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Applicability of a flood forecasting system for Nebraska watersheds

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Abstract
Accurate and timely flood prediction can reduce the risk of flooding, bolster preparedness, and help build resilience. In this study, we have developed a flood forecasting system prototype and checked its potential for carrying out operational flood forecasting in the state of Nebraska. This system builds upon some of the core components of the Iowa Flood Information System (IFIS), which is a state-of-the-art platform widely recognized around the world. We implemented our platform on a pilot basin in Nebraska (Elkhorn River basin) by installing eight stream sensors and setting up the hydrologic model component of IFIS, i.e., the Hillslope Link Model (HLM). Due to their importance in the Midwest, we particularly emphasized the snow processes and developed an improved HLM model that can account for different aspects of snow (rain-snow-partitioning, snowmelt, and snow

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accumulation) through simple parameterizations. Results show that the more thorough treatment of snow processes in the hydrologic model, as proposed herein, leads to better flood peak simulations. In this paper, we discuss different steps involved in developing the flood forecasting system prototype, along with the associated challenges and opportunities.

Keywords: Flood forecasting, Snow hydrology, IFIS, HLM, Bridge vulnerability

1. Introduction

The Midwestern United States region shows substantial spatial heterogeneity in flood peaks with discrete seasonality (Villarini et al., 2011). Nebraska has distinct hydrologic and hydroclimatic characteristics, which show sharp seasonal peaks in flood frequencies. One remarkable feature of The Great Plains of Nebraska is the maximum summer rainfall (Zhang et al., 2001). The storms originating from the Rocky Mountains and traveling across Midwest and causing heavy precipitation, mainly from May to July over Nebraska, are responsible for some of the major floods in the Great Plains of Nebraska (Villarini et al., 2011). Flood peaks associated with these storms have a significant influence on the upper tail of the flood peak distribution of Nebraska (Villarini et al., 2011).

1.1. Major floods, their drivers, and impacts in Nebraska

Mesoscale convective system (MCSs) storms play an important role in Nebraska's climatology, and they lead to a sharp seasonal flood peak in the region during late June of the year (Budikova et al., 2010; Changnon and Kunkel, 2006; Junker et al., 1999). These storms caused the disastrous flood in 1993 in Midwest, significantly impacting Nebraska (Kunkel et al., 1994). A similar anomalous total rainfall of 400mm, along with high surface soil moisture and antecedent conditions, resulted in the flood of 2008 and massive damage worth more than two million dollars (Budikova et al., 2010; Xiao et al., 2013). The United States Geological Survey (USGS) has characterized both the 1993 and 2008 floods in the Midwest as "500-year floods" (Dirmeyer and Kinter, 2009). There is also a link between the tornadic system of thunderstorms and the climatology of floods in the Great Plains of Nebraska (Zhang et al., 2001). Zhang et al. (2001) showed these characteristics through a study of heavy floods in Pebble and Maple Creeks because of storms that occurred in late June and early August of 1996. Recently in 2019, eastern Nebraska, western Iowa, and southeastern South Dakota got shallow temperatures and a historic high snowfall during the early days of the year, resulting in a large amount of SWE of 30–100 mm by March (Flanagan et al., 2019). During the same period, this region had frozen rivers and ground with 60–90 mm frost depth, preventing the usual infiltration (Flanagan et al., 2019). These conditions, combined with the record-breaking storm causing rain-on-snow events and rapid melting of snow, produced excessive runoff and overwhelmed the rivers and streams in the region (Flanagan et al., 2019). As of August 2019 estimates, this flooding cost has reached more than three billion dollars (Flanagan et al., 2019). These major flood events call for an efficient flood monitoring system for the state to mitigate the impacts of such disasters in the future.

1.2. Existing flood monitoring efforts in Nebraska

Currently, the Nebraska Department of Natural Resources (NeDNR) and the U.S. Army Corps of Engineers (USACE) monitor the incoming precipitations, carry out hydrologic modeling, and examine the variations in streamflow (NeDNR, 2022). NeDNR provides information regarding present flood conditions in Nebraska through various flood maps (NeDNR, 2022). NeDNR's Floodplain Interactive Map is an interactive interface that dispenses knowledge about floodplains and management (Interactive Maps Department of Natural Nebraska Department of Natural Resources, 2022). It runs with the support of resources like Federal Emergency Management Agency (FEMA) National Flood Hazard Layer data (NHFL), constituting the present-day flood data for the entire United States (FEMA, 2022). Besides FEMA-NFHL, NeDNR utilizes the service of USGS real-time flows and NOAA flood stage maps to monitor flood conditions in Nebraska (NOAA, 2022). NeDNR takes care of flood hazard mitigation in the state to reduce the risk and severity caused by flooding (NeDNR, 2022). Besides NeDNR, other agencies such as USACE, FEMA, Nebraska Emergency Management Agency (NEMA), Nebraska Department of Transportation (NDOT), and National Flood Insurance Program (NFIP) help in developing and interpreting flood and flood plain data as a part of their Floodplain Management Services

(NeDNR, 2022). National Weather Service (NWS) Advanced Hydrologic Prediction Services provides stream forecasts at certain locations in Nebraska (NOAA, 2022). Moreover, the state makes use of the National Water Model (NWM) forecasts of streamflow at around 4000 locations in the continental United States (CONUS) and guides millions of sites that lack traditional stream forecasts (Office of Water Prediction, 2022). National Center for Atmospheric Research's (NCAR) Weather Research and Forecasting hydrologic model (WRF-Hydro) is the core model behind NWM (Gochis et al., 2020). Over the CONUS, the short-range streamflow forecasts of NWM are available every hour (Maidment and Dugger, 2016).

Even though there are existing resources for flood-related assessments, the state of Nebraska will benefit significantly from the development of a state-of-the-art system to enable seamless flood monitoring and forecasting. This will address some of the shortcomings of the existing resources. For example, increasing forecast lead and reducing forecast uncertainty are two pressing needs to provide accurate and timely warnings to the community. Also, many flood forecasting systems operate on a continental scale, where the underlying rainfall-runoff models generally work with a larger spatial resolution. This factor can compromise the accuracy of flood prediction locally. Besides, many of the underlying models of the regional hydrologic monitoring systems in Nebraska do not consider snow processes, while the runoff generation in Midwestern basins is highly affected by snow accumulation (Bradley et al., 2013; Flyr et al., 2013; HDR Engineering, 2013). This often leads to an inaccurate flood prediction.

1.3. Applicability of the Iowa Flood Information System (IFIS) prototype in Nebraska

There exist several state-of-the-art flood forecasting systems around the world. **Table 1** provides details of some well-known operational flood forecasting systems. The details are taken from Emerton et al. (2016) and Kauffeldt et al. (2016). Many of these models include snow parameterizations. For instance, the WRF-Hydro model uses snowpack and frozen ground parameterizations based on Koren et al. (1999), which was later modified to incorporate the effects of canopy processes (Gochis et al., 2020; Niu and Yang, 2004). Similarly,

Table 1 Operational large-scale flood forecasting systems.

