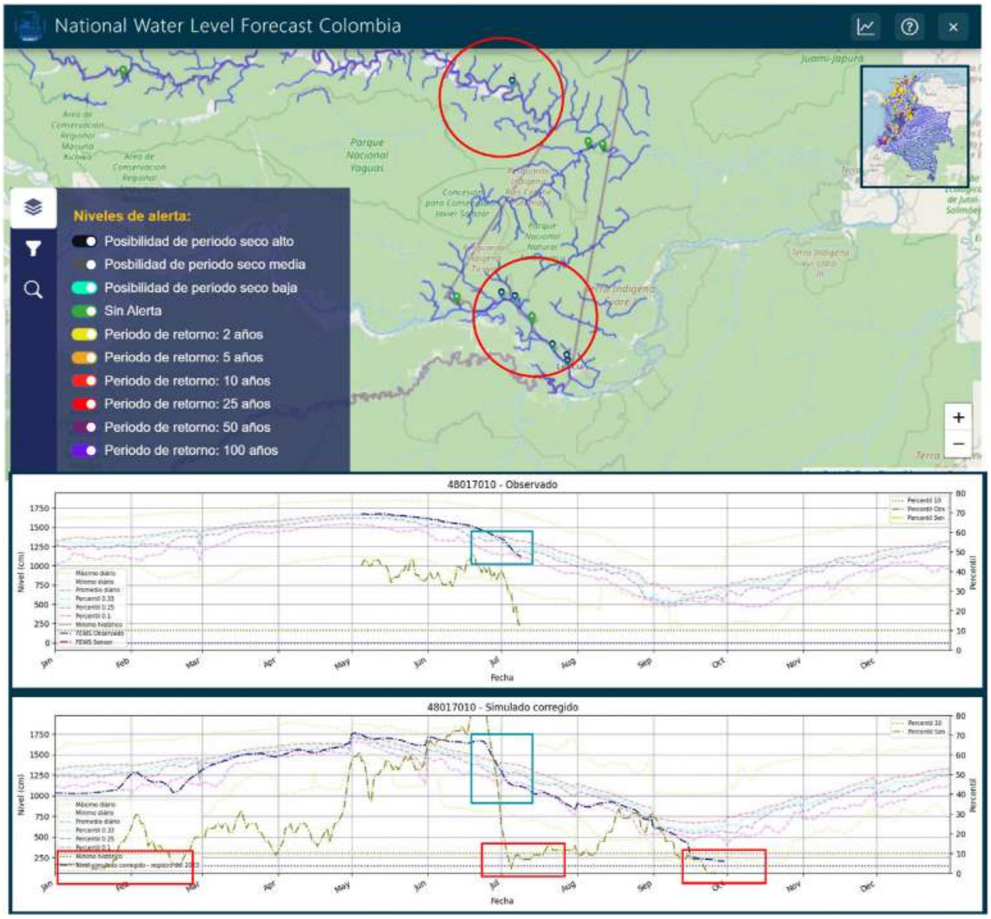

Fig. 13. NWLF performance during low water level events along the Amazon River in 2023. The top panel shows a spatial map of Colombia zoomed in on the Amazon River with color-coded low water level alerts. Two key clusters of warnings are circled. The middle panel displays observed water levels at the Leticia - AUT [48017010] station, highlighting a significant drop from mid-June to mid-July (blue box). The bottom panel presents simulated-corrected water levels, identifying three critical low-level periods: January to March, mid-June to mid-July, and mid-September to October (red boxes). The hydrographs illustrate daily maximum, minimum, and average water levels, percentiles (10th, 25th, and 33rd), and the percentile rank of observed and simulated data on the secondary axis.

4.1. The NWLF architecture

The configuration of the NWLF application, with its backend designed to handle data downloads and preprocessing before visualization, offers significant advantages over the setup used in the HVT, as described by Sanchez Lozano et al. (2021). In the HVT, data processing and analysis were performed ‘on the fly,’ meaning calculations were made in real time as users interacted with the application. In contrast, the NWLF backend pre-computes the necessary data, improving application response times. Additionally, by storing temporary copies of the GEOGLOWS model's simulated data, the NWLF system will still offer results in cases of any interruptions or failures in the GEOGLOWS Model REST API due to the pre-processed data will still be available for use.

