MID-AMERICA TRANSPORTATION CENTER

Report # MATC-UNL: 004-61

Final Report
WBS: 25-1121-0005-004-61

University of Nebraska Lincoln
The University of Iowa
The University of Kansas
Missouri S&T
Lincoln University Missouri
Nebraska Indian Community College
University of Nebraska Omaha
University of Nebraska Medical Center
KU Medical Center The University of Kansas

Incorporating Snow Processes in the Iowa Flood Information System (IFIS) and Evaluating its Applicability for Nebraska

Tirthankar Roy, PhD
Assistant Professor
Department of Civil and Environmental Engineering
University of Nebraska-Lincoln

Witold Krajewski, PhD
Professor
Department of Civil and Environmental Engineering
University of Iowa

Muhammed Sinan Rasiya Koya, B. Tech.
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Nebraska-Lincoln

University of Nebraska Lincoln

2023

A Cooperative Research Project sponsored by
U.S. Department of Transportation- Office of the Assistant Secretary for Research and Technology

MATC

Incorporating Snow Processes in the Iowa Flood Information System (IFIS) and Evaluating its Applicability for Nebraska

Tirthankar Roy, PhD
Assistant Professor
Civil and Environmental Engineering
University of Nebraska-Lincoln

Witold Krajewski, PhD
Professor
Civil and Environmental Engineering
University of Iowa

Muhammed Sinan Rasiya Koya, B.Tech.
Graduate Research Assistant
Civil and Environmental Engineering
University of Nebraska-Lincoln

A Report on Research Sponsored by

Mid-America Transportation Center

University of Nebraska–Lincoln

January 2023

Technical Report Documentation Page

1. Report No. 25-1121-0005-004-61	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Incorporating Snow Processes in the Iowa Flood Information System (IFIS) and Evaluating its Applicability for Nebraska		5. Report Date January 2023
		6. Performing Organization Code
7. Author(s) Tirthankar Roy, PhD ORCID: 0000-0002-6279-8447 Muhammed Sinan Rasiya Koya, B. Tech., ORCID: 0000-0001-5559-7869 Witold Krajewski, PhD ORCID: 0000-0002-3477-9281		8. Performing Organization Report No. 25-1121-0005-004-61
9. Performing Organization Name and Address Department of Civil and Environmental Engineering University of Nebraska-Lincoln 900 N 16th St Lincoln, NE 68588-0531		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. 69A3551747107
12. Sponsoring Agency Name and Address Mid-America Transportation Center Prem S. Paul Research Center at Whittier School 2200 Vine St. Lincoln, NE 68583-0851		13. Type of Report and Period Covered Final Report July 2020 – November 2022
		14. Sponsoring Agency Code MATC TRB RiP No. 91994-64
15. Supplementary Notes		

16. 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 Forecasting 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 accumulation) through simple parameterizations. Results show that the more thorough treatment of snow processes in the hydrologic model, as proposed herein, the better the performance of 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.

17. Key Words Flooding, Transportation Safety, Snow Hydrology, Iowa Flood Information System, Hillslope Link Model		18. Distribution Statement	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 45	22. Price

Table of Contents

List of Figures

List of Tables

List of Abbreviations (optional)

Mid-America Transportation Center (MATC)
Nebraska Transportation Center (NTC)

Acknowledgements

Other Contributors to this research and report include: Nicolas Velasquez (University of Iowa), Marcela Rojas (University of Iowa), Ricardo Mantilla (University of Iowa, now at University of Manitoba), Kirk Harvey (Nebraska Department of Transportation), Daniel Ceynar (University of Iowa), and Felipe Quintero (University of Iowa).

Disclaimer

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 Forecasting 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 accumulation) through simple parameterizations. Results show that the more thorough treatment of snow processes in the hydrologic model, as proposed herein, the better the performance of 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.

Chapter 1 Introduction

The Midwest region shows substantial spatial heterogeneity in flood peaks with discrete seasonality (Villarini et al., 2011). Nebraska has distinct hydrological and hydroclimatic characteristics, which show sharp seasonal peaks in flood frequencies. One remarkable feature of The Great Plains of Nebraska is the summer maximum rainfall (Y. Zhang et al., 2001). These storms originating from the Rocky Mountains and traveling across Midwest US and causing heavy precipitation from May to July over Nebraska, are responsible for some of the major floods in the Great Plains . 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).

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 (Budikova et al., 2010; Changnon & Kunkel, 2006; Junker et al., 1999). These storms caused the disastrous flood in 1993 in the Midwest (Kunkel K. E., Changnon S.A., 1994), significantly impacting Nebraska. A similar anomalous total rainfall of 400 mm, along with high surface soil moisture and antecedent conditions, resulted in the flood of 2008 and massive damage (Budikova et al., 2010). Besides these, there is a link between the tornadic system of thunderstorms and the climatology of floods in the Great Plains of Nebraska (Y. 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, the states of Nebraska, Iowa, and South Dakota witnessed a historic flood which was the first of its kind in many ways. Eastern Nebraska, western Iowa, and southeastern South Dakota got shallow temperatures and a historic high snowfall during the early days of 2019, resulting in a large amount of snow water equivalent of 30-100 mm by March.

During the same period, this region had frozen rivers and ground with 60-90 mm frost depth, preventing the usual infiltration. 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).

The United States Geological Survey (USGS) has characterized both the 1993 and 2008 floods as “500-year floods” (Dirmeyer & Kinter, 2009). These floods had an enormous impact on the economy, health, and livelihood of Nebraska. The 1993 flood in the Midwest is regarded as the costliest flood during the 20th century in the entire United States (Perry, 2000). The 1993 flood impacted the economy of the Midwest, including Nebraska. There were significant changes in the unemployment rate after the flood event in 1993 (Xiao et al., 2013). During this event, many counties had substantial damage, greater than five million in residential damage. Besides, the 1993 flood induced some significant interruptions in the local market, which can be linked to the unemployment rate during this time (Xiao et al., 2013).

Though the 2008 flood was comparatively less disastrous than 1993 overall, it created a significant economic loss in the Midwest counties, which were more vulnerable in 2008. As a result of the 2008 flood, these counties, on average, had financial losses of more than two million dollars in property damage. There were eight counties in the Midwest with more than fifty million dollars in property damage (Xiao et al., 2013). In March 2019, quick flooding caused by rain-on-snow and frozen ground happened, leading to devastating losses. As of August 2019 estimates, this flooding cost has reached more than three billion dollars. Along with that, some lives were lost, cattle were stranded, and significant damage occurred to infrastructures such as dams, levees, bridges, and roads after this extreme event (Flanagan et al., 2019).

Currently, the Nebraska Department of Natural Resources (NeDNR) and the US Army Corps of Engineers (USACE) monitor the incoming precipitations, carry out hydrological modeling, and examine the variations in streamflow. NeDNR provides information regarding present flood conditions in Nebraska through various flood maps. NeDNR's Floodplain Interactive Map is an interactive interface that dispenses knowledge about floodplains and management. 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. Besides FEMANFHL, NeDNR utilizes the service of USGS real-time flows and NOAA flood stage maps to monitor flood conditions in Nebraska. NeDNR takes care of flood hazard mitigation in the state to reduce the risk and severity caused by flooding. Above mentioned services come under non-structural flood mitigation, where these agencies inform and change how people interact with flood-prone areas. Along with that, flood mitigations include structural mitigation to divert water away from areas that might cause more damage. For this, NeDNR, together with USACE, construct various structures such as dams and levees.

National Water Model (NWM) forecasts streamflow around 4000 locations in the continental United States (CONUS) and guides millions of sites that lack traditional stream forecast (Office of Water Prediction, 2022). National Center for Atmospheric Research's (NCAR) Weather Research and Forecasting hydrological model (WRFHYDRO) 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 & Dugger, 2016).

Besides NeDNR, other agencies such as USACE, FEAM, Nebraska Emergency Management Agency (NEMA), Nebraska Department of Roads (NDOR), and National Flood Insurance

Program (NFIP) help in developing and interpreting flood and flood plain data as a part of their Floodplain Management Services.

One of the significant drawbacks of the flood forecasting systems of the agencies mentioned above is that they have a more extended delay in the forecast. This often causes a shorter lead time in giving flood warnings to the community. Also, most of these 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, most of the underlying models of these systems do not consider snow processes, while the runoff generation in Midwestern basins is highly affected by snow accumulation. This often leads to an inaccurate flood prediction.

Flood monitoring with hydrological modeling and forecasting is a pivotal research area in Hydrology and Water Resource Engineering. Across the world, numerous hydrological models have been developed and applied at an operational level for flood forecasting. These models include data-driven models, lumped models, distributed conceptual models, and physically based models. All these models are regularly studied and improved for better realization of flood events.

Data-driven models, leveraging machine learning and statistical approaches, try to generate streamflow forecasts from different variables based on their statistical relationship. These predictor variables often include precipitation, temperature, potential evapotranspiration, humidity, pressure, windspeed, etc., but it is not necessary to have more predictor variables all the time. The advantages of data-driven models are that they are easy to set up and have minimum requirements for input data. Besides that, these models often produce excellent streamflow estimates and outperform other conceptual or physically based models (Piotrowski et al., 2006; Sahoo & Ray, 2006). Many of the earlier hydrological models were conceptual hydrological models. These models conceptualize the watershed as different storage layers and estimate the water flow through each layer, keeping the water balance consistent. Leaky bucket models are classic examples of conceptual models. These models come in lumped and distributed manners. These conceptual models must be calibrated with existing data to find the best parameters for each basin. Physically based models try to represent the actual physical processes in a watershed with existing parameterizations. Noah-MP (Niu et al., 2011) is a popular physically based model widely used in hydrology research. One of the significant disadvantages of conceptual and physically based models is their data requirements. They vary based on the complexity of these models. Hydrologists often have difficulty finding all the required data to run these models.

