Technical Memorandum FY26RU3

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1. Introduction

The Flood Assessment System for TxDOT (FAST) is a web-based framework for depicting and forecasting flood impact on the road and bridge system of Texas. It is developed under TxDOT Project 0-7095-01 which runs from February 2024 to January 2027. The purpose of this report is to document progress on the project during FY26, from September 2025 to August 2026. It follows on from Research Update 2 completed in August 2025.

> Maidment, D., et al. (2025) Flood Assessment System for TxDOT: Update on Research in FY25, Technical Memorandum FY25RU2, TxDOT Project 0-7095-01,14 p.[1]

The FAST project activity is divided into six tasks, Task 1 being Project Management, Tasks 2-5 containing the main body of work on FAST itself, and Task 6 on Forecast Data Analytics being the foundational research underlying FAST. For each of the tasks 2-5, reports of type P have been submitted in recent months that provide additional technical detail. These reports are:

> Evans, H., et al. (2026) Exercises for FAST Flood Map Services, Report P2C TxDOT Project 0-7095-01, 6p.[2]

> Avant, J., et al. (2026) Flood Decision Support Gauge Network, Report P3C, TxDOT Project 0-7095-01, 9p.[3]

> Whiteaker, T., et al. (2026) Culverts and Low Water Crossings, Report P4B, TxDOT Project 0-7095-01, 52p.[4]

> Carter, A. et al. (2026) Flood Data Services, Report P5C, TxDOT Project 0-7095-01, 42p.[5]

In this report, results are summarized for Tasks 2-5 and a longer description is provided for Task 6, Forecast Data Analytics.

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[1]https://caee.webhost.utexas.edu/prof/maidment/FAST/Documents/TMFY25RU2Project0_7095_01.pdf

[2]https://caee.webhost.utexas.edu/prof/maidment/FAST/Documents/ReportP2CProject0_7095_01.pdf

[3]https://caee.webhost.utexas.edu/prof/maidment/FAST/Documents/Report%20P3CProject0_7095_01.pdf

[4]https://caee.webhost.utexas.edu/prof/maidment/FAST/Documents/ReportP4BProject0_7095_01.pdf

[5]https://caee.webhost.utexas.edu/prof/maidment/FAST/Documents/ReportP5CProject0_7095_01.pdf

2. Flood Map Services

A key focus of activity in the FAST project during FY26 was to transform the draft state-wide FAST system that existed in August 2025 into a system that is useful and usable by TxDOT. This goal was achieved. Three FAST exercises were conducted with Maintenance staff in TxDOT Districts during the summer of 2026. There was significant flooding in Texas during July 2026, and FAST was used in the TxDOT State Operations Center for helping with flood operations during this event. The user interface to FAST is shown in Figure 1. It can be accessed on the web at: https://bridges.txdot.kisters.cloud/ It comprises three components: a Production system where the live version of FAST resides, a Development system where alternatives in the process of being tested are included, and a Training sytem for datasets supporting training exercises.

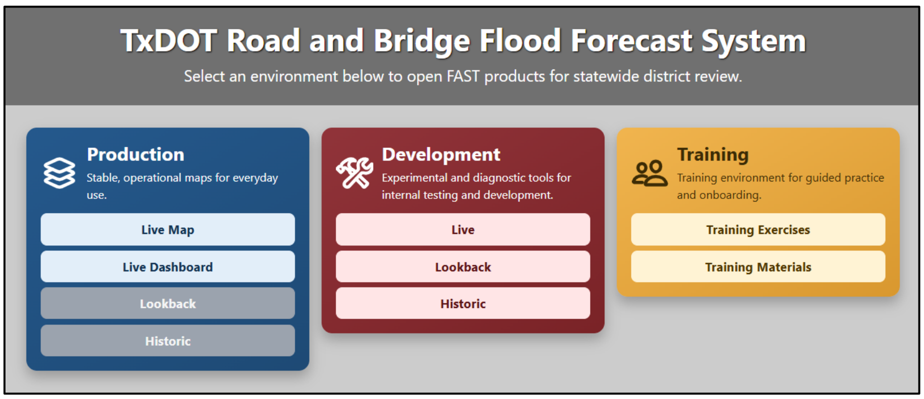

Figure 1. FAST user interface

2.1. Training Exercises

Three training exercises were conducted with TxDOT personnel in Austin, Houston, and Fort Worth to introduce FAST and gather feedback on its usefulness, functionality, and potential application in flood response operations. The exercises generated feedback from a broad cross-section of TxDOT personnel representing multiple Districts, Areas, and Maintenance Sections (Figure 2, Figure 3).

AUS Exercise – Stassney Campus
June 2, 2026 / 9-12pm
Districts: Waco, San Antonio, SOC, Austin, H&H

HOU Exercise – Houston Campus
June 10, 2026 / 1-4pm
Districts: Houston, Montgomery, Beaumont, Bryan, Yoakum

FTW Exercise – Fort Worth District HQ
July 28, 2026 / 1-4pm
Districts: Fort Worth, Dallas, Wichita Falls, Paris, Waco

During these exercises, the total number of participants was 79, and the total number of feedback surveys was 63. The overall response was strongly positive: 59 participants said they would use FAST in their job, while only 3 said they would not — approximately 95% positive intent to use.

Users repeatedly called it easy to use, intuitive, simple, user-friendly, easy to digest, and easy to interpret. They liked the dashboard, map navigation, toggles and overall accessibility. That is significant because FAST presents fairly complex hydrologic and transportation information. Users generally don't appear to think the underlying complexity makes the application difficult to understand.

The feedback indicates that users like the concept, interface, visualization and operational potential of FAST. The primary concerns are not about whether FAST is useful; they center on whether its information is accurate, timely, actionable, and tailored to the user's operational area.

Figure 2. FAST exercise participants during the Fort Worth exercise (image 1)

2.2. Assessment of FAST

Users want FAST to do three things exceptionally well:

TRUST IT - Accurate, timely forecasts with understandable confidence.
ALERT ME - Tell me when *my* roads and crossings require attention.
SHOW ME MY AREA - Give me a simple, mobile-friendly operational view of *my* Maintenance Section.

The primary barriers to operational adoption are forecast accuracy and trust, timeliness of information, lack of automated alerts, and the need for more localized and mobile functionality.

Future development should prioritize forecast reliability and confidence, user-configurable alerts, Maintenance Section-level views, improved mobile functionality, expanded structure coverage and historical event analysis.

A particularly important finding is that participants see FAST as more than a source of flood information. They see its potential as an operational decision-support tool. Participants identified applications including pre-staging crews, planning resources, identifying potential trouble spots, anticipating road and bridge closures, and improving emergency response. The ability to look ahead and understand where flooding may occur was repeatedly identified as one of FAST's most valuable capabilities.

Participants want to know clearly whether the information they are viewing represents what is happening now or what is expected to happen in the future. Comments also identified a desire for more current information, shorter forecast horizons, and more obvious nowcasting capabilities. Establishing a clear distinction between observed conditions, current conditions, and forecast conditions will be important to building user confidence.

Another consistent request was the addition of an alert and notification capability. Participants expressed interest in receiving notifications when a bridge, roadway, or low-water crossing is projected to reach a critical condition. Suggestions included user-specific alerts, push notifications, geographic thresholds, and notifications tied to Maintenance Sections or regions. This capability could significantly increase FAST's operational value by allowing users to monitor conditions without continuously watching the application.

Participants also identified a need to expand FAST's coverage beyond the structures currently represented. Low-water crossings, culverts, pump stations, and other vulnerable roadway locations were repeatedly mentioned. Several participants emphasized the importance of low-water crossings, particularly in rural areas where flooding can present significant safety risks. Expanding FAST's infrastructure coverage would allow the system to address a broader range of flood-related roadway hazards.

Mobile functionality was another significant area of interest. Participants appreciated being able to access FAST from a phone but indicated that the mobile experience could be improved substantially. Suggestions included a dedicated mobile application, better field functionality, location awareness, and the ability to access maps and forecasts when cellular service is unavailable or unreliable during major storms.

Participants also expressed interest in historical data and integration with other systems and datasets. Historical flood information could allow users to compare current conditions with previous events and better understand recurring problem locations. Suggested integrations included existing TxDOT GIS layers, HCRS, GeoTab, local municipal gauges, pump stations, lake releases, flood gates, and other sources of relevant flood information.

Taken together, the training feedback suggests that the fundamental concept behind FAST is well received and addresses a genuine operational need within TxDOT. The training exercises did not identify significant concerns with the basic usability or overall concept of the application. Instead, the primary challenge identified by users is establishing sufficient confidence in the accuracy, timeliness, and reliability of the information for operational decision-making.

Figure 3. FAST Exercise Participants during the Fort Worth exercise (image2)

Based on this feedback, the FAST project team’s next steps are to start work on the requests in Table 1.

Table 1. Improvements recommended in FAST exercises

Request Type	Task
Functionality	Location Search
	Include scour bridges
	Symbology changes
	Add counties and/or Maintenance Sections
	Improve Mobile Functionality
	Alerting / Notification
	Geographic Filtering
App Configuration	Improve delay in Forecast
	Real-time forecast
	Improved historical functionality
	Improve lookback functionality
Data	Add more bridges
	Accuracy / Reliability
Documentation	Establish a way to update bridges when needed (new LIDAR?)

3. Flood Decision Support Gauges

3.1. RQ-30 Gauge Network Status

The RQ-30 streamflow gauge network remains nearly fully operational, with 78 of 80 sites currently transmitting surface-velocity and water-level data. The two outages include one site that was destroyed by a vehicle collision and is awaiting reconstruction and another one temporarily offline due to an ongoing bridge replacement project. USGS field crews continued semiannual site visits in accordance with **Subtask 3.1.** Activities included equipment inspections, battery replacement, solar-panel cleaning, discrete discharge measurements, and verification of elevation readings using installed wire-weight reference devices. All operational gauges have been inspected within the past 12 months, and field-visit logs have been updated. Elevation corrections were applied where necessary to maintain consistent referencing to independent wire-weight or surveyed benchmarks.

ADCP measurement collection continued to support gauge calibration under **Subtask 3.2**. As of August 2026, 344 discharge measurements (262 ADCP measurements and 82 midsection measurements) have been collected at RQ-30 sites, an increase from 310 measurements as of June 30, 2025. The number of sites with at least one measurement increased from 65 to 68, leaving 12 sites without measurements (Figure 4). Three sites were relocated during the reporting period, and their measurement counts were reset following relocation. The expanded measurement dataset has resulted in 45 sites with calibration-quality data. Measurements were collected to represent both moderate- and high-flow conditions in support of dual-condition calibration using in-channel and floodplain flow conditions.

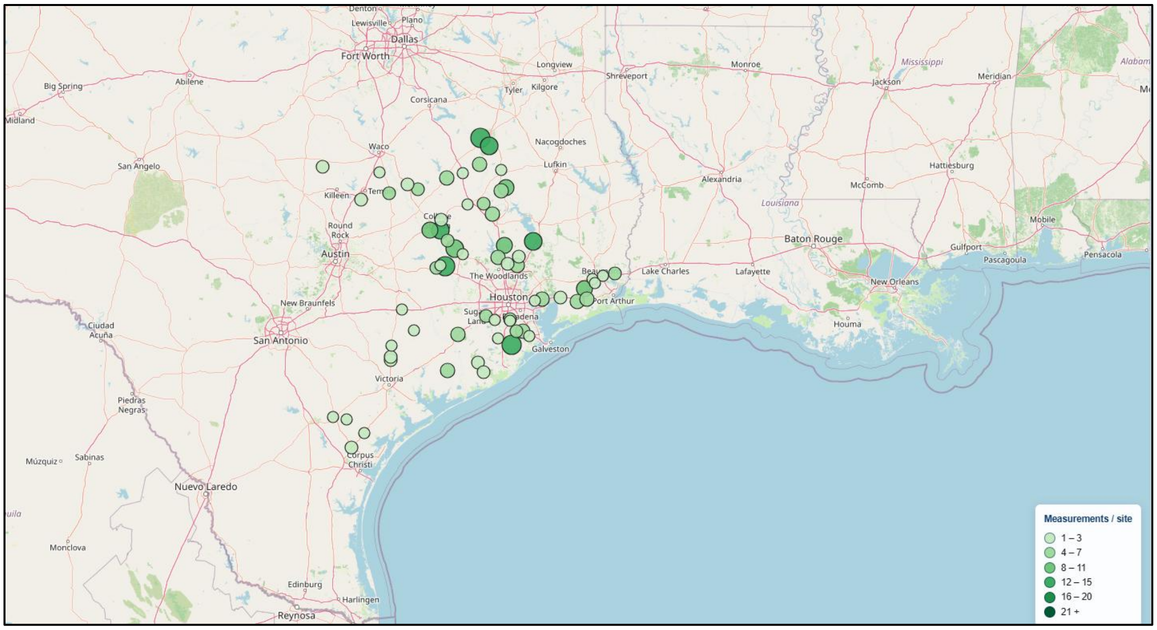

Figure 4. Heat map of ADCP measurements at RQ-30 gauge sites

3.2. Iridium Satellite Telemetry

Real-time data transmission at some RQ-30 sites faces challenges, especially during extreme weather or with poor cellular coverage. Data gaps may occur due to database or cellular issues. To address this, the project is actively deploying Iridium satellite telemetry at selected sites. An additional Sutron XLINK at select sites enable dual telemetry of both cellular and Iridium transmission. At sites with XLINK, both methods are operated to assess performance. Iridium data is integrated into USGS systems via the LRGS network.

By the reporting period, 21 out of 80 sites had XLINK installed, with 16 transmitting via Iridium; five are waiting for transmission cards expected in November 2026. These sites cover diverse network conditions for testing satellite telemetry. Early results show Iridium improves data continuity where cellular service is weak (Figure 5). During a May 2026 storm in Leander, Texas, Iridium maintained a continuous record while cellular transmission had gaps. Ongoing comparisons will inform satellite telemetry reliability across the network.

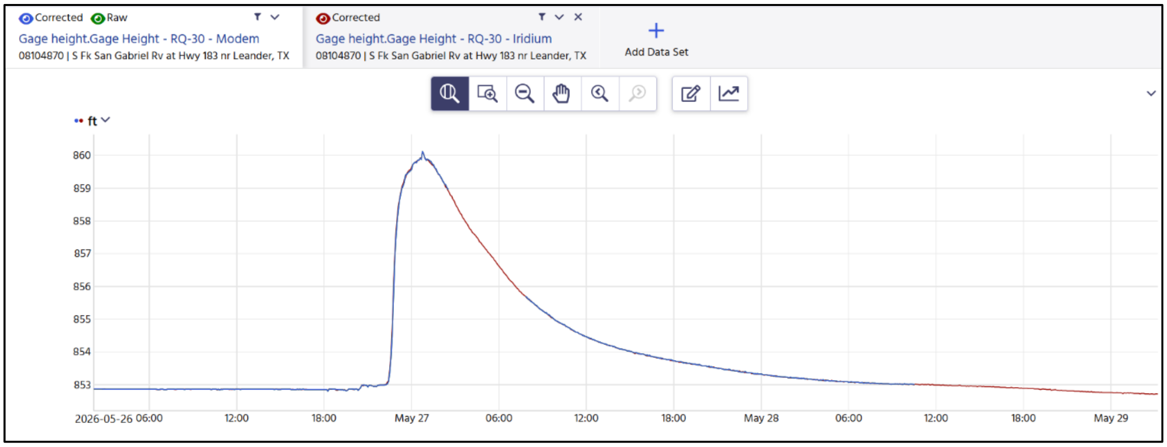

Figure 5. Gauge height at site 08104870, S Fk San Gabriel Rv at Hwy 183 nr Leander, TX, May 26–29, 2026. Blue trace = cellular (modem) transmission; red trace = Iridium satellite transmission. Where the cellular record contains gaps, the Iridium record remains continuous

3.3. FDST Integration

Integration of RQ-30 gauges into the USGS Flood Decision Support Toolbox (FDST) continued under **Subtask 3.3**. The FDST provides a web-based interface for visualizing inundation extents associated with streamflow conditions. Each candidate site undergoes a model-fit evaluation to determine whether synthetic or empirical rating curves can support the flood-mapping interface. A comprehensive evaluation of all RQ-30 sites has been completed and 43 of the 80 sites have been incorporated into the FDST and are currently active (Figure 6). Thirty sites were determined unsuitable for integration because of one or more limiting factors, including compound-flooding effects, poor model fit to the site-specific rating curve, or model edge effects. Four sites remain under library review, and three sites are pending upload.

