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FIMserv v.1.0: A Tool for Streamlining Flood Inundation Mapping (FIM) Using the United States Operational Hydrological Forecasting Framework

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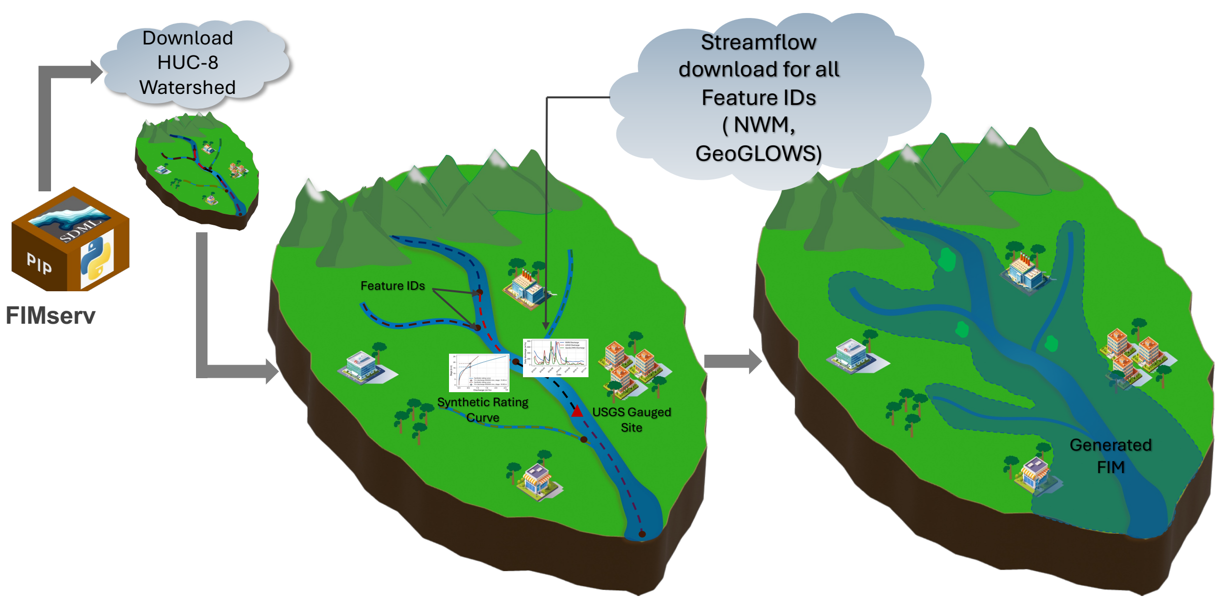
Graphical Abstract



Highlights

1. A user-friendly Python package is developed for generating Flood Inundation Maps (FIM) using the United States Operational hydrological model.
2. Execute seamlessly on local systems and cloud platforms like Google Colab and 2i2c interactive computing.
3. Integrates National Water Model (retrospective and forecast) and GeoGLOWS discharge in FIM generation.

Abstract

In the United States, the National Oceanic and Atmospheric Administration-Office of Water Prediction (NOAA-OWP) utilizes the National Water Model (NWM) for operational hydrological forecasting. Its Flood Inundation Mapping (FIM) framework translates NWM discharge to inundation extent using the Height Above the Nearest Drainage (HAND) approach. The simplicity of the OWP HAND-FIM framework enables rapid, large-scale FIM predictions across the U.S., fostering a growing user and developer community beyond NOAA. In this paper, we introduce "FIM as a Service (FIMserv)", an open-source toolset that streamlines OWP HAND-FIM predictions with enhanced functionalities: (1) FIM generation from retrospective and forecasted NWM discharge, (2) Simultaneous simulations of multiple watersheds for various flood events, (3) FIM from Group on Earth Observations Global Water Sustainability (GeoGLOWS) discharge, (4) evaluation of NWM and GeoGLOWS discharge against USGS observations. FIMserv operates as a standalone notebook on local/cloud systems and as a Community Resource within the CIROH cloud cyberinfrastructure.

Keywords: Operational flood forecasting model, Global discharge, cloud computing, United States, fluvial flood

1. Introduction

The global rise in flood events driven by climate change, environmental challenges, and rapid urbanization has heightened the need for rapid Flood Inundation Mapping (FIM) at large scales (Zhou et al., 2021; Fohringer et al., 2015; Tran & Lakshmi, 2024; Tapas et al., 2024; Do et al., 2024, Baruah et al., 2023, Devi et al., 2022). Currently, several approaches are employed for flood mapping, including high-resolution satellite imagery for near-real-time flood mapping/monitoring (Mason et al., 2012; Shen et al., 2019; Annis et al., 2022), one-dimensional and two-dimensional high-fidelity models (Zhang et al., 2016; Zahura et al., 2020; Jafarzadegan et al., 2023), low-fidelity terrain models (Afshari et al., 2018; Gutenson et al., 2022), and Machine Learning (ML) and Deep Learning (DL) methods (Hosseiny, 2021; Bentivoglio et al., 2022; Zhou et al., 2022)

In recent years, the Height Above the Nearest Drainage (HAND) method has been commonly used in FIM. It involves extensive hydro-conditioning of a Digital Elevation Model (DEM) and converts it into a series of relative elevations (HAND grids) based on the nearest channel flow paths. In this approach, a water stage value is assigned to neighbouring pixels in the HAND grids to generate FIM for any given stream segment (Godbout et al., 2019). Tarboton et al. (2018) proposed a novel approach that determines the stage-discharge relationship using Synthetic Rating Curves (SRCs). This method involves sampling reach-averaged parameters from DEM and applying Manning's equation (Gauckler, 1867; Manning et al., 1890) to calculate the stage. It is worth noting that the HAND-FIM approach represents a trade-off between accuracy and applicability, enabling the generation of large-scale flood maps within a very short computational time (Garousi-Nejad et al., 2019).

The HAND approach has been employed by the National Oceanic and Atmospheric Administration (NOAA) Office of Water Prediction (OWP) to generate an operational fluvial FIM across the United States. The OWP HAND-FIM utilizes discharge data from the National Water Model (NWM) to produce hourly flood maps at the watershed scale (Hydrologic Unit Code (HUC)-8). The model translates a static discharge value for each NWM stream into a stage using a reach specific SRC. This approach has been validated through various case studies (e.g. Johnson et al., 2019; Aristizabal et al., 2023).

Although the OWP HAND-FIM is an open-source model (https://github.com/NOAA-OWP/inundation-mapping) that is actively used and developed by OWP, end users often face challenges in configuring and running the model to generate FIMs. The published version requires Docker for FIM execution, which limits its usability in cloud environments and creates compatibility issues across different operating systems.

In this paper, we present the OWP HAND-FIM 'as a service' (FIMserv), an open-source Python toolset for running the FIM generation procedures of the OWP HAND-FIM framework using its operational input data. This approach leverages virtual .env files to define essential environment variables, such as input and output directories for the OWP HAND-FIM's FIM generation module. By replicating Docker's role in environment configuration in a simplified manner, this method bypasses containerization while maintaining a consistent and portable setup. The script dynamically adjusts to the local system's structure, ensuring dependencies and file paths are properly aligned for successful execution. FIMserv includes the following additional functionalities:

1. User-friendly and customizable notebook interface
2. Embedded visualization
3. Flexibility to run both locally and on the cloud
4. Domain filtering based on stream order
5. Multi-watershed simulations for different flood events
6. Capability to process both retrospective and forecast (short- and long-range) NWM discharge for FIM generation
7. Visualization of SRCs for any reach within a HUC-08 boundary
8. Comparison of USGS and NWMv3.0 retrospective discharge data.
9. Ability to subset from the HUC-08 scale FIMs based on user-defined polygons or coordinates.
10. Inclusion of daily discharge from the Group on Earth Observations Global Water Sustainability (GeoGLOWS) for FIM generation.

2. Methodology

2.1 The OWP HAND-FIM Framework

The NOAA-OWP HAND-FIM is a fully operational, national-scale framework developed to generate high-resolution FIM (Aristazabal et al., 2023). The model involves a series of DEM hydro-conditioning processes, including flow path identification, elevation smoothing to ensure monotonically decreasing terrain, bathymetry excavation, stream thalweg breaching, and levee enforcement (Aristazabal et al., 2023). The framework's hydro fabric includes components such as the relative elevation model (REM), or HAND grids, catchment data in both vector and raster formats, and a comma-separated value file (hydrotable.csv) containing NWM river ID (feature-id), catchment ID (HydroID), DEM derived reach averaged channel geometry parameters (hydraulic radius, wetted perimeter) and Synthetic Rating Curves (SRCs). These post-processed HAND grids are used to generate FIM using discharge input (operationally from the NWM) and SRCs. SRCs are calculated for each NWM river segment using Manning's equation to translate the discharge (m^3/sec) into a stage (m). These stage values are used to inundate the floodplain and produce a binary FIM output saved in GeoTiff format.

2.2 Dependencies and libraries used in FIMserve

FIMserv relies on a set of dependencies, including a range of geospatial libraries, each chosen to support different functionalities (defined as modules within the framework), ensuring seamless integration. In FIMserv, *rasterio* and *geopandas* are used for reading, writing, and processing raster and vector datasets. All the CSV files within the framework are handled by *pandas*, whereas *NumPy* is used in numerical operations and array manipulation (Harris et al., 2020). *Scipy* and *Bottleneck* are used as a performance optimization tool within the framework. Cloud interaction is facilitated by *boto3* (https://pypi.org/project/boto3/) and *botocore*, which integrate with Amazon Web Service (AWS), while *AWSCLI* (https://github.com/aws/aws-cli) streamlines data retrieval from AWS S3 bucket to framework workflows. FIMserv framework integrates Tools for Exploratory Evaluation in Hydrologic Research (TEEHR) (https://github.com/RTIInternational/teehr) to streamline the retrieval of NWMv3.0 and United States Geological Survey (USGS) retrospective discharge data. TEEHR leverages iterative processing and distributed computing with its computation engine built on *PySpark*, which makes it efficiently utilize available resources, resulting in accelerating data downloading and processing.