There exist several state-of-the-art flood forecasting systems around the world. Table 1.1 provides details of some well-known operational flood forecasting systems. The details are taken from (Emerton et al., 2016) and (Kauffeldt et al., 2016).

Table 1.1 Operational large-scale flood forecasting systems

Forecasting System	**Domain**	**Forecast Frequency**	**Rainfall Runoff Model**	**Spatial Resolution**
EFAS (European Flood Awareness System)	Europe	12-h	Lisflood Europe	5 km, Regular grid
E-HYPE (European Hydrological Predictions for the Environment)	Europe	Daily	HYPE	~15 km, Irregular grid, varies by Basin
FFWS (Flood Forecasting &Warning Service)	Australia	6–12-h	GR4J (daily), GR4H (hourly), URBS	~10 km
HEFS (Hydrologic Ensemble Forecast Service)	USA	Sub-daily to daily	Suite of Models	Varies by Basin
GloFAS (Global Flood Awareness System)	Global	Daily	HTESSEL	10 km, Regular grid
GLOFFIS (Global Flood Forecasting Information System)	Global	6-h	PCR-GLOBWB, W3RA	10 km, 50 km, Regular grid
VIC with Global Flood Monitoring System (GFMS)	Global	3-h	Dominant river tracing Routing Integrated with VIC Environment (DRIVE) model	~12km
NWM (National Water Model) - Experimental	USA	1-h	Weather Research Forecasting Hydro (WRF-Hydro)	1km and 250m grids

Iowa Flood Information System (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). IFIS is developed and maintained by the Iowa Flood Center (IFC) at the University of Iowa. IFIS's operation is supported by a conceptual rainfall-runoff model called Hillslope Link Model (HLM). 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). To solve these tree-structured ODEs, we use the Asynch solver.

A critical strength of the IFIS system is the lead time in flood forecasting. 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 1.1.

Presently, the HLM does not incorporate any snow processes in its system. Though we can provide SWE as an external variable, HLM 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. This led to a failure of delivering an early alert to the communities. Snow has a substantial role in the hydrology of catchments in the Midwest. This region receives significant snow during winter. Snow accumulation Field 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 Hillslope Link Model 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 Iowa Flood Center, 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 the simulated hydrograph anywhere in the basin.

Chapter 2 Materials and Methods

2.1 Data

2.1.1 NLDAS-2

For the preliminary validation of the proposed parameterization of the snow process, which is newly added to the Hillslope Link Model (HLM) structure, we used North American Land Data Assimilation System (NLDAS-2) precipitation and temperature forcing. NLDAS is a multi-institutional partnership project created to develop land-surface model datasets with quality control consistent across space and time from observations and reanalysis (Mitchell et al., 2004). NLDAS data consists of hourly surface forcing in a gridded format with a spatial resolution of 0.125 ° x 0.125 °. NLDAS-2 is an improved version of NLDAS that determines and improves existing errors in forcing data and models (Xia et al., 2012). These improvements include changes in forcing data sources and their inherent biases, upgrading the model and recalibrating its parameters, and an increased period of forcing data and simulations (Xia et al., 2012). NLDAS-2 data provides thirteen forcing variables, including precipitation, temperature, radiation fluxes, potential evapotranspiration, pressure, specific humidity, and ground wind speeds. For this study, we use precipitation and temperature data from 2015 to 2020. Data is obtained for the entirety of Nebraska and then extracted for two specific locations. While the temporal resolution of data is hourly, it is later aggregated into a daily resolution for running the prototype model.

2.1.2 NSIDC

To validate the proposed snow parameterization, we acquired SWE data from "Daily 4 km Gridded SWE and Snow Depth from Assimilated In-Situ and Modeled Data over the Conterminous US, 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 information at a spatial resolution of 4km x 4km for the conterminous United States (CONUS). The SWE data collected is for the same period as the simulation (2015-2020) and re-gridded through linear interpolation to match the resolution of NLDAS-2 forcing data.

2.1.3 MRMS-QPE

We used Multi-Radar Multi-Sensor Quantitative Precipitation Estimate (MRMS-QPE) of the HLM model for precipitation forcing. MRMS-QPE is a completely systematized dataset that combines information from multiple sensors and radars, numerical weather prediction (NWP) models, surface and satellite observations, and precipitation climatology across the nation to integrate into a gridded dataset of high spatial and temporal resolution. MRMS-QPE products have an update cycle of as low as two minutes and a latency of around 1.5 hours, making them suitable for operational flood forecasting systems (J. Zhang et al., 2016). The 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 US utilizes MRMS-QPE products to monitor flood conditions (J. Zhang et al., 2016).

2.1.4 USGS

We used the observed data obtained from USGS stations to evaluate the model performance. There are eight USGS stations in the Elkhorn River basin for which we had 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. We also used the USGS observed data to update the river stages in our retrospective flood forecasting model for 2019.

2.1.5 IFC Sensors

The Iowa Flood Center has advanced streamflow gauging sensors, which automatically collect the stream level data and transfer it to the Iowa Flood Information System (IFIS) every 15 minutes. These sensors, mounted to the bridge side, emit sonar signals toward the stream and measure the distance from the sensor to the water level. From this information, we can measure the river stage, and with the help of the rating curve, we can estimate flow at these locations. This data can be later assimilated into the flood modeling system to correct the river stages. We installed eight sensors across the Elkhorn River basin, which were already functional. Figure 2.1 shows the locations of installed sensors 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.

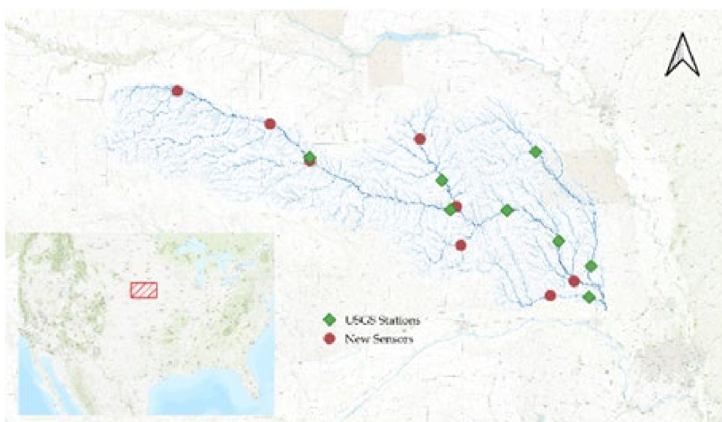

Figure 2.1 Sensor installation locations

Table 2.1 List of datasets used

Variable	Dataset	Resolution	Time period	Citation
Precipitation	MRMS	1 km x 1 km	2018-19, Hourly	J. Zhang et al., 2016
Temperature	NLDAS 2	0.125 ° x 0.125 °	2018-19, Hourly	Xia et al., 2012
SWE	NSIDC	4 km x 4 km	2018-19, Hourly	Broxton et al., 2019
Streamflow	USGS	Point data	2018-19, Hourly	USGS

2.2 IFIS System

After the disastrous flood of 2008, the Iowa Flood Center (IFC) was established with one primary aim being to develop 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 the state of Iowa that works based on the Hillslope Link Model (HLM) and can make predictions every fifteen minutes for nearly 2000 locations (Krajewski et al., 2017). Later, IFC developed the Iowa Flood Information System (IFIS), a web-based platform to provide real-time flood information to the communities of Iowa. IFIS provides services that include flood inundation maps, real-time flood conditions, flood forecasts, flood-related data, applications, information, and visualizations (Demir & Krajewski, 2013).

The current operational real-time flood monitoring system relies on the Hillslope Link Model (HLM; Figure 2.2; Table 2.2). 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 Figure 2.3a. Equations 2.1, 2.2 and 2.3 represent a change of storage with respect to time in each layer of a hillslope. These hillslopes are connected in a tree-structured format where water from each hillslope combines 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.

$$\frac{dS_p}{dt} = P(t) - q_{pL} - q_{pT} - e_p \tag{2.1}$$

$$\frac{dS_T}{dt} = q_{pT} - q_{Ts} - e_s \tag{2.2}$$

$$\frac{dS_s}{dt} = q_{Ts} - q_{sL} - e_s \tag{2.3}$$

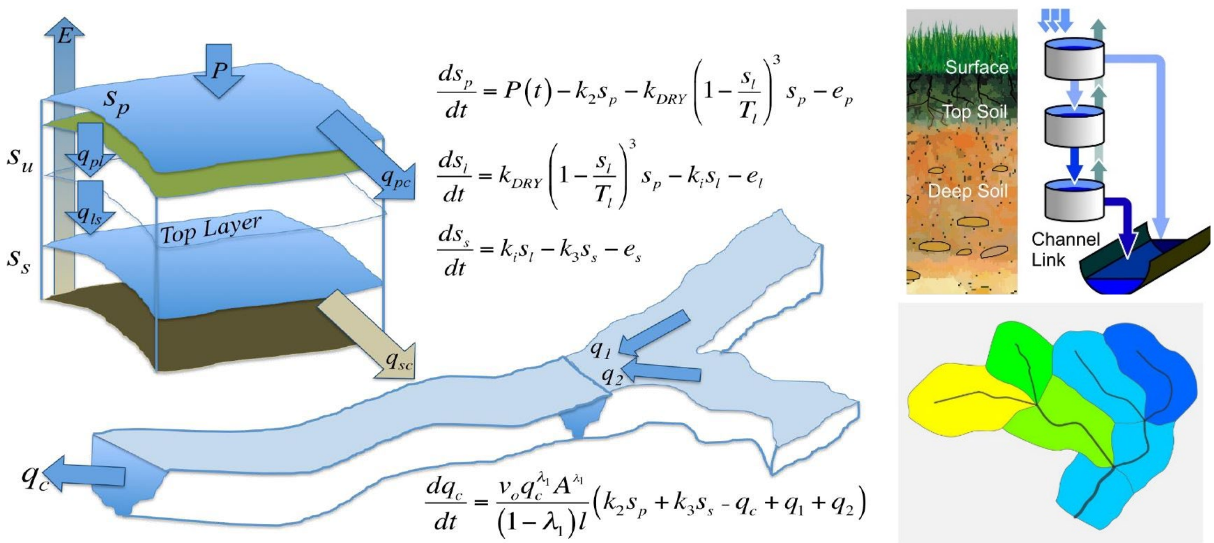

Figure 2.2 Schematic figure of HLM

Table 2.2 Parameters in HLM

Variable	**Name**
P	Precipitation
S_p	Storage in the first layer
S_l	Storage in the second layer
S_s	Storage in the third layer
e	Evapotranspiration
T_l	Size of top layer storage
A	Sum of the areas for all upstream links
L	Length of link i
V_o	Reference flow velocity
λ_1	Exponent for flow velocity discharge
λ_2	Exponent for flow velocity upstream area
q	Discharge
K_2, K_{dry}, K_3	Constants