Forecasting System	*Domain*	*Update Frequency*	*Rainfall Runoff Model*	*Spatial Resolution*	*Reference*
EFAS (European Flood Awareness System)	Europe	12-h	LISFLOOD Europe	5 km, Regular grid	Thielen et al. (2009)
E-HYPE (European Hydrological Predictions for the Environment)	Europe	Daily	HYPE	~15 km, Irregular grid, varies by basin	Lindström et al. (2010)
FFWS (Flood Forecasting & Warning Service)	Australia	6–12-h	GR4J (daily), GR4H (hourly), URBS	~10 km	Pagano et al. (2016)
HEFS (Hydrologic Ensemble Forecast Service)	USA	Sub-daily to daily	Suite of Models	Varies by basin	Demargne et al. (2014)
GloFAS (Global Flood Awareness System)	Global	Daily	HTESSEL	10 km, Regular grid	Alfieri et al. (2013)
GLOFFIS (Global Flood Forecasting Information System)	Global	6-h	PCR-GLOBWB, W3RA	10 km, 50 km, Regular grid	Werner et al. (2013)
VIC with Global Flood Monitoring System (GFMS)	Global	3-h	Dominant river tracing Routing Integrated with VIC Environment (DRIVE) model	~12km	Wu et al. (2014); Yilmaz et al. (2010)
NWM (National Water Model) - Experimental	USA	1-h	Weather Research Forecasting Hydro (WRFHydro)	1km and 250m grids	Office of Water Prediction, 2022

the variable infiltration capacity (VIC) model uses parameterizations equivalent to that proposed by (Anderson, 1968)to simulate snow accumulation and snowmelt (Liang et al., 1994). However, the flood forecasting systems using these models often lack focus on community-level flood information and run on larger grid scales that might not coincide with the actual local-scale physical process. IFIS addresses these aspects of flood forecasting along with resolving several flood-related challenges.

IFIS is a web platform that provides facts and figures of real-time flood conditions, flood-related data, visualizations, flood forecasts, etc., for more than a thousand communities in Iowa (Krajewski et al., 2017). After the disastrous flood of 2008, the Iowa Flood Center (IFC) was established with one of the key goals of developing hydrologic models and real-time flood forecasting tools for better predictions and information about floods (Krajewski et al., 2017). IFC developed a high-resolution streamflow forecasting system for Iowa state that works based on Hillslope Link Model (HLM) and could make predictions every 15 min for nearly 2000 locations (Krajewski et al., 2017). Later, IFC developed the IFIS, a web-based platform to provide real-time flood information to the communities of Iowa. IFIS's operation is supported by a conceptual rainfall-runoff model HLM (Mantilla et al., 2022; Quintero et al., 2016, 2020b). This model consists of multiple Ordinary Differential Equations (ODEs) in a tree-structured format, representing the water flow and balance in each hillslope (Small et al., 2013). IFIS provides services that include flood inundation maps, real-time flood conditions, flood forecasts, flood-related data, applications, information, and visualizations (Demir and Krajewski, 2013).

A critical strength of the IFIS system is real-time flood estimations. IFIS calculates rainfall accumulations products at 5-min, daily, and two-week intervals (Krajewski et al., 2017). This enables IFIS to deliver flood information and alerts almost instantly. Compared to many other operational real-time flood forecasting systems, this is a remarkable feature, as given in Table 1. IFIS system runs the model at a higher resolution (hillslope scale of size 0.1 km^2) compared to the flood forecasting systems in Table 1, and it provides risk estimates in a community-oriented way (IFC, 2022; Mantilla et al., 2022). HLM, the underlying model of the IFIS system, has been used in various studies, demonstrating the strength of the model. El Saadani et al. (2017) show that the non-linear routing method used in HLM performs better than the routing in Routing Application for Parallel Computation of Discharge (RAPID) which uses a Muskingum-based method. Quintero et al. (2020a) use HLM-based simulations to develop a flood potential index for Iowa. HLM has undergone several previous modifications to improve performance (Mantilla et al., 2022).

Presently, there is a potential for improvement in the representation of snow processes in HLM. Although the model can receive snow forcing, it does not have any parameterizations to estimate SWE, snowmelt, or frozen ground. This absence of snow parameterization is speculated as the main reason for IFIS's failure in the prediction of the historic spring flood that occurred in 2019 across the states of Iowa, Nebraska, and South Dakota. Snow could play a substantial role in the hydrology of catchments in the Midwest. This region receives significant snow during the winter (Suriano, 2022). Snow accumulation heavily affects runoff generation in the Midwest (Suriano, 2022). Therefore, incorporating snow processes in flood prediction models in the Midwestern region, including Nebraska, is crucial.

Through this work, we are trying to improve the HLM by introducing snow processes in the model structure. We modified the existing design by adding a new storage layer holding snow water equivalent (SWE). This new parameterization encompasses a simple degree day factor model (Martinec, 1975) for estimating meltwater. We introduced different rain-snow portioning schemes into the system and evaluated the performance of HLM. We also refined the present parameterizations to account for the occurrence of frozen ground and its effect in assessing streamflow. After successfully testing the parameterization, we implemented the upgraded model for a pilot basin in Nebraska to show the potential of an operational flood forecasting system for the state. To support our case, similar to the IFC, we installed streamflow gauging stations across the pilot basin where we can collect data and assimilate it into the model. We also developed a simple web interface showing simulated hydrographs anywhere in the basin.

This article discusses the materials and methods required for implementing an improved HLM model in a pilot basin in Nebraska, including the improved model equations with snow parameterization. Then we show the results obtained, followed by some discussion about possible amendments and challenges related to an operational flood forecasting system. Finally, we finish the article by concluding with remarks from this work.

2. Materials and methods

2.1. Data

In this study, for the preliminary validation of the proposed parameterization of the snow process, which is newly added to the HLM structure, we used North American Land Data Assimilation System (NLDAS-2) precipitation, potential evapotranspiration, and temperature forcing from 2015 to 2020 (Mitchell et al., 2004; Xia et al., 2012). We used precipitation and temperature (aggregated into a daily resolution) for two different locations in Nebraska for the initial validation of modified model equations. The hourly temperature aggregated for the Elkhorn basin (**Fig. 1**) was used in HLM simulations. We provided monthly aggregated potential evapotranspiration, as a lower frequency does not significantly improve the results.