For the statistical evaluation between NWMv3.0 and USGS retrospective discharge, FIMserv uses *Scikit-learn*, specifically its metrics module (Pedregosa et al., 2018). Additionally, the framework utilizes Python's *Requests* library to fetch NWMv3.0 forecasted data from Google Cloud Storage, using *BeautifulSoup* to parse HTML responses and identify the required netCDF files based on user-defined date requests. These files are processed with the *netCDF4* library, which extracts the discharge data based on different NWM stream segments according to user-defined instructions. For data visualization and plotting, *Matplotlib*, *geemap* (Wu, 2020) and *localtileserver* packages are used.

2.3 Installation and Run

The FIMserv package is now available in the PyPI repository and can also be downloaded from GitHub (https://github.com/sdmlua/FIMserv). FIMserv currently utilizes the Jupyter Notebook interface for installation and execution.

A usage sample code (*code_usage.ipynb*) describing all arguments is provided on GitHub (https://github.com/sdmlua/FIMserv/tree/main/docs). User can download this code on their local machine and install the FIMserv tool using "*pip install fimserve*". It automatically downloads all dependencies that are needed to run the tool. The FIMserv package can also be installed and imported into cloud environments such as Google Colab and CIROH's interactive 2i2C cloud computing Jupyter Notebook. To install in the cloud, use the command "*pip install fimserve*", and then import it with "*import fimserve*". The sample usage code for using FIMserv in Google Colab is provided here. All required and optional arguments for different modules in FIMserve are listed in Table 1, and detailed usage of all arguments is described in the following sections.

Table 1. Modules in FIMserv are listed in order of execution.

Serial No	Module	Purpose	Arguments
1	*DownloadHUC8*	Download the HUC8 level FIM-Hydrofabric dataset hosted in CIROH S3 Bucket.	hucID*, stream_order
2	*getNWMretrospectivedata*	Download the NWMv3.0 retrospective discharge data.	start_date, end_date, hucID, value_time, huc_event_dict
3	*plotNWMDischarge*	Plot the discharge time series for NWM reach.	hucID*, start_date*, end_date*, feature_id
4	*GetUSGSIDandCorrFID*	Get the USGS gauge station IDs intersecting with NWM reaches.	hucID*

Serial No	Module	Purpose	Arguments
5	*getUSGSsitedate*	Download the USGS retrospective discharge data.	start_date*, end_date*, usgs_sites*, hucID*
6	*plotUSGSDischarge*	Plot the USGS discharge.	hucID*, usgs_sites*, start_date*, end_date*
7	*CalculateStatistics*	Statistical evaluation of NWMv3.0 discharge with USGS discharge.	hucID*, feature_id*, usgs_site*, start_date*, end_date*
8	*plotSRC*	Plot the Synthetic Rating Curves of different NWM reaches.	hucID*, hydro_id*, branch_id*, discharge value
9	*getNWMForecasteddata*	Download the NWMv3.0 short, medium and long-range discharge forecasts.	hucID*, forecast_range*, forecast_date, hour, sort_by,
10	*runOWPHANDFIM*	Run the OWP HAND-FIM model.	hucID*
11	*subsetFIM*	Subset the HUC8 level flood inundation map to a user-defined extent.	boundary*, hucID*, method*
12	*vizualizeFIM*	Visualize the flood inundation map on different base maps.	inundation_raster*, hucID*, MapZoom*

* Indicates the essential argument when calling the corresponding module.

2.3.1 Directory Setup and Data Downloading

The flowchart of the work is shown in Figure 1(a), illustrating the development and configuration process up to the final outputs generated by FIMserv. Within the working directory, the *DownloadHUC8* module generates three primary subdirectories: code, input, and output (Figure 1b). It also retrieves pre-processed HAND grids based on the user-defined HUC-08 identifier (hucID) and stores them in the output directory These datasets are hosted in a public Amazon Web Services (AWS) S3 bucket from the Cooperative Institute for Research to Operations in Hydrology (CIROH) (https://ciroh-owp-hand-fim.ciroh.org/index.html), which includes data for approximately 2,400 HUC-08 across the United States. The CIROH S3 bucket is a copy of the OWP 'request-payer' S3 bucket. To facilitate this, an ArcGIS Online Repository has been developed offering the location and IDs of HUC-08 watersheds (Table 2). Using the same module (*DownloadHUC8*), users can input multiple hucIDs in a (.csv) file, allowing the framework to download HAND grids for multiple HUC8s and store them in the output directory.

The second step is to clone the OWP HAND-FIM source code from GitHub into the code directory (https://github.com/NOAA-OWP/inundation-mapping). This process also creates a localized environment (.env) file within the code directory to manage essential variables.

In the third step, FIMserv enables users to automatically retrieve discharge data from NWMv3.0 and GeoGLOWS from the cloud.

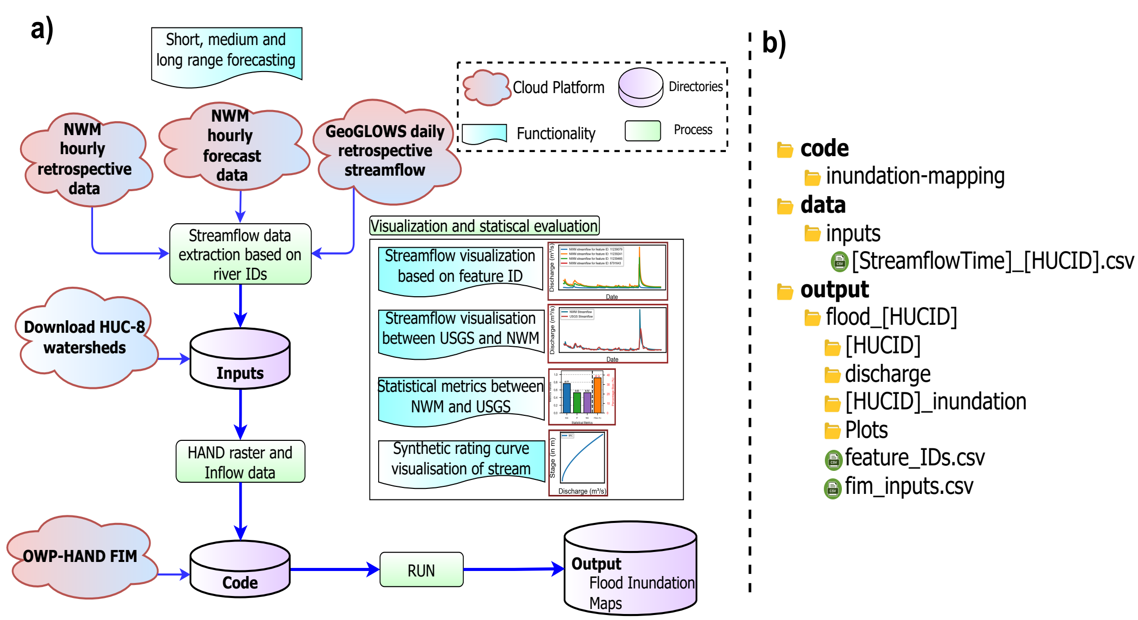


Figure 1. (a) A complete pipeline demonstrating how the framework is designed (b) the directory structure on the user's end when the code is executed.

The *getNWMretrospectivedata* and *getNWMForecasteddata* modules can download both NWMv3.0 retrospective and forecast discharge data. The NWM is a large-scale operational hydrological simulator for the United States developed by the National Weather Service (Frame et al., 2020). It is based on the WRF-Hydro framework including a large number of permutations in the suite of land surface, hydrologic, and hydraulic physics (Read et al.,2023). In the NWM system, land surface processes are represented by the Noah Multi-Parameterization (Noah–MP) land surface model (LSM), while flow routing is represented by the Muskingum-Cunge method. Currently, NWMv3.0 provides discharge data for more than 2.7 million stream segments available in the National Hydrography Dataset (NHDPlus) across the United States (Buto et al., 2020).

The NWMv3.0 retrospective dataset consists of hourly simulated historical discharge data available from 1979 to 2023. These datasets are stored in a public NOAA AWS S3 bucket (https://noaa-nwm-retrospective-3-0-pds.s3.amazonaws.com/index.html) and are provided in parquet format, which can be downloaded using the unique identifiers (feature_id) of the NWM stream network. To simplify access, the OWP HAND-FIM hydrofabric (river network) and their associated feature_ids are hosted in the same ArcGIS Online Repository as the HUC-08 watersheds. Using the user defined hucIDs and the specified event period, FIMserv downloads the retrospective discharge data and stores it in the input directory. This entire process is fully automated, which helps to significantly simplify the entire workflow.

NWMv3.0 discharge forecasts are available for three forecast horizons: (a) short-range (18 hours), (b) medium-range (10 days), and (c) long-range (30 days) (Aristizabal et al., 2023). This dataset is stored in Google Cloud (https://console.cloud.google.com/storage/browser/national-water-model/nwm.20180917) and is provided in NetCDF (.nc) format. The forecast data can also be downloaded using feature-ids of the NWM stream network. Similar to the retrospective module, FIMserv automatically retrieves forecast discharge based on user-defined hucID, date and time (UTC 00Z–23Z), and stores it as a CSV file in the input directory.

2.3.2 Running FIMserv with NWMv3.0 discharge

In the final step, the "*runOWPHANDFIM*" module uses discharge data from the input directory and the downloaded HAND grids (HUC-08 scale) to generate binary FIMs at a 10-meter resolution. The outputs are then saved in the output directory as GeoTIFF files. FIMs can be created at a temporal scale corresponding to the resolution of the discharge data. Each flood map is assigned a unique name based on the event date, ensuring that end users can easily navigate the map in the output directory.

Users can provide a boundary shapefile to subset a specific region of interest from the HUC8 scale flood map. Sub-setting enables users to mask and extract the desired region, which is then saved in the output directory. Additionally, the framework also provides functionality for visualizing flood maps overlaid with OpenStreetMap (OSM) and Google Satellite imagery. Table 2 shows the list of different types of datasets that can be accessed and utilized for FIMs using FIMserv across CONUS.