Moreover, by performing calculations beforehand, the NWLF can display the alert levels for each station when the application is loaded, coloring the stations accordingly. This pre-computation enhances user experience by providing quicker insights into the data and alert statuses. However, it's important to note that while NWLF visualizes the pre-calculated values, it does not perform real-time operations on the data. Unlike HVT, which offers more interactive and dynamic data processing, NWLF cannot dynamically retrieve, process, and manipulate data during user interactions. This is a key characteristic of traditional web applications, typically defined as software systems operating through a web browser, dynamically interacting with backend systems to process and present data in real-time (Murugesan, 2008). As a result, NWLF might not fully align with this traditional definition, relying instead on pre-computed results.

4.2. Limitations of return period-based warnings

The NWLF application defines flood alerts based on return periods derived from frequency analysis of historical water level simulations. This approach provides a standardized method for classifying flood risks, but it doesn't fully capture the complex interaction of local conditions that influence actual flood risk. While return periods provide a statistical measure of flood frequency, they do not account for the specific vulnerabilities and preparedness levels of different locations. An effective flood warning system should integrate data on the characteristics of the flood event (hazard), the assets and populations at risk (exposure), and the degree to which these assets are susceptible to damage (vulnerability). This multi-dimensional approach ensures that risk assessments move beyond statistical flood frequency measures and incorporate localized factors that influence the actual impact of flooding (Merz et al., 2010; Ward et al., 2011). As flood risk is not only determined by the probability and intensity of high river flows but also by societal factors such as land use, population density, and flood mitigation infrastructure, a more adaptive approach to defining warning thresholds is necessary to improve the accuracy and applicability of NWLF's alerts.

For example, in locations where flood mitigation infrastructure (e.g., levees, reservoirs, drainage systems) significantly reduces flood impacts, water levels associated with historically severe return periods (e.g., 50-year or 100-year floods) may not pose a substantial risk. However, NWLF will trigger a high alert level for such cases. Conversely, in regions lacking effective flood management, even events with a 2-year or 5-year return period can lead to severe socioeconomic and infrastructural damage. Nonetheless, NWLF will flag such events as significant, the system might classify them using the lowest alert thresholds presented in the app despite the potential damage they can cause. This reflects a broader challenge in hydrological forecasting, where hazard assessments must be complemented by exposure and vulnerability factors to improve risk communication and preparedness strategies (Alfieri et al., 2013; Ward et al., 2013).

This discrepancy between statistical probability and actual flood risk highlights the importance of considering local specific conditions (Perera et al., 2020). Population density significantly influences flood risk, as densely populated areas are more exposed to flooding due to the concentration of people, infrastructure, and economic assets, increasing the potential for damage and displacement (Ibrahim et al., 2024; Jongman et al., 2012). However, urban and densely populated areas often invest in flood control infrastructure, such as levees, drainage systems, and flood barriers, which can mitigate risks to some extent. While these measures reduce vulnerability, they will not fully eliminate risks (Merz et al., 2010). In addition, flood control policies, including building codes, land use regulations, and evacuation plans, play a critical role in reducing vulnerability by mitigating physical, economic, and social impacts of flooding, particularly in urban areas, where high population density and asset concentration increase exposure to flood risks (Hallegatte et al., 2013). Other local parameters, such as topography, soil type, drainage capacity, and the presence of wetlands influence flood risk by affecting water flow and accumulation during flood events. Incorporating these factors into risk assessments is essential for accurate and region-specific flood risk management (Acreman and Holden, 2013; Sugianto et al., 2022). Therefore, relying solely on return periods without integrating these factors can lead to inaccurate risk assessments and ineffective warning systems. As research suggests, flood risk is inherently vulnerability-dependent, varying considerably based on local conditions, preparedness, and the interplay between exposure and mitigation measures (Sene, 2008).

Recognizing these limitations, a key improvement in NWLF implementation involves working closely with national hydrological and disaster risk management agencies to refine alert thresholds. Thresholds are typically defined through a combination of expert experience, analysis of historical data, and evaluation of previous flood events. Over time, thresholds are refined based on new observations and evolving conditions (Sene, 2008), rather than relying exclusively on return periods or frequency analysis.