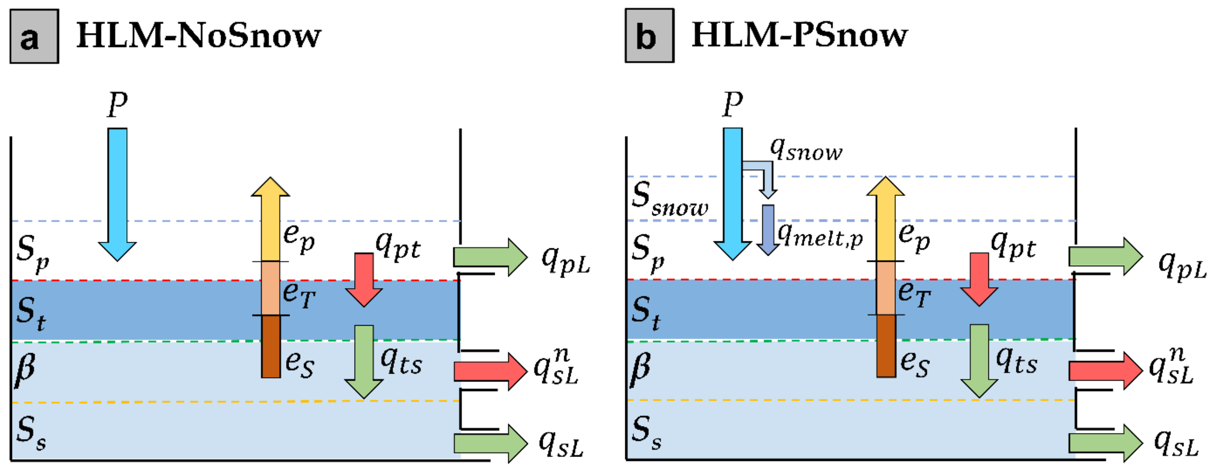

Figure 2.3 Schematic representation of different models

2.3 Improvements to the HLM Model

HLM-PSnow is an updated conceptual model structure for HLM that includes snow processes. In this upgrade, there are two major components added to the system: 1) rain-snow partitioning (RSP) schemes and 2) a new storage layer of snow water equivalent (Figure 2.4).

2.3.1 Rain-Snow Partitioning

This model adds 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 (shown in Figure. 2.5). 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.

2.3.2 Parameterizing Snow Accumulation

The new storage layer (Ssnow) is conceptually located above the ponding layer (Sp) in the earlier version of HLM (HLM-NoSnow). This new layer stores the accumulated snow, and the change in Snow Water Equivalent (SWE) with respect to time is given as the incoming snow subtracted by outgoing melt water and snow evaporation, as represented using equation 2.4. The amount of meltwater is calculated using a simple degree day factor (DDF) model (Martinec, 1975) as described in equation 2.5, where D 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 (Prain) and snow (Psnow), the amount of snow is added to this layer, and rain is directly entered into the ponding layer. That means, instead of the precipitation term in the current version of HLM, it is replaced by just the rainfall share from rain-snow partitioning. Also, 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 2.6. 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 Hillslope Link Model can now simulate SWE as a new output variable, which can be used to further study the role of snow in the hydrology and water resources of the region. A previous update in the HLM considered including SWE as an external forcing (HLM-FSnow).

$$\frac{dS_{SWE}}{dt} = P_{snow} - q_{melt,p} - e_{snow} \tag{2.4}$$

$$q_{melt,p} = \min(D \cdot T(t), S_{SWE}) \tag{2.5}$$

$$\frac{dS_p}{dt} = P_{rain} - q_{pL} - q_{pT} + q_{melt,p} - e_p \tag{2.6}$$

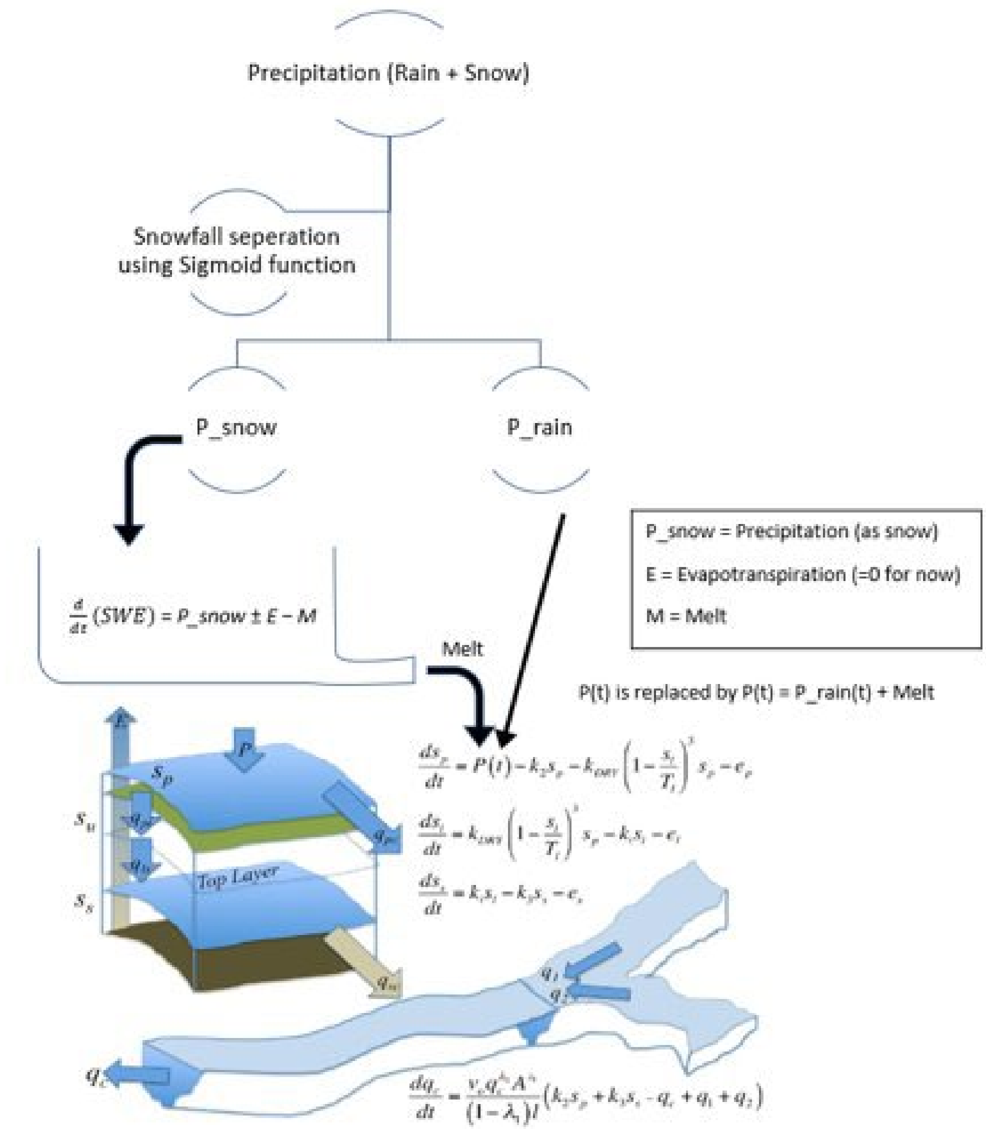

Figure 2.4 Schematic diagram of adding snow parametrization

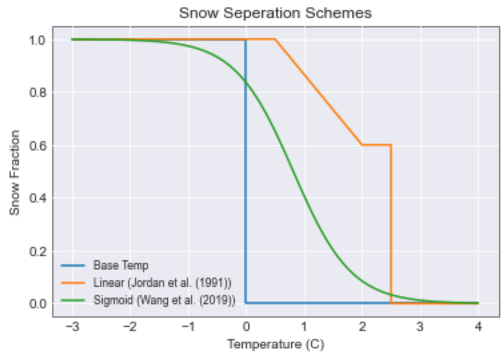

Figure 2.5 Rain Snow Partitioning (RSP) schemes used in the new modeling framework

2.3.3 Initial Validation of New Parameterization

To validate the above-proposed improvements to the current structure of the Hillslope Link Model, we developed a prototype system of new ODEs in MATLAB. This prototype code represents the vertical water flow in a single hillslope. By solving this system of ODEs using the ode45 solver from MATLAB, we could obtain preliminary results of patterns of water in each storage layer, including the snow-water equivalent from the newly added layer.

2.4 Implementation of the Improved Prototype

Figure 2.6 shows the steps in the implementation of the improved prototype.