Table 2. Dataset used in FIMserv

Data	Description	Source
OWP-HAND raster	10m HAND raster across CONUS	CIROH s3 bucket (s3://ciroh-owp-hand-fim)
NWMv3.0 retrospective discharge	Hourly Discharge across CONUS (1979-2023)	https://noaa-nwm-retrospective-3-0-pds.s3.amazonaws.com/index.html
NWMv3.0 forecast discharge	Long-range (6 hourly for 30 days) Medium -range (3 hourly for 10 days) Short-range (hourly for 18 hours)	https://tinyurl.com/yt3ampk2
GeoGLOWS	Global 3 hourly/Daily Discharge data (1940-Current)	http://GeoGLOWS-v2-retrospective.s3-website-us-west-2.amazonaws.com
HUC-08 ID, NWM River ID and USGS gauge sites	HUC-08 watersheds, NWM river identifiers and USGS-Discharge gauge stations across CONUS	ArcGIS Online*: Link*

2.4 Running FIMserv with GeoGLOWS discharge

GeoGLOWS is a global discharge data set based on the European Centre for Medium-Range Weather Forecasts (ECMWF). The GeoGLOWS-ECMWF(GEES) uses runoff depth forecasts generated by ECMWF and applies the Muskingum method for channel routing (Hales et al., 2023; Gutenson et al., 2024; Hales et al., 2022; Lozano et al., 2021). The latest version, GeoGLOWS v2.0, includes more than 7 million streams and 125 computational watersheds. GeoGLOWS provides two types of datasets, including (a) retrospective discharge data based on reanalyzed ERA5 precipitation data, available for 80 years (1940–2020) at a daily temporal resolution, and (b) forecasted discharge data ranging from 3-hour to 15-day (2021-Current?).

To evaluate the potential of GeoGLOWS discharge in improving flood inundation mapping, NWM flowlines were spatially joined with GeoGLOWS flowlines (Figure 2), transferring their attributes to the NWM flowlines. This integration allows GeoGLOWS discharge to be used in FIMserv for flood inundation mapping. The GeoGLOWS (v2.0) datasets are available at (https://data.GeoGLOWS.org/available-data) and can be retrieved using their unique identifier (LINKNO). For spatial joining, a conservative 100 m buffer was created around the GeoGLOWS streamlines. This buffer facilitated a spatial join with the midpoints of the NWM flowlines, ensuring that at least half of each corresponding NWM flowline fell within the buffer. Flowlines with midpoints intersecting the GeoGLOWS buffer were then extracted. This approach ensured that NWM flowlines spatially aligned with GeoGLOWS streams could be identified with greater precision.

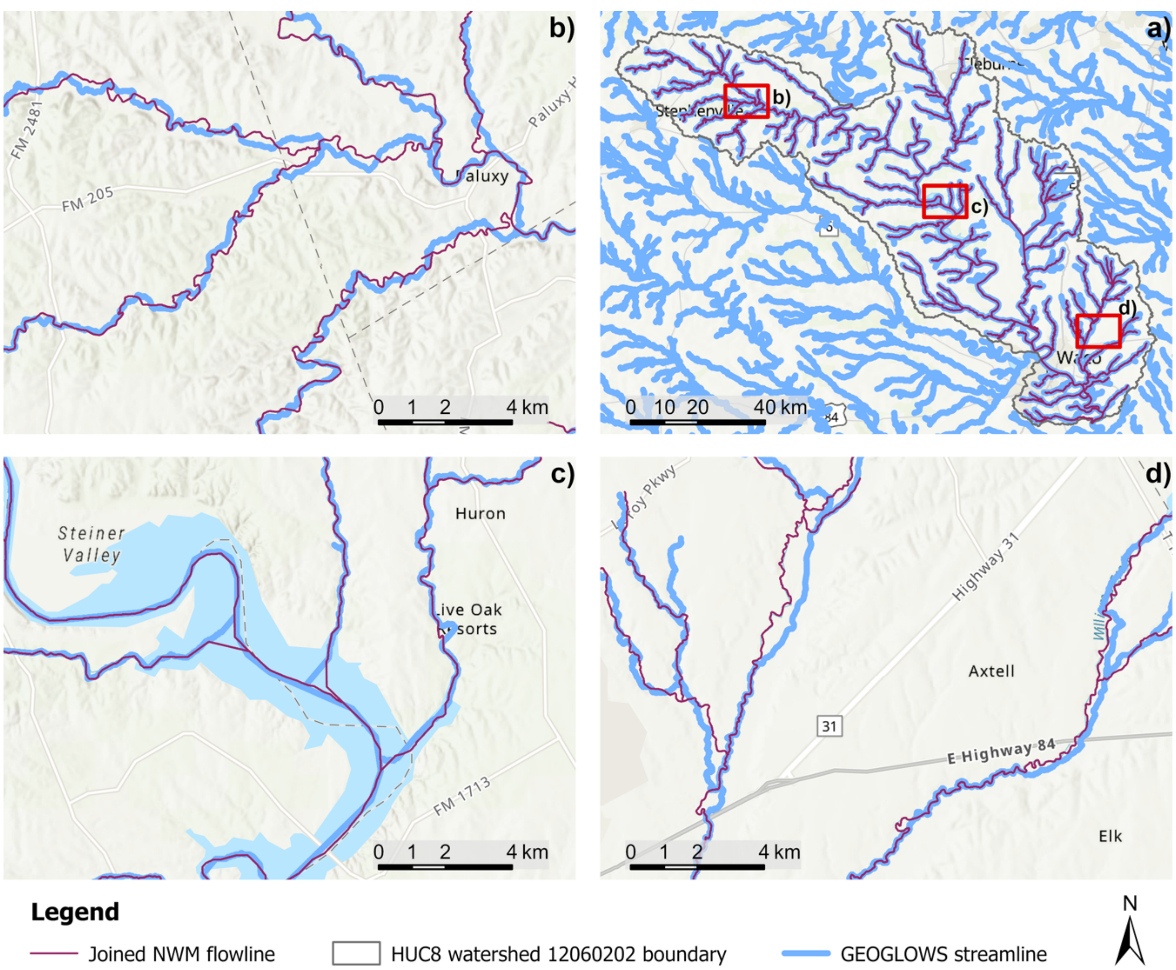


Figure 2. (a) Overview of the GEOGLOWS streamlines and the NWM flowlines for Middle Brazos Lake Whitney watershed (hucID 12060202), (b-d) enlarged view of joined NWM flowlines and GEOGLOWS flow lines.

Once the intersecting NWM flowlines are identified, their connectivity is traced using the 'ID' field and the "to" field (downstream flowline identifier) in the attribute table. Starting from each identified flowline, downstream tracing is performed until the most downstream flowline is reached. This process extracted additional NWM flowlines that are not initially identified through the buffer but spatially corresponded to GeoGLOWS streamlines. The midpoint of each NWM flowline is then used to locate the nearest GeoGLOWS streamline, ensuring alignment over at least half the flowline. After this, the LINKNO field from the GeoGLOWS streamline was appended to the corresponding NWM flowline in the attribute table. Then GeoGLOWS discharge can be used in FIMserv via the unique identifier of NWM flowlines in OWP HAND-FIM (i.e. feature_id), with LINKNO serving as an intermediate. All spatial joins are performed in ArcGIS Pro (v3.3.2), and custom scripts are developed to automate this process at the HUC-08 scale. This approach is adaptable for joining line features from other sources with NWM flowlines within the ArcGIS environment. Although this study demonstrated the spatial joining for one HUC-08 (hucID 12060202), we plan to extend this process to NWM flowlines across the United States. The resulting joined NWM flowlines, including the appended LINKNO field, will be made publicly available.

3. Applications and Functionalities

In this section, we have demonstrated all the functionalities of FIMserv in different case studies

3.1. Computational efficiency

To assess FIMserv's computational efficiency, the framework is tested on 25 randomly selected HUC-08s across the United States (Figure S1 in supplementary material) with varying catchment areas. Hourly discharge data for 72 hours is downloaded for all the stream reaches within each watershed, and the model is executed for each HUC-08. Our results showed that for the range of catchment area tested, a factor of four increase in catchment area (2000 to 8000 km^2) yielded a computational time increased by a factor of 3 (30 seconds to 90 seconds; Figure 3).

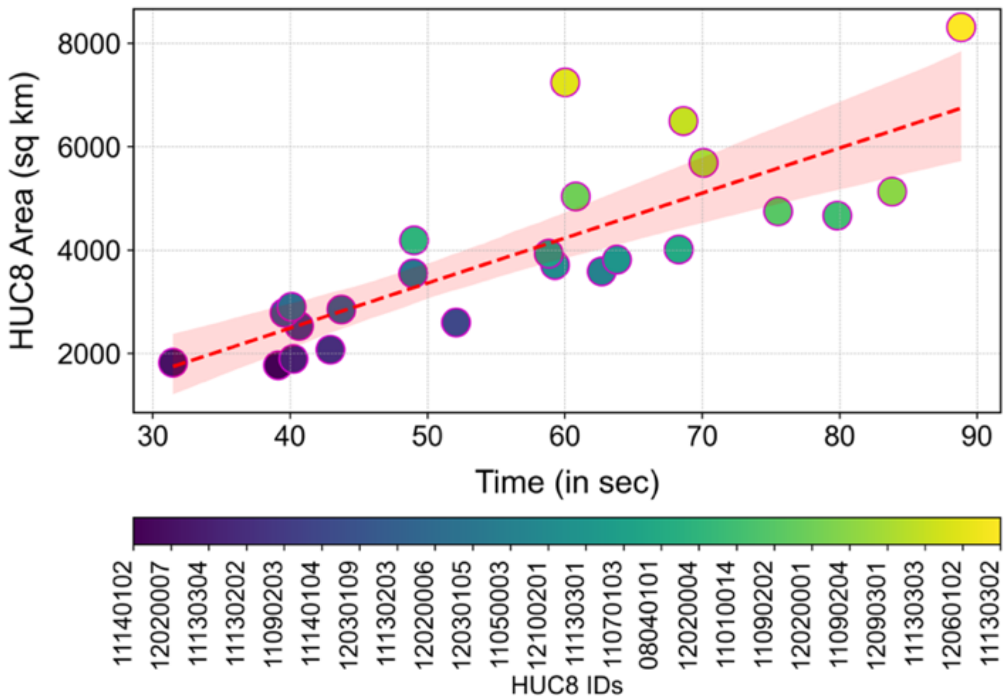


Figure 3. Computational time versus HUC-08 watershed area.