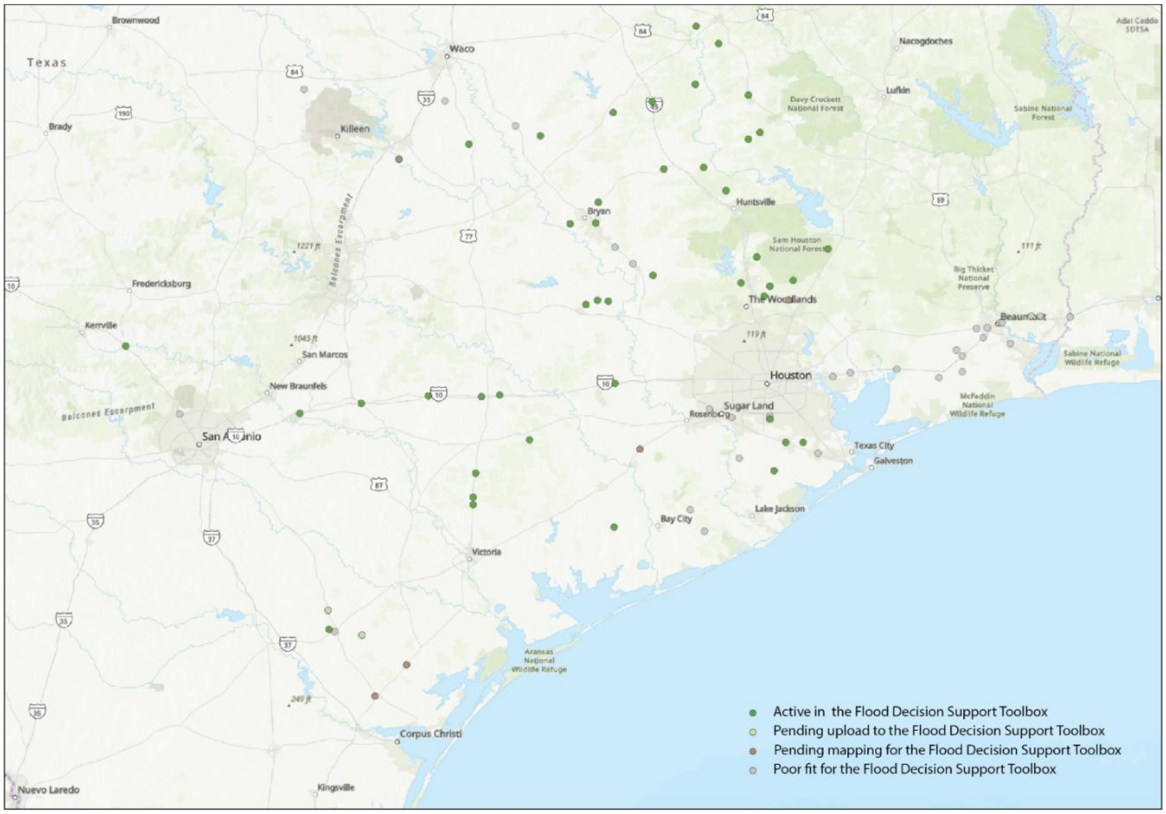

Figure 6. Map showing locations of the RQ30 sites and Flood Decision Support Toolbox status.

3.4. K-Factor Calibration Tool

A primary objective of the FAST project is to calibrate RQ-30 radar measurements so that measured surface velocity can be converted to mean-channel velocity and discharge. The calibration relationship is represented by a stage-dependent factor, k(h), such that mean velocity is calculated as (V=k(h)V_{surface}), with discharge subsequently calculated from mean velocity and the surveyed cross-sectional area, (Q=V A(h)).

Recently, a software application was developed to support and partially automate the calibration workflow. The application integrates surveyed cross sections, existing rating tables, USGS field discharge measurements, and processed ADCP measurements. It generates stage-discharge rating curves and calculates surface-to-mean velocity calibration factors as a function of stage (Figure 7). Additional capabilities include channel-roughness estimation, adjustment of imported ratings using recent field measurements, hydraulic-geometry review, export of rating and calibration-factor tables, discharge calculation from surface-velocity measurements, and comparison of predicted and measured discharge using standard goodness-of-fit statistics.

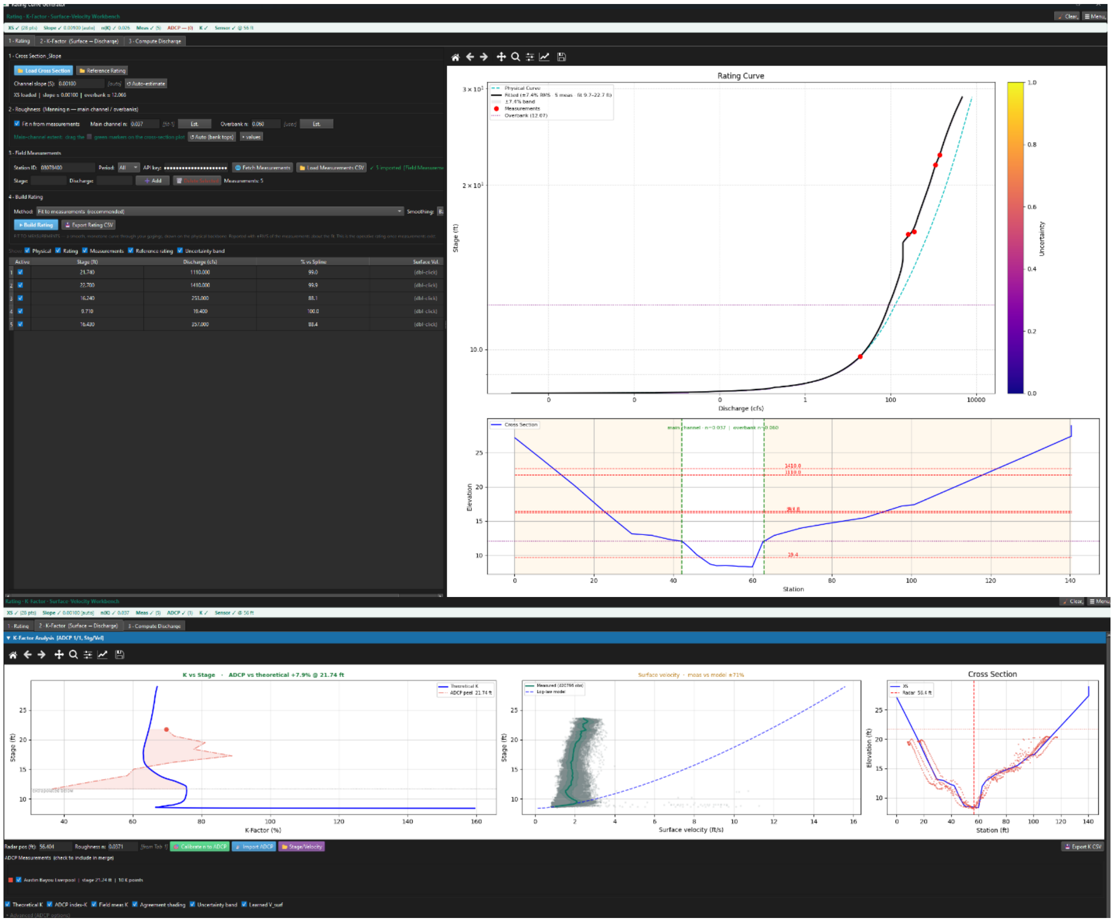

Figure 7. The initial K-Factor calibration tool

The project also developed a new approach for deriving calibration factors from full ADCP transects. The method analyzes the measured velocity field from the water surface downward and progressively reconstructs the relationship between surface velocity and mean velocity across a range of synthetic water levels. This approach is intended to extract calibration information across multiple stages from a single high-flow ADCP measurement while providing a transparent and repeatable calculation process. The method and application remain under testing.

Initial testing indicates that calibration factors generated by the application are broadly consistent with those produced by established commercial k-factor processing software. The project-developed approach provides visibility into the calculation and allows the underlying procedures to be inspected and adjusted. Continued testing and refinement will focus on validating the approach and preparing the tool for systematic application across the RQ-30 network.

4. Flood Transportation Geodatabase

4.1. Roads and Bridges

The geospatial description of roads and bridges is a key foundation of FAST. During FY25, two separate descriptions of roads and bridges were made. The first description, focused on bridges alone, which were identified by collections of LIDAR points classified as bridges in a procedure known as Tx-Bridge.[6] This procedure produced a series of "bridge envelopes, these being two lines, one representing the bridge deck surface profile and the second representing the stream cross-section profile, the lines closing at the end points at the bridge abutments. A third line representing the low chord elevation was added using a set of rules for bridge thickness devised by TxDOT, as illustrated in Figure 8. From this dataset, the bridges actually to be inserted into FAST were selected using a quality assurance procedure.[7]

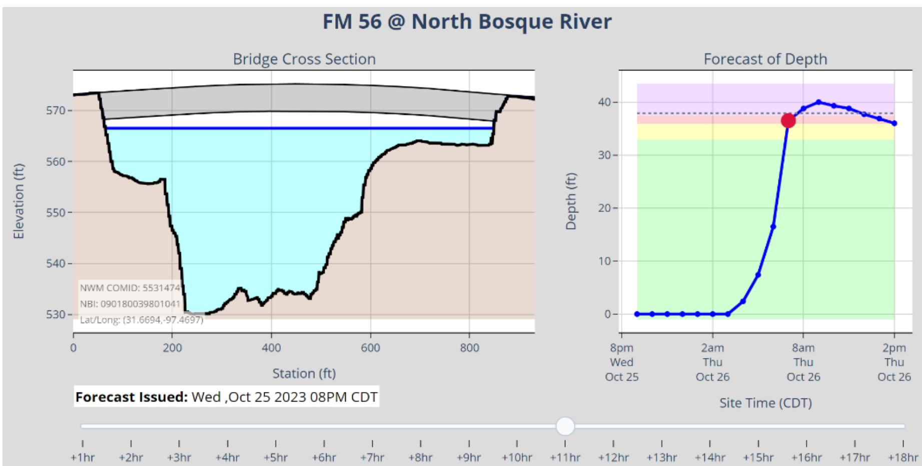

Figure 8. Bridge envelope used in a FAST forecast

The second procedure, focused on roads alone, was carried out using high-performance computing at Oak Ridge National Laboratory, and resulted in three formats of Road Elevation Model data[8]: a 3D road line/polygon GeoPackage (GPKG), a road lidar LAZ and COPC LAZ, and a road digital surface model (DSM). The project team was instructed by TxDOT to use the OpenStreetMap road lines for this analysis, rather than the TxDOT Roadway Inventory. All the connector roads and residential streets in OpenStreetMap were used, creating a coverage of 470,000 miles of roads and streets in Texas (Figure 9). By contrast, the TxDOT Roadway Inventory contains 349,000 miles of roads of which 102,000 miles are TxDOT On-System roads. It follows that the OpenStreetMap dataset provides a more complete coverage of the public road system of Texas than does the TxDOT Roadway Inventory.

[6] https://github.com/andycarter-pe/tx-bridge
[7] https://caee.webhost.utexas.edu/prof/maidment/FAST/Documents/BridgeQualityAssurance1.pdf
[8] https://doi.ccs.ornl.gov/dataset/c98c7f32-00f1-53c0-bbf0-831ab3e1dcf0

A copy of this Road Elevation Model, with separate datasets for each TxDOT District is accessible.[9] A poster describing the computational procedure is available.[10] The road and bridge information just described was inserted into FAST and was used for the FAST exercises carried out during the summer of 2026.

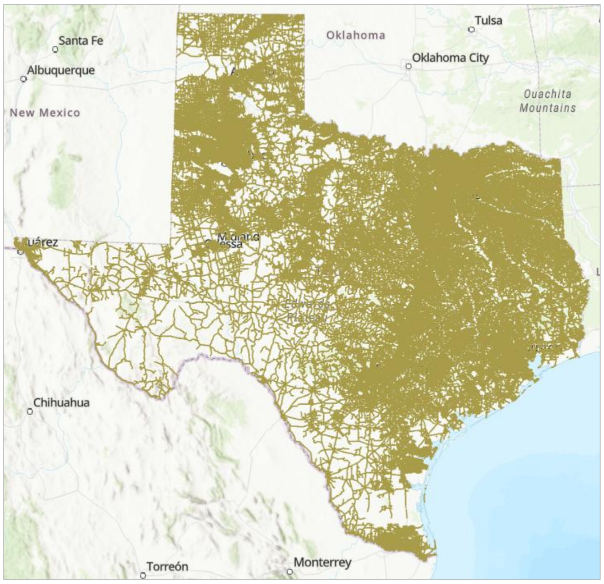

Figure 9. Road Elevation Model of Texas, describing the road network of the state in (x,y,z) for the first time

A particularly useful form is the 3m Digital Surface Model[11] (Figure 10).

Figure 10. Road Elevation Model as a 3m Digital Surface Model

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[9] https://web.corral.tacc.utexas.edu/nfiedata/road3d/
[10] https://web.corral.tacc.utexas.edu/nfiedata/road3d/docs/CIROH-ORNL-REM-poster-pub.pdf
[11] https://web.corral.tacc.utexas.edu/ras2fim/

4.2. Road and Bridge Line Model

A shortcoming of the FY25 version of FAST road and bridge description was that the road and bridge datasets were developed independently of each other. During FY26, these were unified using a Road and Bridge Line Model. The elements of this description are taken from the Bridge Geometry Manual of the Federal Highway Administration.[12] As shown in Figure 11, the horizontal profile of a road is described by a centerline whose individual segments are defined by a sequency of (x,y) vertices representing the location of the points in (East, North) coordinates. Along a bridge profile, a similar set of coordinate pairs defines the (Station, Elevation) coordinates, where Station refers to the distance along the Profile Grade Line from an initial reference point.

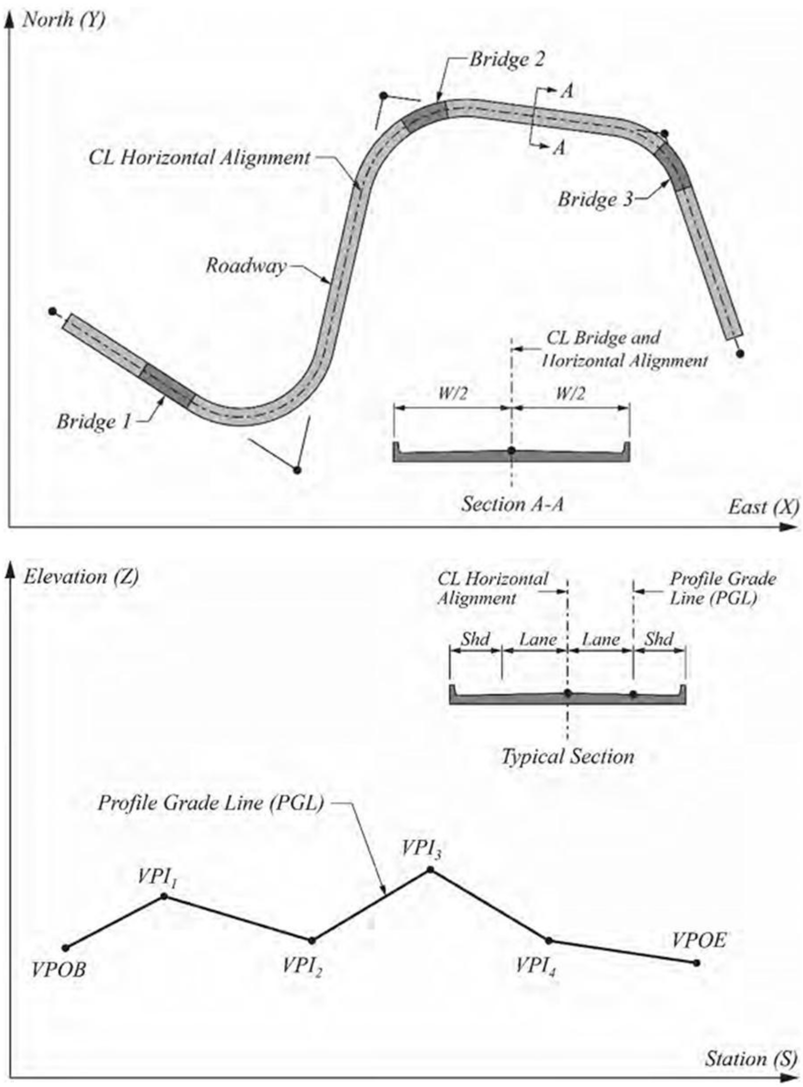

Figure 11. Horizontal profile for a road and vertical profile for a bridge

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[12] https://www.fhwa.dot.gov/bridge/pubs/hif22034.pdf

If these two ideas are combined, the road profile everywhere over the land surface is described by a sequence of (x,y,z) points, spaced at 3m intervals, as shown in Figure 12.