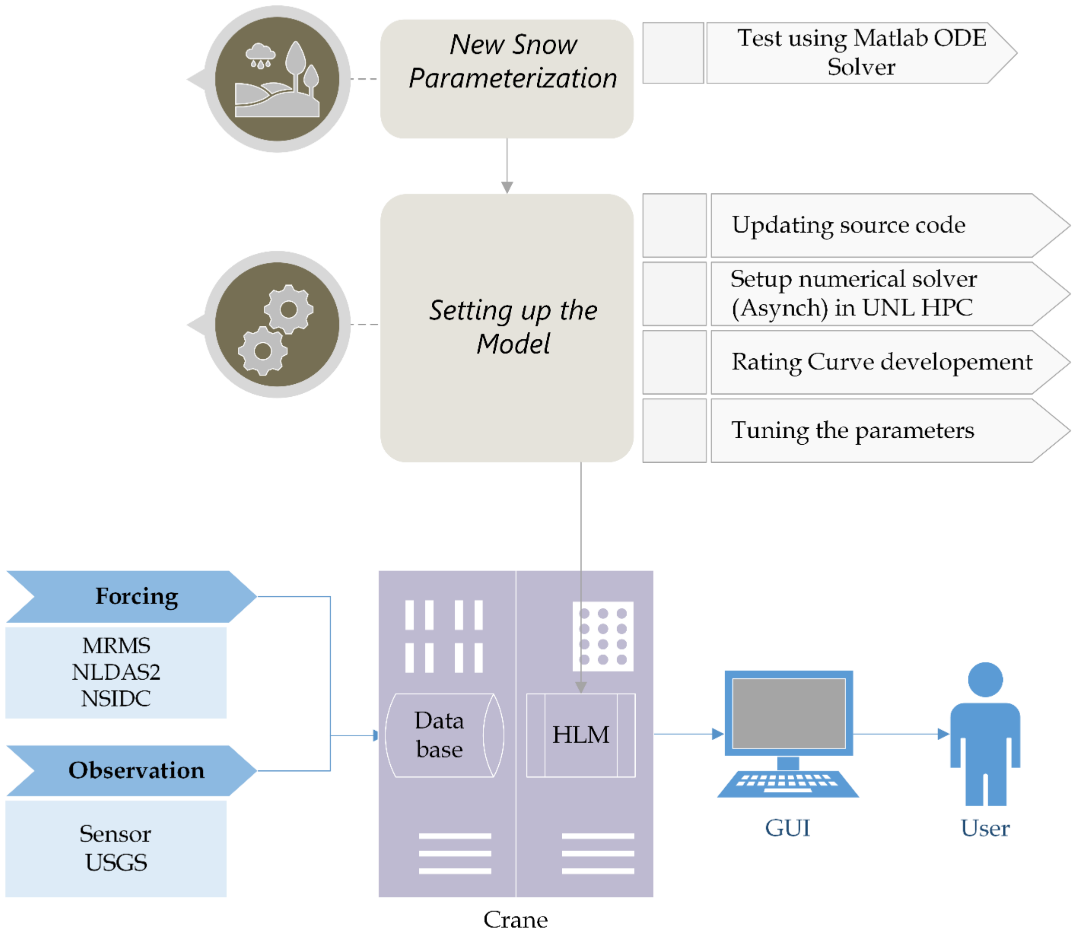

Figure 2.6 Flow chart showing the implementation of the Prototype flood forecasting system

2.4.1 Implementation in UNL HPC

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 introduced a new simple parameterization, as discussed in section 2.3. Initially, we tested this new set of ODEs using MATLAB ODE solvers. 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 in the Holland Computing Center at the University of Nebraska-Lincoln. The required forcings are made available in Crane. 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. We ran the model for 2018 with calibrated parameters to be used as the initial condition for the 2019 simulation. Running the simulation by separating different batches of time would save a significant amount of time as it avoids running dry hillslopes.

2.4.2 PostgreSQL Database

Next, we created a PostgreSQL (Stonebraker & Rowe, 1986) database to insert observed discharge measurements from USGS stations and the newly installed sensors. This database updated the model-simulated river stages with observations.

2.4.3 Rating Curve Development

The Iowa Flood Center (IFC) developed and installed eight Bridge-Mounted River Stage Sensors (BMRSS) in different locations of the Elkhorn River basin (section 2.1). These sensors can measure the water level elevation of the river in these locations. To convert these into streamflow data, we used rating curves. The IFC developed one-dimensional (1D) hydraulic models for every location where sensors were installed to obtain a stage discharge relationship.

The IFC developed a methodology to obtain a stage-discharge relationship using the step backwater model from the Hydrologic Engineer Center's River Analysis System (HECRAS) (Quintero et al., 2021). 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. The uncertainty for Manning's roughness coefficient is not available because this parameter is not directly measured but assessed through visual comparison of previous studies (Arcement & 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).

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). Figure 2.7 shows, in green, the cross sections surveyed for each site, and table 2.3 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. The Manning's coefficient range was set to between 0.03 and 0.045, which is used in the channel sections of the step-backwater HEC-RAS 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 Nebraska Department of Natural Resources (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; US Army Corps of Engineers, 2010) (fig. 2.8).

Figure 2.7 Arial view of sensor installation sites and cross sections surveyed for rating curve development.

Table 2.3 Design Discharge (cfs)

Site	Equation	Q2	Q10	Q25	Q50	Q100	Q500
S020 27627	Beckman	411	1,350	2,201	3,121	4,268	7,682
S020 31087	Drainage Area Comparison	2,179	6,848	9,961	12,607	15,565	23,347
S020 36393	Strahm/Admiraal	1,454	4,148	6,292	8,496	10,622	17,213
S032 03971	Cordes/Hotchkiss	1,680	6,754	N/A	16,093	21,987	42,516
S275 13258	USACE Hydrologic Study	5,200	19,500	30,100	44,100	49,400	78,500
S275 07714	Strahm/Admiraal	3,637	9,499	13,874	18,287	22,293	33,879
S275 02146	Strahm/Admiraal	1,000	3,000	4,800	6,750	8,800	15,700
S079 05122	Strahm/Admiraal	3,807	9,810	14,407	19,095	23,534	36,599

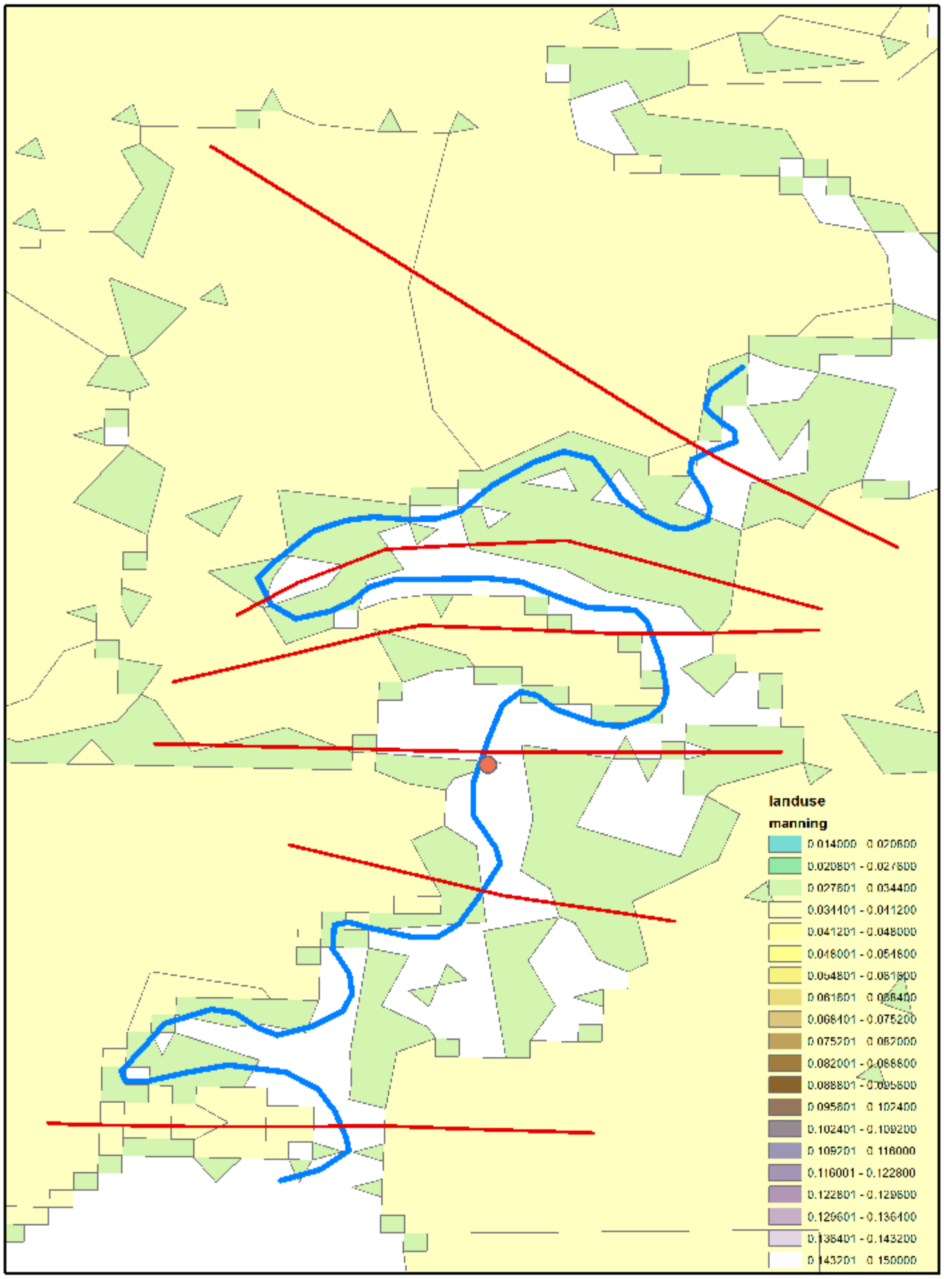

Figure 2.8 Land Use Map – Floodplain Manning's roughness values.