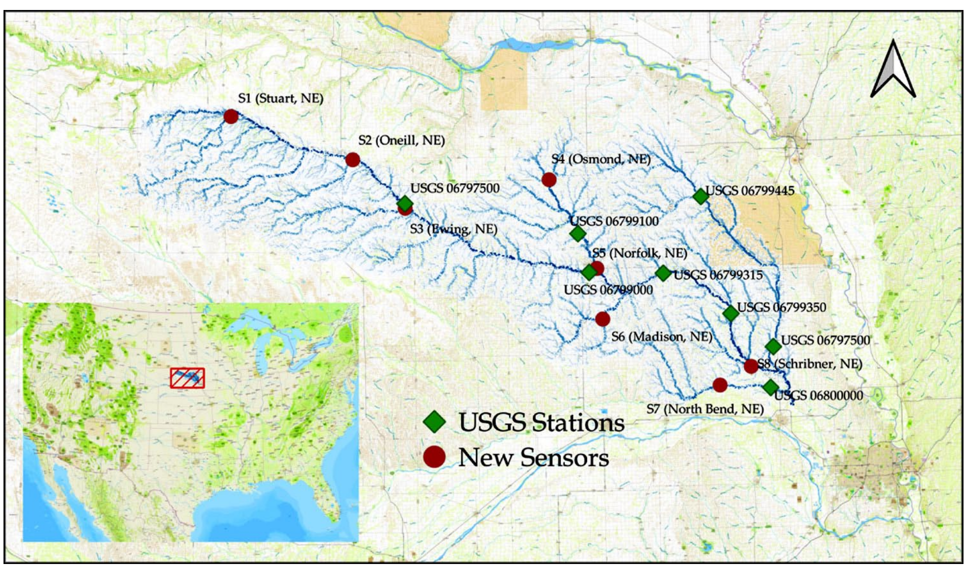

Fig. 1. The Elkhorn River basin and discharge measurement locations. The inset map shows the location of the basin in the CONUS. S1-8 are the new sensor locations.

For validating the proposed snow parameterization, we acquired SWE data of *Daily* 4 km *Gridded SWE and Snow Depth from Assimilated In- Situ and Modeled Data over the Conterminous U.S., Version 1* (Broxton et al., 2019; Zeng et al., 2018) from the National Snow and Ice Data Center (NSIDC). This data provides daily SWE and snow depth at a spatial resolution of 4km × 4km for the conterminous United States (CONUS). We collected the SWE data for the same period as the simulation (2015–2020) and resampled it to the resolution of NLDAS-2 forcing data using linear interpolation.

We use Multi-Radar Multi-Sensor Quantitative Precipitation Estimate (MRMS-QPE) for precipitation forcing to the HLM model-based flood forecasts. MRMS QPE products have an update cycle of as low as 2 minutes and a latency of around 1.5 hours, making them suitable for operational flood forecasting systems (Zhang et al., 2016). MRMS system incorporates data from about 180 radars and almost 7000 rain gauges at an hourly scale to correct the biases in radar data. Many operational flood forecasting systems in the eastern U.S. utilizes MRMS QPE products to monitor flood conditions (Zhang et al., 2016).

We use the observed data obtained from USGS stations to evaluate the model's performance. There are eight USGS stations in the Elkhorn River basin for which we have hourly discharge data. Although there is a gap in many of the discharge data during the winter period, these were filled with estimated values by USGS (Kimbrough et al., 2006; USGS, 2023). We also use the USGS observed data to update the river stages in our retrospective flood forecasting model for 2019.

The IFC has advanced streamflow gauging sensors, which automatically collect the stream level data and transfer it to IFIS every 15 minutes. This data can be later assimilated into the flood modeling system to correct the river flow estimates. We have installed eight sensors across the Elkhorn River basin, which are already functional. These sensors, mounted to the bridge side, emit sonar signals toward the stream to measure the distance from the sensor to the water level. **Fig. 1** shows the locations of sensors we installed across the Elkhorn River basin. These locations were decided based on field visits and GIS analysis, where we tried to cover streams of different orders.

IFC creates an ensemble of rating curves to account for the uncertainty of channel roughness and energy surface slope. A set of 100 combinations for slope and Manning's values sampled uniformly over their feasible ranges was selected. Each set of combinations gives a different rating curve. The resulting ensemble of equally likely rating curves can be described using quantiles that represent uncertainty through the range of variation of discharge and stage. The representation of ratings is presented in the form of the 50% (median), 5%, and 95% quantiles.

Topographic and hydrologic information was provided by the Nebraska Department of Transportation (NDOT). Supplementary Fig. 1 shows, in green, the cross sections surveyed for each site, and Supplementary Table 1 shows the hydrologic data used to set up a steady flow model. Downstream boundary conditions were based on a normal depth assumption using an energy surface slope estimated from the bottom of the channel profile captured in the survey data near the downstream study limit. Manning's coefficient range was set to between 0.03 and 0.045, which is used in the channel sections of the step-backwater HECRAS model. The selected range is supported by the experience of previous projects and the literature (Barnes, 1969; Gilles et al., 2012; Quintero et al., 2021). For the floodplain, we used the Nebraska land use data map - 2015 produced by the NeDNR (NeDNR, 2022) to assign roughness values that were selected based on typical values provided by the HEC-RAS Hydraulic Reference Manual Version 4.1 (Chow, 1959; French, 1985; U.S. Army Corps of Engineers, 2010) (Supplementary Fig. 2). A summary of datasets used in this study is given in **Table 2**.

2.2. Hillslope Link Model (HLM)

The current operational real-time flood monitoring system relies on HLM (Mantilla et al., 2022). This conceptual model employs the quintessential leaky bucket perception of a watershed. HLM divides the entire watershed into a large number of individual hillslopes. Each hillslope has multiple water storage layers where water from each layer flows to the subsequent layer below as well as to the stream, based on parameterizations relevant to the processes. A schematic representation of this parameterization (HLM-NoSnow) is given in **Fig. 2**a. Equation (1), 2&3 represents a change of storage with respect to time in each layer of a hillslope. The change in each layer equals the

Table 2 List of datasets used.

Variable	*Dataset*	*Resolution*	*Time period*	*Source*
Precipitation	MRMS-QPE	1 km × 1 km	2018–19, Hourly	J. Zhang et al. (2016)
Temperature	NLDAS 2	0.125° × 0.125°	2018–19, Hourly	Xia et al. (2012)
Potential Evapotranspiration	NLDAS 2	0.125° × 0.125°	2018–19, Hourly	Xia et al. (2012)
SWE	NSIDC	4 km × 4 km	2018–19, Hourly	Broxton et al. (2019)
Streamflow	USGS, Sensors	Point data 2018–19,	Hourly	USGS
Topography & Hydrology	NDOT	Point data		NDOT