#	X (Meters)	Y (Meters)	Z (Meters
99	871,581.83	1,506,638.12	843.58
100	871,581.97	1,506,641.13	843.68
101	871,582.11	1,506,644.13	843.55
102	871,582.25	1,506,647.14	843.56
103	871,582.39	1,506,650.14	843.57
104	871,582.53	1,506,653.15	843.58
105	871,582.66	1,506,656.15	843.58
106	871,582.80	1,506,659.16	843.65
107	871,582.94	1,506,662.16	843.61

Figure 12. The road line as a sequence of (x,y,z) points

The LIDAR data provided by TxGIO have two forms: a set of LIDAR (x,y,z) points that represent the terrain surface, and a bare-earth 1m Digital Elevation Model calculated from the LIDAR points with all structures removed, including bridges. If these two surfaces are sampled at each 3m point along the road line, then where the elevation of road surface diverges consistently from the elevation of the bare earth surface, that indicates the road is crossing a river or another road, as illustrated in for SH 136 NB over the Canadian River (Figure 13). Here, the green line is the road elevation along the bridge deck, the brown line is the stream cross-section sampled from the bare-earth elevation model, the blue line is an estimate of the low chord elevation, and the red dots are the points where the low chord intersects the stream cross-section. The lower of these two red points is the critical elevation that indicates when flood waters will start impacting the bridge structure.

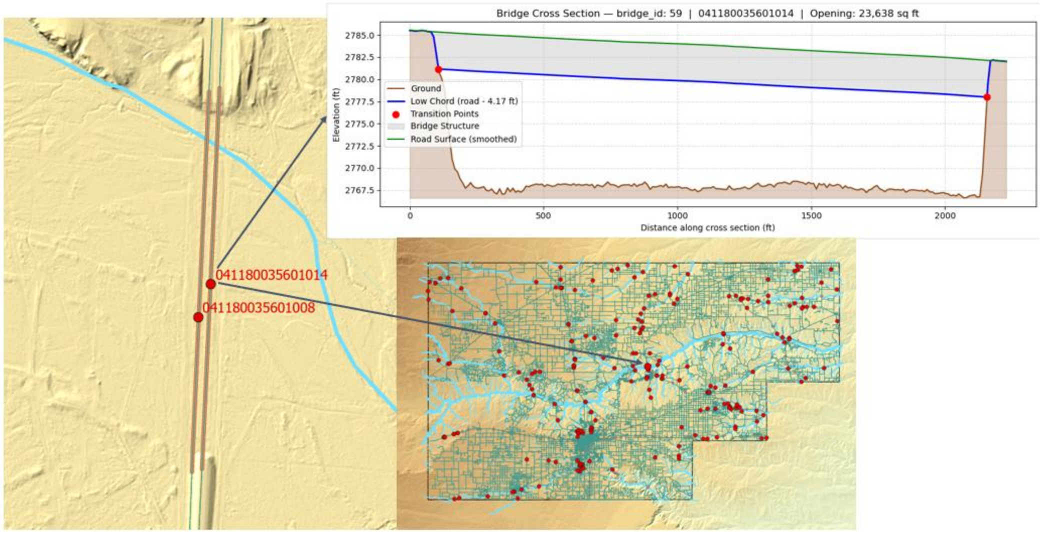


Figure 13. Bridge Cross-Section for Bridge 041180035601014, SH 136 NB over the Canadian River, Amarillo District

The first state-wide computation of the road and bridge line model was completed on 28 June 2026, and labelled as Alpha10[13]. A methodology was defined for transferring the bridges from this process into FAST.[14] A screening procedure was devised to select the set of bridges[15], as illustrated in Figure 14. The criteria used in this procedure are:

- The bridge has a SNBI number (SNBI is the Specification for the National Bridge Inventory, the new way TxDOT uses to describe bridges).
- The bridge intersects an ORNL stream, derived from the Digital Elevation Model profile.
- The opening under the bridge has a minimum conveyance area
- The bridge deck does not exceed a threshold steepness slope
- The bridge envelope is closed – there are transition points at each end of the bridge deck where the bridge deck and the stream cross-section join.

[13] https://web.corral.tacc.utexas.edu/nfiedata/sf3/alpha10/
[14] https://web.corral.tacc.utexas.edu/ras2fim/ornl_to_fast/
[15] https://roadflood.com/bridge_accounting/snbi_fgb_viewer.html?district=0_TEX

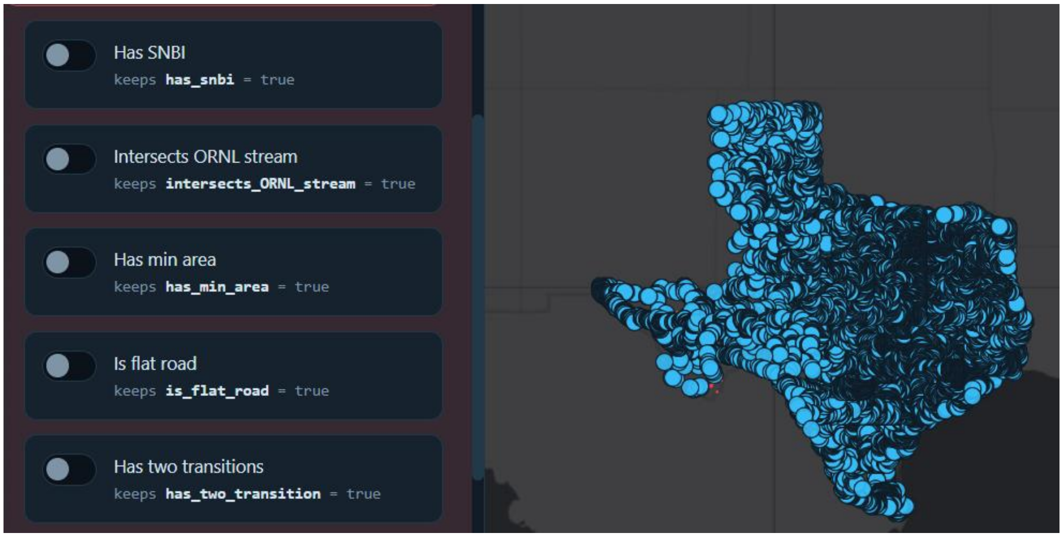


Figure 14. Screening procedure to select FAST bridges

Further revisions of the Road and Bridge Line model will be carried to increase the number of bridges identified as passing threshold criteria and be able to be inserted into FAST.

4.3. Culverts and Low Water Crossings

FAST uses rating curves to convert forecasted streamflow into forecasted water surface elevation, which can then be used to forecast road and bridge flooding. By default, FAST uses synthetic rating curves derived using the Height Above Nearest Drainage (HAND) method, which assume a uniform rating curve for a given stream segment. These reach-averaged rating curves represent culvert and road geometry at low water crossings (LWCs) or bridge class culverts (BCCs).

Modeling culverts may improve flood estimates at such crossings. To achieve this, we need data about culvert configurations at LWCs (typically collected in the field since data are not otherwise readily available), a model to compute the rating curves, and a go-between to feed survey data into the model. For the model, we use HY-8, a culvert hydraulic analysis program developed by the U.S. Federal Highway Administration. Since TxDOT has access to ArcGIS technology, we use ArcGIS Field Maps for data collection and Arc Hydro as a go-between. Arc Hydro can automate HY-8 execution for simple culvert configurations, greatly reducing the time required to compute rating curves for a significant number of culverts throughout the state. Note that the exact number of simple culvert configurations in use is not available since such data do not exist statewide, but in example surveys conducted for this project, 51 out of 58 culvert locations were compatible with automated processing. Locations of low water crossings where field surveys were carried out are shown in Figure 15.

The field survey procedure used is the third in a sequence developed during the project, each simpler than the ones before. A key simplication in the latest survey procedure is to treat the Road Elevation Model as a definitive reference surface and to measure culvert elevations relative to the road elevation. This can be done with a measuring staff and laser level and does not require using GPS equipment.

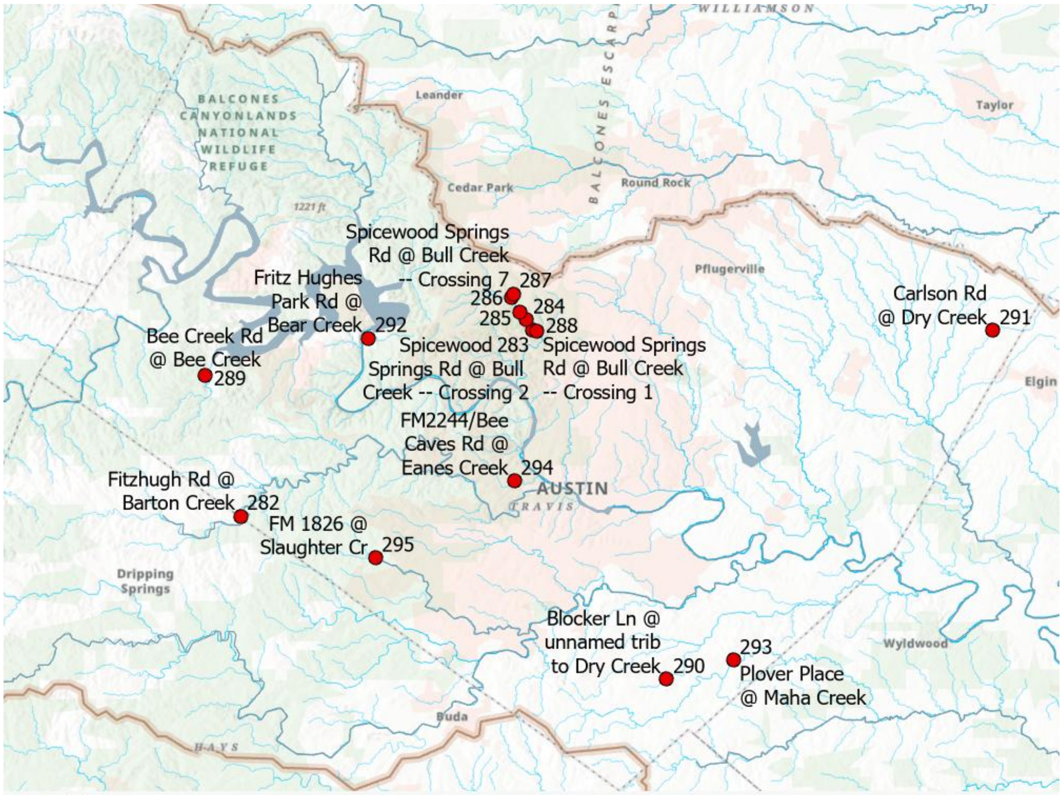


Figure 15. Locations of Low Water Crossing surveys

When surveying culverts, one needs a database design for storing survey results. For this project, the design includes a StreamCrossing table representing the location of the LWC or BCC, a Culverts table where each row represents a single culvert barrel at a given crossing, and a collection of zero or more photos associated with a crossing.

The Culverts table describes a culvert with these attributes:

- Culvert_ID (GUID) - Globally unique identifier for each culvert.
- Crossing_ID (GUID) - Identifier of related StreamCrossing.
- SequenceNum (short) - Sequence number of the culvert barrel, starting at 1, from left to right while standing downstream of the crossing and facing the crossing.
- CulvertShape (Text) - Culvert shape, e.g., Circular.
- CulvertMaterial (Text) - Culvert material, e.g., concrete.
- CulvertHeight_ft (Double) - Culvert height in feet.
- CulvertWidth_ft (Double) - Width of the culvert opening in feet.
- CulvertLength_ft (Double) - Length of the culvert opening in feet.

- USRoadHtAbvInvert (Double) - Height from bottom of culvert to top of road on the upstream side, measured in feet.
- DSRoadHtAbvInvert (Double) - Height from bottom of culvert to top of road on the downstream side, measured in feet.
- Culvert_Comments (Text) - Comments for the given culvert.

StreamCrossing attributes describe the overall crossing:

- GlobalID (GUID) - Globally unique identifier for each StreamCrossing, i.e., a GUID.
- SurveyStatus (Text) - Status of survey.
- SurveyorName (Text) - Name of person or people conducting the survey.
- SurveyDate (Date) - Date and time of survey.
- RoadName (Text) - Road name.
- StreamName (Text) - Stream name.
- RoadSurface (Text) - Road surface material.
- RoadWidth_ft (Double) - Road width in feet.
- CrossingType (Text) - Type of stream crossing, e.g., vented ford.
- AllCulvertsUniform (Text) - Indicates whether all culverts at this crossing are uniform.
- NumCulverts (Short) - Number of culverts.
- Comments (Text) - Comments.
- Label (Text) - Human-friendly short name for the stream crossing.

For simplicity of the ArcGIS Field Maps user interface when entering data for a crossing where all culverts are uniform, the StreamCrossing table supports attributes describing the same characteristics as the Culverts table. This way, the user only has to enter the uniform culvert characteristics once instead of adding rows containing the identical characteristics for each culvert. The relationship between the tables is shown in Figure 16.

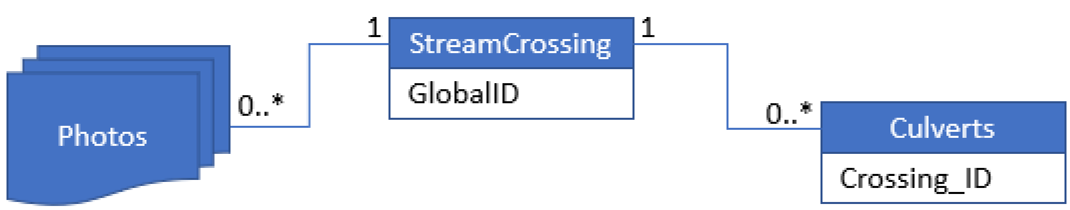


Figure 16. Culvert Survey Relationships

To collect stream crossing data, the user goes to an LWC or BCC with at least one partner and measures the culvert characteristics described above, reporting results via ArcGIS Field Maps. The FAST project team created an ArcGIS StoryMap to guide surveyors as to what equipment to bring and how to conduct the field survey. The StoryMap is at https://storymaps.arcgis.com/stories/fa738abceca9410aa5ba962a64944dfc. An example of an illustration from the StoryMap is shown in Figure 17.