2.4.4 Setting Up the Forcing Files

We downloaded the MRMS data from archives of Iowa Environmental MESONET of Iowa State University. These files were initially in gridded format, which we later cropped for the Elkhorn region and converted to binary file format in the Holland Computing Center HPC. These binary files are the fastest way for the model to read the forcing data. Since the intention is 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. Within this, 2018 is considered a spin-up time for the model. A PostgreSQL database consisted of observed streamflow measurements from USGS, from which the model streamflow stages were regularly updated. This process automatically replaces the model-produced values with observed values at these locations.

2.4.5 ASYNCH Solver

The Hillslope Link Model 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 Iowa Flood Center (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, evapotranspiration, and temperature, can be transferred through several file formats as well as taken from a Structured Query Language (SQL) database. Similarly, outputs can be produced and displayed in different formats to use them for studies.

2.4.6 Web Interface

In the present world, web interfaces are the most viable way of providing information to the public. We developed a simple web interface 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). Figure 2.9 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.

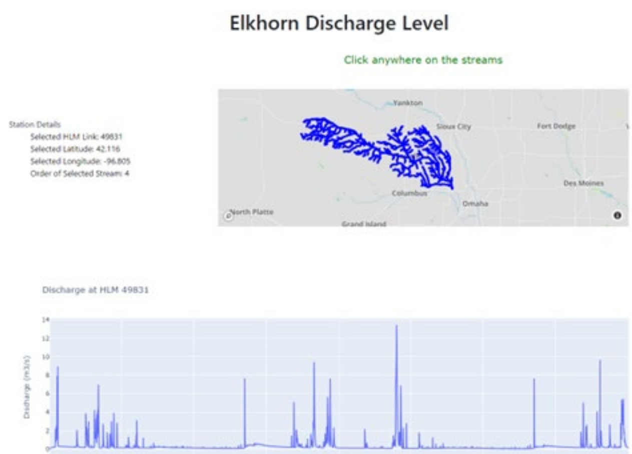

Figure 2.9 Screenshot of web interface for flow stages across the Elkhorn basin.

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 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 uniform storm files (.ustr) 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.

Chapter 3 Results

3.1 Initial Tests

From the prototype system of ODEs created in MATLAB for initial validation, with an additional storage layer for snow, we obtained the simulated SWE. Figure 3.1 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. Figure 3.1b 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.

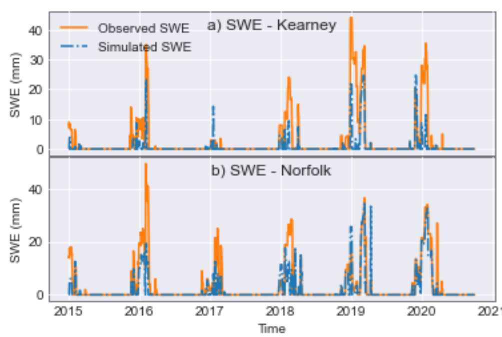

Figure 3.1 Comparison of SWE output from prototype system of HLM ordinary differential equations. a) grid near Kearney and b) grid near Norfolk.

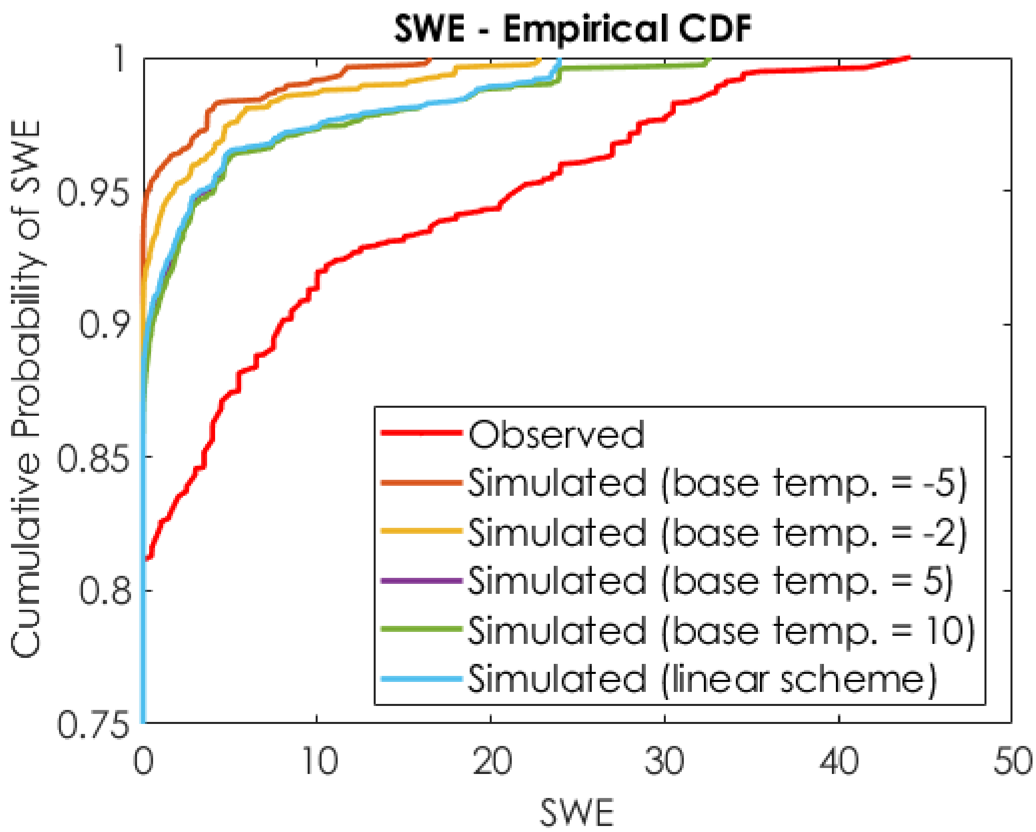

Figure 3.2 Cumulative Probability of SWE

3.2 Retrospective Flood Forecasting

We simulated the hydrographs for 2019, as the historic flood during March was our point of interest (Flanagan et al., 2019), using the Hillslope Link Model and a new version of the model that includes 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. Figure 3.3 shows that the HLM without snow could not capture the peak flow at any 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.

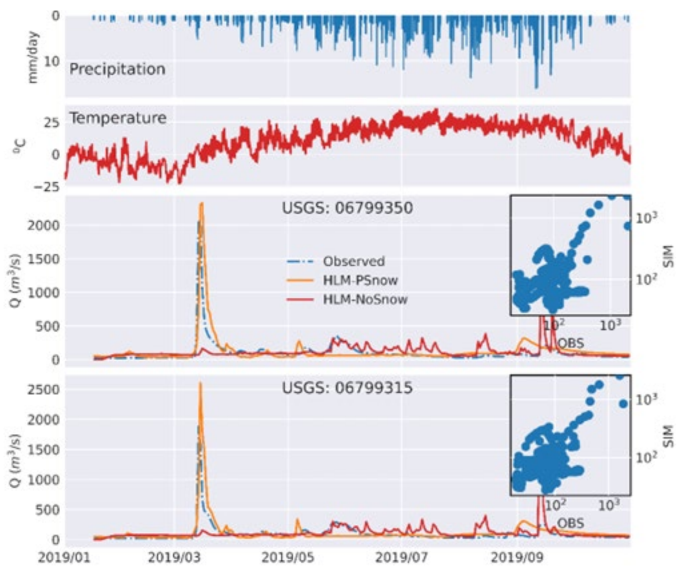

Figure 3.3 Simulated hydrographs from HLM with and without snow. The forcings used are on the top left. The scatter plot comparing observed and simulated discharges is on the right.