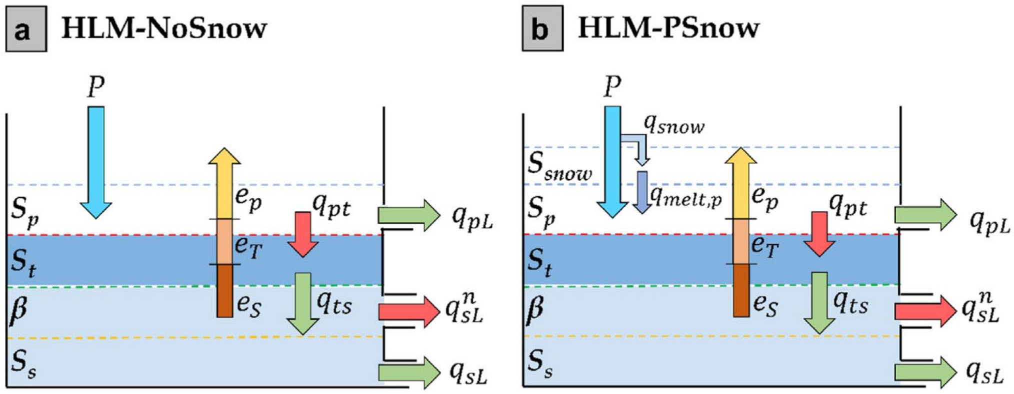

Fig. 2. Schematic representation of different models in HLM. This study introduces the HLM-PSnow.

difference between the incoming and outgoing water flux. Equation (1) represents the change in storage in the ponding (top) layer, where the incoming flux is precipitation (*P(t)*), and outgoing fluxes are infiltration (q_{pT}), surface runoff (q_{pL}), and evaporation from surface (e_p). For the second layer, represented by Equation (2), the incoming flux is infiltration, and outgoing fluxes are deep percolation (q_{Ts}) and evaporation from the second layer (e_T). Similarly, for third layer, the incoming flux is deep percolation, and outgoing fluxes are subsurface runoff (q_{sL}) and evaporation from the third layer (e_s), as represented by Equation (3). The hillslopes are connected in a tree-structured format where water from each hillslope adds up and contributes to the streamflow. This results in a massive system of ODEs linked as a tree structure. Solving this system of ODEs provides outputs of desired variables such as streamflow.

$$\frac{dS_p}{dt} = P(t) - q_{pL} - q_{pT} - e_p \tag{1}$$

$$\frac{dS_T}{dt} = q_{pT} - q_{Ts} - e_T \tag{2}$$

$$\frac{dS_s}{dt} = q_{Ts} - q_{sL} - e_s \tag{3}$$

2.3. Improvements to the HLM model

We introduce an updated conceptual model structure for HLM by including snow processes (HLM-PSnow), as shown in Fig. 2b. In this update, there are two major components we added to the system 1) rain-snow partitioning (RSP) schemes and 2) a new storage layer of SWE. This study compares the two models (previous and updated) and reports the results.

We considered the option of using different rain-snow partitioning of the incoming precipitation. This precipitation provided as forcing is divided into snow and rainfall based on three different RSP schemes. These schemes are shown in **Fig. 3**. The first RSP scheme is premised on a base temperature (Tb). If the temperature exceeds Tb, all precipitation is considered rainfall and, otherwise, snow. The base temperature (Tb) should be calibrated to find the optimum performance. The second RSP scheme is characterized by representing snow fraction (fraction of snow in the incoming total precipitation) as a linear stepwise function of the air temperature (Jordan, 1991). The third RSP scheme is based on that proposed by Wang et al. (2019), where snow fraction is obtained following a sigmoid function of wet bulb temperature. In this scheme, the parsimony of the model is compromised compared to earlier versions, as the implementation of this scheme requires an additional input of relative humidity.

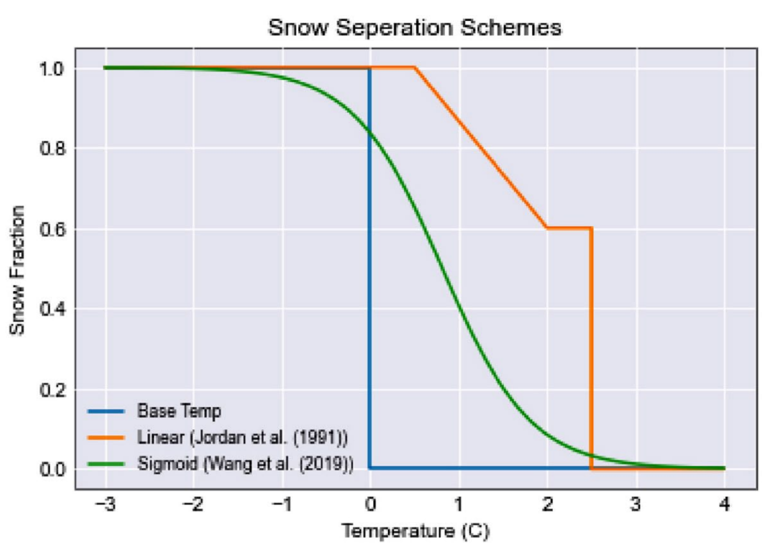

Fig. 3. Rain-snow partitioning (RSP) schemes used in the new modeling framework.

The SWE storage layer (S_{snow}) is conceptually located above the ponding layer (S_p). This new layer stores the accumulated snow, and the change in SWE with respect to time is given by the addition of new snow and subtraction of outgoing melt water and snow evaporation, as represented using Equation (4). The amount of meltwater is calculated using a simple degree day factor (DDF) model (Martinec, 1975) as described in Equation (5), where D (mm°Cd^{-1}) is the degree day factor. The amount of meltwater cannot be greater than the existing SWE. Therefore, the minimum of meltwater and SWE is taken. After portioning the total precipitation into rainfall (P_{rain}) and snow (P_{snow}), the amount of snow is added to this layer, and rain is directly entered into the ponding layer. The ponding layer will have an additional meltwater component from the snow accumulation layer above it. As a result, the equation representing the ponding layer looks like Equation (6). For subsequent layers, there are no changes. Therefore, the equations remain the same as that of the earlier version. With the new snow layer implementation, the HLM can now simulate SWE as a new output variable which can be used to study further the role of snow in the hydrology and water resources of the region. We should note that a previous update in the HLM considered including SWE as an external forcing (Velasquez et al., in review).

$$\frac{dS_{SWE}}{dt} = P_{snow} - q_{melt,p} - e_{snow} \tag{4}$$

$$q_{melt,p} = min(D \cdot T(t), S_{SWE}) \tag{5}$$

$$\frac{dS_p}{dt} = P_{rain} - q_{pL} - q_{pT} + q_{melt,p} - e_p \tag{6}$$

2.4. Implementation of the improved IFIS system prototype

In this study, we found that the absence of snow processes in the modeling framework shortens the ability of HLM to predict streamflow efficiently, especially in the Midwest, where snow plays a vital role in the water cycle. We introduce a new simple parameterization, as discussed in Section 2.3. The methodology followed to implement the prototype flood forecasting system with the new parameterization is