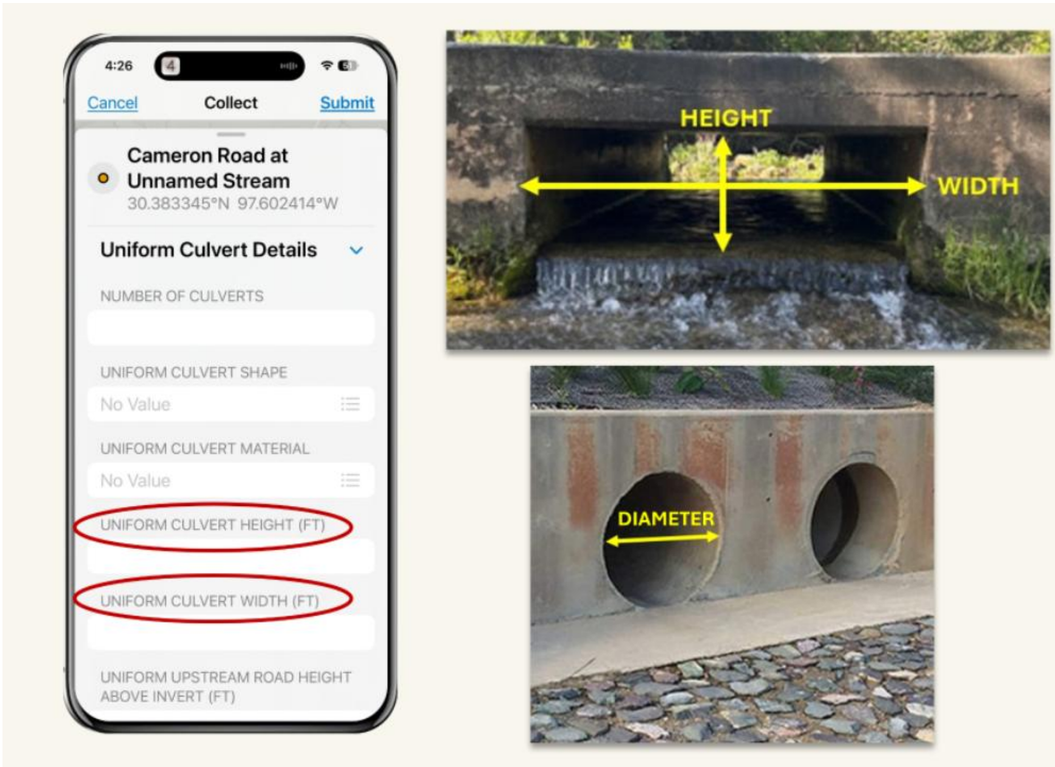


Figure 17. Field surveying of culvert dimensions

Once data are collected, they can be downloaded and prepared for use with Arc Hydro and HY-8. Stream crossings with culverts can be modeled manually in HY-8, but if the culvert configuration is uniform and simple enough (e.g., only box or circular culverts), then Arc Hydro can model multiple stream crossings at once to update rating curves in batch. At a high level, this workflow involves these steps:

1. Download stream crossing survey results.
2. Select crossings simple enough to run with Arc Hydro. Criteria:
    a. Uniform culvert configuration.
    b. Box or circular culverts.
    c. Steel or concrete culvert material.
3. Load selected crossing data into Arc Hydro feature classes.
4. Use additional data from FAST and the Arc Hydro tools to prepare and run HY-8 models. Additional data from FAST includes:
    a. Polyline XYZ roads for FAST. You can download them by district from https://web.corral.tacc.utexas.edu/nfiedata/road3d/. The file to get is **road_centerlines_xyz_3d.gpkg**.
    b. Streams are used to associate a stream crossing with its rating curve. Rating curves come from HAND, which has its own stream network independent of the one used by the National Water Model.

You can download HAND streams as "Flowline dataset for the entire Texas (FileGDB format)" from https://web.corral.tacc.utexas.edu/nfiedata/pin2flood/texas/.

c. FAST uses HAND rating curves that have been improved to remove artifacts from burning streams. These rating curves are delivered with FAST in Esri file geodatabase format in **HydroTable.gdb**.

5. Use the computed rating curves to determine flood thresholds for each LWC or BCC modeled.

Examples of rating curves calculated with HY-8 compared to HAND are shown in Figure 18 and Figure 19. If the Low Water Crossing has adequate flow capacity and a low embankment of 3-4 ft high, the existence of the culvert has little impact on the computed water surface elevation (Figure 18). If the low water crossing has a high embankment (> 6ft high) and inadequate pipe capacity, the rating curves computed by HY-8 and HAND are very different because the culvert is under inlet control (Figure 19). Most of the culverts surveyed and modeled in Figure 15 behaved similarly to the response shown in Figure 18.

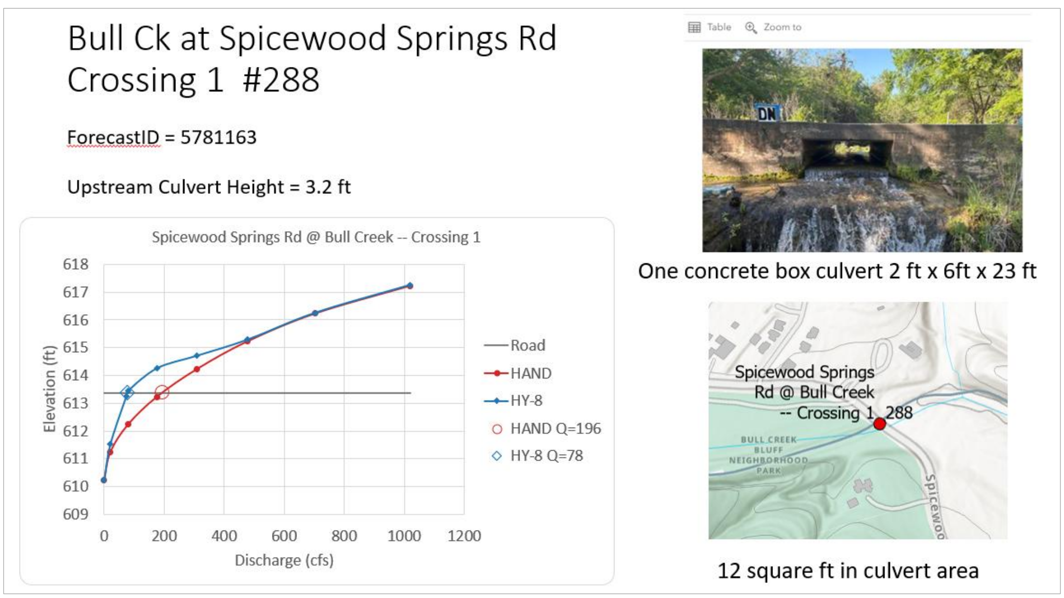


Figure 18. Culvert rating curve for Bull Ck at Spicewood Springs Rd

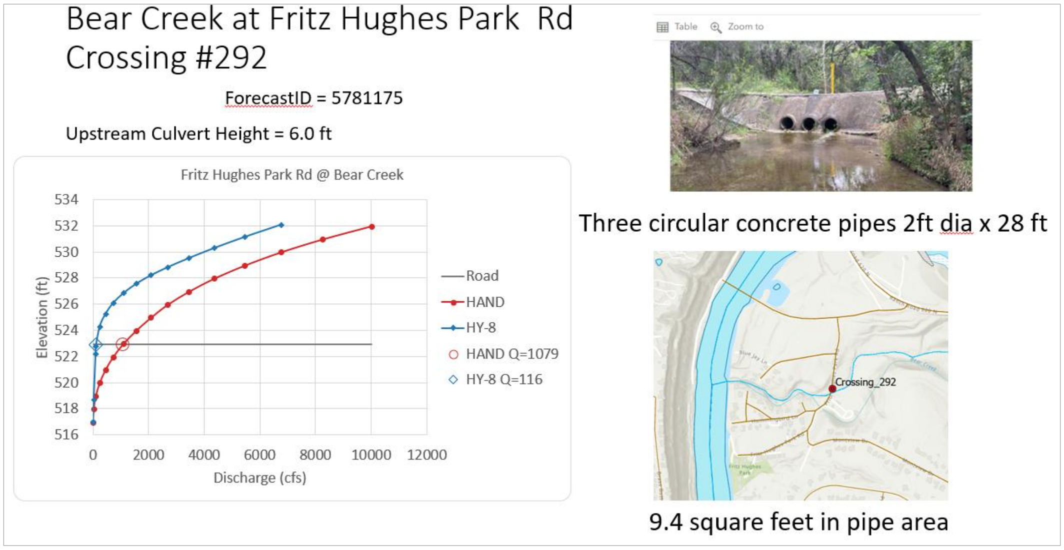


Figure 19. Culvert rating curve for Bear Creek at Fritz Hughes Park Rd

Adding LWCs and BCCs to the FAST map is beyond the scope of this project. However, on the FAST development site, there is an example LWC layer for a few locations in Austin. The FAST site is maintained by KISTERS, so to display these features in FAST, one must prepare a GeoPackage of the data and send it to KISTERS. The GeoPackage includes a dataset with stream crossing locations, where each crossing has attributes for flood thresholds and other attributes (such as road name).

5. Flood Data Services

The Flood Assessment System for TxDOT (FAST) is an operational, statewide tool that predicts which roads and bridges are likely to flood over the next 18 hours and publishes that assesment on an interactive map that refreshes every hour. Its purpose is to give TxDOT staff and maintenance crews an actionable view of flood risk so they can plan closures, position resources, and respond before conditions become dangerous.

FAST works by continuously ingesting federal flood forecasts and matching them against a pre-built library of Texas flood scenarios. Because the FIM library modeling was completed in advance, the system can turn a new national forecast into road and bridge warnings automatically and without human intervention. Task 5 delivered (1) a set of districtwide databases, (2) the automated backend services that generate the warnings, and (3) the web viewers that present them.

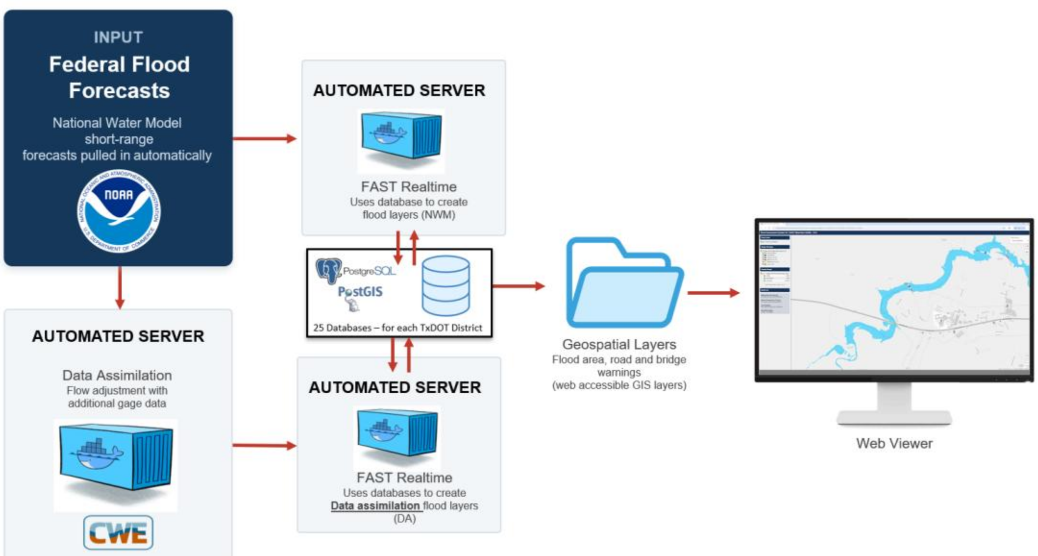


Figure 20. FAST flood data services overview – from forecast to web view

5.1. Statewide flood databases

A spatial database was built for each of the 25 TxDOT districts, pre-loaded with the reference data needed to translate a stream forecast into a map of affected assets including the road network, bridge inventory, and precomputed flood extents. Together these databases represent roughly 63 GB of data available for download. Splitting the state by district keeps each forecast run fast and manageable, and ensures a problem in one district never stalls the others.

5.2. Automated backend services

The backend is the automated engine of FAST. Running continuously in the cloud on Amazon Web Services, it detects each new national forecast, compares it against the flood library, and republishes three warning layers including (1) roads predicted to flood, (2) the extent of the floodwater, and (3) bridges where water is climbing toward the underside of the span. The application code is open source and publicly available[16]. The same system supports real-time, present-condition, and historic-replay modes from a single codebase.

Each update cycle is triggered automatically when the National Weather Service publishes a new short-range forecast (typically every hour) and runs through a fixed sequence of steps: pull the forecast, find the peak flow expected at each location, select the matching flood map, and derive the flooded roads and at-risk bridges. Processing naturally takes longer during large events, simply because more land is underwater. The schematic shows how the stored reference layers feed the forecast products delivered to users.

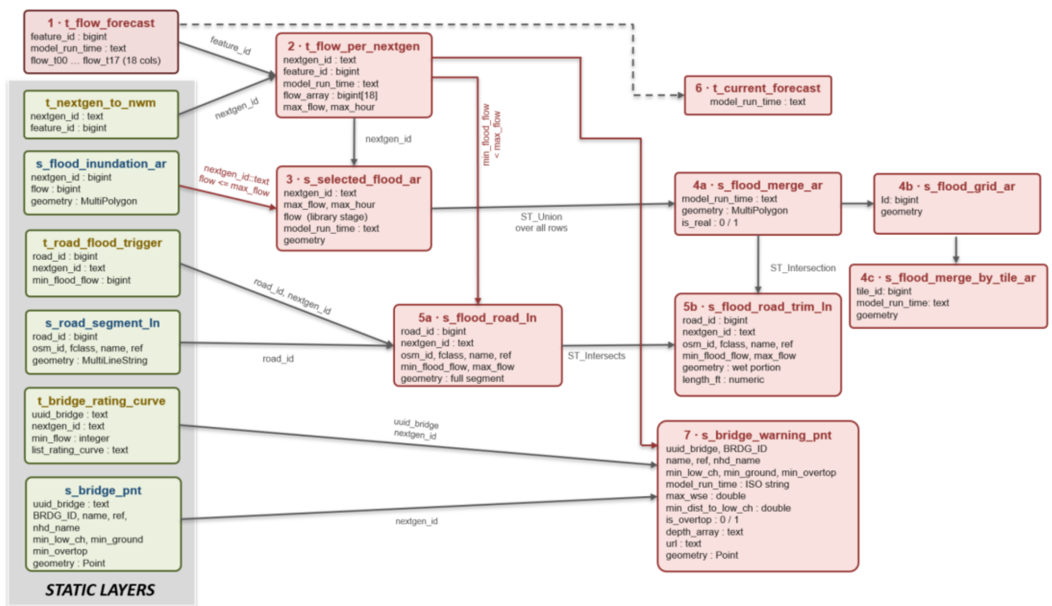


Figure 21. Table generation schematic: Hhow stored reference layers (left) produce the live road, flood, and bridge warning products

5.3. Web viewers

The results are delivered through the https://bridges.txdot.kisters.cloud web application, developed jointly by KISTERS and UT Austin. The system is organized into three environments including (1) a stable Production environment for everyday operational use, (2) a Development environment for testing new

[16] https://github.com/attilabibok/fast_realtime

capabilities, and (3) a Training environment where district staff learn the tool against real past events before working live.

The primary product is the Live Map which is an interactive, statewide view of predicted flooding that staff can pan, zoom, and filter. Bridges are color-coded by how much clearance remains before overtopping, and flooded road segments are tallied by road type, so a user can immediately gauge both severity and scope. Users can view forecasts from two flow sources which include the National Water Model and an observation-corrected “Data Assimilation” estimate that blends live stream-gage readings with the model.

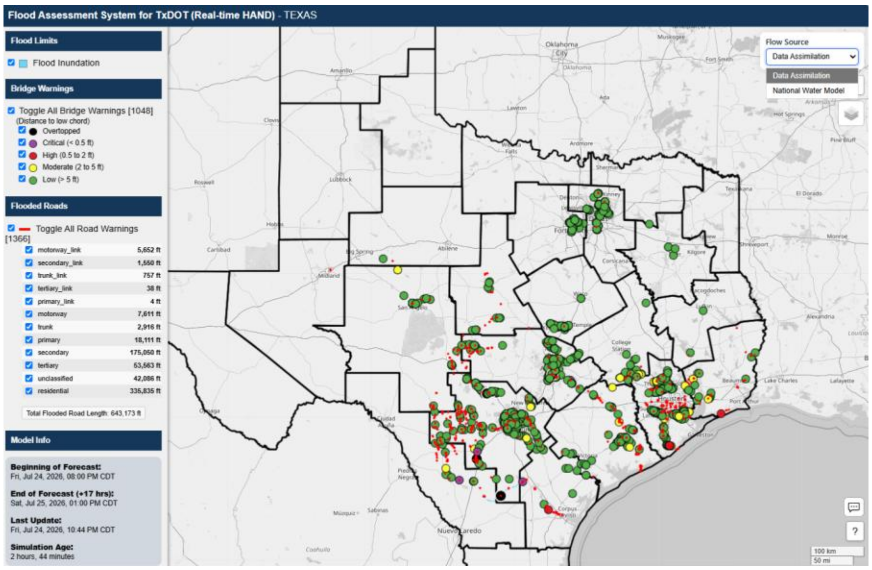
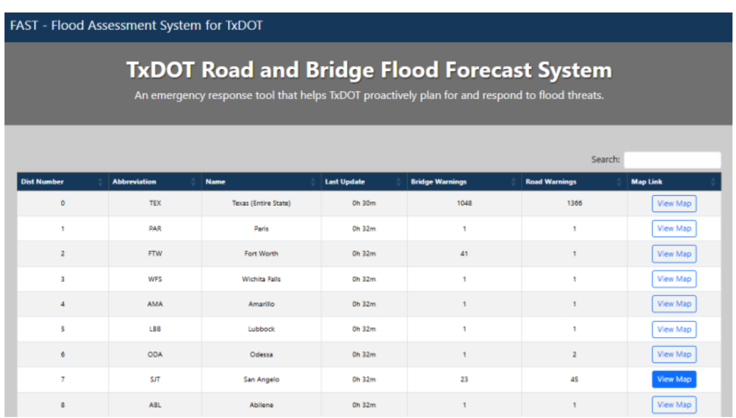


Figure 22. Production Live Map — statewide bridge warnings and flooded roads for a single forecast cycle.