3.2. Automated FIM generation with NWM retrospective and forecast discharge

FIMserv automatically generate multiple flood maps using the NWM retrospective and forecasted discharge data. After installation and import, the "*DownloadHUC8"* module downloads HAND grids for the user-defined HUC-08 and stores them in the output directory, while the "*getNWMRetrospectiveData*" module retrieves NWM retrospective hourly discharge data for each feature_id based on the specified date and time (Figure 4a). The "*runOWPHANDFIM"* module then uses the HAND grids, and the extracted discharge to generate FIM.

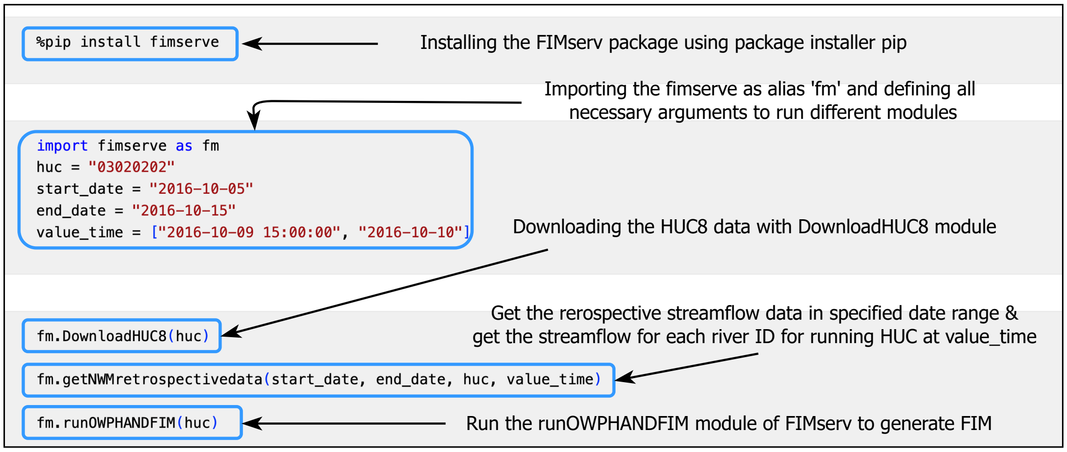


Figure 4(a). Sequential steps for FIM generation using FIMserv in Jupyter Notebook.

FIMserv also enables users to perform simultaneous simulations in multiple watersheds having different flood events. For instance, if a user intends to generate FIM in two different HUC-08 having different flood events, they need to provide a dictionary specifying the hucIDs and corresponding event date-times (Figure 4b). FIMserv will automatically retrieve the retrospective discharge data for the designated watersheds to generate the FIM.

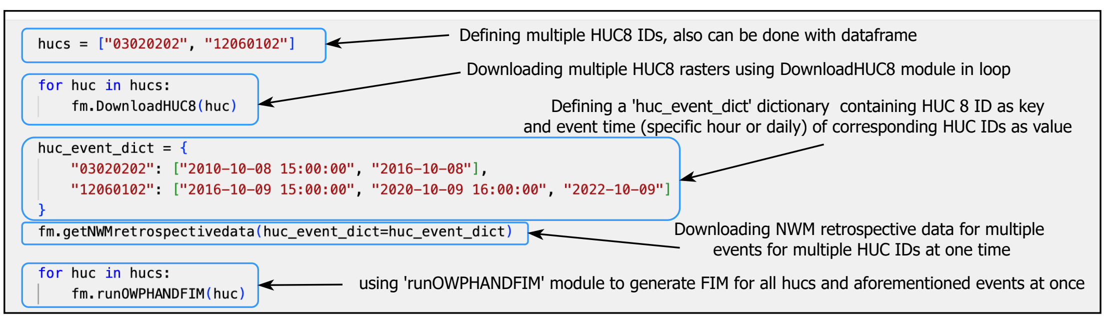


Figure 4(b). FIM generation steps across multiple watersheds using FIMserv in Jupyter Notebook.

To generate forecast FIMs, we utilized NWM short, medium, and long-range discharge data. The short-range forecast provides deterministic discharge predictions at an hourly interval for up to 18 hours. The medium-range forecast provides deterministic discharge predictions every 3 hours for up to 10 days, generating a total of 80 forecasts. The long-range forecast is generated every 6 hours (0z, 06Z, 12Z, 18Z), producing a 16-member ensemble forecast over 30 days, resulting in a total of 120 forecasts.

The “*getNWMForecastedData*” module in FIMserv retrieves discharge forecasts from Google Cloud (link) based on user-defined hucIDs and date-time (Figure 5). These forecasts are in UTC and are stored in the FIMserv input directory.

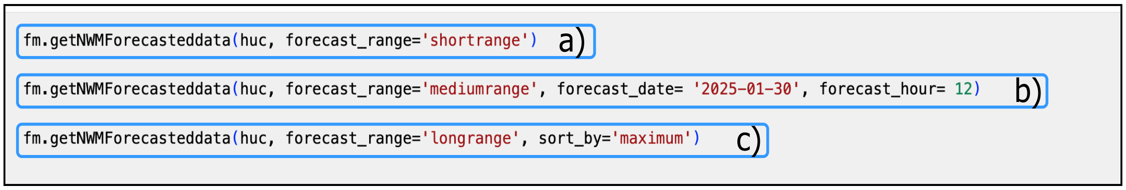


Figure 5. Customizing and downloading Long-Range, Medium-Range, and Short-Range Forecasts using FIMserv in Jupyter Notebook

For short-range forecasts, if no specific date-time is provided, FIMserv defaults to the current date-time and generates 18 flood maps at hourly intervals (Figure 5a). For medium- and long-range forecasts, if no date is specified, FIMserv uses the current date and downloads a 10-day forecast for medium-range and a 30-day forecast for long-range predictions. By default, FIMserv selects the maximum discharge values from the forecast, but users can customize this using the “*getNWMForecastedData(sort_by="")*” argument to generate FIMs based on maximum, minimum, or average discharge. The forecast_hour parameter in medium- and long-range forecasts indicates that FIMserv is retrieving discharge data for January 30, 2025, at 12Z (Figure 5b, 5c).

In this example, we used the Middle Neuse watershed (hucID-03020202) and NWM retrospective data to generate FIMs for a historic flood event in North Carolina caused by Hurricane Matthew on October 15, 2016, at 8 PM (Figure 6a). We have presented the forecasted FIMs for the Middle Neuse watershed (catchment area 2279 km2; Figure 6b, c, d), with the starting date set to 2024-11-14. For the long-range forecast, daily maximum FIMs for 30 days are generated and saved as binary raster in GeoTIFF format in the output directory. The medium-range forecast generates 10 daily maximum FIMs, while the short-range forecast produces 18 hourly FIMs.

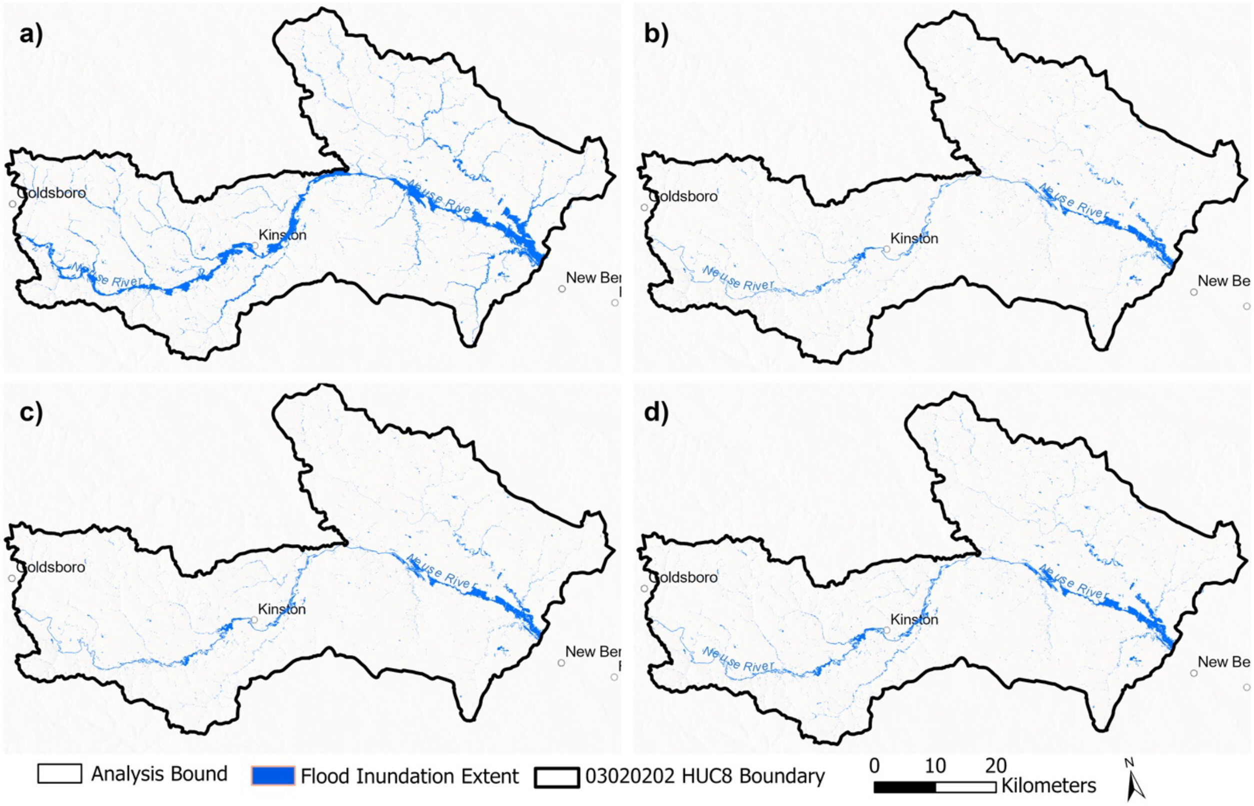


Figure 6. FIMserv generated FIMs (a) using retrospective NWM discharge on October 15, 2016, at 8 PM, (b) using short-range NWM forecasted discharge (start date: 2024-11-14), (c) using the maximum value from medium-range forecasted discharge (start date: 2024-11-14), and (d) using the maximum value from long-range forecasted discharge (start date: 2024-11-14).