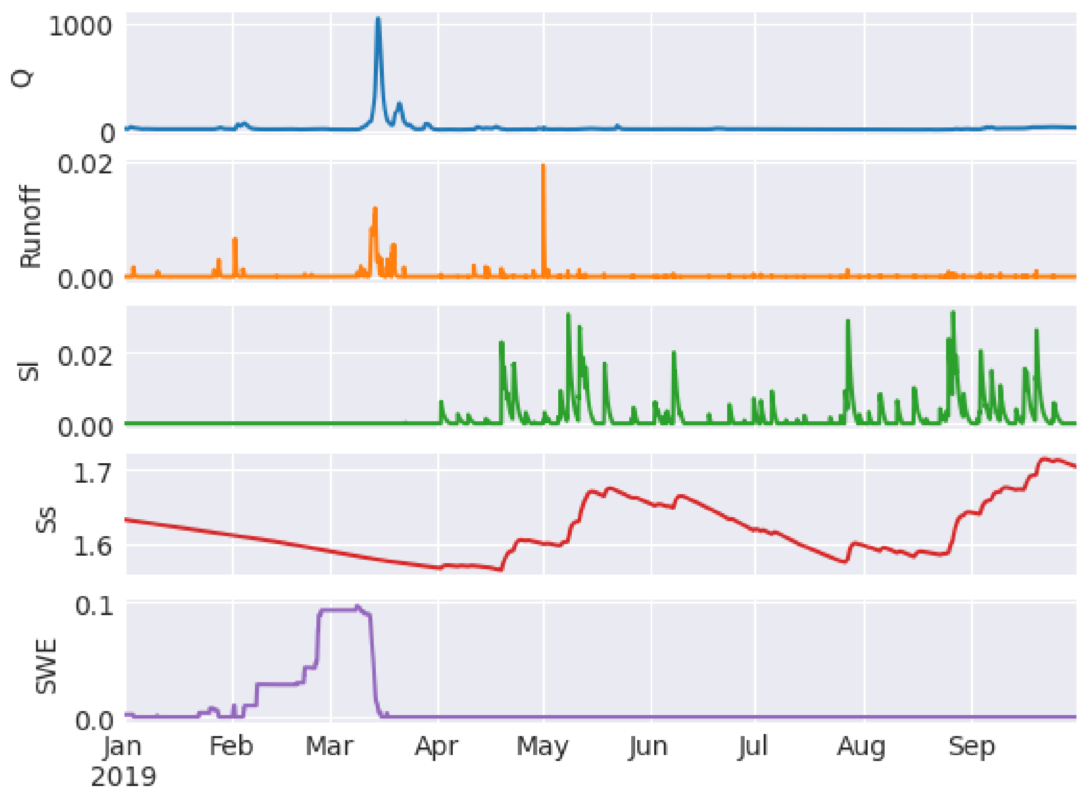

Figure 3.4 State variables in one of the link in HLM setup for Elkhorn

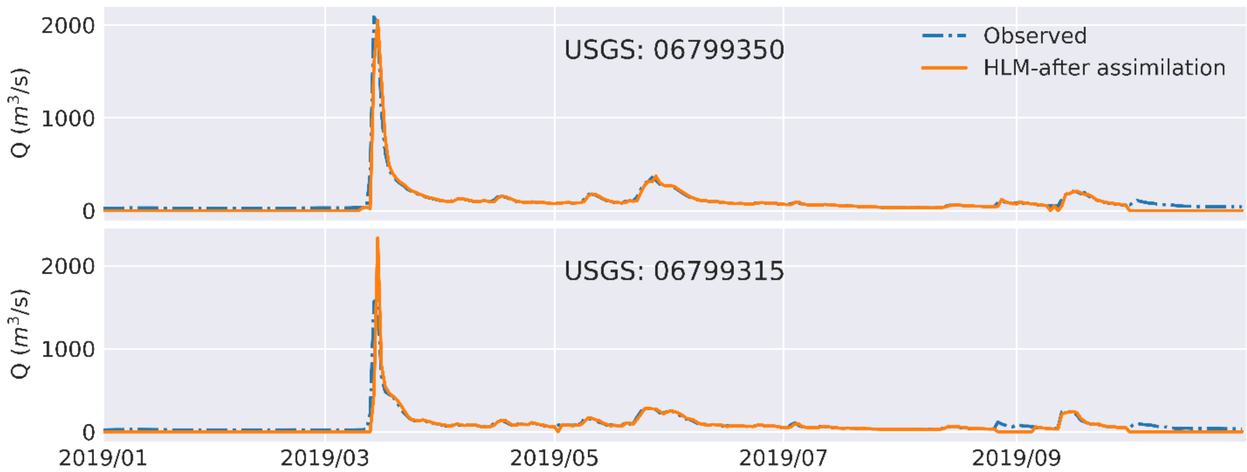

Figure 3.5 Simulated hydrographs at locations after assimilating discharge measurements.

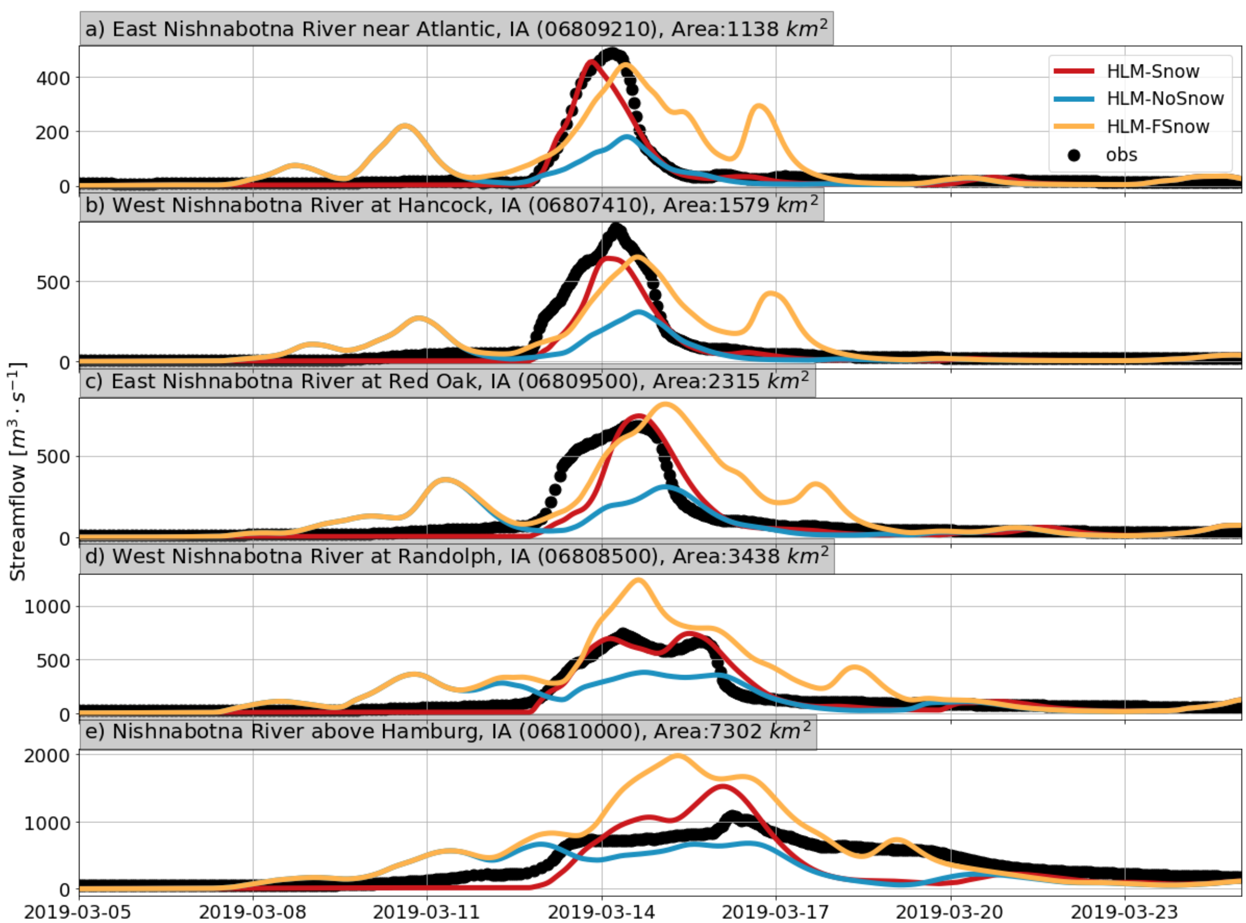

Figure 3.6 HLM flow simulations (color lines) and USGS gauges flow observations (black dots) during the flood of March 2019. Blue lines correspond to HLM-no-snow, yellow to HLM-F-snow and red to HLM-Snow.

3.3 Bridge Vulnerability

Figure 3.7 shows the plot between 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. Results showed the bridge near Stuart, NE, is the most vulnerable to flood disasters, whereas the bridge near Norfolk, NE, is the least vulnerable.

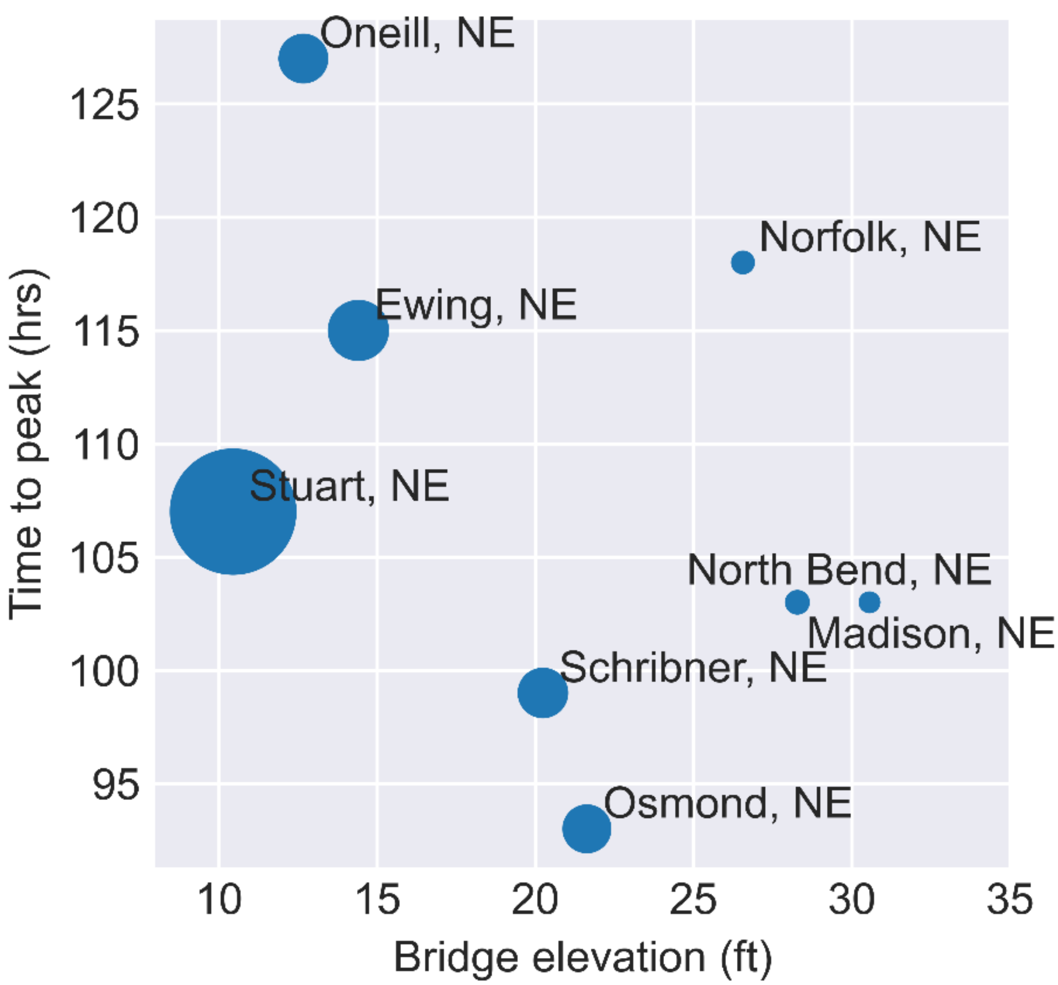

Figure 3.7 Different exposure levels of the eight bridges across the Elkhorn basin. The larger the circle, the large the vulnerability of the bridge.