For a higher-level view, the Live Dashboard rolls the same results up to a single sortable table with one row per district. A statewide reviewer can see at a glance which districts are under the most pressure — counts of bridge and road warnings side by side — and jump straight into the relevant map. This is the view best suited to command-level situational awareness during an active event.



Dist Number	Abbreviation	Name	Last Update	Bridge Warnings	Road Warnings	Map Link
0	TEX	Texas (Entire State)	0h 30m	1048	1366	View Map
1	PAR	Paris	0h 32m	1	1	View Map
2	FTW	Fort Worth	0h 32m	41	1	View Map
3	WFS	Wichita Falls	0h 32m	1	1	View Map
4	AMA	Amarillo	0h 32m	1	1	View Map
5	LBB	Lubbock	0h 32m	1	1	View Map
6	ODA	Odessa	0h 32m	1	2	View Map
7	SJT	San Angelo	0h 32m	23	45	View Map
8	ABL	Abilene	0h 32m	1	1	View Map

Figure 23. Production Live Dashboard — a statewide roll-up of bridge and road warnings by district.

5.4. Operational Coverage and Status

FAST provides statewide flood-warning coverage across all 25 TxDOT districts, refreshed hourly. To do this, it divides the Texas road network into more than 2.6 million individual segments, each assigned its own flood threshold, and it draws on real-time flood forecasts at approximately 14,000 bridges across the state. The underlying district databases are publicly available[17].

The system's "Production" environment has been operational since August 2025 covering the entire state of Texas. Alongside it, a "Development" environment is piloting a set of new capabilities, including district-level filtering, stream-gage comparisons, low-water-crossing display, and embedded bridge cross-sections. Additional features such as Lookback and Historic review modes and a formal training program continue to mature. In practical terms, the core flood-warning capability is already delivered and running. The remaining work centers on broadening features, validating results, and onboarding users.

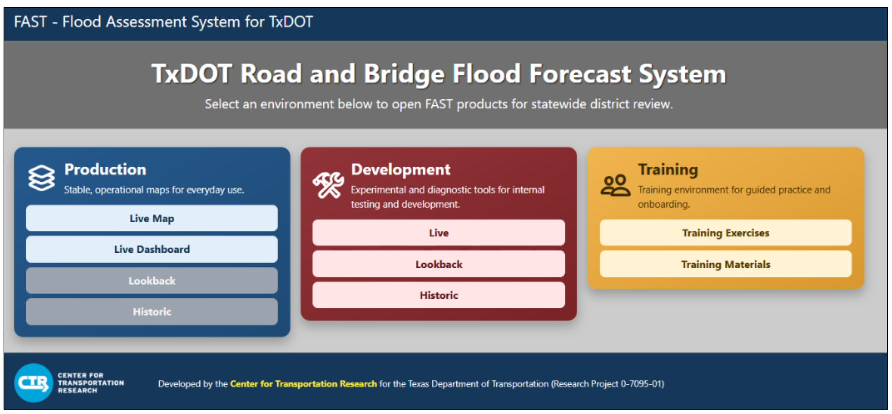


Figure 24. FAST Landing page exposing Production, Development and Training modes

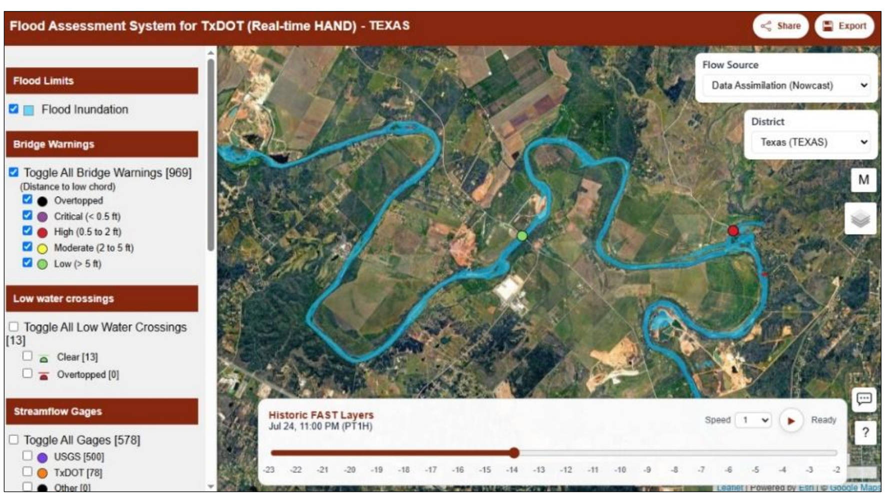


Figure 25. FAST "Development" sample tools and interface

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17 https://knatempstorage.s3.us-west-1.amazonaws.com/tx-fast-pgis-db/pgis_dumps.html

6. Forecast Data Analytics

6.1. Accuracy assessment of FAST discharge forecasts

Earlier in this project, Timilsina and Passalacqua (2025) assessed the accuracy of streamflow discharge predictions produced by the National Water Model versions 2.1 and 3.0 in Texas. They concluded that while version 3.0 performed better than version 2.1, there were still issues of underprediction of streamflow during very large storm events.

The FAST system improves on the National Water Model by introducing Data Assimilation (DA) to adjust the discharge forecasts to better allow for observed discharge measurement than the nudging procedure used by the National Water Model.

In Oh & Bartos (2025), the accuracy of the FAST system was evaluated for the San Antonio and Guadalupe river basins over a storm season extending from 4/1/2023 to 7/1/2023. This assessment showed that the data assimilation system used by FAST significantly outperformed the National Water Model for short-range forecasts of discharge with lead times ranging from 1-12 hours.

To further address this issue, we have initiated a full accuracy assessment of the FAST hydrologic forecasting system for the Texas-Gulf Coast HUC2 region considering the nine largest storm events from the past decade. This assessment seeks to (i) quantify the absolute accuracy of FAST discharge forecasts, (ii) determine the relative skill of the FAST data assimilation system versus the National Water Model, (iii) estimate the improvement in discharge prediction skill at ungaged locations, and (iv) quantify the improvement in prediction performance attributable to the network of 80 RQ-30 gauges deployed in previous stages of the FAST project.

For assessment of Oh and Bartos (2025), the FAST DA system consisted of a Muskingum routing model that fused observational data using a Kalman Filtering scheme. The FAST DA system then produced probabilistic forecasts via time-lagged ensembles and adjusted forecasts based on past ensemble member performance using a multi-model weighting scheme. The forecasts produced by this system were compared against the National Water Model, which used a Muskingum-Cunge routing model that assimilated gauge data via a Nudging scheme, with time-lagged ensembles also applied to generate probabilistic forecasts. A summary of the two model configurations is presented in Table 2.

Table 2. Summary of model configurations used in Oh & Bartos (2025

	FAST	National Water Model
Forcings	NWM runoff + baseflow	NWM runoff + baseflow
Routing module	Muskingum	Muskingum-Cunge
Data assimilation	Kalman Filter	Nudging
Forecast ensemble	Time-lagged ensemble	Time-lagged ensemble
Forecast enhancement	Multi-model weighting	-

While this prior work demonstrated that enhanced data assimilation methods like Kalman Filtering improve forecasting skill, the results were demonstrated for the San Antonio and Guadalupe river basins only, and not for the entire hydrologic domain simulated within FAST.

The San Antonio and Guadalupe basins do not completely capture the hydrologic behavior that is observed over the rest of the state given that (i) the western and eastern parts of Texas feature distinct arid and humid hydrologic regimes, respectively, and (ii) the San Antonio and Guadalupe river basins feature very few reservoirs, while reservoirs exert a significant influence over flood dynamics in other parts of the state like the Dallas-Fort Worth metroplex. Moreover, the multi-model weighting scheme employed in Oh & Bartos (2025) cannot easily be replicated across the entire FAST domain, given the relative sparsity of gauges in many parts of the state. For these reasons, it was resolved to conduct a comprehensive accuracy assessment of the FAST system as it is currently implemented.

6.1.1. Forecasting accuracy assessment methodology

Building on the analysis established in Oh & Bartos (2025), a comprehensive forecasting accuracy assessment is conducted over the Texas-Gulf Coast HUC2 region for major storm events occurring over the past decade. Forecasting accuracy is assessed by first forcing the state-wide hydrology model with a series of major storm events, assimilating observed discharge data at gage locations, and then comparing forecasted discharges against gauge observations at lead times ranging from 1-12 hours.

First, a storm catalog representing the 9 largest storm periods over the past decade was compiled. To determine the largest storm periods, we collected gridded AORC rainfall forcings for the state of Texas and then determined the time periods corresponding to the largest fourteen-day moving averages of rainfall. This method resulted in the following storm periods, representing the wettest fourteen-day periods over the past decade, shown in Table 3.

Table 3. List of storm periods used in comprehensive accuracy assessment

Storm periods considered in accuracy assessment	
2021-05-16 – 2021-05-29	2024-10-28 – 2024-11-10
2021-06-26 – 2021-07-09	2025-04-24 – 2025-05-07
2022-05-22 – 2022-06-04	2025-05-25 – 2025-06-07
2022-08-20 – 2022-09-02	2025-06-30 – 2025-07-13
2023-05-08 – 2023-05-22	

For these dates, forcings (runoff and baseflow) and outputs (discharge) were downloaded from the National Water Model archive. Observed data from USGS gages were also downloaded from the National Water Information System (NWIS) over the same time period. Overall, 606 gages were available over the decade-long historical period. A map of the included gage sites is shown in Figure 26Figure 26. Gages used within the forecasting accuracy assessment, including USGS gages (magenta) and RQ30 gages (green)

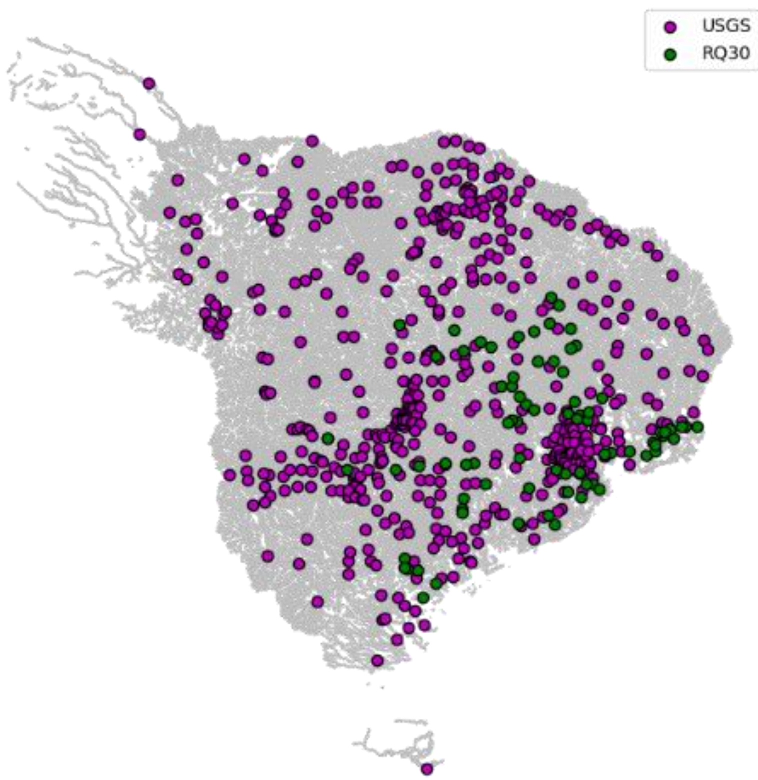

Figure 26. Gages used within the forecasting accuracy assessment, including USGS gages (magenta) and RQ30 gages (green)

6.1.2. Model calibration

Before conducting the accuracy assessment, the Muskingum routing model was calibrated over the Texas-Gulf Coast HUC2 region. Muskingum K and X parameters for the Texas-Gulf Coast region were calibrated to the National Water

Model Muskingum-Cunge routing model using the calibration procedure described in Oh & Bartos (2025). Figure 27 shows the NSE and KGE of the calibrated Muskingum model for all reaches in the Texas-Gulf Coast region (where a perfect score is one that perfectly reproduces NWM Muskingum-Cunge discharge outputs). Overall, routing model performance is strong, except for the western part of the state, where streamflow is often intermittent, and discharges were close to zero during the calibration period.

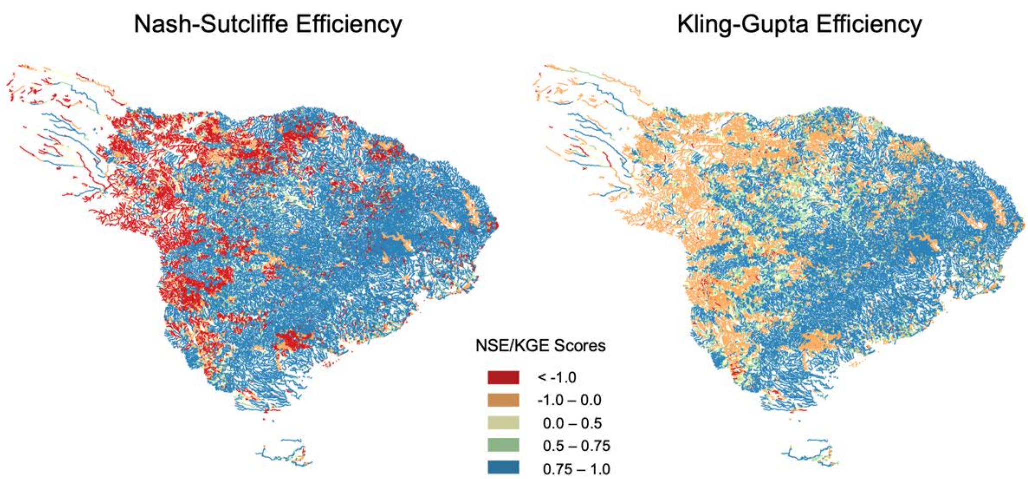

Figure 27. NSE (left) and KGE (right) after Muskingum model calibration across Texas-Gulf Coast region

6.1.3. Process noise covariance

For the present accuracy assessment, we investigate the effect of incorporating correlation into the Kalman Filter's covariance matrix. This change to the methodology allows for spatial correlation in the rainfall field to inform the correction imposed by the Kalman Filter (which is a more realistic modeling assumption, given that error in the rainfall field is correlated in space). This change has the effect of increasing the 'impact zone' of the correction imposed by each gauge within the Kalman Filter.

In Oh & Bartos (2025) the process noise covariance was assumed to be uncorrelated between reaches, such that the covariance matrix is diagonal, with the diagonal elements corresponding to the variance of the process noise (runoff uncertainty) at each reach:

$$Q = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{bmatrix}$$

For the present study, we apply a correlated covariance matrix, similar to the approach applied in Timilsina & Passalacqua (2026):

$$Q = \begin{bmatrix} \sigma_1^2 & r_{21} & r_{31} & r_{41} \\ r_{21} & \sigma_2^2 & r_{32} & r_{42} \\ r_{31} & r_{32} & \sigma_3^2 & r_{43} \\ r_{41} & r_{42} & r_{43} & \sigma_4^2 \end{bmatrix}$$

Where the cross-covariance terms are defined via an exponential kernel with respect to the reach-wise distance:

$$r_{ij} = e^{-\alpha d_{ij}}$$

Where d_{ij} is the shortest-path distance between reaches i and j, and α is a scaling parameter.

