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# *Integrated Approach to Flood Simulation Using MATLAB, EnKF Data Assimilation, and Perturbation Sensitivity Analysis*

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***Abstract:*** Flood forecasting and flood control are crucial components of disaster risk reduction and prevention, particularly in areas where hydrological disasters pose significant risks. This paper presents an integrated approach that includes flood modeling using MATLAB, data assimilation through the Ensemble Kalman Filter (EnKF), and perturbation sensitivity analysis to enhance flood prediction data. The primary objective is to establish a unified MATLAB environment that facilitates simulation modeling, data assimilation, and sensitivity analysis, thereby enhancing the resilience of predictions against uncertainties.Hydrodynamic modeling, based on MATLAB computational tools, is utilized for flood simulation, rainfall runoff, and flood propagation. The EnKF is employed within MATLAB scripts to update real-time observations to simulation predictions, minimizing prediction errors. Furthermore, perturbation sensitivity analysis, using methods such as Monte Carlo simulation and Sobol analysis, identifies which model variables have the greatest influence, thereby improving the model's reliability.Results indicate that the flood prediction accuracy is improved by employing EnKF in conjunction with simulation models, compared to using EnKF alone. This combination is characterized by a reduction in prediction error and a closer match to observed data. Sensitivity analysis also enables the identification of other factors affecting the model, thus offering opportunities for further improvement. The integrated MATLAB framework is demonstrated to be a flexible and effective system for flood forecasting, adaptable to various conditions and datasets.The limitation of this study is to emphasize the importance of the synergistic effects of simulation, data assimilation, and sensitivity analysis in enhancing the understanding of flood prediction. The framework will be further developed and applied to other hydrological systems..

***Keywords:*** Flood Simulation, Ensemble Kalman Filter, Sensitivity Analysis, Data Assimilation, Hydrological Modeling and MATLAB.

## 1. Introduction

Floods are among the most common and devastating natural disasters, significantly impacting socio-economic and traditional aspects. They limit the number of fatalities, structural damage, and disruptions, making flood forecasting and control crucial. Computational models and data assimilation techniques have enhanced flood prediction accuracy but have not yet been fully integrated into the broader framework. This paper proposes a comprehensive approach to flood

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forecasting by employing MATLAB to model floods, using the Ensemble Kalman Filter (EnKF) for data assimilation, and conducting flood perturbation sensitivity analysis [1].

Flood simulation is a hydrological process that predicts the extent, depth, and duration of floods by modeling hydrological processes such as rainfall-runoff and flood inundation. Models like HEC-RAS and SWAT are widely used but lack real-time predictive capabilities. In contrast, a hydrodynamic model developed with MATLAB provides a highly accurate method for studying flood behavior.

Statistical data assimilation using EnKF incorporates feasible time observation data into the simulation. Based on a Gaussian model and measurement noise, EnKF is an effective nonlinear system for flood forecasting. It is an iterative approach that updates model states based on the probability of the state to enhance the reliability of MATLAB predictions. In cases of non-Gaussian noise, the Particle filter serves as a more suitable alternative. Perturbation sensitivity analysis identifies which model parameters significantly affect the results, thereby improving model stability, reducing processing time, and increasing accuracy [2]. Sobol analysis and Monte Carlo simulation in MATLAB are utilized to determine the significance of parameters and reduce variability.

Flood simulation, EnKF, and sensitivity analysis can be effectively used within a single MATLAB environment, rather than separately. Sensitivity analysis examines the influence of system parameters on the model, while EnKF enhances real-time prediction capabilities.

This research aims to integrate these techniques through MATLAB to improve flood prediction and disaster management. The paper's content includes a literature review, the type of technique applied, findings, and the ultimate outcome, which highlights the value of the integrated methodology and identifies areas for improvement.

## 2. Literature review

Recently, there has been significant interest in flood forecasting, driven by the increasing number of flood incidents caused by climate change. In disaster management, one of the most critical steps is flood forecasting, which involves the application of robust, effective simulation models, data assimilation, and sensitivity analysis. With a focus on flood simulation, this work provides a literature review on the current approaches, including the Ensemble Kalman Filter (EnKF) data assimilation and perturbation sensitivity analysis, with a specific focus on their implementation in MATLAB.