4.3. Building trust in NWLF for operational use

The NWLF application was developed within the framework of the SERVIR-Amazonia Project, a collaborative initiative under the SERVIR Global program—a joint venture between NASA and the United States Agency for International Development (USAID). Despite its scientific foundation and extensive consultations with national hydrological services to customize the tool to their informational needs and interests, the desired impact and adoption of the application have not been fully realized.

This hesitation stems from concerns within national hydrological services about using NWLF to issue official alerts. These concerns primarily orbit around fears about the tool's precision, including the risk of disseminating inaccurate data, issuing false alarms that could generate public panic, or failing to provide timely alerts, thereby undermining the institution's credibility (Mileti and Sorensen, 1990), However, NWLF does not intend to independently resolve flood or drought alert decisions. Instead, it should be integrated with other hydrological or meteorological tools to support comprehensive decision-making processes. Furthermore, only through frequent use of the tool can institutions build confidence in its capabilities, measure its performance through metrics like correct alerts and false alarms, and drive continuous improvement to enhance its reliability and accuracy over time.

While the NWLF is based on the application of the DWLT method to a global model using local data, opportunities for improvement lie in iterative performance evaluations. By regularly comparing NWLF-generated warnings to observed flood or drought events and using quantitative metrics to assess forecast accuracy, institutions can refine operational thresholds and better align alerts with regional conditions. These feedback loops could further build trust in the application and provide a foundation for future enhancements.

4.4. Future directions for NWLF development

The NWLF application demonstrates the potential for global hydrological models to support local decision-making through innovative, user-focused design. However, its real value is its capacity to evolve through continuous collaboration, refinement, and integration with other tools. By addressing current limitations and raising trust through constant improvements and stakeholder engagement, NWLF can serve as a cornerstone for advancing flood and drought risk management in the Amazon region and beyond.

While the current validation efforts focusing on four South American countries provide a robust foundation, we recognize the need to expand NWLF validation beyond South America and to incorporate forecast validation as a separate line of research. This will allow us to assess the performance of the NWLF application in different hydrological and climatic conditions, further enhancing its reliability and applicability. Additionally, we recognize the importance of forecast validation, which involves comparing NWLF-derived forecasts to actual observed events. This step is critical for building confidence in the system's predictive capabilities and ensuring its operational utility. Therefore, future work will focus on these two key areas: (1) expanding validation efforts to additional hydrological regions to assess NWLF's applicability in diverse climatic and hydrological contexts, and (2) validating forecast accuracy by systematically comparing NWLF-based forecasts with real-time observed water levels. These steps will ensure that NWLF remains a reliable and adaptable tool for hydrological risk assessment.

Platforms like the Hydroweb Theia project [https://hydroweb.theia-land.fr/, accessed on March 2022] already offer more than 24,000 satellite-based gauging stations worldwide for stream water level monitoring (Rosmorduc and Vayre, 2021). Additionally, the Surface Water and Ocean Topography (SWOT) satellite mission promises to revolutionize river monitoring by creating over 200,000 virtual stations globally, providing water level measurements for rivers, lakes, and reservoirs (Altenau et al., 2021). As demonstrated by Rojas Lesmes et al. (2024), the DWLT methodology is applicable to these satellite-based water level datasets, addressing the challenges of ungauged basins, where ground-based observations are scarce or unavailable. This opens the door to developing a global water level forecast service using the same computational structure as NWLF, combining GEOGLOWS discharge forecasts with satellite water level information, offering flood and drought forecast services, and expanding the reach and utility of the NWLF approach.

5. Conclusions

The NWLF application significantly advances using global hydrological models to address local decision-making needs. By leveraging the GEOGLOWS ECMWF Global Hydrological Model and integrating locally observed data, NWLF bridges the gap between global-scale simulations and regional hydrological challenges. Its backend-driven architecture, pre-computed results, and focus on user-friendly visualizations make it a powerful tool for flood and drought risk management.