3.4 Rating Curves

Figure 3.8 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.

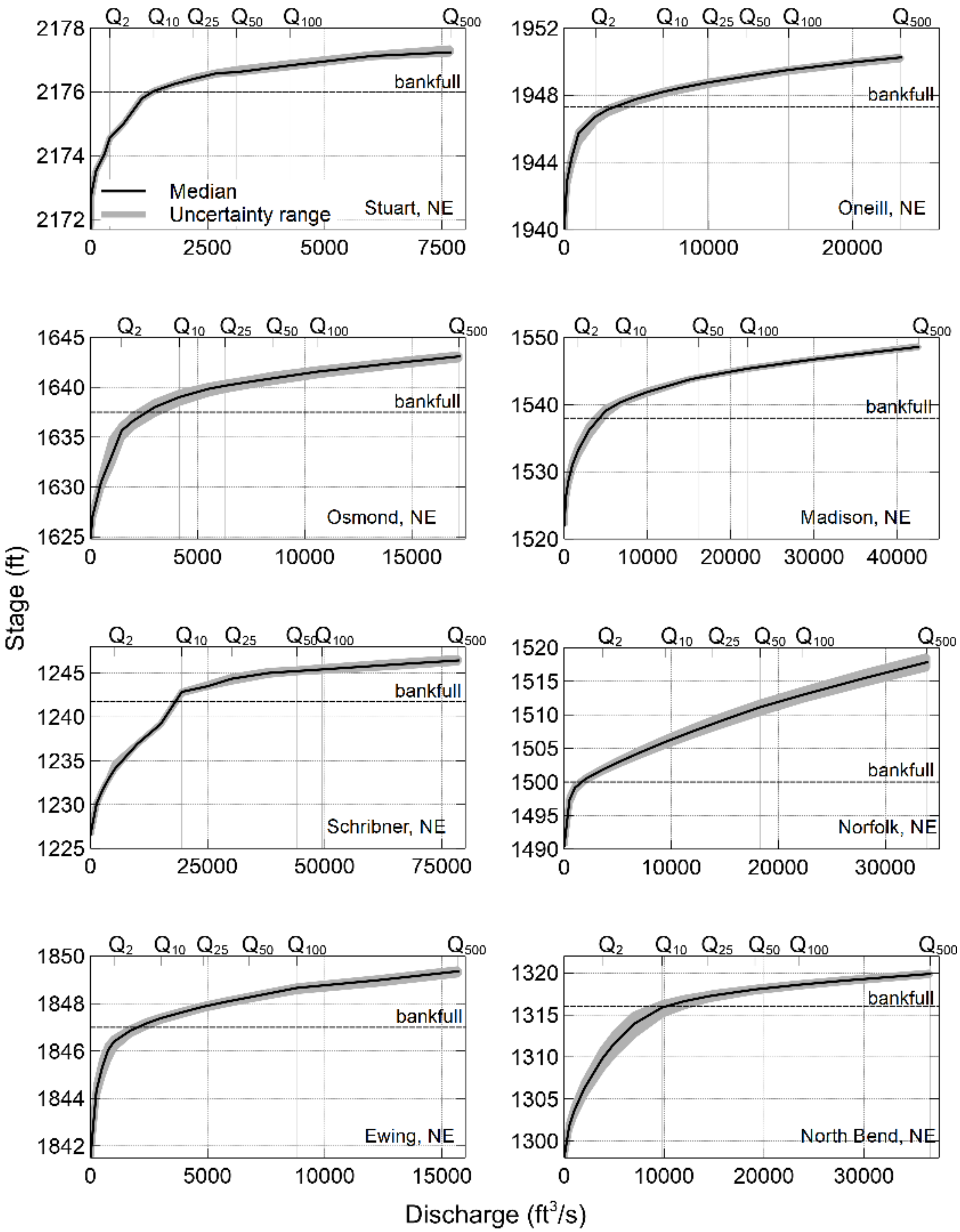

Figure 3.8 Synthetic Rating Curves

Chapter 4 Discussion

This study has investigated the potential of a real-time flood forecasting system for Elkhorn, a pilot basin in Nebraska. We found that improving HLM with snow parameterization would be a good candidate. We have implemented the asynch solver along with HLM source codes in the University of Nebraska-Lincoln's high-performance computer. While this can serve as a hydrological model to simulate river discharge, it requires further work to apply as an operational real-time flood forecasting system.

Firstly, 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), the ability to model across the basin, combining the observed discharge data from the sensors, and updating a user interface to disseminate the flood information to the people in need in a timely manner. The most critical and challenging task is to make all these components simultaneously run smoothly and seamlessly in an automatic manner.

Secondly, the model should integrate real-time forcing data with a minimum possible lag time. Many possible datasets could be utilized, such as Multi-Radar/Multi-Sensor Quantitative Precipitation Estimation (MRMS-QPE) rainfall products with lower latency. Lower latency means we can predict an imminent flood earlier, which helps deliver an efficient, early warning.

Establishing an operational flood forecasting system comes with multiple challenges, one being the efficient integration of all components in the flood forecasting system. This involves running the model, collecting and assimilating data, and circulating the information. For such a task to accomplish, we need more experts from the fields of hydrology, water resource engineering, and computer 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 interfaces. In Nebraska, the Holland Computing Center (HCC) at the University of Nebraska-Lincoln can greatly assist a future full-fledged flood forecasting system.

Another big challenge in realizing an operational flood forecasting system is calibrating the model for all basins in the state. The Hillslope Link Model currently does not have an automatic calibrating system. 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. There are multiple methods available in the literature for automatic model calibration. For example, the Shuffle Complex Evolution (Vrugt et al., 2003) algorithm has been successfully integrated with the HYMOD2 (Roy et al., 2017) model. Combining such a framework with HLM itself would comprise a separate project.

In addition to the abovementioned challenges, we must continuously monitor an operational flood forecasting system to maintain efficiency. Some of the undertakings necessary to achieve this are 1) we have to frequently examine the functioning of sensors, 2) data management: check and filter the data coming into the model, 3) Bug identification and fixes in the model source code, and 4) Upkeeping the web interface. A dedicated team of experts is essential to accomplish these tasks.

Besides the above-stated future goals, we also need to develop a system that translates the river stages obtained from model simulations to estimated and extended flood depths. We could think of a python library that includes all the necessary functions for information extraction.

Iowa Flood Center currently has a similar library developed by them. This would help with keeping efficient communication with the public by including all necessary information about the flood.

Chapter 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 hydrological model (HLM) to include snow processes. We discuss the opportunities and challenges in developing a full-fledged operational flood forecasting platform. Besides, we analyze 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 for 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, which is also supported by the literature (Mai et al., 2022; Roy et al., 2017a). 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.

Chapter 6 Disseminations

Peer-reviewed Journals

- Rasiya Koya, S., Velasquez, N., Mantilla, R. I., Rojas, M., Harvey, K., Ceynar, D., Krajewski, W. F., & Roy, T. (2022) . A Prototype Flood Forecasting System for Nebraska Watersheds. *Environmental Modelling & Software (under review).*
- Velasquez, N., Quintero, F., Rasiya Koya, S., Roy, T. & Mantilla, R. I., (2022) . Application of HLM-Snow to assess the flood of spring 2019 in Western Iowa*. Journal of Hydrology: Regional Studies (under review).*

Conference Presentations

- Rasiya Koya, S., N. V. Giron, R. Mantilla, M. Rojas, K. Harvey, D. Ceynar, W. F. Krajewski, and T. Roy (2021), Development of a Flood Monitoring System Prototype for a Pilot Basin in Nebraska, *AGU Fall Meeting*, Dec 13-17, New Orleans.
- Rasiya Koya, S. and T. Roy (2022), Incorporating Snow Processes in the Iowa Flood Information System (IFIS) and Evaluating its Applicability to Nebraska, *Student Research Days*, UNL, Lincoln.

Seminar Presentations

- Rasiya Koya, S. (2022), Flood Prediction in Nebraska: Comparison of Machine Learning Models and Conceptual Hydrological Model, *UNL Graduate Student Symposium*, Feb 25, Lincoln.
- Rasiya Koya, S. (2022, March 4). Research Towards an Integrated Flood Information System for Nebraska [PowerPoint slides]. *Environmental and Water Resources Engineering Seminar Series*, University of Nebraska-Lincoln.

References

Arcement, G. J., & Schneider, V. R. (1984). Guide for Selecting Manning 's Roughness Coefficients for Natural Channels and Flood Plains. United States Geological Survey Water-Supply Paper 2339.

Barnes, H. H. (1969). Roughness characteristics of natural channels. Journal of Hydrology.

Bray, D. I. (1979). Estimating average velocity in gravel-bed rivers, (Alberta). Journal of the Hydraulics Division, ASCE, 105(HY9, Proc.Paper, 14810).

Broxton, P., Zeng, X., & Dawson, N. (2019). Daily 4 km gridded SWE and snow depth from assimilated in-situ and modeled data over the conterminous US, version 1. NASA National Snow and Ice Data Center Distributed Active Archive Center, Boulder, CO.