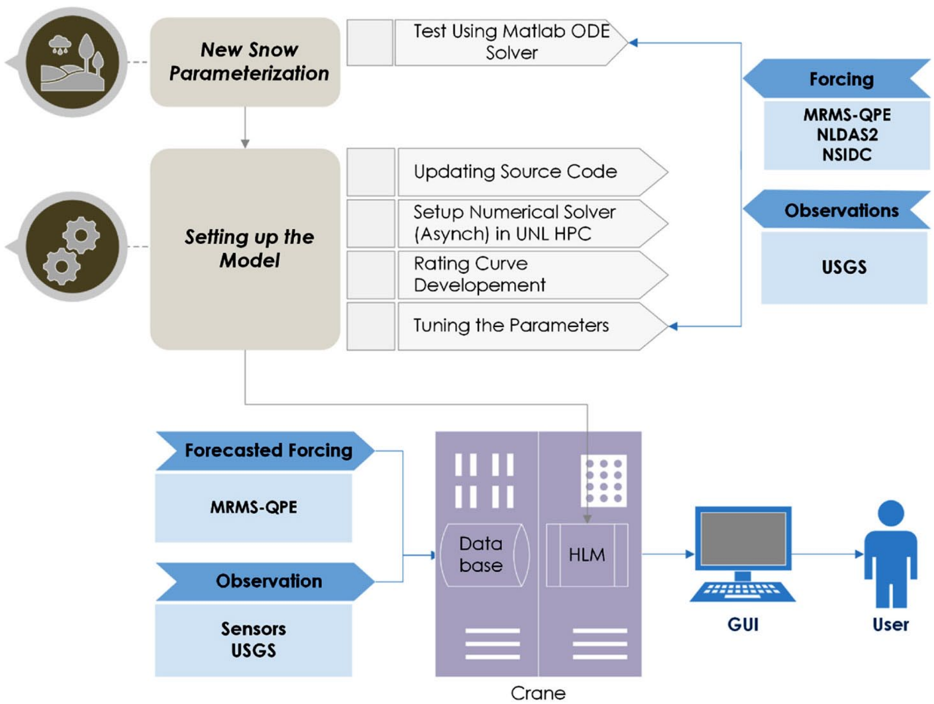

Fig. 4. Flow chart showing the implementation of the Prototype flood forecasting system.

shown in **Fig. 4**. Initially, we tested this new set of ODEs using MATLAB ODE solvers. By writing a prototype code representing the vertical water flow in a single hillslope and solving the ODEs, we could obtain preliminary results of patterns of water in each storage layer, including SWE from the newly added layer. This allowed a proof-of-concept on whether the new parameterization could be representative of the actual process before altering the source code. Once tested successfully, we updated the model source code by adding this improved HLM structure as a new model inside the numerical solver toolbox for HLM differential equations. Additional forcing of temperature can be provided in the format of regular storm files, binary storm files, or uniform storm files. When the updated source code was ready, we set up and compiled these source codes in Crane, a High-Performance Computer of Holland Computing Center at the University of Nebraska-Lincoln. The required forcings are made available in Crane. In HLM, the inputs can be provided in several formats, including ASCII text files (e.g., .str, .ustr, and .mon files), databases (e.g., PostgreSQL database), and binary files. In our case, precipitation files are stored in binary format, whereas temperature recordings are aggregated for the basin and provided through uniform storm (.ustr) files. Then we manually tuned the parameters to obtain the realistic runoff from the model and compared them with observed USGS discharge measurements. Next, we created a PostgreSQL (Stonebraker and Rowe, 1986) database to insert observed discharge measurements from USGS stations and the newly installed sensors. This PostgreSQL database aids the smooth assimilation of sensor measurements into HLM. We can add the real-time measurements into this database and update the model simulated river discharges instantly.

To convert the stream level data measured by new sensors into streamflow data, we developed rating curves. The IFC developed a methodology to obtain a stage-discharge relationship using the step-back water model with the Hydrologic Engineer Center's River Analysis System (HEC-RAS) (Quintero et al., 2021). We set up one-dimensional (1D) hydraulic models for every location where sensors are installed to obtain a stage-discharge relationship (Supplementary Fig. 1). Rating curves are subject to multiple sources of uncertainty. In particular, synthetic curves developed with hydraulic models are sensitive to the characterization of the channel geometry (e.g., the number of cross sections and the spacing between them, bottom slope, and discretization of the finite-element mesh, among others) as well as model parameters (e.g., Manning's roughness coefficient) of the channel (Quintero et al., 2021). The uncertainty for Manning's roughness coefficient is not available because this parameter is not directly measured but assessed through a visual comparison of previous studies (Arcement and Schneider, 1984). Despite extensive efforts to determine channel roughness, its estimation continues to be subjective and can lead, even for common situations, to errors as high as 30% (Bray, 1979).

We downloaded the MRMS data from the archives of Iowa Environmental MESONET of Iowa State University. These files were initially in GRIB format, which we later cropped for the Elkhorn region and converted to binary file format in Holland Computing Center HPC. These binary files are the fastest way for the model to read the forcing data. Since in this work we intend to show the potential of a flood forecasting system for Nebraska through a retrospective analysis, we forced the model for a time period of 2018 and 2019. Of this, 2018 is considered a spin-up time for the model. We saved the model "snapshot" at the end of 2018 (HLM provides the option of saving the model stages at any time-step as a .rec file) and provided it as an initial condition for the 2019 simulation. We also set up a PostgreSQL database consisting of observed streamflow measurements from USGS, from which we regularly update the model streamflow stages. This process automatically replaces the model-produced values with observed values at these locations.

The HLM works based on a system of ordinary differential equations arranged in a tree topology structure, as discussed in section 2.2. The computation of solutions for this system of ODEs is achieved using the asynchronous (ASYNCH) software package created by IFC (Small et al., 2013). The primary application of ASYNCH solvers is finding solutions for distributed hydrologic models of catchments. ASYNCH uses dense output Runge-Kutta methods to solve the equations at each hillslope. The input forcing, such as precipitation, potential evapotranspiration, and temperature, can be transferred through several file formats as well as taken from a Structured Query Language (SQL) database. Similarly, we can produce outputs in different formats and display and use them for studies.

In the present world, web interfaces are the most viable way of providing information to the public. We developed a simple web interface (code available in GitHub repository) that shows the stream network map of the Elkhorn basin, where the user can click anywhere, and the hydrograph at that location will be displayed. This web interface is developed using python with *dash* and *plotly* libraries (Plotly Technologies Inc., 2015). We use Mapbox tools to develop a basemap for this web interface. **Fig. 5** shows the screenshot of the web interface. It is essential to note that this interface is a part of our prototype flood forecasting system and a preliminary version to set the ground for improvisation.