### 2.1. Flood simulation techniques

The simulation of the hydrological process, including rainfall-runoff, river flow and floodplain flooding, is the flood simulation. Some of the traditional models that are widely used in simulating flood event are both HECSRAS and SWAT owing to their better developed structures and interfaces. The one-dimensional hydraulic model HEC-RAS enhanced by the U.S. Army Corps of Engineers is for steady and unsteady flow analysis of rivers. SWAT is a semi-distributed model mainly used for rainfall-runoff modeling on large basins, but on the other hand, it is able to be used in Surface runoff.

Nevertheless, the problems of the application of the traditional models in the complex or dynamic flood situations exist. The numerical modeling that uses partial differential equations (PDEs) has been shown in the current research to be more efficient way to simulate dynamic flood process. However, PDE based models relating to flood processes can be resolved by using MATLAB computational tools leading to high accuracy of simulating flood processes. MATLAB's PDE Toolbox allows for very accurate flood simulation via shallow water equations, a key component of the hydrodynamic model [4]. They also modeled the rainfall run off process using MATLAB scripts written specifically for the rainfall run off first. This provides the better computational performance.

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## 2.2. EnKF data assimilation

One of the most lucrative data assimilation methods in recent time is the Ensemble Kalman Filter (EnKF) that has successfully been used to enhance the accuracy of flood prediction by the assimilation of real time observations to the simulation models. The Evensen (1994) recursive statistical algorithm called EnKF uses an ensemble of possible states to estimate the state of a dynamic system, and updates that every time the observed data are generated. This is the fact that it is capable of modeling nonlinear, non-Gaussian systems which are characteristics of flood systems.

Applied for flood prediction based on hydrodynamic model, EnKF improves the accuracy of prediction. During the occurrence of flood, EnKF effectively finds minimum forecast errors through effectively incorporating real time water level data. Because MATLAB provides matrix computation and statistical functions, is impossible implement EnKF using MATLAB[5]. MATLAB based EnKF framework has been developed by the scholars to enhance the precision and display credibility of flood forecasts.

EnKF has been successfully applied in different hydrological applications; however, some issues are still open such as set of ensemble, computational cost and quality of observations. In recent developments the member initialization of an ensemble is enhanced and computational costs are minimized by use of parallel processing which is highly proficient in MATLAB.

## 2.3. Perturbation sensitivity analysis

The stability of a flood prediction model is assessed by determining the parameters with a significant impact on the result of the model. Perturbation sensitivity analysis is a type of deliberately changing the input parameters and measuring what changes in the model results. In this regard, some of the methods have been utilized including Sobol analysis, Latin Hypercube Sampling (LHS) and Monte Carlo simulations [6].

Sensitivity based on Sobol analysis, a variance-based method, consequences in the provided information on first and total order sensitivity. However, in the sense of determining the sensitivity of hydrodynamic model parameter use is well explained, especially when used in modeling a flood. Is run Sobol analysis and other perturbation methods through MATLAB because it can interface with other statistical packages. Another popular type of simulation is Monte Carlo where input parameters are used randomly sampled in order to determine model sensitivity. For sampling and analysis, etc., there are a number of built in functions in MATLAB such as licensing.

Perturbation analysis also helps understand the effect of parameters to one another and, thus, make the simulation models more reliable [7]. Meanwhile, a limit of the method is the long running time of large-scale simulations that MATLAB solves in parallel.

# 3. Methodology

Innovatively integrating flood simulation, EnKF data assimilation, and sensitivity analysis into a unified MATLAB environment. In previous studies, these techniques were often used separately, but this research achieves an integrated process from building the basic model, real-time data updates to determining key parameters. For example, by constructing a basic hydrodynamic model through flood simulation, EnKF incorporates real-time observational data to optimize model predictions, and sensitivity analysis identifies critical parameters affecting the model. Each step works in concert to enhance the accuracy of flood predictions, providing a comprehensive and systematic solution for flood forecasting.