Budikova, D., Coleman, J. S. M., Strope, S. A., & Austin, A. (2010). Hydroclimatology of the 2008 Midwest floods. Water Resources Research, 46(12), 1–16. https://doi.org/10.1029/2010WR009206

Changnon, S. A., & Kunkel, K. E. (2006). Severe storms in the Midwest. Illinois State Water Survey, Informational/Educational Material 2006-06, 74.

Chow, V. T. (1959). Open-channel hydraulics. McGraw-Hill.

Demir, I., & Krajewski, W. F. (2013). Towards an integrated Flood Information System: Centralized data access, analysis, and visualization. Environmental Modelling and Software, 50, 77–84. https://doi.org/10.1016/j.envsoft.2013.08.009

Dirmeyer, P. A., & Kinter, J. L. (2009). The "Maya Express": Floods in the U.S. Midwest. Eos, 90(12), 101–102. https://doi.org/10.1029/2009EO120001

Emerton, R. E., Stephens, E. M., Pappenberger, F., Pagano, T. C., Weerts, A. H., Wood, A. W., Salamon, P., Brown, J. D., Hjerdt, N., Donnelly, C., Baugh, C. A., & Cloke, H. L. (2016).

Continental and global scale flood forecasting systems. Wiley Interdisciplinary Reviews: Water, 3(3), 391–418. https://doi.org/10.1002/wat2.1137

Flanagan, P. X., Mahmood, R., Umphlett, N. A., Ray, C., Sorensen, W., Shulski, M., Stiles, C. J., Pearson, D., & Fajman, P. (2019). A Hydrometeorological Assessment of the Historic 2019 Flood of Nebraska, Iowa, and South Dakota. 817–829.

French, R. H. (1985). Open-channel hydraulics. McGraw-Hill.

Gilles, D., Young, N., Schroeder, H., Piotrowski, J., & Chang, Y. J. (2012). Inundation mapping initiatives of the iowa flood center: Statewide coverage and detailed urban flooding analysis. Water (Switzerland), 4(1). https://doi.org/10.3390/w4010085

Gochis, D. J., Barlage, M., Cabell, R., Casali, M., Dugger, A., FitzGerald, K., McAllister, M., McCreight, J., RafieeiNasab, A., Read, L., Sampson, K., Yates, D., & Zhang, Y. (2020). The WRF-Hydro® modeling system technical description, (Version 5.2.0). https://ral.ucar.edu/sites/default/files/public/projects/wrf-hydro/technical-description-user-guide/wrf-hydrov5.2technicaldescription.pdf

Jordan, R. E. (1991). A one-dimensional temperature model for a snow cover: Technical documentation for SNTHERM. 89.

Junker, N. W., Schneider, R. S., & Fauver, S. L. (1999). A study of heavy rainfall events during the great midwest flood of 1993. Weather and Forecasting, 14(5), 701–712. https://doi.org/10.1175/1520-0434(1999)014<0701:ASOHRE>2.0.CO;2

Kauffeldt, A., Wetterhall, F., Pappenberger, F., Salamon, P., & Thielen, J. (2016). Technical review of large-scale hydrological models for implementation in operational flood forecasting schemes on continental level. Environmental Modelling and Software, 75, 68–76. https://doi.org/10.1016/j.envsoft.2015.09.009

Krajewski, W. F., Ceynar, D., Demir, I., Goska, R., Kruger, A., Langel, C., Mantilllla, R., Niemeier, J., Quintero, F., Seo, B. C., Smallll, S. J., Weber, L. J., & Young, N. C. (2017). Real-time flood forecasting and information system for the state of Iowa. Bulletin of the American Meteorological Society, 98(3), 539–554. https://doi.org/10.1175/BAMS-D-15-00243.1

Kunkel K. E., Changnon S.A., A. J. R. (1994). Climatic Aspects of the 1993 Upper Mississippi. 811–822.

Mai, J., Shen, H., Tolson, B.A., Gaborit, É., Arsenault, R., Craig, J.R., Fortin, V., Fry, L.M., Gauch, M., Klotz, D., 2022. The Great Lakes Runoff Intercomparison Project Phase 4: the Great Lakes (GRIP-GL). Hydrol. Earth Syst. Sci. 26, 3537–3572.

Maidment, D. R., & Dugger, A. (2016). National Water Model. August.

Martinec, J. (1975). Snowmelt-runoff model for stream flow forecasts. Hydrology Research, 6(3), 145–154.

Mitchell, K. E., Lohmann, D., Houser, P. R., Wood, E. F., Schaake, J. C., Robock, A., Cosgrove, B. A., Sheffield, J., Duan, Q., Luo, L., Higgins, R. W., Pinker, R. T., Tarpley, J. D., Lettenmaier, D. P., Marshall, C. H., Entin, J. K., Pan, M., Shi, W., Koren, V., … Bailey, A. A. (2004). The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system. Journal of Geophysical Research: Atmospheres, 109(7), 1–32. https://doi.org/10.1029/2003jd003823

Nebraska Department of Natural Resources (NeDNR). (2022, October 13). Landuse Data. https://dnr.nebraska.gov/data/landuse-data

Niu, G., Yang, Z., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., & Rosero, E. (2011). The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. Journal of Geophysical Research: Atmospheres, 116(D12).

Office of Water Prediction. (2022). Information About the National Water Model.

Perry, C. A. (2000). Significant floods in the United States during the 20th century: USGS measures a century of floods. US Department of the Interior, US Geological Survey.

Piotrowski, A., Napiorkowski, J. J., & Rowiński, P. M. (2006). Flash-flood forecasting by means of neural networks and nearest neighbour approach–a comparative study. Nonlinear Processes in Geophysics, 13(4), 443–448.

Plotly Technologies Inc. (2015). Collaborative data science. Plotly Technologies Inc. https://plot.ly

Quintero, F., Rojas, M., Muste, M., Krajewski, W. F., Perez, G., Johnson, S., Anderson, A., Hunemuller, T., Cappuccio, B., & Zogg, J. (2021). Development of Synthetic Rating Curves: Case Study in Iowa. Journal of Hydrologic Engineering, 26(1). https://doi.org/10.1061/(asce)he.1943-5584.0002022

Roy, T., Gupta, H. V, Serrat-capdevila, A., & Valdes, J. B. (2017). Using satellite-based evapotranspiration estimates to improve the structure of a simple conceptual rainfall – runoff model. 879–896. https://doi.org/10.5194/hess-21-879-2017

Sahoo, G. B., & Ray, C. (2006). Flow forecasting for a Hawaii stream using rating curves and neural networks. Journal of Hydrology, 317(1–2), 63–80. https://doi.org/10.1016/j.jhydrol.2005.05.008

Small, S. J., Jay, L. O., Mantilla, R., Curtu, R., Cunha, L. K., Fonley, M., & Krajewski, W. F. (2013). An asynchronous solver for systems of ODEs linked by a directed tree structure. Advances in Water Resources, 53, 23–32. https://doi.org/10.1016/j.advwatres.2012.10.011

Stonebraker, M., & Rowe, L. A. (1986). The Design of POSTGRES. ACM SIGMOD Record, 15(2). https://doi.org/10.1145/16856.16888

Suriano, Z. J. (2022). Nebraska snowfall: a climatological perspective. Physical Geography, 43(3), 265–284. https://doi.org/10.1080/02723646.2020.1843821

US Army Corps of Engineers. (2010). HEC-RAS River Analysis System, User's Manual Version 4.1. US Army Corps of Engineers Hydrologic Engineering Center, Davis CA, January.

Villarini, G., Smith, J. A., Baeck, M. L., & Krajewski, W. F. (2011). Examining Flood Frequency Distributions in the Midwest U.S. Journal of the American Water Resources Association, 47(3), 447–463. https://doi.org/10.1111/j.1752-1688.2011.00540.x

Vrugt, J. A., Gupta, H. V., Bouten, W., & Sorooshian, S. (2003). A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. Water Resources Research, 39(8). https://doi.org/10.1029/2002WR001642

Wang, Y. H., Broxton, P., Fang, Y., Behrangi, A., Barlage, M., Zeng, X., & Niu, G. Y. (2019). A Wet-Bulb Temperature-Based Rain-Snow Partitioning Scheme Improves Snowpack Prediction Over the Drier Western United States. Geophysical Research Letters, 46(23), 13825–13835. https://doi.org/10.1029/2019GL085722

Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Lettenmaier, D., Koren, V., Duan, Q., Mo, K., Fan, Y., & Mocko, D. (2012). Continental-scale water and energy flux analysis and validation for the North

American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. Journal of Geophysical Research Atmospheres, 117(3). https://doi.org/10.1029/2011JD016048

Xiao, Y., Wan, J., & Hewings, G. J. D. (2013). Flooding and the Midwest economy: Assessing the Midwest floods of 1993 and 2008. GeoJournal, 78(2), 245–258. https://doi.org/10.1007/s10708-011-9415-9

Zeng, X., Broxton, P., & Dawson, N. (2018). Snowpack change from 1982 to 2016 over conterminous United States. Geophysical Research Letters, 45(23), 12–940.

Zhang, J., Howard, K., Langston, C., Kaney, B., Qi, Y., Tang, L., Grams, H., Wang, Y., Cockcks, S., Martinaitis, S., Arthur, A., Cooper, K., Brogden, J., & Kitzmillller, D. (2016). Multi-Radar Multi-Sensor (MRMS) quantitative precipitation estimation: Initial operating capabilities. Bulletin of the American Meteorological Society, 97(4), 621–638. https://doi.org/10.1175/BAMS-D-14-00174.1

Zhang, Y., Smith, J. A., & Baeck, M. L. (2001). The hydrology and hydrometeorology of extreme floods in the Great Plains of Eastern Nebraska. Advances in Water Resources, 24(9–10), 1037–1049. https://doi.org/10.1016/S0309-1708(01)00037-9