One of NWLF's most notable strengths is its scalability and adaptability. Designed to be adapted for different countries, the application has successfully been customized for Brazil, Colombia, Ecuador, and Peru. This flexibility highlights its potential for broader adoption across diverse regions, with the ability to accommodate unique hydrological and administrative requirements. By integrating various layers of data—including national political and hydrological divisions—the NWLF aligns closely with the operational needs of its users.

The exercises in Brazil and Colombia demonstrated the NWLF application's practical value for flood and low-water level monitoring. In Brazil, the tool effectively identified varying flood risks during the Rio Grande do Sul event, providing critical early warnings based on return period thresholds and enabling localized preparedness actions. Similarly, in Colombia, NWLF successfully escalated warnings during the Quetame flood event, showcasing its ability to provide progressive and opportune alerts. The tool's success in monitoring low-water levels along the Amazon River also highlights its versatility in addressing diverse hydrological challenges.

The pre-computed backend architecture of NWLF enhances response times and user experience compared to earlier tools like the HVT. This approach allows NWLF to provide real-time insights into station alert statuses while maintaining functionality even during interruptions in data sources, such as the GEOGLOWS REST API. Unlike the HVT, which processes data dynamically in real-time, NWLF relies on pre-calculated results. Although this approach enhances performance, it may limit the app's ability to fully align with the interactivity expected of traditional web applications.

The performance evaluation conducted on retrospective data highlights the reliability of the DWLT methodology in transforming discharge simulations into water level predictions. Across 2788 stations in the Amazonia region, the Kling–Gupta Efficiency (KGE) showed a median value of 0.47 and an interquartile range (IQR) of 0.19–0.67, indicating generally strong agreement between transformed historical simulations and observed data, particularly within the Amazon basin. However, similar evaluations have not been systematically applied to the forecasted water level data. This gap represents an important avenue for future research, as validating forecasts against observed outcomes is critical for building confidence in NWLF's predictive capabilities.

Despite its technical advancements, NWLF's reliance on return periods to define flood alerts presents limitations. These thresholds, derived from historical simulations, do not fully account for local conditions such as flood protections, population density (a key factor in determining potential impacts), or other vulnerability-dependent factors. This can lead to scenarios where frequently recurring floods with significant impacts are classified as low-risk or, conversely, where robustly protected areas trigger high alerts for extreme events that pose little actual threat. These limitations underscore the need for continued collaboration with national hydrological services to develop alert thresholds that reflect localized conditions and integrate broader risk factors.

The implementation exercises also revealed challenges related to observational data availability and the need for enhanced stakeholder confidence. Addressing these gaps through expanded data networks and continued stakeholder engagement will be critical to maximizing NWLF's potential in operational decision-making. Furthermore, Institutional trust remains a critical barrier to NWLF's broader adoption. National hydrological services have expressed concerns about relying on the application for official alerts due to fears of issuing false alarms or missing critical events. It is strongly advised the frequent use of the tool to build confidence, evaluate its performance using metrics such as correct and false alarms, and implement continuous improvements. This iterative process will establish NWLF as a reliable and trusted decision-support system.

Future work on NWLF should expand its applicability and address existing challenges, including broader geographic application, forecast validation, integration of vulnerability-based risk assessments, and the extension of services to ungauged basins where ground-based observations are unavailable. While extending the DWLT methodology applied in NWLF to ungauged basins poses challenges due to the arbitrary zero level of water levels measured at gauging stations, it will be possible to integrate satellite water level information from projects such as Hydroweb and SWOT. Furthermore, integrating vulnerability maps and coupling NWLF with other meteorological or hydrological tools could enhance its effectiveness in ranking flood and drought risks based on potential damages and affected populations. Additionally, institutions or individuals interested in implementing a forecast system based on GEOGLOWS or any global hydrological model for a specific ungauged location can install a simple hydrometric rule at the site of interest. After just one year of observed data, both retrospective and forecast water level values can be reliably produced. This development will enable NWLF to serve as a globally scalable, cost-effective forecasting platform that supports flood and drought risk management even in the most data-limited regions.