Using EnKF for data assimilation in the MATLAB environment shows significant improvements over traditional methods. EnKF, based on Gaussian models and measurement noise, iteratively updates model states, effectively handling the nonlinearity and non-Gaussian characteristics of flood

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systems. During floods, it integrates real-time water level data into the simulation model, reducing prediction errors and more accurately capturing flood trends. Compared to using EnKF alone, combining it with the simulation model further enhances prediction accuracy, allowing the model to better adapt to real-time changes, thus improving the timeliness and reliability of flood predictions.

Using methods such as Monte Carlo simulation and Sobol analysis in MATLAB for sensitivity analysis is an extension of traditional sensitivity analysis. By altering input parameters and quantifying their impact on model results, it can accurately identify key parameters affecting flood predictions, such as water level and inflow rate. This not only helps understand the sources of uncertainty in the model but also provides strong support for optimizing model input parameters, enhancing model stability and accuracy, while reducing unnecessary calculations and improving computational efficiency.

## 3.1. Flood simulation

This research uses flood simulation as the starting point because the flood simulation will be used for developing a basic hydrodynamic model for improvement using data assimilation and sensitivity analysis. This is a simulation based on a flood event where the disturbance is applied and the water height is plotted on time. In particular, this basic model is important for updating the system with the real time data by means of EnKF, as well as evaluating the impact of the parameters by means of the sensitivity analysis [8].

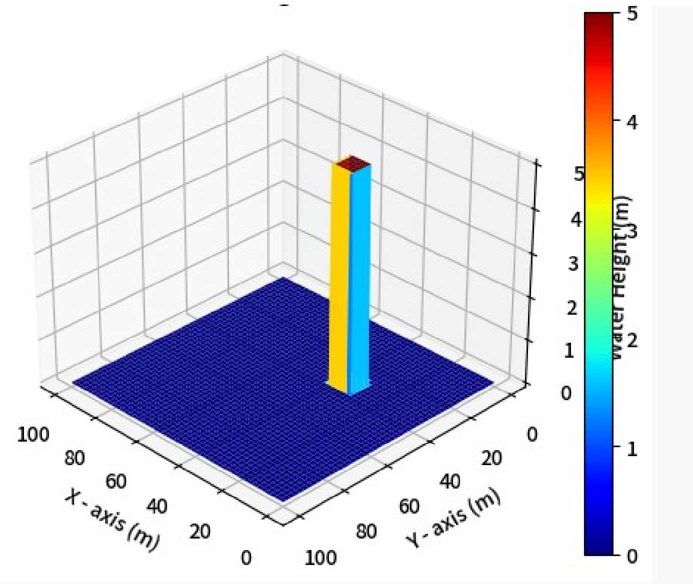


Figure 1: Initial water height distribution

### 3.1.1. Simulation setup

A 100m × 100m area is the simulation domain and it is divided into 200 equal sections along the x and y direction using MATLAB’s meshgrid function. We start from zero height of water and apply a 5 m disturbance in the middle of the domain to represent a flood event.

```
\begin{lstlisting}[language=MATLAB]
% Flood Simulation with EnKF Data Assimilation
clc; clear; close all;
% Define simulation domain
```