6.1.4. Model configurations tested

After downloading the required forcings, gauge measurements, and calibrating the Muskingum routing model, the state-wide hydrology model was simulated under different modeling and data assimilation configurations to test the improvement in discharge forecast accuracy under each approach. The following model configurations were tested:

<u>Data assimilation method</u>
Nudging (NWM)
Kalman Filtering
Kalman Filtering with correlated process noise covariance

<u>Ensemble generation</u>
Standard time-lagged ensemble (7 members)
Time-lagged ensemble with varying window size (1-12 members) *[planned]*

<u>Reservoirs</u>
No reservoirs
Reservoirs with level-pool routing
Reservoirs with level-pool routing and RFC forecasts *[planned]*

6.1.5. Forecasting performance metrics

The accuracy of discharge forecasts is evaluated in terms of the following metrics:
Continuous Ranked Probability Score (CRPS): The CRPS extends the definition of the mean absolute error to probabilistic forecasts, measuring the 'distance' between the observed value and the probability distribution of the prediction:

$$CRPS = \frac{1}{N}\sum_{t=1}^{N}\int_{-\infty}^{\infty}\left[P(Q_t < q) - 1(q - Q_{obs,t})\right]^2 dq$$

Where $Q_{obs,t}$ is the observed discharge at time t, and Q_t is the modeled discharge at time t. For probabilistic forecasts defined by M discrete ensemble members this definition reduces to:

$$CRPS = \frac{1}{N}\sum_{t=1}^{N}\sum_{i=1}^{M}|Q_{i,t} - Q_{obs,t}| + \frac{1}{N}\sum_{t=1}^{N}\sum_{i=1}^{M}\sum_{j=1}^{M}|Q_{i,t} - Q_{j,t}|$$

Where the first sum corresponds to the mean absolute error of the observation with respect to all forecasts, and the second sum corresponds to the spread of the forecast members. Thus, in the present context, CRPS measures the accuracy of ensemble discharge predictions with respect to observed discharges, while also penalizing spread within the ensemble.

'Within Bounds' Score (WBS): The 'within bounds' score indicates the fraction of the time that the observation is less than the maximum discharge predicted by the ensemble:

$$WBS = \frac{1}{N}\sum_{t=1}^{N} I\,[Q_{obs,t} \ < \ max(Q_{i,t})]$$

Where $Q_{obs,t}$ is the observed discharge at time t, and $max(Q_{i,t})$ is the maximum discharge predicted by the ensemble.

Within FAST, alerts are triggered when the maximum discharge over a 12-hour forecast window is greater than the bridge overtopping discharge. This score was thus created to give TxDOT emergency managers a simple and interpretable metric for the overall reliability of bridge flooding alerts, by quantifying the proportion of flood events that are captured by the ensemble.

Brier Score (BS): The Brier Score quantifies the binary detection accuracy of flood events:

$$BS = \ \frac{1}{N}\sum_{t=1}^{N}[P\big(Q_t > Q_{flood}\big) - o_t]$$

Where o_t is an indicator variable for an event (i.e. 1 means flooding occurred at time t and 0 means no flooding occurred at time t), and $P\big(Q_t > Q_{flood}\big)$ is the probability of a flood event occurring at time t, as determined by the model ensemble.

Given the lack of actual bridge overtopping events in the period of record, the 'flood discharge' (Q_{flood}) is taken to be the two-year exceedance discharge. A lower Brier Score indicates better performance (with a score of 0 being perfect and a score of 1 meaning that every prediction is incorrect).

Receiver-operating characteristic (ROC) [planned]: For a given binary classifier, the receiver-operating characteristic quantifies the relationship between the true positive rate (TPR) and false positive rate (FPR) over all classification thresholds. The area under the ROC curve (AUC) thus provides a metric of the overall detection accuracy, accounting for both true and false positive rates, with a score of 1.0 indicating perfect detection performance and a score of 0.5 indicating performance equivalent with random chance. As with the Brier Score, we use the ROC AUC to quantify the binary detection accuracy of two-year flood events. This analysis is currently ongoing.

6.1.6. Preliminary results

While the accuracy assessment is currently ongoing, a basic analysis of the forecasting accuracy of the FAST system has been performed over the state of Texas. Provisional results largely confirm the results of Oh & Bartos (2025), showing improved forecasting skill when using the FAST system with Kalman Filtering relative to the National Water Model with nudging. In addition to confirming previous results, we find that the process noise covariance matrix and time-lagged ensemble scheme have a significant effect on forecasting accuracy: Applying a correlated process noise covariance matrix improves forecasting skill compared to the previously-used uncorrelated covariance matrix.
Time-lagged ensembles are found to reduce the variance of the forecast error, but do not have a significant effect on the mean forecast error. In other words, time-lagged ensembles smooth the short-range forecast and make it less jumpy from hour to hour, but they do not improve the mean forecast error.

For the preliminary results that follow, we examine the storm period occurring from 5/9/2023 – 5/16/2023. The reported Kalman Filter results refer to those obtained using a correlated process noise covariance matrix, which generally delivers the best performance. All reported metrics are produced using time-lagged ensembles with an ensemble size of 7 members. The reported results for the FAST system use level-pool routing for all reservoirs.

Continuous Ranked Probability Score (CRPS): Overall, the FAST system with Kalman Filtering outperforms the NWM with nudging in terms of discharge forecast accuracy as measured by CRPS. Figure 28 shows the mean CRPS score by lead time (left) along with a map of the CRPSS skill score by gage site (right). Kalman Filtering results in a lower aggregate CRPS score (indicating better performance) for all lead times from 1-12 hours (left). In terms of performance at individual sites, roughly half of gage sites show stronger CRPS performance under Kalman Filtering (right), while the remaining half show stronger CRPS performance under nudging. Ongoing work is seeking to explain the circumstances under which Kalman Filtering underperforms nudging, with differences in the handling of reservoir forecasts being the primary culprit.

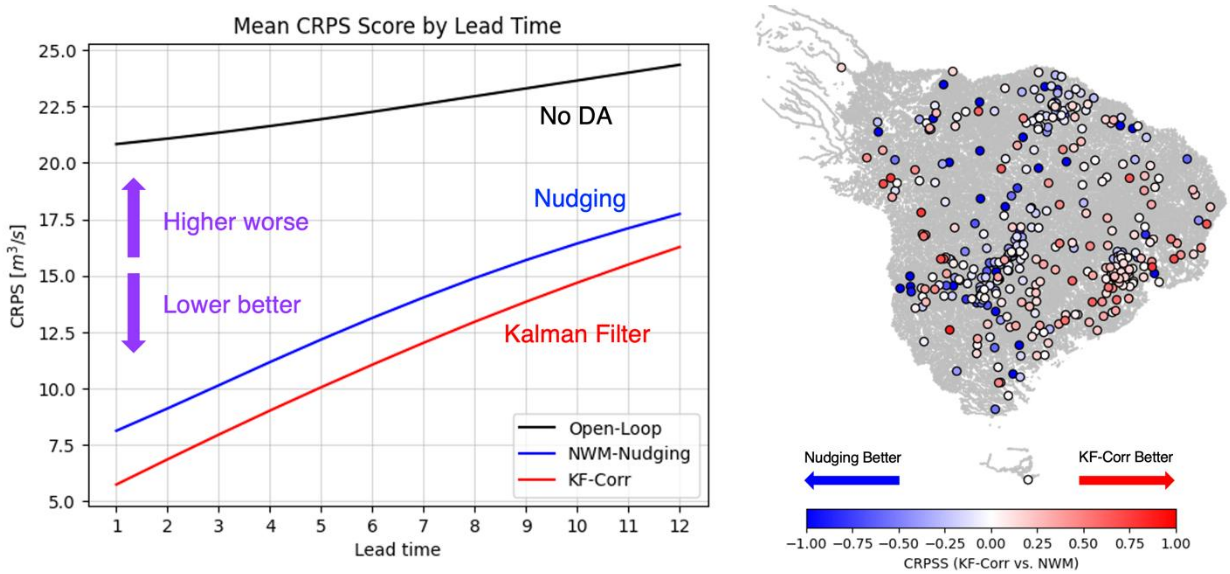

Figure 28. Mean continuous ranked probability score (CRPS) by lead time (left) and CRPSS Skill Score by gauge location (right) for Open-Loop, Nudging, and Kalman Filter runs

'Within bounds' score (WBS): Overall, discharge observations are found to lie within the bounds of the ensemble forecast envelope about 80% of the time. Figure 29 shows histograms indicating the fraction of the time that observations lie within the forecast bounds over all sites (left), along with a map of the relative performance of Kalman Filtering vs. NWM nudging with respect to WBS at each site. In general, observations are more likely to lie within the bounds of the forecast envelope under the Kalman Filter configuration compared to the NWM.

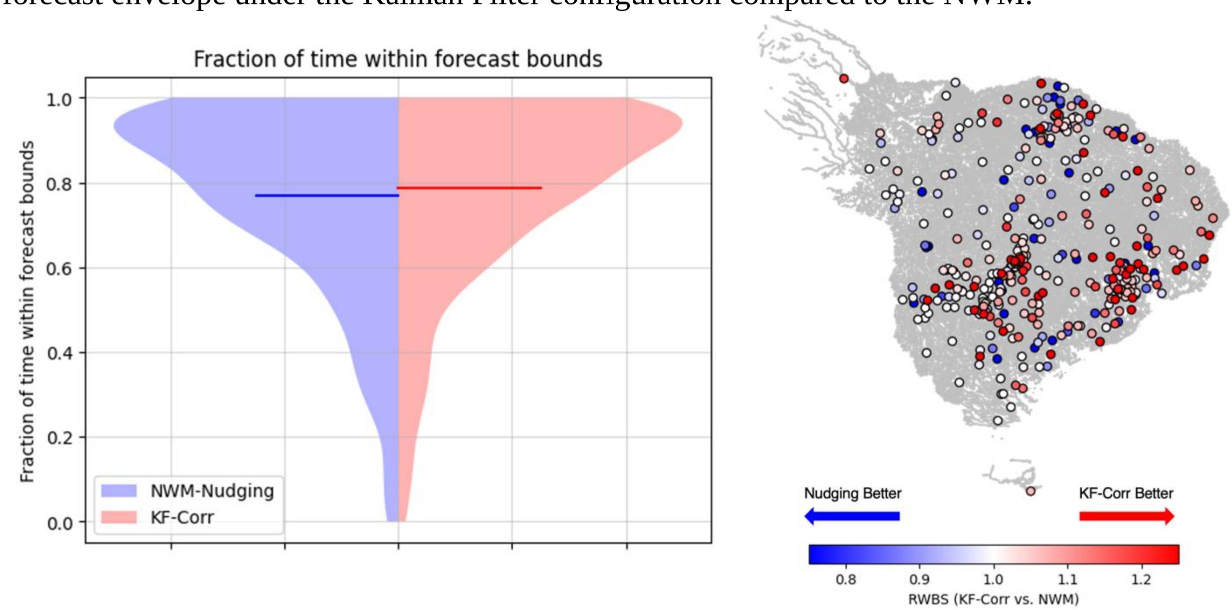

Figure 29. Histogram of 'within bounds' score by site (left) and map of relative within bounds score by site for Nudging, and Kalman Filter runs

Brier Score (BS): In aggregate, the FAST system with Kalman Filtering outperforms the NWM with nudging at prediction of bankfull flooding events (corresponding to exceedance of 2-year discharges), as measured by the Brier

Score. Figure 30 shows the mean Brier Score by lead time (left) along with a map of the BSS Brier Skill Score for sites where the 2-year discharge was exceeded (right). Currently, nudging appears to offer slightly better performance under short lead times, while Kalman Filtering offers better performance at longer lead times. The cause of this discrepancy is currently being investigated.

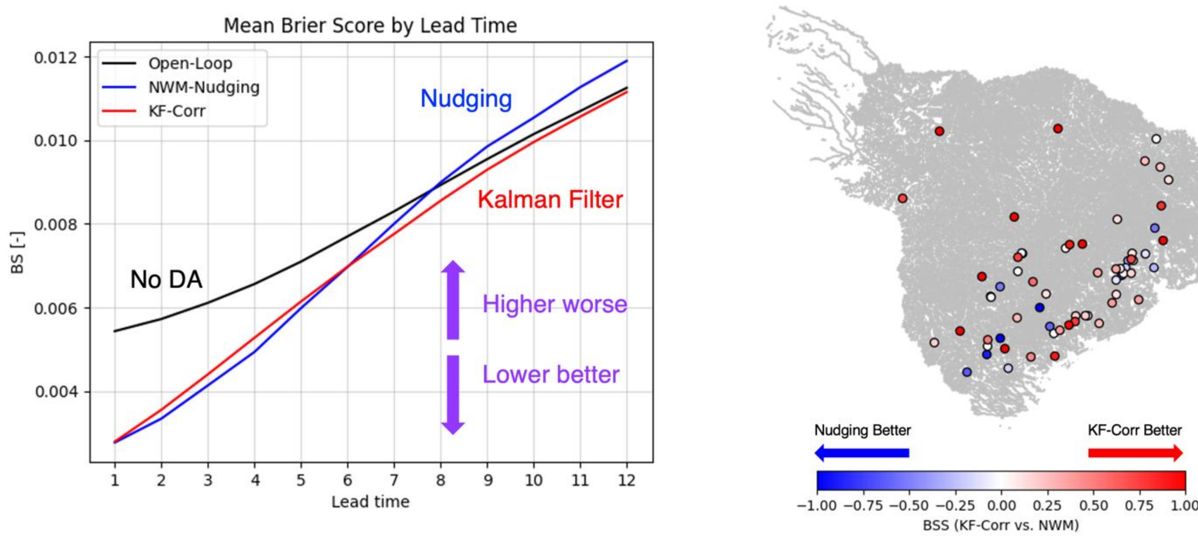

Figure 30. Mean Brier Score (BS) by lead time (left) and BSS Skill Score by gauge location (right) for Open-Loop, Nudging, and Kalman Filter runs

6.1.7. Planned work

Work on the accuracy assessment is expected to continue through the remainder of the FAST project. Apart from characterizing the accuracy of flooding predictions, a major part of the work is focused on further improving the accuracy of the FAST predictions through (i) incorporation of river forecast center (RFC) forecasts at reservoirs, (ii) accurate specification of covariance matrices for the Kalman Filter, (iii) diagnosis of problematic and malfunctioning gauges, (iv) inclusion of RQ-30 sensor data in the accuracy assessment, and (v) fusion of gauge data after the start of the forecast window with a scheme for increasing measurement variance over time, in a manner similar to the exponential weighting scheme used by the National Water Model's nudging scheme. In the remaining project period, we also plan to characterize the uncertainty in the rating curves used to translate discharge predictions into flood stage predictions, which also have a significant effect on the accuracy of flood warnings.

6.2. Implementing reservoirs

Initial results of the state-wide accuracy assessment determined that the forecasting skill of the FAST DA system underperformed the National Water Model at gage locations downstream of reservoirs. The reason for this underperformance is that the Muskingum model used within the FAST DA system does not account for reservoirs, while the National Water Model uses either level-pool routing or direct assimilation of river center forecasts to represent these components (Figure 31). Given that gages are often located downstream of reservoirs, this lack of reservoirs in the FAST DA system meant that state-wide forecasting scores were significantly impacted. To improve the overall accuracy of FAST discharge forecasts, it was resolved to implement reservoirs within the FAST hydrologic forecasting system.

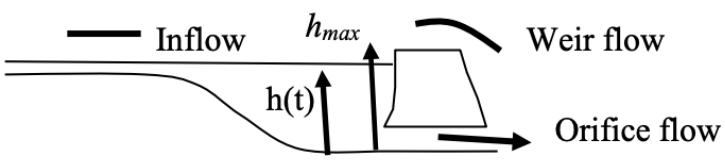

Figure 31. Reservoir routing schematic (from WRF-Hydro Modeling System Technical Description)

6.2.1. Reservoir implementation scheme

Within FAST, reservoirs are implemented using a level pool routing scheme in a manner identical to the National Water Model. Here, each reservoir is represented as a single control volume of water, such that the rate of storage within the reservoir is equal to the sum of inflows minus outflows:

$$\frac{dS}{dt} = i(t) - o(t)$$

As with the National Water Model, the surface area of the reservoir is a constant with respect to the water depth, such that the mass balance can be expressed:

$$A\frac{dh}{dt} = i(t) - o(t)$$

The inflow $i(t)$ is taken to be the sum of the inflows from all upstream tributary reaches to the reservoir. The outflow $o(t)$ is governed by a combination orifice and overflow weir:

$$o(t) = o_o(t) + o_w(t)$$

$$o_o(t) = C_o O_a\sqrt{2gh}$$

$$o_w(t) = \begin{cases} C_w L_w\left[L_d(h-h_{max})^{\frac{3}{2}} + (h-h_w)^{\frac{3}{2}}\right], & h > h_{max} \\ C_w L_w (h-h_w)^{3/2}, & h_w \le h \le h_{max} \\ 0, & h < h_w \end{cases}$$

Where h is the depth of water in the reservoir, C_o is the orifice coefficient, O_a is the orifice area, C_w is the weir coefficient, L_w is the length of the main weir, L_d is the length multiplier of the overtopping weir, h_w is the elevation of the main weir above the bottom, and h_{max} is the maximum allowable water level before overtopping. Parameter values for each reservoir are obtained from the National Water Model.