3.3 Domain sub-setting and flexible input selection

FIMserv can filter and subset the (HUC-08) study domain based on river stream order. The HUC-08s typically consist of multiple stream orders, ranging from first to tenth-order streams. Sub-setting module in FIMserv provides more flexibility and meets different requirements of the users, for example, generating FIM for higher order streams, visualizing and evaluating FIM for a specific land use-landcover etc.

One important implication of domain sub-setting is during the evaluation the model flood maps with the benchmark. Benchmarks flood inundation maps derived from remote sensing imagery, often exclude small tributaries which complicate their use in FIM evaluation. To address this, users can opt to exclude minor tributaries and headwater streams from model flood maps, retaining only the major streams for simulation. In FIMserv, the *stream_order* argument in the

“*DownloadHUC8*” module subsets the study domain based on the user-defined minimum stream order and the “*runOWPHANDFIM*” module is used to generate FIM.

This functionality is demonstrated in the Middle Neuse watershed, North Carolina (hucID -03020202) in which the FIMs are generated (Figure 7) for all order streams as well as for higher-order streams (*stream_order>3).*

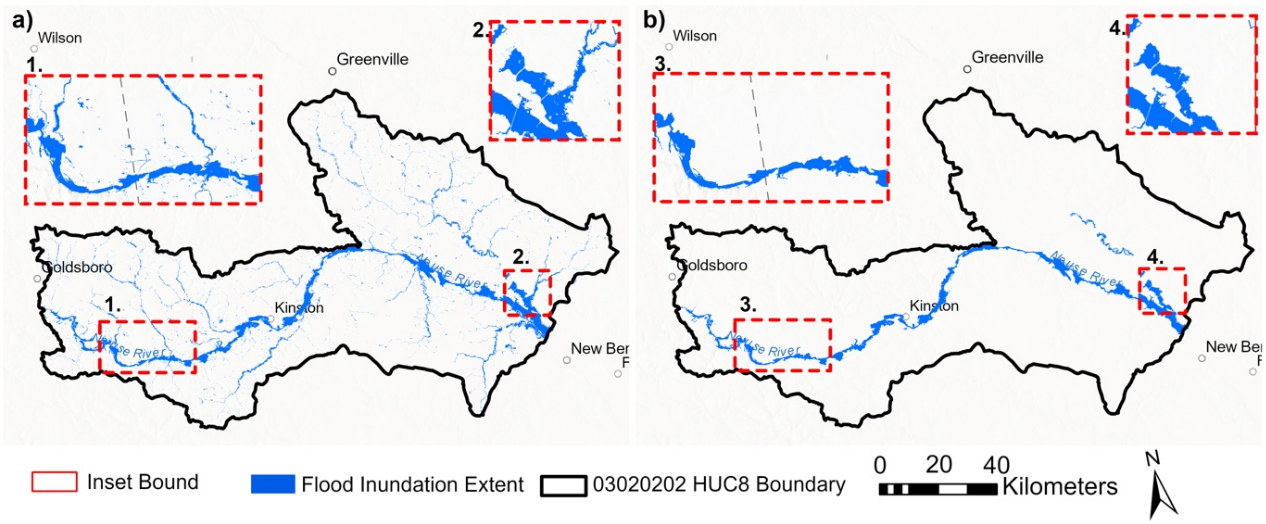


Figure 7. Demonstration of FIMserv sub-setting functionality for the Middle Neuse watershed, North Carolina: (a) FIM with all stream orders, and (b) FIM using stream order 3 and higher.

Another sub-setting functionality, “*subsetFIM*”, allows users to mask out specific portions of the flood inundation maps based on an Area of Interest (AOI) shapefile. Users can upload a boundary shapefile corresponding to the benchmark extent, and the framework will mask out that extent from the original FIM. We demonstrated this functionality using HUC ID 03020202, where FIM for the entire HUC-08 is generated, followed by a subset FIM based on a user-provided AOI (Figure 8-a,b).

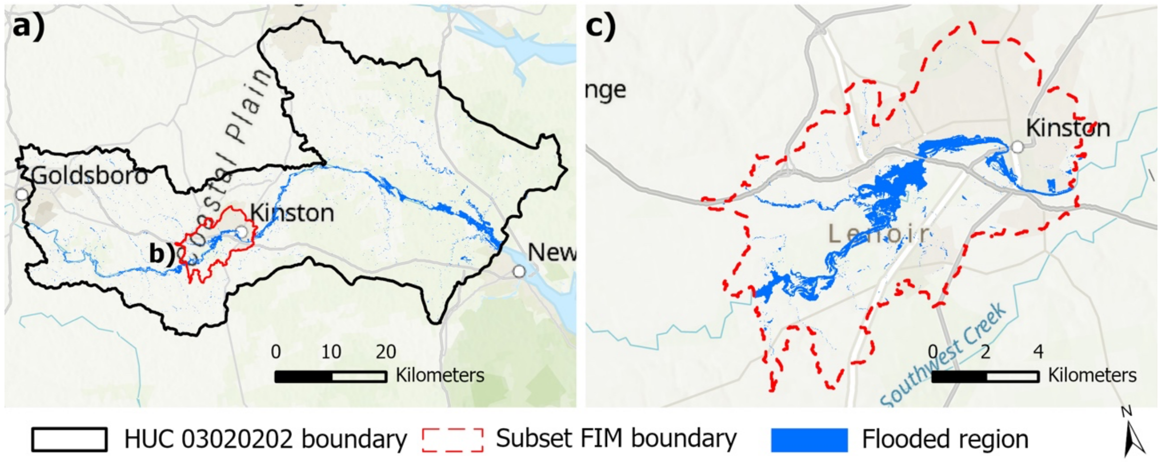


Figure 8. (a) FIM for the entire HUC8 (hucID-03020202), and (b) AOI polygon for subsetting (c) Subset FIM obtained from *subsetFIM* module

3.4. Statistical Analysis of NWM and USGS observed discharge

The availability of NWM discharge data for the entire US river network makes it a valuable input for large-scale flood modeling. Hydrological models, however, introduce uncertainties which propagate into the FIM accuracy (Abdelkadir et al., 2023; Cosgrove et al., 2023). Quantifying input biases is therefore important, but often not properly analyzed and reported. FIMserv includes functionality for statistical evaluation of NWM discharge predictions against USGS gauge data (Figure 9). This functionality is limited to NWM streams that have an associated USGS station within the user-selected HUC-08s. In FIMserve, "*plotNWMDischarge*" modules are used to visualize the downloaded NWM retrospective discharge for the user-defined streams (feature_id). "*GetUSGSIDandCorrFID*" identifies USGS gauges located within the HUC-08 boundary and their corresponding feature-ids of the NWM stream segments. Additionally, USGS gauge locations are hosted in the ArcGIS Online Repository, providing easy access for users.

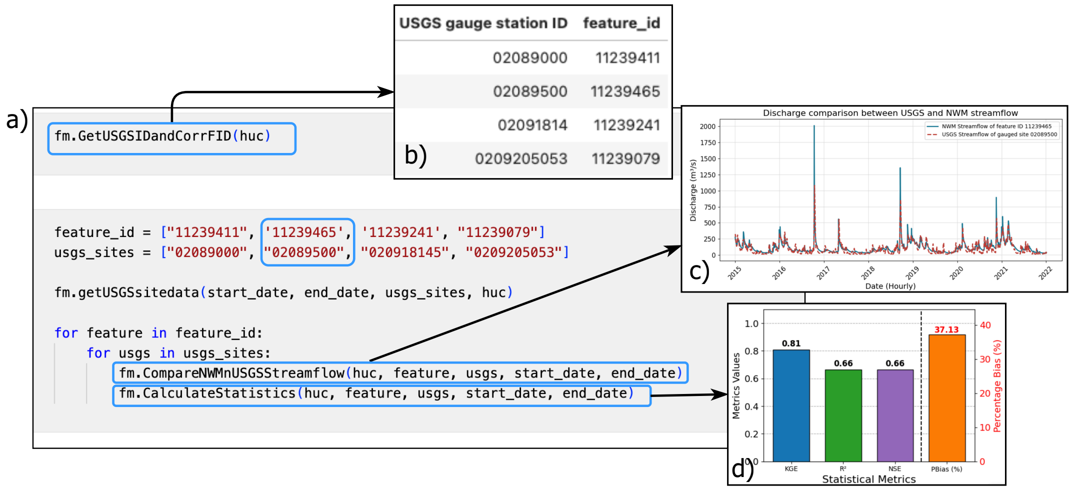


Figure 9. a) Getting the USGS gauges and the corresponding NWM stream segments. b) Available USGS gauges intersecting with NWM stream segments, c) comparing the NWM discharge with USGS discharge, and d) calculating the evaluation scores between the NWM and USGS discharge.