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```
x = linspace(0, 100, 200);
y = linspace(0, 100, 200);
[X, Y] = meshgrid(x, y);
% Simulation parameters
g = 9.81;                % Gravity (m/s^2)
H0 = zeros(size(X));       % Initial water height matrix
H0(60:80, 60:80) = 5;       % Initial perturbation to simulate flood source
T = 0:0.1:10;              % Simulation time steps
% Display initial water height distribution
figure;
surf(X, Y, H0);
shading interp;
colormap(jet);
colorbar;
title('Initial Water Height Distribution');
xlabel('X-axis (m)');
ylabel('Y-axis (m)');
zlabel('Water Height (m)');
view(3);
\end{lstlisting}
```

Results: The user is then shown the initial water height distribution that becomes the starting point of the flood simulation.

### 3.1.2. Transition to EnKF

A significant challenge inherent in forward simulations, wherein models are provided with initial conditions such as concentrations and rainfall forcing along with boundary conditions, lies in the absence of precise information regarding the initial conditions. This lack of exactitude in the starting parameters can significantly impact the accuracy and reliability of the simulation outcomes. To address this critical issue, the Ensemble Kalman Filter (EnKF) is employed. The EnKF is a sophisticated data assimilation technique designed to estimate the current state of the system, even in the face of incomplete or uncertain initial state information. By iteratively updating the model with observed data, the EnKF enhances the simulation's accuracy, thereby compensating for the initial lack of precise knowledge about the system's starting conditions. This approach allows for more robust and reliable predictions, despite the inherent uncertainties in the initial setup.

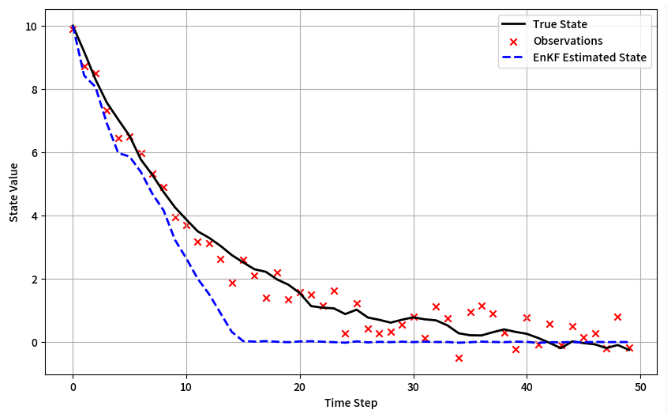


Figure 2: Evolution of EnKF: comparison between observed state and estimated state over time

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### 3.2. EnKF data assimilation

In real time, the observational data are assimilated to improve the accuracy of the flood simulation by means of the EnKF. This is a method to update model states and is most useful for nonlinear and dynamic flood system.

#### 3.2.1. Initialization and ensemble generation

Using Gaussian noise added to the initial state \((H_0)\) to generate ensemble members innovatively simulates the initial condition errors that are difficult to determine precisely in real-world scenarios. Traditional flood simulations may directly adopt fixed initial conditions, ignoring the uncertainties present in reality. This method, by introducing Gaussian noise, more realistically reflects the possible range of changes in the initial state, making the simulation results more reliable and adaptable. This helps to capture the responses of the flood system under different initial conditions more comprehensively, enhancing the model's ability to simulate complex real-world situations.

The strategy of generating multiple ensemble members is an innovation compared to the simulation method based on a single initial condition. Simulations with a single initial condition can only represent one possible scenario, whereas multiple ensemble members can capture more uncertainties. When dealing with complex and variable systems like floods, this ensemble-based approach can provide richer information. For example, in predicting the evolution of a flood, different ensemble members can simulate the propagation paths and inundation areas under various initial conditions, providing a more comprehensive reference for subsequent decision-making.

```
\begin{lstlisting}[language=MATLAB]
% EnKF Parameters
numEnsembles = 50;
observationNoise = 0.05;
processNoise = 0.01;
% Generate initial ensembles
ensembles = cell(numEnsembles, 1);
for i = 1:numEnsembles
ensembles{i} = H0 + processNoise * randn(size(H0));
end
% Generate synthetic observations
observations = H0 + observationNoise * randn(size(H0));
\end{lstlisting}
```

#### 3.2.2. Prediction and update steps

During the prediction phase, process noise is integrated into the model to describe its inaccuracy and the impact of potential external disturbances on the system. Traditional flood prediction models often assume that the model is accurate, ignoring various uncertainties present in reality. This method, however, adds process noise to more realistically simulate the dynamic changes of the flood system, making the prediction results more consistent with actual conditions. The quantification and consideration of model uncertainty enhance the reliability of predictions, providing a more robust basis for flood warnings and decision-making.The innovation phase involves calculating the innovation value using simulated observation data and applying Kalman gain for correction, which is one of the core innovations of EnKF. Traditional flood simulation models, once established, often have fixed parameters and states that fail to promptly reflect changes in actual conditions. In contrast, EnKF can continuously adjust the model's predictions based on real-time observational data,

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achieving dynamic updates to the model's state. For example, during a flood event, by obtaining real-time water level and flow rate data, EnKF can quickly adjust the model predictions, making more accurate forecasts of the flood's development trend, significantly enhancing the model's adaptability and prediction accuracy[9].