To insert reservoirs into the FAST Muskingum routing model, the following procedure was implemented (Figure 32):

1. For each Lake ID, the reaches contained within the lake were identified.
2. Reaches beginning outside of the lake and pointing to a downstream reach located within the lake were identified as the reservoir *entry points*.
3. Reaches beginning within the lake and pointing to a downstream reach located outside the lake were identified as the reservoir *exit points*.
4. The hydrofabric was severed at the entry and exit points.
5. The Muskingum models corresponding to the reaches within each reservoir were replaced with level pool routing models.
6. Reservoir models were reconnected to the surrounding river network at the previously-identified entry and exit points.

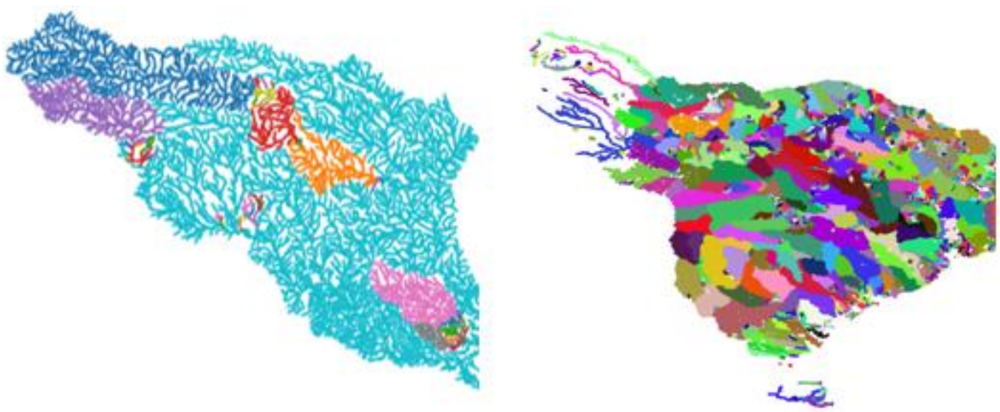

Figure 32. Partitioning of river network after inclusion of reservoirs for San Antonio and Guadalupe River Basins (left) and Texas-Gulf Coast region (right)

In the National Water Model, more than half of the reservoirs within Texas produce discharge and stage forecasts using direct insertion of river forecast center forecasts, rather than level-pool routing. Ongoing work is currently underway to assimilate river forecast center predictions into the reservoir models used within FAST model.

6.2.2. Evaluating reservoir performance

To determine the accuracy of the reservoir level-pool routing scheme, the output of the FAST hydrologic modeling system with reservoirs was compared against National Water Model outputs under the 'no-data-assimilation' configuration. Overall, outputs of the reservoir model were similar to those obtained under the National Water Model, indicating that the level pool routing scheme accurately replicated the dynamics of the National Water Model reservoir implementation. Time series plots for selected reservoirs are shown in Figure 33.

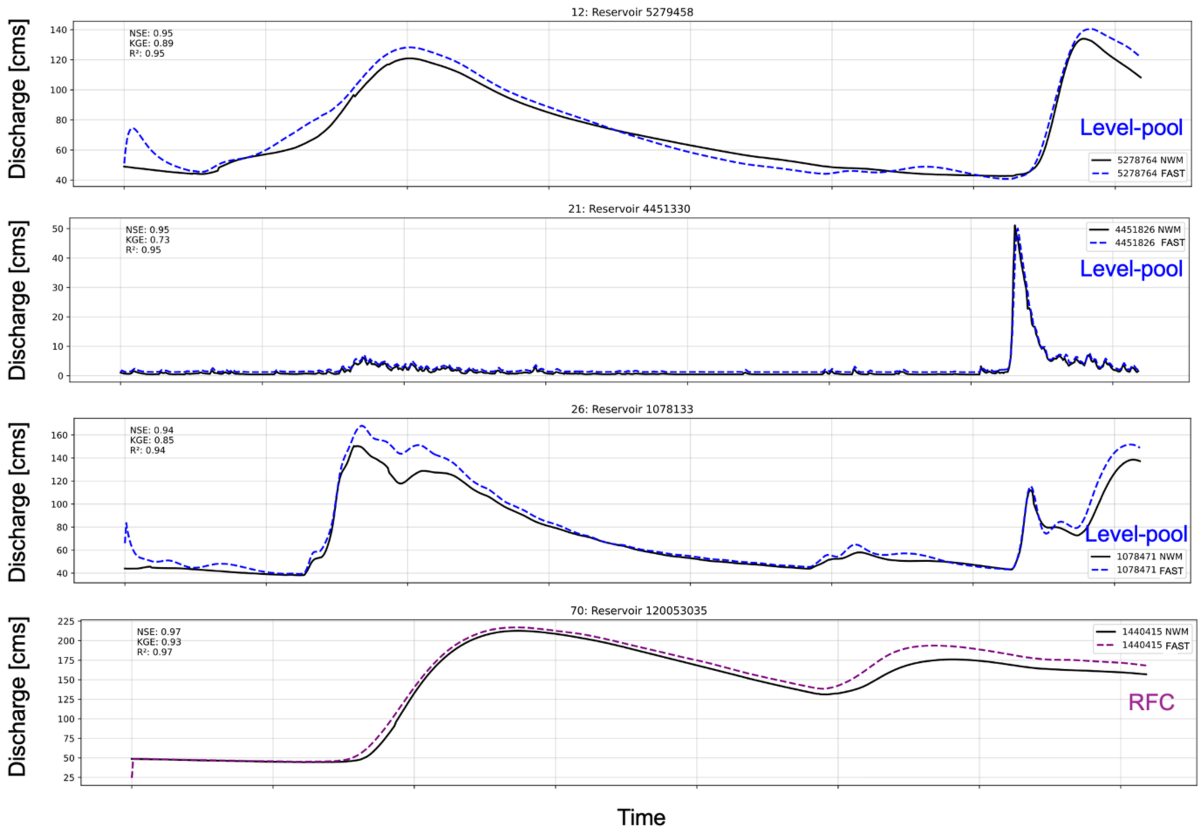

Figure 33. Performance of FAST reservoir routing model vs. National Water Model for four example reservoirs in Texas

6.3. Development of a rainfall-runoff model for rapid forecasts

Reliance on the National Water Model poses inherent limitations on the timeliness and accuracy of flood forecasts. Currently, the FAST system relies on NWM runoff and baseflow forecasts as inputs to the Muskingum routing model. The Muskingum model routes these runoff and baseflow forecasts through the channel network to produce forecasts of discharge and river stage that are subsequently used to predict bridge impacts. However, NWM runoff and baseflow forecasts suffer from several limitations that constrain their ability to predict rapidly-evolving flood events:

1. National Water Model outputs are generally published with a 2-hour delay. This means that the most recently-available forecasts are 2 hours old. As such, NWM forecasts do not provide sufficient lead time for flash flood events like those that occurred during the Hill Country flooding of 2025.

2. National Water Model short-range forecasts provide only a single ensemble member, which is insufficient for characterizing the uncertainty range of future streamflow predictions.
3. National Water Model forecasts rely on the HRRR/RAP rainfall products, which do not account for all available local observational rainfall data sources (such as gages or local radar systems). More accurate rainfall forecasts could be obtained by assimilating observed rainfall data into the modeled rainfall data product.

At the same time, recent developments have made more accurate rainfall forecasts available across Texas. The National Wind Institute (NWI) at Texas Tech University (TTU) is currently installing three new radar systems in the Texas Hill Country and extending its West Texas Mesonet weather station network into the Hill Country. These data are being assimilated into a high-resolution weather forecasting model to create ensemble precipitation forecasts. This high-resolution data source is not currently available within the National Water Model. To take advantage of this new data source, it is necessary to create a hydrologic (rainfall-runoff) model that can partition the generated rainfall fields into infiltration and runoff, and then route the runoff through the channel network to produce discharge forecasts.

6.3.1. Hydrologic model description

To overcome the limitations of NWM forecasts, we have developed and tested a rainfall-runoff model for the FAST system that circumvents the need for NWM forecasts. This rainfall-runoff model transforms gridded rainfall forcings directly into runoff and baseflow forecasts that are subsequently routed through the previously-developed Muskingum routing model to generate more timely and accurate streamflow forecasts. This hydrologic modeling layer decouples the FAST system from the National Water Model, allowing for faster forecasts during flash floods, incorporation of more accurate rainfall data sources, and assimilation of rainfall and soil moisture data for improved forecast accuracy (Figure 34).

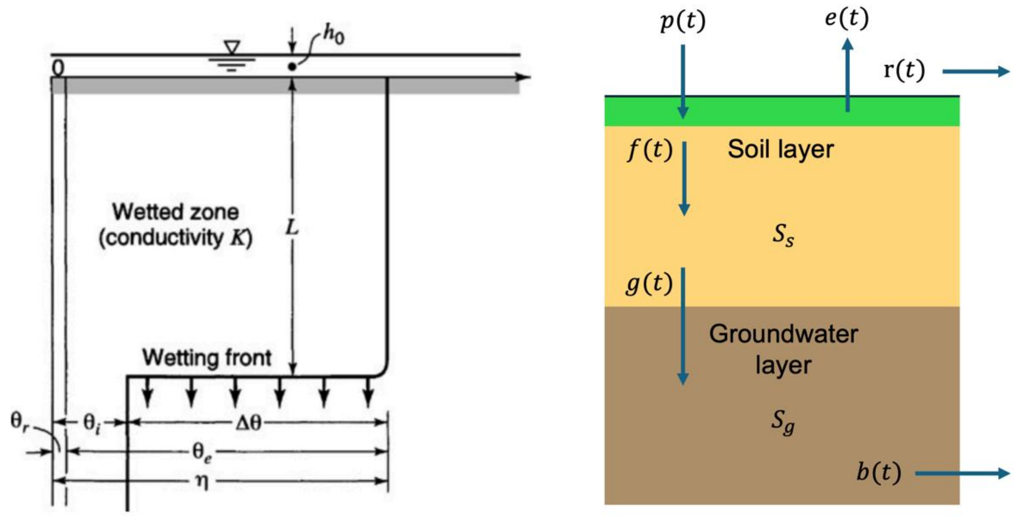

Figure 34. Left: Green-Ampt infiltration scheme (from Chow et al. 1988). Right: overall water balance scheme for rainfall-runoff model

To enable faster and more accurate flood forecasts, an internal hydrologic model was developed that supplements the existing Muskingum-based flow routing model used within FAST. This hydrologic model is based on a mass balance between a soil layer and deeper groundwater layer (see Figure 34), with infiltration into the soil layer governed via a continuous-time form of the Green-Ampt equation, and water flux out of the soil layer governed by percolation to the groundwater layer and evapotranspiration to the atmosphere:

$$\frac{dS_s}{dt} = f(t) - e(t) - g(t)$$

$$\frac{dS_g}{dt} = g(t) - b(t)$$

$$r(t) = p(t) - f(t)$$

Where S_s is the storage in the soil layer [m], S_g is the storage in the groundwater layer [m], $f(t)$ is the infiltration rate [m/s], $e(t)$ is the evapotranspiration rate [m/s], $g(t)$ is the rate of percolation to groundwater [m/s], $b(t)$ is the baseflow to the receiving channel [m/s], $p(t)$ is the precipitation rate [m/s], and $r(t)$ is the runoff rate [m/s]. The infiltration dynamics are given by the Green-Ampt formulation:

$$f(t) \ = \ min\left\{K_h^*\left(\frac{|\psi_f|\Delta\theta \ + \ F(t)}{F(t)}\right), \ p(t)\right\}$$

Where $f(t)$ is the infiltration rate [m/s], K_h^* is the saturated hydraulic conductivity [m/s], ψ_f is the suction head at the wetting front [m], $\Delta\theta$ is the initial soil moisture deficit [-], $F(t)$ is the depth of the wetting front [m], and $p(t)$ is the precipitation rate [m/s]. The evaporation rate is described by a linear function bounded between zero and the potential evapotranspiration rate (PET), for soil moisture contents between zero and field capacity (S_{thresh}).

$$e(t) = \begin{cases} PET, & S_s \geq S_{thresh} \\ PET \cdot \dfrac{S_s}{S_{thresh}}, & 0 \leq S_s \leq S_{thresh} \\ 0, & S_s = 0 \end{cases}$$

The percolation rate to groundwater is a linear function of the soil water storage parameterized by a percolation parameter K_{perc}:

$$g(t) = K_{perc} S_s$$

Similarly, baseflow rate is a linear function of the storage in the groundwater layer parameterized by a linear reservoir parameter K_{gw}:

$$b(t) = K_{gw} S_g$$

To define the soil moisture deficit in a way that is amenable to continuous simulation, the initial soil moisture content (θ_0) is defined as the wilting point (θ_{wp}) of the soil:

$$\theta_0 = \theta_{wp}$$

6.3.2. Model evaluation methodology

The new hydrologic model is evaluated against 8 years of observed streamflow data for the San Antonio and Guadalupe river basins (2016-2023). For this assessment, the Green-Ampt based hydrologic model is forced using hourly rainfall inputs from the Analysis of Record for Calibration (AORC) gridded rainfall dataset. The runoff and baseflow outputs from the rainfall-runoff model are then fed into the Muskingum routing model to generate streamflow predictions at all reaches within the river network. These modeled discharges are then compared against discharge observations from USGS gages. For our assessment, we focus on USGS gage 08188570 located at the outlet of the San Antonio river basin as shown in Figure 35. The performance of the hydrologic model is measured in terms of Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE).

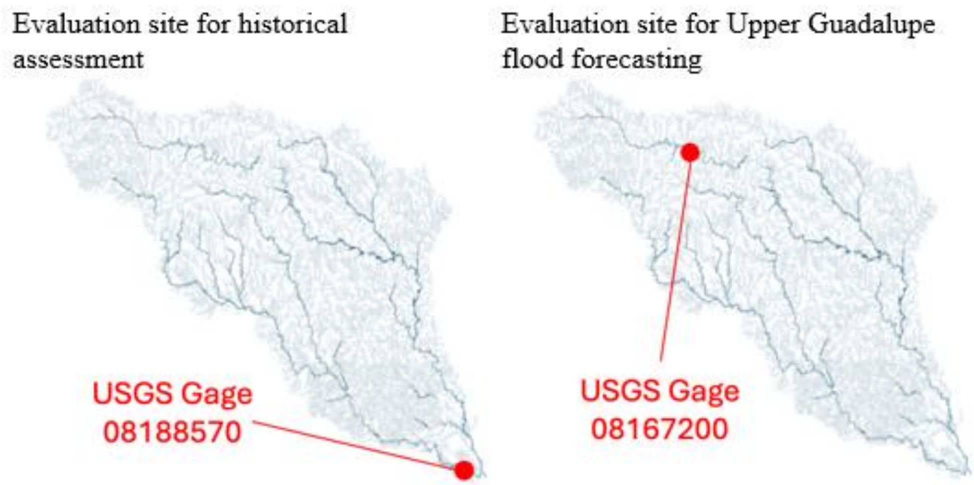

Figure 35. Evaluation gage sites for historical assessment using AORC data (left) and forecast assessment using NWI forecast data (right)

For this assessment, the Green-Ampt model is parameterized using standard gridded soil property data from SSURGO. Relevant soil properties derived from SSURGO include the porosity, wilting point, air entry pressure, and log-slope of the soil water retention curve. Calibration of soil parameters to stream gage data has not yet been performed.

6.3.3. Model evaluation results

Overall, the FAST hydrologic model produces acceptable prediction of discharge hydrographs for the Hill Country region without calibration. Fig. 11 shows timeseries of discharge for the model (black) and gage (blue) for 8 years of data at the most downstream gage within the San Antonio river basin. In general, modeled hydrograph peaks align with observed discharges. KGE ranges from -1.332 (2022) to 0.656 (2023) with a median KGE of 0.429. These scores are comparable to the performance of the National Water Model.