2.5. Bridge vulnerability

For the eight newly installed sensor locations, we estimated the vulnerability of bridges to flood peril. Two critical factors on which the bridge vulnerability depends are the time-to-peak at these locations

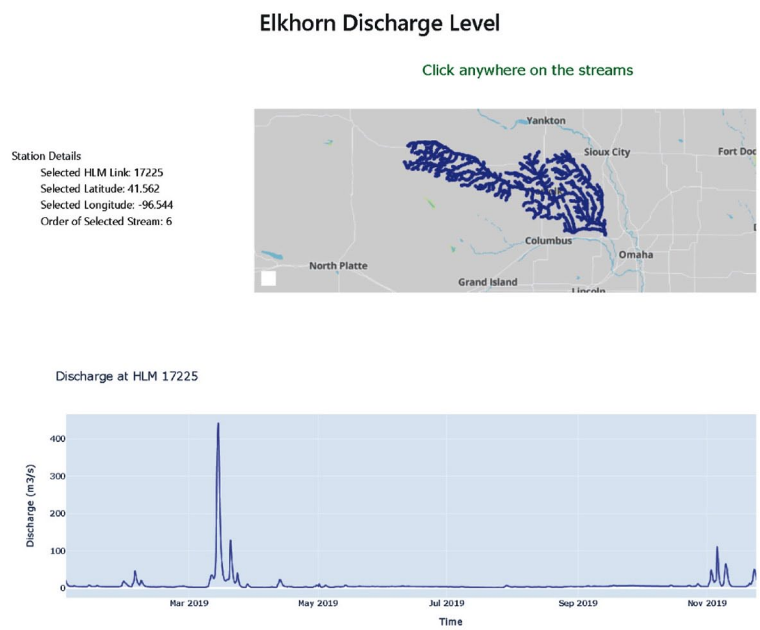

Fig. 5. Screenshot of web interface showing the flow rates across the Elkhorn basin.

and the elevation of bridges from the bottom of the river. The higher the time-to-peak, the lower the vulnerability, and the higher the elevation of bridges, the lower the vulnerability. The time-to-peak values are calculated by ingesting the model with an arbitrary constant rainfall across the basin. This was realized with the uniform storm files (.ustr) type of forcing in HLM. Then we obtained the streamflow at these locations produced by the model and the time difference between the peak flow and centroid of the storm, which gives time-to-peak. The elevation of bridges from the bottom of the river was already measured during their installation. Once these two quantities were obtained, simply plotting one across another would give a sense of the vulnerability of bridges to flood peril.

3. Results

From the prototype system of ODEs created in MATLAB for initial validation, with an additional storage layer for snow, we obtained the simulated SWE. Supplementary Fig. 3 shows the comparison of simulated SWE with that of observed values from NSIDC data. We compared this for two different locations in Nebraska. Initial results were satisfactory, as the output from the new storage layer could pick up the SWE patterns well. Supplementary Fig. 3b shows that the model produced similar values for the Norfolk region in 2019 and 2020. However, since these were preliminary results from a single grid data, it does not represent the connection between different hillslopes as in HLM.

We simulated the hydrographs for 2019, as the historic flood during March is our point of interest (Flanagan et al., 2019), using the currently used HLM and a new version of the model, including the snow parameterization. We compared both hydrographs with the observed hydrographs at five locations across the Elkhorn basin. The results suggest that the HLM with Snow parameterization outperforms the current version of HLM in predicting the peak flow in the Midwest during March 2019. **Fig. 6** shows that the HLM without snow could not capture the peak flow at any seven stations. In contrast, the hydrographs from the model with snow parameterization show peaks corresponding to observed peaks. This implies that snow processes majorly drove the flooding in March 2019. Supplementary Fig. 5 shows the model-simulated streamflow after assimilating the USGS data (note that we could not use streamflow measurements from the newly installed sensors because they were not available at the time of the 2019 Spring flood event).

Fig. 7 shows the plot between the time to peak and bridge elevation, illustrating the different exposure levels of eight bridges across the Elkhorn River basin. The higher the time-to-peak, the lower the vulnerability, and the higher the elevation of bridges, the lower the vulnerability. Therefore, the vulnerability increases as we move closer to the plot's origin. We can see that bridge near Stuart, NE, is the most vulnerable to flood disasters, whereas the bridge near Norfolk, NE, is the least vulnerable. The bridge vulnerability study demonstrates a practical application of HLM. We can use this model to assess bridge vulnerability for any point in the river network, given the height of the bridge, highlighting its application of the model in the transportation sector.

Fig. 8 shows the results of synthetic rating curves obtained with the hydraulic model for each site. The solid black line and the gray area around it show the median and the 5% and 95% quantiles of the uncertainty range based on the 100 rating curves using the model.

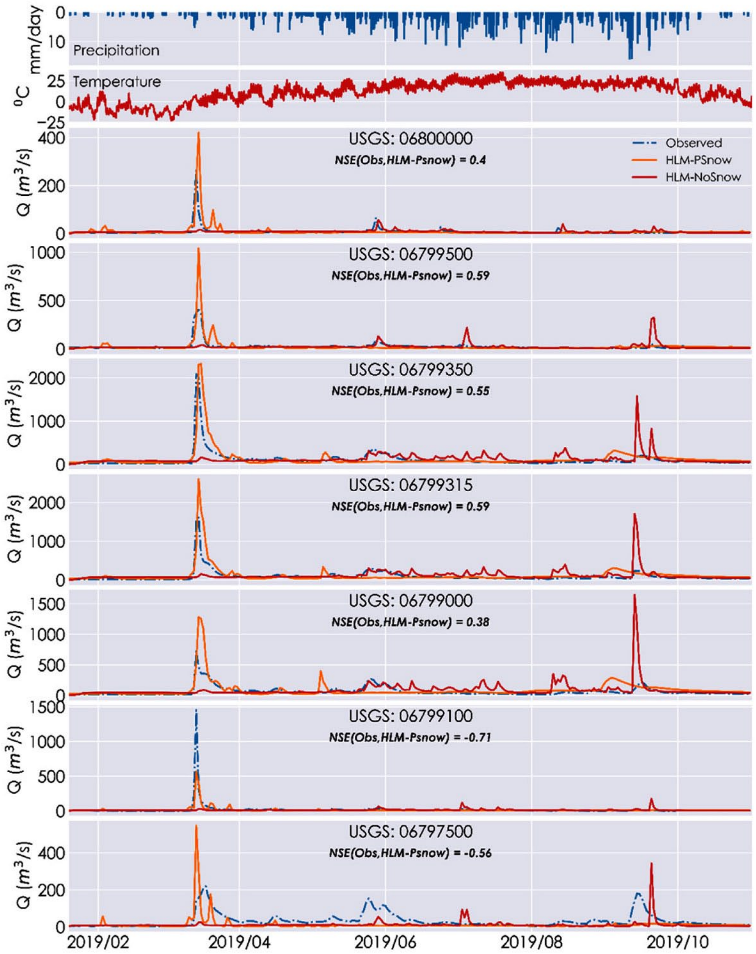

Fig. 6. Simulated hydrographs from HLM with and without snow at USGS stations in the Elkhorn River. The forcings used (precipitation and temperature) are on the top.