We demonstrated this functionality in the Middle Neuse watershed (Figure 10a) for two NWM river segments (feature_ids=11239465, 11239241) having USGS gauges (ID:02089500, 02091814) for the year 2016. To compare NWM discharge with USGS gauge discharge, the "*CompareNWMnUSGSDischarge*" module is used (Figure 10 d,g). This module plots the discharge data from both USGS and NWM for the user-defined feature_ids. To calculate the evaluation statistics between NWM and USGS discharge, the "*CalculateStatistics*" module is applied. Kling-Gupta efficiency (KGE) (Gupta et al., 2009), Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), Coefficient of determination (R^2) (Moriasi et al., 2015), and percent bias (pBIAS) is considered to quantify the error between the NWM and USGS discharge (Table 3). This analysis shows that NWM discharge exhibits a good correspondence with the observed flow, with a KGE > 0.7 and R^2 > 0.5, and a percent bias > 30% (Figure 10 e, f). This provides a quantitative estimate of the discharge data used in FIM.

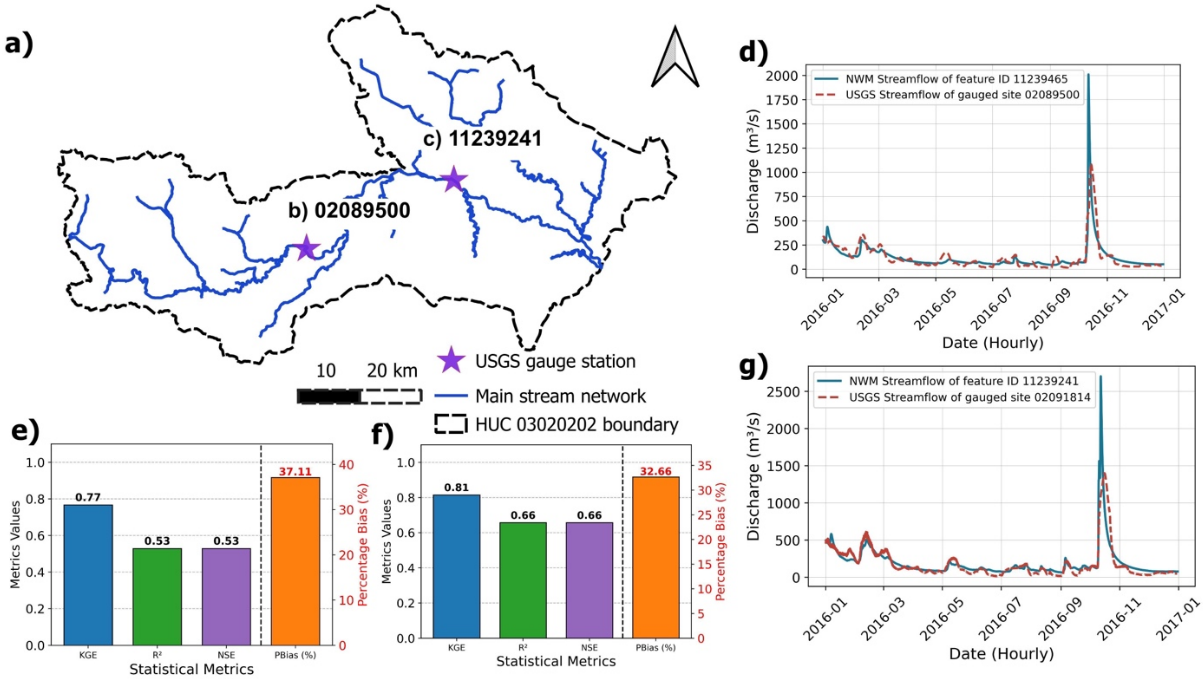


Figure 10. Visualization and statistical comparison of NWM discharge and USGS observed discharge for (a) Middle Neuse watershed (hucID-03020202) at USGS gauge ids, (b) 02089500, (c) 02091814. (d, g) Plot between NWM discharge with USGS discharge obtained from "*CompareNWMnUSGSDischarge"* module, (e, f) Evaluation statistics between NWM and USGS obtained from "*CalculateStatistics*".

Table 3. Statistical metrics used in discharge comparison.

Metrics	Expression	Limit
KGE	1- $(r-1)^2 + (\mathrm{b}-1)^2 + (\mathrm{g}-1)^2$	-α to 1
NSE	1 - $\frac{\sum_{i=1}^{n}(Q_G - Q_M)^2}{\sum_{i=1}^{n}(Q_G - Q_{mean})^2}$	-α to 1
R^2	1 - $\frac{\sum_{i=1}^{n}(Q_G - Q_M)^2}{\sum_{i=1}^{n}(Q_G - Q_{mean})^2}$	0 to 1
pBIAS	100* $\frac{\sum_{i=1}^{n}(Q_G - Q_M)}{\sum_{i=1}^{n}(Q_G)}$	-α to +α

**Q_G= USGS observed discharge, Q_M= Discharge from models, Q_{mean}= Mean value of the observed discharge, r = Pearson correlation coefficient between Q_G and, b= ratio between mean of Q_M to the mean of, g= ratio of the coefficient of variation of Q_M to Q_G.*

Identifying the relevant NWM flowlines that intersect with USGS gauges (Figure 9), users can also assign the gauge discharge data to these flowlines and update the input discharge file from the input directory, while using NWM-predicted discharge for the other reaches to generate the FIM.

3.5. Synthetic Rating Curves for the river segments

Synthetic Rating Curves (SRCs) provide the stage (m) and discharge (m^3/s) relationships for any stream within a watershed. These curves are derived using the cross-sectional average parameters of each reach through Manning's equation (Zheng et al., 2018; Scriven et al., 2021; Gordon et al., 2023). The OWP HAND-FIM model utilizes these SRCs to calculate the stage for a given discharge. The "*plotSRC*" module in FIMserv allows users to visualize SRCs for any specified reach and check the stage values corresponding to the user-defined discharge data. This functionality is demonstrated for the Middle Neuse Watershed (hucID-03020202) in Figure 11 with SRCs for two feature-ids (5490493 and 5490541). The "*plotSRC*" module also identifies the corresponding stage values based on the user-defined NWM discharge for specific stream segments. For example, for feature-id 5490493, a discharge of 3,000 m^3/s corresponds to a stage of 8.23 m (Figure 11d), while for feature-id 5490541, a discharge of 3,500 m^3/s corresponds to a stage of 9.75 m (Figure 11e). Users can input multiple feature-ids to visualize their respective SRCs.

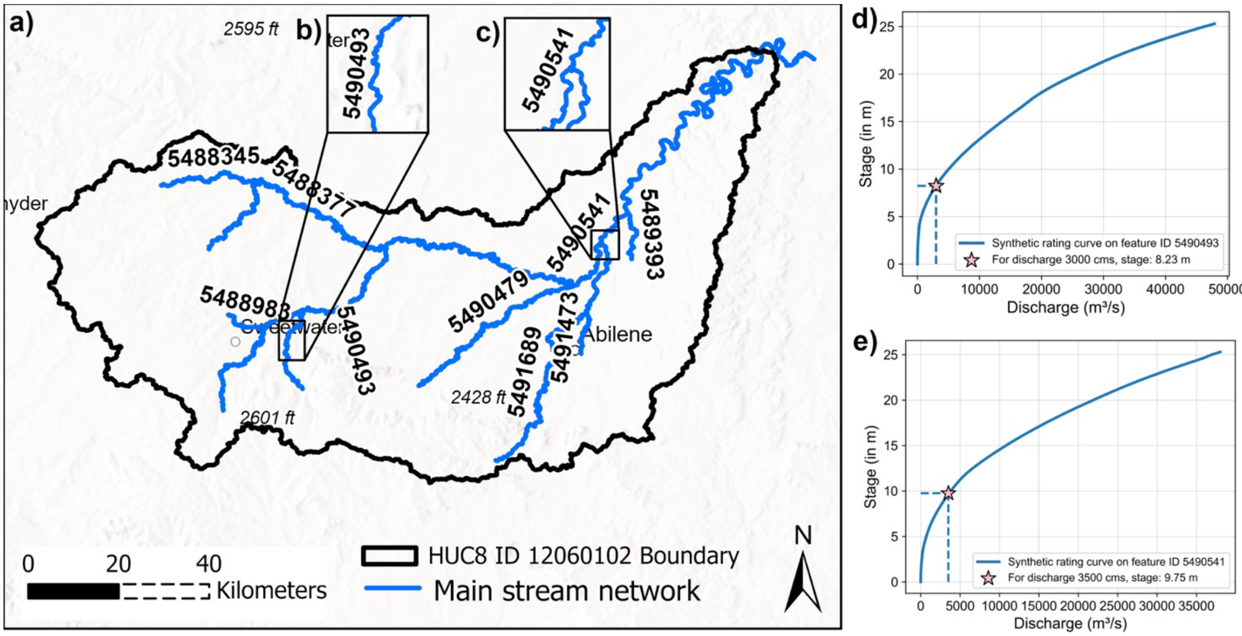


Figure 11. (a) Watershed boundary of Upper Clear Fork Brazos (hucID-12060102) with the mainstream network and feature_ids, (b, c) feature_id-5490493, 5490541 and (d, e) plot of SRCs, generated using the *plotSRC* module, indicating stage (8.23m, 9.75m) corresponding to an input discharge of 3000 and 3500 m³/sec for feature_ids 5490493, 5490541.

3.6. FIM with NWM and GeoGLOWS retrospective data

FIMserv can retrieve retrospective daily discharge data from GeoGLOWS (cf. section 2.4). The GeoGLOWS daily discharge data is transferred to the corresponding NWM flowlines and stored in the input directory as a CSV file. The '*runOWPHANDFIM*' module then uses this discharge to generate the binary FIM, which is saved as a GeoTIFF file in the output directory.Currently, the framework only supports the use of retrospective GeoGLOWS discharge data. However, in future versions, GeoGLOWS forecast discharge will also be integrated. We demonstrated this functionality using the Middle Brazos Lake Whitney HUC-08 (hucID-12060202) for daily discharge data from 2016. Since GeoGLOWS provides daily data, the NWM hourly discharge is aggregated to daily mean values to ensure consistency between the datasets. Using USGS observed discharge as a benchmark, FIMserv computes and displays key statistical metrics, including KGE, NSE, R^2, and pBIAS for both NWM and GeoGLOWS discharge data (Figure 12, Table 4). Based on the statistical scores, users can select the discharge dataset with less bias for more reliable flood mapping (Figure 12).