In summary, the NWLF application demonstrates the potential of integrating global hydrological models with localized data for effective water resource management. Through ongoing refinement, stakeholder engagement, and strategic integration with complementary tools, NWLF can develop into a cornerstone for enhancing hydrological forecasting and risk management in the Amazon region elsewhere.

CRediT authorship contribution statement

Darlly Rojas-Lesmes: Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Jorge Sanchez-Lozano:** Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **E. James Nelson:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition, Conceptualization. **Juseth Chancay-Sanchez:** Writing – review & editing, Writing – original draft, Software. **Jhonatan Rodriguez-Chaves:** Writing – review & editing, Writing – original draft, Software. **Karina Larco-Erazo:** Writing – review & editing, Writing – original draft, Software. **E. Giovanni Romero:** Software, Writing – original draft, Writing – review & editing. **Mario Trujillo-Vela:** Writing – review & editing, Writing – original draft. **Riley C. Hales:** Writing – review & editing, Funding acquisition. **Daniel P. Ames:** Writing – review & editing, Writing – original draft. **Angelica L. Gutierrez:** Writing – review & editing, Writing – original draft.

Data availability statement

The stream network data used for GEOGLOWS model simulations is publicly accessible through HydroShare at https://www.hydroshare.org/resource/37d01a27e82f49a28440b59c0dc51831/(accessed on November 29, 2024). Observed water level station networks are available via HydroServer at https://hydroserver.geoglows.org/. For country-specific observed data, Brazil's data can be accessed through the National Water Agency (ANA) at http://telemetriaws1.ana.gov.br/ServiceANA.asmx (accessed on June 26, 2022), and Colombia's data are available through IDEAM's platform at http://dhime.ideam.gov.co/atencionciudadano/(accessed on June 26, 2022). Observed water level data for Ecuador and Peru, used in this study, are not publicly accessible but are stored on HydroServer at https://hydroserver.geoglows.org/. The GEOGLOWS retrospective simulation and forecast data can be accessed via the GEOGLOWS REST API at https://geoglows.ecmwf.int/documentation. The Discharge-to-Water Level *Trans*-formation (DWLT) using monthly duration curves method applied in this study builds on the Monthly Flow Duration Curve Quantile-Mapping (MFDC-QM) method, with its implementation available in the GEOGLOWS Python package. The package can be accessed through GitHub at https://github.com/geoglows/pygeoglows/, installed via PyPI at https://pypi.org/project/geoglows/, or installed through Anaconda at https://anaconda.org/conda-forge/geoglows. All open-access data and software are provided under the Creative Commons Attribution license or equivalent, allowing reuse with proper attribution. Some observed data remain restricted due to access limitations set by the contributing agencies.

Funding

This research was funded by a grant from the US National Aeronautics and Space Administration (NASA) numbers NNX16AN45G ROSES, and 80NSCC18K0440 GEOGLOWS. This project also received funding under award NA22NWS4320003 from the NOAA Cooperative Institute Program. The statements, findings, conclusions, and recommendations are those of the author(s) and do not necessarily reflect the views of NOAA.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank the numerous collaborators from hydrometeorological agencies across the Amazon region, including the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM), Brazil's National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN), Ecuador's National Institute of Meteorology and Hydrology (INAMHI), and Peru's National Meteorology and Hydrology Service (SENAMHI). We are grateful to NASA GE-OGLOWS and NASA SERVIR-Amazonia for their invaluable assistance in acquiring observed data for this research and their ongoing support in promoting the GEOGLOWS model in various countries. We also appreciate ECMWF hosting the GEOGLOWS REST API and its leadership in advancing and validating global hydrological models. We acknowledge the contributions of students at Brigham Young University who assisted in collecting and processing hydrological data.

Supplementary Materials

The web applications can be accessed online at the following links: Brazil: https://cemaden.geoglows.org/apps/national-water-level-forecast-brazil/ (accessed on November 29, 2024), Colombia: https://ideam.geoglows.org/apps/national-water-level-forecast-colombia/ (accessed on November 29, 2024), Ecuador: https://inamhi.geoglows.org/apps/national-water-level-forecast (accessed on November 29, 2024), and Peru: https://senamhi.geoglows.org/apps/national-water-level-forecast-peru/ (accessed on November 29, 2024).

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