Over the 8 years of data, there are no consistent trends in the storm events that are accurately captured (Figure 36), meaning that the discrepancy between modeled and observed discharges is most likely attributable to inaccuracy in rainfall forcings rather than model parameterization. While further improvements can be made through calibration, this assessment shows that the proposed hydrologic model can achieve reasonable predictions of streamflow even without calibration to observed discharge data, using only standard soil parameter data (e.g. SSURGO, POLARIS) that is available for the entire state of Texas.

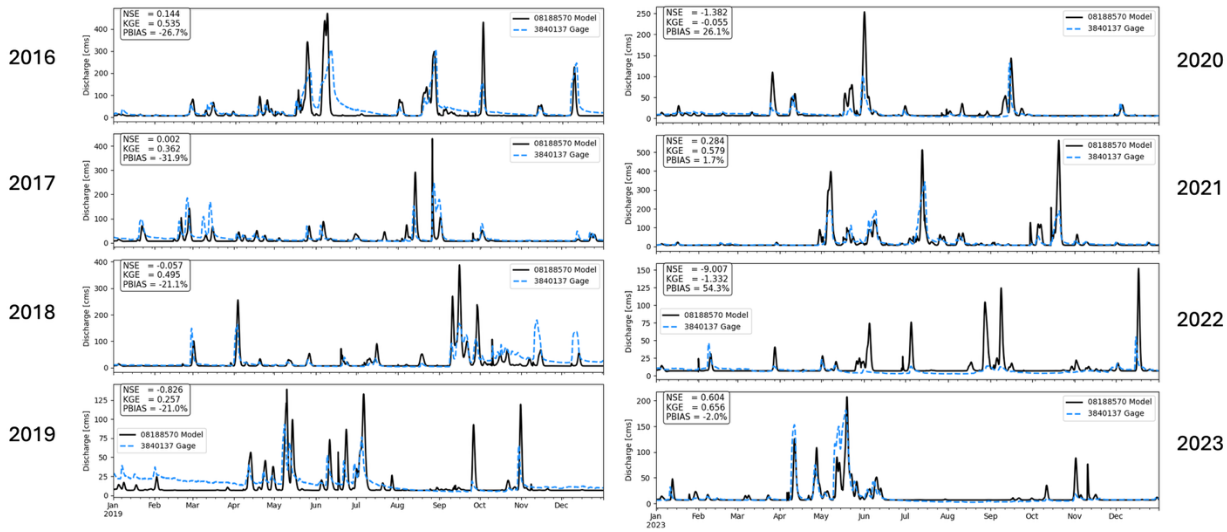

Figure 36. Comparison between Green-Ampt-based hydrologic model and gage data for 2016-2023. Results are shown for the most downstream USGS gage within the San Antonio watershed

6.3.4. Performance of hydrologic model under gridded rainfall forecasts

To demonstrate the real-time forecasting potential of the new hydrologic model, we apply the new hydrologic model to prediction of the July 4, 2025 flooding event in the Upper Guadalupe river. Here, gridded rainfall forecasts obtained from the National Wind Institute are applied to the rainfall-runoff model to predict discharges within the river network. To isolate the skill of the hydrologic model from the skill of the rainfall forecasts, we also generate discharge predictions using gridded AORC rainfall forecasts over the same time period. Discharge predictions using NWI and AORC rainfall data are compared against gaged discharge from USGS station 08167200 near Kerrville in the Upper Guadalupe basin (Figure 37).

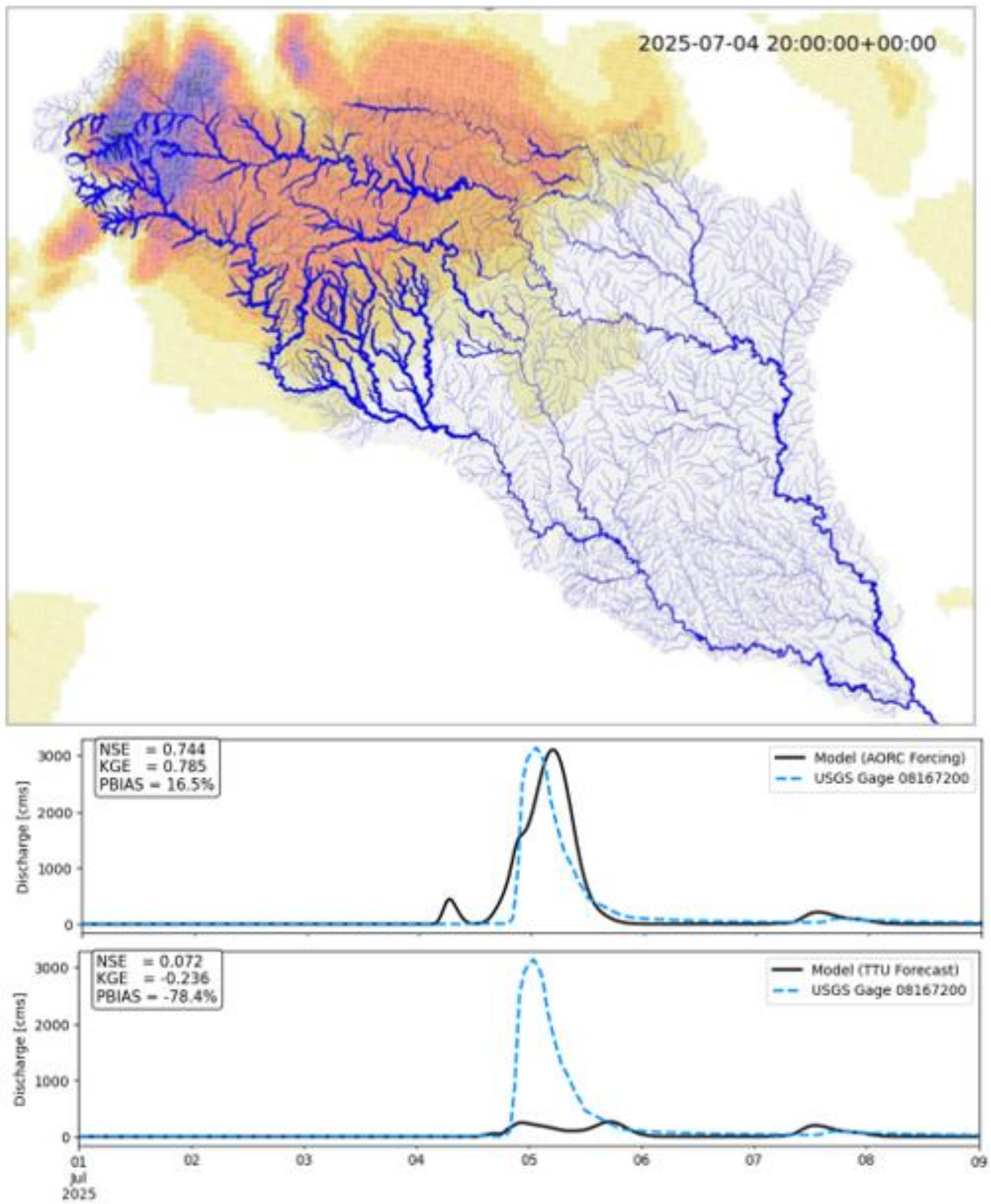

Figure 37. Simulation of the July 4, 2025 flooding in the San Antonio and Guadalupe basins. Left: Map of discharges near peak of storm. Top right: modeled vs. gauged discharge using AORC rainfall. Bottom right: modeled vs. gauged discharge using NWI (TTU) forecast

Figure 37 shows the map of the discharges near the peak of the rainfall event (left) along with timeseries of the discharge obtained using AORC forcings (top right) and NWI forecasts (bottom right). Overall, the hydrologic model performs well when using the AORC forcings, obtaining an NSE of 0.744 and KGE of 0.785. However, the prediction using the NWI forecast data does not capture the hydrograph peak, achieving an NSE of 0.072 and KGE of -0.236. This result confirms that the accuracy of the rainfall data is the primary determinant of flood forecasting accuracy.

6.3.5. Conclusions and future work

Overall, the preceding analysis has demonstrated that a scalable hydrologic model can be developed using standard soil datasets available throughout Texas, and that this model is capable of generating discharge predictions with accuracy comparable to the National Water Model in Central Texas. Unlike the National Water Model, this state-specific hydrology model can be executed using local gridded rainfall datasets that are more accurate and timely than those provided by the National Water Model. Additional work is needed to evaluate the hydrology model over the entirety of Texas, ensuring that the Green-Ampt infiltration model delivers acceptable performance in the humid eastern parts of the state. Furthermore, additional work is needed to develop a scalable calibration procedure that will allow soil properties to be calibrated to match observed discharges. While these tasks extend outside the scope of the current project, this work presents a promising direction for future efforts to develop real-time flood modeling capabilities for the state of Texas.

6.4. Rating Curves

A particular concern for the accuracy of FAST is to ensure that the rating curves are realistic. A rating curve is a table compiled for each stream reach that defines the relationship between the stage height and discharge, where the stage height is the average depth along the stream reach. Usually these curves are defined by using USGS rating curves at stream gauge sites. However, such curves are point values and gauging sites are often located on bridges where the stream is confined and not representative of the width of a the natural free-flowing stream reach. An alternative approach is to use measurements of water surface elevation derived from the NASA Surface Water and Ocean Topography (SWOT) satellite and correlate these with estimates of the streamflow discharge in the river reach at the time of the satellite measurements (Figure 38). A draft paper on this subject. “Application of SWOT Derived Data for Estimating Discharge-Depth Relationships and Improving Rating Curves in Texas Rivers”, by Sujana Timilsina and Paola Passalacqua, is being prepared.

The current set of FAST rating curves was developed several years ago in an earlier project supported by the Texas Division of Emergency Management. Since that time, the National Water Center has carried out a considerable amount of study of rating curve accuracy, and has derived a revised set of rating curves that have improvements in the stream slope and the application of Manning’s n roughness values. The FAST project team has downloaded the National Water Model rating curves and the geospatial data upon which they depend, and is examining how the present FAST rating curves could be improved.

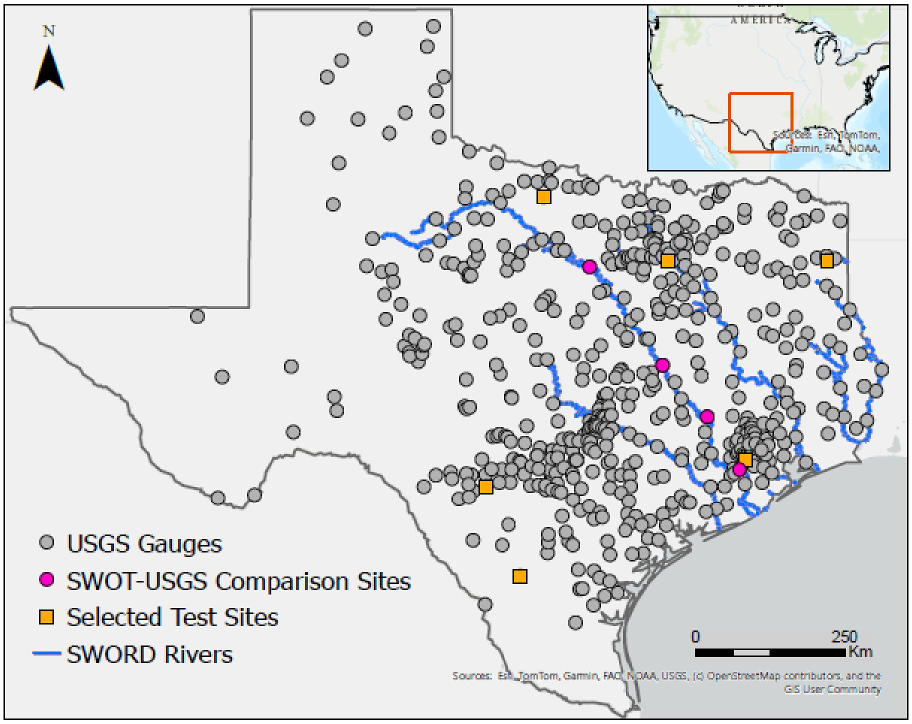

Figure 38. Comparing satellite and gauge-based rating curves

7. Conclusions

This report summarizes activity during FY26, September 2025 to August 2026 on the TxDOT Project 0-7095-01, Flood Assessment System for TxDOT (FAST). The principal focus during this year was in developing a form of FAST that TxDOT could use and apply that during training exercises. This goal was achieved and three training exercises in the Austin, Houston and Fort Worth Districts were conducted, with personnel from a total of 12 TxDOT Districts involved, along with representatives of the State Operations Center, and the Hydrology and Hydraulics group.

Participants in the FAST exercises, repeatedly called FAST easy to use, intuitive, simple, user-friendly, easy to digest, and easy to interpret. They liked the dashboard, map navigation, toggles and overall accessibility. That is significant because FAST presents fairly complex hydrologic and transportation information. Users generally don't appear to think the underlying complexity makes the application difficult to understand. Of 63 written user surveys after the exercises, 59 participants said they would use FAST in their job, while only 3 said they would not — approximately 95% positive intent to use.

The exercise participants indicated that future development should prioritize forecast reliability and confidence, user-configurable alerts, Maintenance Section-level views, improved mobile functionality, expanded structure coverage and historical event analysis. The FAST project team is working on implementing these priority goals.

The Flood Decision Support Gauges and Toolbox continue to be maintained and integrated. Of 80 gauges, 78 are operational, and two are off-line at present because of bridge maintenance issues. A total of 344 field measurements of discharge have been made at these sites, and 68 of the 80 sites now have at least one field measurement of discharge. At present, 45 of the sites are considered to have calibration-quality data and Iridium satellite telemetry is being used to increase reliability of data delivery, especially in areas with less reliable cell phone coverage. More than half (43) of the velocimetry gauge sites have been incorporated into the Flood Decision Support Toolbox. At each site a hydraulic engineering model is used to create flood inundation maps linked to the velocimetry gauge measurements.

A customized software package is being developed by the USGS to facilitate calibration of these velocimetry gauges. Initial testing indicates that calibration factors generated by the application are broadly consistent with those produced by established commercial k-factor processing software. The project-developed approach provides visibility into the calculation and allows the underlying procedures to be inspected and adjusted. Continued testing and refinement will focus on validating the approach and preparing the tool for systematic application across the RQ-30 network.

A Road Elevation Model for Texas has been created that specifies the (x,y,z) coordinates of the road network lines, and supports a 3m Digital Surface Model of the road surface and bridge deck that has proven to be fundamental to flood operations on the road and bridge system. A Road and Bridge Line model has been created to integrate the bridge envelope development with the road line profile and a first coverage of bridges developed from this approach has been entered into the FAST system. Further work using this method will increase the number of bridges incorporated into FAST.

Culverts and Low Water Crossings have been studied. A simplified field survey procedure for culvert properties has been developed and applied to a set of Low Water Crossings in the Austin District. The field survey data are integrated into the FHWS Culvert program HY-8 using an integrated with Arc Hydro so that the field data are automatically processed to provide culvert rating curves. Where the culverts have adequate flow capacity and a low road embankment the existence of the culvert does not greatly impact the stream rating curve that would exist if the culvert were not there. Conversely, when the culverts have inadequate flow capacity and a higher embankment, the presence of the culvert significantly impacts the rating curve at the road crossing.

FAST Data Services are by a data processing engine that operates within the KISTERS Datasphere software implemented in the Amazon East cloud facility. Statistics are kept continually of the time the system is properly functioning and its reliability is very high, often 100% in any given week. Output information is delivered through a web application that contains three map services, for flooded roads, flooded bridges and a flood inundation map, respectively. Each District has a separate database so that a malfunction in one does not affect operation in other Districts. Summary results are provided at the District level and for the state as a whole.

Research on Flood Data Analytics continues to be performed to improve the system accuracy. The Data Assimilation scheme has been extended to incorporate surface water reservoir routing as well as river routing. A rapidly executing hydrology model has been added to the Data Assimilation package so that FAST can use forecast rainfall as an input rather than relying solely on the National Water Model. The accuracy of the FAST rating curves is being studied by comparing them to those used in the National Water Model and those being measured using data from the NASA Surface Water and Ocean Topography (SWOT) mission.

Now that all the FAST exercises have been completed, the project team is focused on improving the functionality of the system to meet the needs ot TxDOT Maintenance staff, on increasing the number of bridges in FAST, on improving the accuracy of the forecasts, and on documenting the system and creating the required project reports.

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