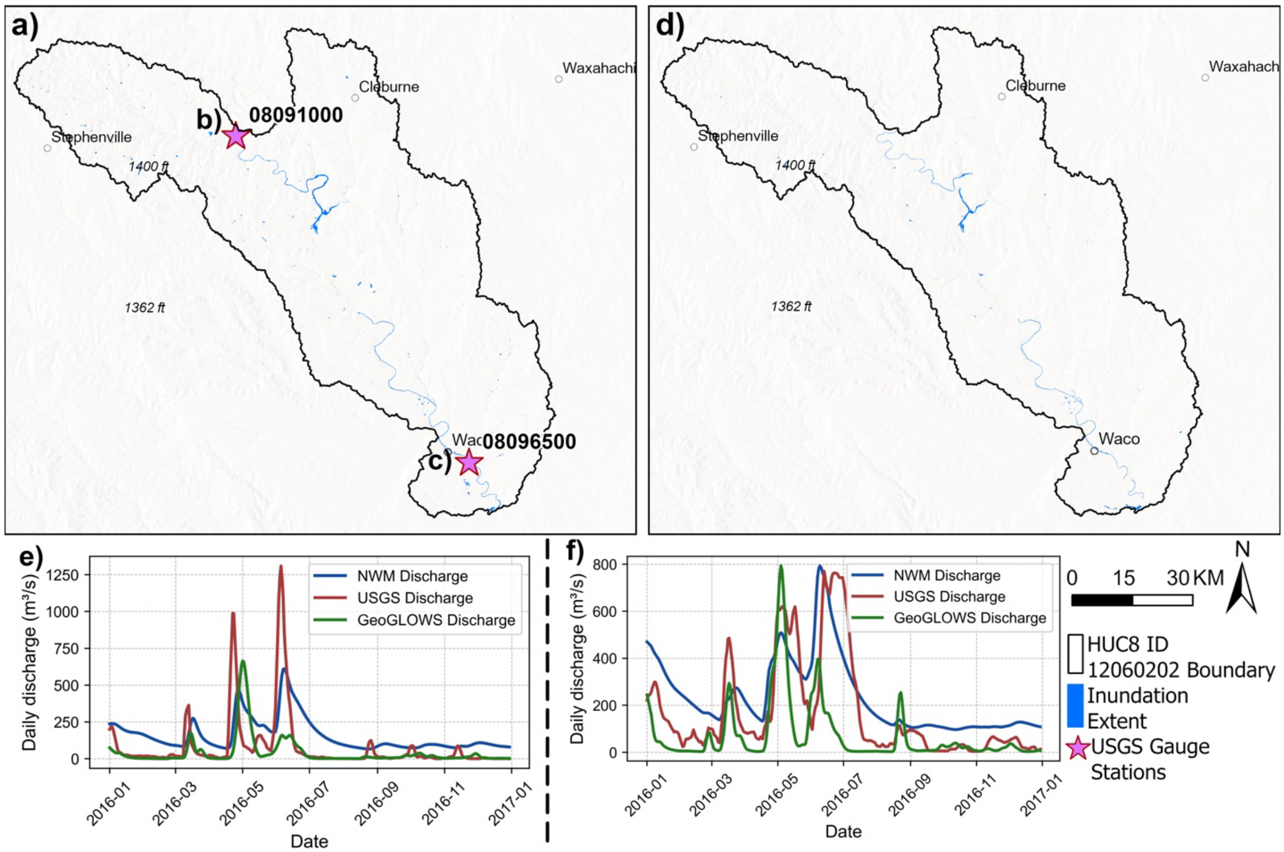


Figure 12. Output FIMs in Middle Brazos Lake Whitney HUC-08 using the "*runOWPHANDFIM*" module for (a) NWM discharge, and (d) GeoGLOWS discharge for October 15, 2016. Hydrographs of NWM, USGS, and GeoGLOWS discharge at USGS stations (b, e) 08091000 and (c, f) 08096500.

Table 4. Comparison of GeoGLOWS and NWM discharge for the year 2016.

	R^2	KGE	NSE	pBIAS (%)
		USGS gauge ID 08091000		
NWM	0.21	-0.08	0.21	158.11
GeoGLOWS	0.01	0.0009	0.01	91.44
		USGS gauge ID: 08091500		
NWM	0.55	0.49	0.55	70.15
GeoGLOWS	0.06	0.16	0.06	69.37

The results show that for both USGS stations, NWM demonstrates a better R^2 compared to GeoGLOWS discharge but also exhibits a higher pBIAS score. The framework does not apply any bias correction or statistical adjustments to the GeoGLOWS or NWM discharge data. Instead, this functionality helps users understand the bias and uncertainty associated with the input flow data.

4. Conclusion

In this paper, we present an efficient and user-friendly Flood Inundation Mapping (FIM) toolset (FIMserv) based on the NOAA Office of Water Prediction (OWP) operational hydrological forecasting framework. FIMserv streamlines the FIM generation module of the OWP HAND-FIM framework and can be run on local workstations and cloud platforms. FIMserv introduces functionalities beyond the original OWP HAND-FIM framework including (1) domain filtering based on river stream order and AOI, (2) accuracy assessment of national water model (NWM) against USGS discharge, (3) ability to dynamically assign USGS discharge values for selected river reaches, (4) flood mapping with NWM retrospective and forecast discharge, (5) visualizing the synthetic rating curves used in flood mapping, (6) use of GeoGLOWS daily discharge. The framework has been tested and run in Windows, macOS and cloud environments (Google Colab and 2i2C interactive computing framework). FIMserv is useful for researchers to integrate operational FIM into their workflows or test different scenarios and flow conditions. FIMserv is poised to be an efficient tool for a broad range of scientists and partitioners, including social scientists, economists, and individuals, enabling them to generate high-resolution (10m) operational flood maps with minimal effort. Further development of FIMserv will include (1) introduction of additional discharge dataset (e.g. SWOT), (2) enhancement of visualization using open-source web mapping, (3) inclusion of building footprints for risk and vulnerability studies, and (4) development of a webGIS portal for deployment as a web service as part of the Cooperative Institute for Research to Operations in Hydrology (CIROH) cyber enterprise (https://docs.ciroh.org/docs/products/Flood%20Inundation%20Mapping/FIMserv/).

Codes and Datasets

Name of tool: FIMserv

Developers: Anupal Baruah, Supath Dhital

Contact: abaruah@ua.edu, sdhital@crimson.ua.edu, sagy.cohen@ua.edu

Program Language: Python

GitHub Repository of FIMserv: https://github.com/sdmlua/fimserv

FIMserv in PyPI repository: https://pypi.org/project/fimserve/

Arc-GIS online dataset: https://arcg.is/1LeqPD1

FIMserv listing on CIROH DocuHub:

https://docs.ciroh.org/docs/products/Flood%20Inundation%20Mapping/FIMserv/

FIMserv in Google Colab: https://tinyurl.com/2z7845re

GeoGLOWS: https://data.geoglows.org/available-data

TEEHR: https://github.com/RTIInternational/teehr

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.

Authors Contribution

Anupal Baruah, Supath Dhital: Conceptualization, module development, writing, editing.

Thanh Nhan Duc Tran, Hesham Elhaddad, Lyn Watts: Docker-free environment development, forecast data extraction, writing, editing.

Yixian Chen: Spatial joining of GeoGLOWS flowlines with NWM flowlines, writing, editing.

Dipsikha Devi: Writing, editing.

Sagy Cohen: Supervision, methodology, funding acquisition.

Carson Pruitt: Methodology

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References

Abdelkader, M., Temimi, M., & Ouarda, T. B. M. J. (2023). Assessing the National Water Model's Discharge Estimates Using a Multi-Decade Retrospective Dataset across the Contiguous United States. Water (Switzerland), 15(13). https://doi.org/10.3390/w15132319

Afshari, S., Tavakoly, A. A., Rajib, M. A., Zheng, X., Follum, M. L., Omranian, E., & Fekete, B. M. (2018). Comparison of new generation low-complexity flood inundation mapping tools with a hydrodynamic model. Journal of Hydrology, 556, 539-556. https://doi.org/10.1016/j.jhydrol.2017.11.036

Annis, A., Nardi, F., & Castelli, F. (2022). Simultaneous assimilation of water levels from river gauges and satellite flood maps for near-real-time flood mapping. Hydrology and Earth System Sciences, 26(4), 1019-1041. https://doi.org/10.5194/hess-26-1019-2022

Aristizabal, F., Salas, F., Petrochenkov, G., Grout, T., Avant, B., Bates, B., & Judge, J. (2023). Extending height above nearest drainage to model multiple fluvial sources in flood inundation mapping applications for the US National Water Model. Water Resources Research, 59(5), e2022WR032039. https://doi.org/10.1029/2022WR032039

Baruah, A., Barman, D., Arjun, B. M., Chyne, B. L., & Aggarwal, S. P. (2024). Holistic framework for flood hazard assessment in a trans-boundary basin. *Acta Geophysica*, *72*(2), 1017-1032.

Buto, S. G., & Anderson, R. (2020). NHDPlus high resolution (NHDPlus HR)---A hydrography framework for the nation (No. 2020-3033). US Geological Survey. 2 p., https://doi.org/10.3133/fs20203033

Cosgrove, B., Gochis, D., Flowers, T., Dugger, A., Ogden, F., Graziano, T., Clark, E., Cabell, R., Casiday, N., Cui, Z., Eicher, K., Fall, G., Feng, X., Fitzgerald, K., Frazier, N., George, C., Gibbs, R., Hernandez, L., Johnson, D., Zhang, Y. (2024). NOAA's National Water Model: Advancing operational hydrology through continental-scale modeling. Journal of the American Water Resources Association, 60(2), 247–272. https://doi.org/10.1111/1752-1688.13184

Devi, D., Baruah, A., & Sarma, A. K. (2022). Characterization of dam-impacted flood hydrograph and its degree of severity as a potential hazard. *Natural Hazards*, *112*(3), 1989-2011.