4. Discussion

This study investigated the potential of a real-time flood forecasting system for Nebraska by implementing a prototype on the Elkhorn River basin. We used the hydrologic model (HLM) of the IFIS system and enhanced it to account for snow processes. Our results demonstrate how a simple conceptual modification in the model can significantly improve its performance, which is also supported by the literature (Mai et al., 2022; Roy et al., 2017a). In Nebraska, snow processes produce the major portion of runoff (Barnett et al., 2005). A recent flood in 2019 showed the importance of snow-generated

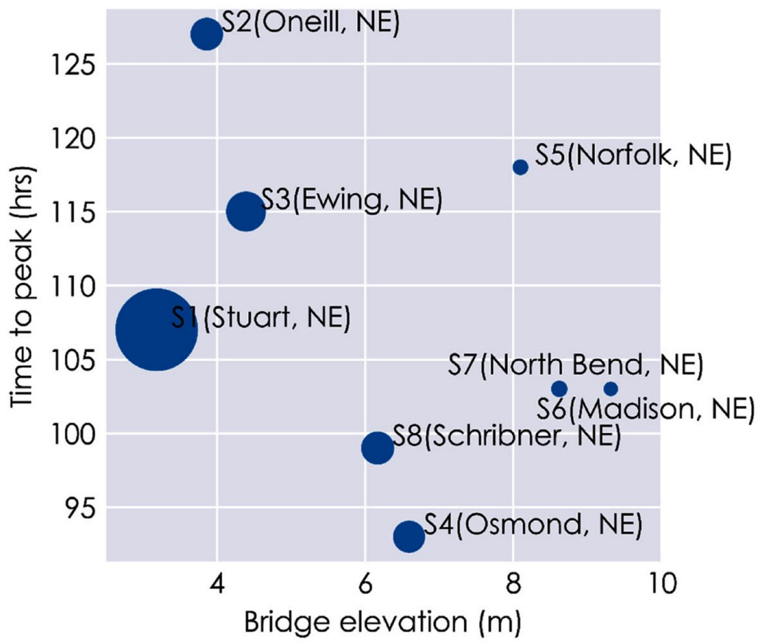

Fig. 7. Different exposure levels of the eight bridges across the Elkhorn basin. The larger the circle, the larger the vulnerability of the bridge.

runoff in the occurrence of peak flows (Flanagan et al., 2019). By including snow parameterizations, HLM could more realistically simulate the hydrology of snow processes, thus improving its peak flow prediction performance. We implemented the HLM source codes on the University of Nebraska-Lincoln's high-performance computer. This flood forecasting framework can be expanded to a larger region, including snow-dominated areas, with minimal requirements for forcing data. Since the HLM conducts simulations by solving ODEs at the hillslope scale, which corresponds to the actual hydrologic processes, it can provide discharge estimates at any stream location (though the accuracy of the first few orders of streams can be low, as seen in Fig. 6). The decomposition of hillslope links from the DEM of a region can be done easily with the help of openly available tools (GitHub, 2023). A major strength of HLM, making it suitable for flood forecasting, is that it is less susceptible to the spatial variability of parameters (Mantilla et al., 2022). The error associated with each hillslope simulation gets canceled as it travels from lower to higher orders of streams, a hypothesis proven by Mandapaka et

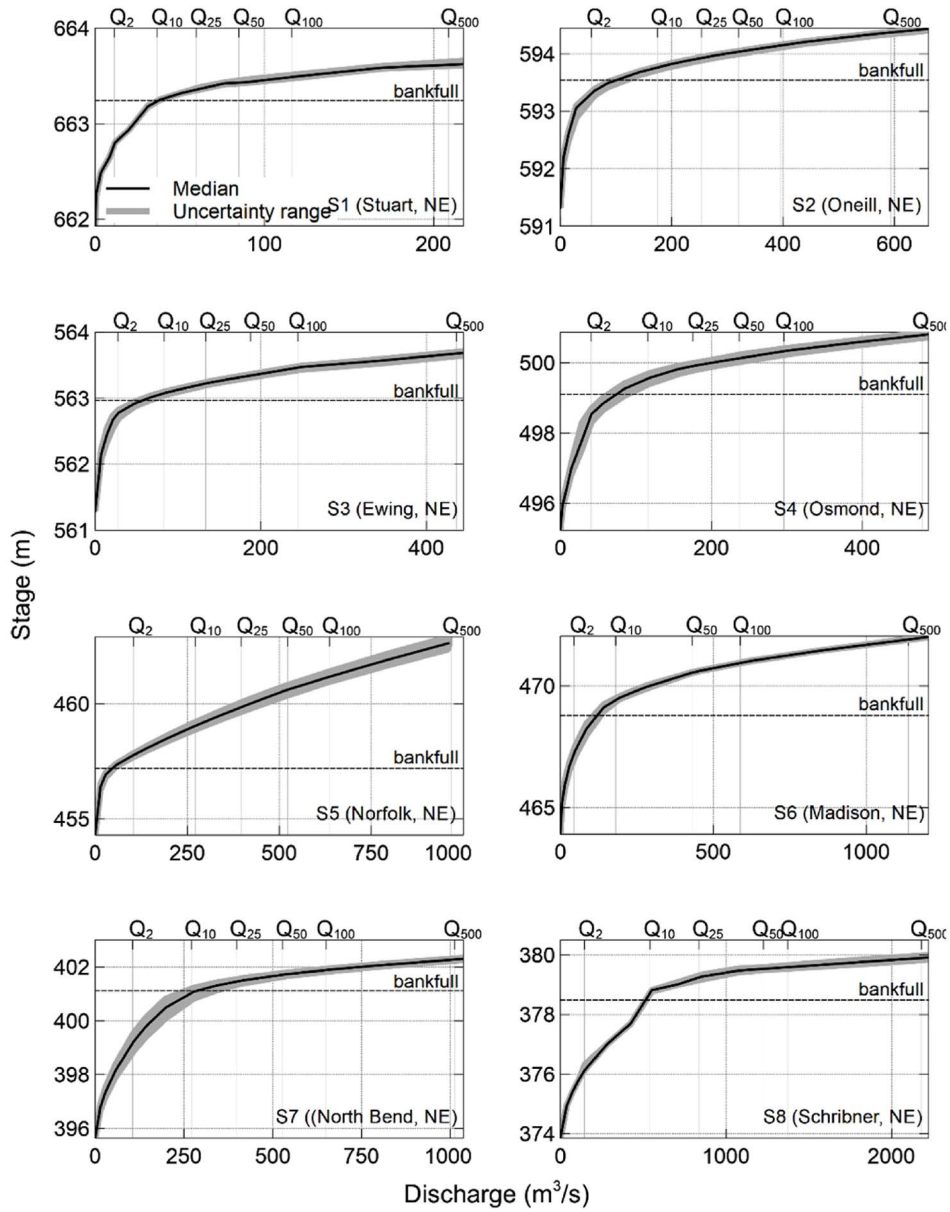

Fig. 8. Synthetic Rating Curves at new sensor locations.

al. (2009). While HLM can serve as a hydrologic model to simulate river discharge, it requires further work to transform it into an operational real-time flood forecasting system.

An operational flood forecasting system should include collecting and inputting the most recent forcing data (such as precipitation and temperature depending on the model used), solving the model across multiple basins, assimilating the observed discharge data (and potentially other variables) from sensors, and timely updating a user interface to disseminate the flood information to the stakeholders. The most critical and challenging task is to make all these components run simultaneously and seamlessly in an automatic manner.

It is crucial to integrate real-time forcing data with the maximum possible lead time. There are several potential candidates for this. For example, Multi-Radar/Multi-Sensor Quantitative Precipitation Estimation (MRMS-QPE) rainfall products are useful to ensure lower latency, which means that we can predict an imminent flood well ahead of time, thereby providing effective early warning. Satellite-based precipitation estimates can also be used for near-real-time streamflow monitoring (Roy et al., 2017b, 2017c, 2020). Numerical precipitation forecasts, such as Global Forecasting Systems (GFS), are useful for forecasting streamflow ahead of time. Streamflow information from upstream can be used to predict streamflow with lead time downstream. Furthermore, time series modeling of streamflow can help generate forecasts with lead.

The IFC uses NEXRAD radar-based rainfall accumulation data, processed every 5 minutes from 7 radars covering Iowa (Krajewski et al., 2013; Seo and Krajewski, 2015). Every 15 minutes, they pull the rainfall estimates (up to the forecast issuance time) to produce a streamflow forecast for up to 10 days. One of the ways to potentially improve forecast skills would be through the use of robust quantitative precipitation forecasts (QPF). The efficiency of the QPF method used for flood forecasting is critical, as the error in QPF would propagate to flow predictions. In IFC, exploring the potential of QPF methods is an ongoing activity (Krajewski et al., 2017). We could also implement time series modeling (using statistical and machine learning methods) to estimate streamflow. In any case, it is important that the forecast errors and uncertainties are thoroughly analyzed and their sources are detected and addressed as necessary.

The flood forecasting system we worked on is based on HLM simulations and streamflow observations. We could leverage data and resources from a variety of sources (e.g., NWS, USGS, USACE, NOAA) and integrate them into the proposed system. This would enable us to disseminate several layers of information. We can add open-flow modeling to provide 3D flood inundation views at several locations across the state, which would assist in efficient communication with the public. This will require the collection and processing of bathymetry data of the channels. Inundation maps can be generated focusing on the communities, and such maps can also assist National Flood Insurance Program (NFIP).

Establishing an operational flood forecasting system comes with multiple challenges. One among them is integrating all components of the flood forecasting system efficiently. This involves running the model, collecting and assimilating data, and circulating the information. For such a task to accomplish, we need experts from the fields of hydrology, water resource engineering, computer science, and social science working together. While hydrologists and water resource engineers work on the modeling and conceptual sides of the system, computer scientists are necessary to aid them in terms of data management, utilizing high-performance computing resources, and web interface. Social scientists can add different dimensions of the community and efficiently gather stakeholder feedback. In Nebraska, we can utilize the Holland Computing Center (HCC) at the University of Nebraska-Lincoln for computational resources.

Another big challenge in setting up an operational flood forecasting system is the calibration of the model across all basins in the state. The HLM currently does not have an automatic calibration scheme. To calibrate the model, we have to identify sensitive parameters based on experience in model runs and manually tune the parameters to give the best results. This process is supported by knowledge about the catchment properties. Manually calibrating the model is often tedious because it involves several trial-and-error simulations, as there can be many combinations with few sensitive parameters. One solution to this problem is to structure an automatic calibration framework for HLM. The way HLM is set up (i.e., at every hillslope), it produces a large number of parameters for a given basin, which can be computationally way too expensive to tackle for the commonly used automatic calibration algorithms. However, parameter regionalization techniques, where distributed model parameters are derived from other hydroclimatic and catchment features, can be useful in this regard.

In addition to the abovementioned challenges, we must continuously monitor an operational flood forecasting system to maintain its efficiency. Some of the undertakings necessary to achieve this are (1) frequent examinations of the sensors, (2) data management: checking and filtering the data coming into the model, (3) bug identification and fixing in the model source code, and (4) upkeeping the web interface. A dedicated team of experts is essential to accomplish these tasks. Along with that, we must constantly work to pursue the challenges of model uncertainties and *how the uncertainty in hydrologic predictions can be communicated to decision makers and the general public,* as proposed by 23 unsolved problems in hydrology (Blöschl et al., 2019). From a technical standpoint, it will be important to develop a system that translates the river stages obtained from model simulations to estimated flood depths and extends. We could think of a Python library that includes all the necessary functions for information extraction. The IFC currently has a similar library, which can be implemented for the Nebraska basins. This would help in the development of the information system for efficient communication with the public through interactive maps and other visualizations.

Water infrastructures, such as reservoirs and groundwater wells, can influence the hydrologic processes which affect the occurrence of floods (Dang et al., 2016). We have not looked into the role of water infrastructure in regulating floods in the region in this study. NeDNR, together with USACE, constructs various structures, such as dams and levees, to divert water away from areas that might cause more damage (NeDNR, 2022). It would be interesting to study how these structures impact flood mitigation.

5. Conclusions

This article presents the methodology we followed to implement a flood forecasting system prototype for a pilot basin in Nebraska. We discuss the IFIS system and our improvements to its underlying hydrologic model (HLM) to include snow processes. We set up the components of a flood forecasting system prototype which includes (1) sensors measuring stream level, (2) synthetic rating curves, (3) hydrologic model (upgraded HLM) with necessary inputs, (4) assimilation of the observed stream data into the model, and (5) web interface. We discuss the opportunities and challenges in developing a full-fledged operational flood forecasting platform. Besides, we analyzed the vulnerability of eight bridges to flood peril based on a methodology that can be expanded to other bridges.

Our results substantiate the fact that incorporating snow processes is crucial in flood forecasting in cold regions (e.g., Nebraska, in this case). This was evident in the simulation of the 2019 Spring flood, where accounting for snow processes improved the simulation of the peak flow. More specifically, the addition of our proposed snow parameterizations to the HLM showed significant improvement in predicting the 2019 March flood in the Elkhorn River basin as compared to the version of the model without snow parameterizations. Furthermore, our results also show that oftentimes simple improvements to the model structure can significantly improve the accuracy of a model. From a modeling perspective, HLM appears to be a strong candidate for the operational implementation of a flood monitoring and forecasting platform in the state of Nebraska. Findings from this work strongly support the idea of a statewide expansion of the platform and the development of an operational flood information system targeting community welfare and engagement. A platform like this will also provide policymakers with accurate information and gainful facts about flooding in a timely manner, thereby enabling more informed decision-making.

Software availability

Name of the software:	asynch (HLM-PSnow)
Developer:	Sinan Rasiya Koya, Nicolas Giron, Tirthankar Roy
Contact Information:	ssinanrk2@huskers.unl.edu
Year first available:	2022
Program language:	C
Source code availability:	https://github.com/sinanrk/asynch.git
Program size:	14.3 MB

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.

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Appendix A. Supplementary data is attached to the archive record for this article.

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