Do, S. K., Nguyen, B. Q., Tran, V. N., Grodzka-Łukaszewska, M., Sinicyn, G., & Lakshmi, V. (2024). Investigating the Future Flood and Drought Shifts in the Transboundary Srepok River Basin Using CMIP6 Projections. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. https://doi.org/10.1109/JSTARS.2024.3380514

Fohringer, J., Dransch, D., Kreibich, H., & Schröter, K. (2015). Social media as an information source for rapid flood inundation mapping. Natural Hazards and Earth System Sciences, 15(12), 2725-2738. https://doi.org/10.5194/nhess-15-2725-2015

Follum, M. L., Vera, R., Tavakoly, A. A., & Gutenson, J. L. (2020). Improved accuracy and efficiency of flood inundation mapping of low-, medium-, and high-flow events using the AutoRoute model. Natural Hazards and Earth System Sciences, 20(2), 625-641. https://doi.org/10.5194/nhess-20-625-2020

Garousi-Nejad, I., Tarboton, D. G., Aboutalebi, M., & Torres-Rua, A. F. (2019). Terrain analysis enhancements to the height above nearest drainage flood inundation mapping method. Water Resources Research, 55(10), 7983-8009. https://doi.org/10.1029/2019WR024837

Godbout, L., Zheng, J. Y., Dey, S., Eyelade, D., Maidment, D., & Passalacqua, P. (2019). Error Assessment for Height Above the Nearest Drainage Inundation Mapping. JAWRA Journal of the American Water Resources Association, 55(4), 952–963. https://doi.org/10.1111/1752-1688.12783

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. Journal of hydrology, 377(1-2), 80-91. https://doi.org/10.1016/j.jhydrol.2009.08.003.

Gordon, C. A., Foulon, E., & Rousseau, A. N. (2023). Deriving synthetic rating curves from a digital elevation model to delineate the inundated areas of small watersheds. Journal of Hydrology: Regional Studies, 50. https://doi.org/10.1016/j.ejrh.2023.101580

Hales, R. C., Nelson, E. J., Souffront, M., Gutierrez, A. L., Prudhomme, C., Kopp, S., Ames, D. P., Williams, G. P., & Jones, N. L. (2022). Advancing global hydrologic modeling with the GeoGLOWS ECMWF discharge service. Journal of Flood Risk Management. https://doi.org/10.1111/jfr3.12859

Hosseiny, H. (2021). A deep learning model for predicting river flood depth and extent. Environmental Modelling & Software, 145, 105186. https://doi.org/10.1016/j.envsoft.2021.105186

Huang, M., & Jin, S. (2020). Rapid flood mapping and evaluation with a supervised classifier and change detection in Shouguang using Sentinel-1 SAR and Sentinel-2 optical data. Remote Sensing, 12(13), 2073. https://doi.org/10.3390/rs12132073

Jafarzadegan, K., Moradkhani, H., Pappenberger, F., Moftakhari, H., Bates, P., Abbaszadeh, P., ... & Duan, Q. (2023). Recent advances and new frontiers in riverine and coastal flood modeling. Reviews of Geophysics, 61(2), e2022RG000788. https://doi.org/10.1029/2022RG000788

Kumar, V., Azamathulla, H. M., Sharma, K. V., Mehta, D. J., & Maharaj, K. T. (2023). The State of the Art in Deep Learning Applications, Challenges, and Future Prospects: A Comprehensive Review of Flood Forecasting and Management. In Sustainability (Switzerland) (Vol. 15, Issue 13). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/su151310543

Kussul, N., Shelestov, A., & Skakun, S. (2008). Grid system for flood extent extraction from satellite images. Earth Science Informatics, 1(3–4). https://doi.org/10.1007/s12145-008-0014-3

Lozano, J. S., Bustamante, G. R., Hales, R. C., Nelson, E. J., Williams, G. P., Ames, D. P., & Jones, N. L. (2021). A discharge bias correction and performance evaluation web application for

GeoGLOWS ecmwf discharge services. Hydrology, 8(2). https://doi.org/10.3390/hydrology8020071

Mason, D. C., Davenport, I. J., Neal, J. C., Schumann, G. J. P., & Bates, P. D. (2012). Near real-time flood detection in urban and rural areas using high-resolution synthetic aperture radar images. IEEE Transactions on Geoscience and Remote Sensing, 50(8), 3041-3052. https://doi.org/10.1109/TGRS.2011.2178030

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. Transactions of the ASABE, 58(6), 1763-1785. https://doi.org/10.13031/trans.58.10715

Munawar, H. S., Hammad, A. W. A., & Waller, S. T. (2022). Remote Sensing Methods for Flood Prediction: A Review. In Sensors (Vol. 22, Issue 3). MDPI. https://doi.org/10.3390/s22030960

Nobre, A. D., Cuartas, L. A., Hodnett, M., Rennó, C. D., Rodrigues, G., Silveira, A., & Saleska, S. (2011). Height Above the Nearest Drainage–a hydrologically relevant new terrain model. Journal of Hydrology, 404(1-2), 13-29. https://doi.org/10.1016/j.jhydrol.2011.03.051

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—A discussion of principles. Journal of Hydrology, 10(3), 282-290. https://doi.org/10.1016/0022-1694(70)90255-6

Notti, D., Giordan, D., Caló, F., Pepe, A., Zucca, F., & Galve, J. P. (2018). Potential and limitations of open satellite data for flood mapping. Remote Sensing, 10(11). https://doi.org/10.3390/rs10111673

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Müller, A., Nothman, J., Louppe, G., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2018). *Scikit-learn: Machine Learning in Python* (arXiv:1201.0490). arXiv. https://doi.org/10.48550/arXiv.1201.0490

Rahman, M. S., & Di, L. (2017). The state of the art of spaceborne remote sensing in flood management. In Natural Hazards (Vol. 85, Issue 2, pp. 1223–1248). Springer Netherlands. https://doi.org/10.1007/s11069-016-2601-9

Scriven, B. W. G., McGrath, H., & Stefanakis, E. (2021). GIS derived synthetic rating curves and HAND model to support on-the-fly flood mapping. Natural Hazards, 109(2), 1629–1653. https://doi.org/10.1007/s11069-021-04892-6

Shen, X., Anagnostou, E. N., Allen, G. H., Brakenridge, G. R., & Kettner, A. J. (2019). Near-real-time non-obstructed flood inundation mapping using synthetic aperture radar. Remote Sensing of Environment, 221, 302-315. https://doi.org/10.1016/j.rse.2018.11.008

Tran, T.-N.-D & Lakshmi, V. (2024). Enhancing human resilience against climate change: Assessment of hydroclimatic extremes and sea level rise impacts on the Eastern Shore of Virginia, United States. Science of The Total Environment, 947, 174289. https://doi.org/10.1016/j.scitotenv.2024.174289

Tran, T. N. D., Nguyen, Q. B., Nguyen, T. T., Vo, N. D., Nguyen, C. P., & Gourbesville, P. (2022). Operational methodology for the assessment of typhoon waves characteristics. Application to Ninh Thuan Province, Vietnam. In Advances in Hydroinformatics: Models for Complex and Global Water Issues—Practices and Expectations (pp. 887-902). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-19-1600-7_55

Tapas, M. R., Do, S. K., Etheridge, R., & Lakshmi, V. (2024). Investigating the impacts of climate change on hydroclimatic extremes in the Tar-Pamlico River basin, North Carolina. Journal of Environmental Management, 363, 121375. https://doi.org/10.1016/j.jenvman.2024.121375

Wang, X., & Xie, H. (2018). A review on applications of remote sensing and geographic information systems (GIS) in water resources and flood risk management. In Water (Switzerland) (Vol. 10, Issue 5). MDPI AG. https://doi.org/10.3390/w10050608

Wu, Q. (2020). geemap: A Python package for interactive mapping with Google Earth Engine. *Journal of Open Source Software*, *5*(51), 2305. https://doi.org/10.21105/joss.02305

Yan, K., Di Baldassarre, G., Solomatine, D. P., & Schumann, G. J. P. (2015). A review of low-cost space-borne data for flood modelling: topography, flood extent and water level. Hydrological Processes, 29(15), 3368-3387. https://doi.org/10.1002/hyp.10449

Zahura, F. T., Goodall, J. L., Sadler, J. M., Shen, Y., Morsy, M. M., & Behl, M. (2020). Training machine learning surrogate models from a high-fidelity physics-based model: Application for real-time street-scale flood prediction in an urban coastal community. Water Resources Research, 56(10), e2019WR027038. https://doi.org/10.1029/2019WR027038

Zhang, T., Feng, P., Maksimović, Č., & Bates, P. D. (2016). Application of a three-dimensional unstructured-mesh finite-element flooding model and comparison with two-dimensional approaches. Water Resources Management, 30, 823-841. https://doi.org/10.1007/s11269-015-1193-6

Zheng, X., Tarboton, D. G., Maidment, D. R., Liu, Y. Y., & Passalacqua, P. (2018). River channel geometry and rating curve estimation using height above the nearest drainage. JAWRA Journal of the American Water Resources Association, 54(4), 785-806. https://doi.org/10.1111/1752-1688.12661

Zhou, Y., Wu, W., Nathan, R., & Wang, Q. J. (2021). A rapid flood inundation modelling framework using deep learning with spatial reduction and reconstruction. Environmental Modelling & Software, 143, 105112. https://doi.org/10.1016/j.envsoft.2021.105112

Zhou, Y., Wu, W., Nathan, R., & Wang, Q. J. (2022). Deep Learning-Based Rapid Flood Inundation Modeling for Flat Floodplains With Complex Flow Paths. Water Resources Research, 58(12), e2022WR033214. https://doi.org/10.1029/2022WR033214