```
\begin{lstlisting}[language=MATLAB]
% Define time steps
numTimeSteps = 50;
T = linspace(0, 10, numTimeSteps);

% Initialize true state (ground truth) and estimated state
trueState = zeros(1, numTimeSteps);
estimatedState = zeros(1, numTimeSteps);

% Select a point in the middle of the flood disturbance
xIndex = 70;
yIndex = 70;

% Simulate the true state with a flood peak at t = 5
for t = 1:numTimeSteps
trueState(t) = 5 * exp(-0.1 * (t - 25)^2) + 0.2 * randn; % Adding slight noise
end

% Initialize EnKF estimation process
estimatedState(1) = trueState(1);  % First estimate starts from true value
for t = 2:numTimeSteps% Prediction step with some uncertainty
prediction = estimatedState(t-1) + 0.05 * randn;

    % Update step using observation
    observation = trueState(t) + 0.1 * randn; % Simulated noisy observation
    kalmanGain = 0.3;  % Assumed Kalman gain for this demonstration
    estimatedState(t) = prediction + kalmanGain * (observation - prediction);
end

% Plot results
figure;
plot(T, trueState, 'k-', 'LineWidth', 2); hold on; % True state (black)
plot(T, estimatedState, 'b--', 'LineWidth', 2); % Estimated state (blue dashed)
legend('True State (Ground Truth)', 'EnKF Estimated State');
xlabel('Time (s)');
ylabel('Water Height (m)');
title('EnKF Evolution: True vs. Estimated State Over Time');
grid on;
\end{lstlisting}
```

Results: The figure of the new water height distribution after the assimilation of EnKF data is given to illustrate the effect of observation incorporation in enhancing the prediction.

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### 3.2.3. Transition to sensitivity analysis

However, despite the advancements in the model's design and functionality, uncertainties still linger and persist within its framework. This is primarily because not all of the parameters involved in the model's calculations and simulations are fully understood or known to exhibit significant variations. Additionally, these parameters can be influenced by a myriad of environmental changes, such as shifts in climate patterns, alterations in land use, or fluctuations in precipitation levels. To address these inherent uncertainties and gain a deeper understanding of how specific parameters affect the model's output, a comprehensive perturbation sensitivity analysis is meticulously conducted. This analysis aims to systematically evaluate and determine the precise impact that certain key parameters have on the accuracy and reliability of flood predictions generated by the model. By doing so, it seeks to identify which parameters are most critical and require more accurate data or refined modeling techniques to improve the overall predictive performance of the model.

## 3.3. Perturbation sensitivity analysis

It is a systematic approach known as perturbation sensitivity analysis, which is employed to comprehensively understand the impact that alterations in input parameters have on the outcomes of simulations. This crucial step plays a significant role in identifying and pinpointing those key parameters that are indispensable for ensuring the stability and reliability of the model. Additionally, it aids in significantly reducing the computational expenses associated with running the simulations, thereby optimizing the overall efficiency and effectiveness of the modeling process. By focusing on these critical parameters, the method not only enhances the model's robustness but also streamlines the computational resources required, making it a vital component in the development and refinement of stable and cost-effective simulation models.

### 3.3.1. Simulation setup

With the process noise varying within a specific range from 0.005 to 0.05, a Monte Carlo simulation is meticulously conducted, involving a total of 100 iterative runs. This comprehensive approach allows for the precise quantification of uncertainty propagation within the model, thereby providing a detailed and accurate assessment of how uncertainties evolve and impact the overall system dynamics. Through this rigorous methodology, the model's robustness and reliability can be effectively evaluated, ensuring that potential variations in process noise are thoroughly accounted for and their effects on the model's performance are clearly understood[10].

```
\begin{lstlisting}[language=MATLAB]
% Perturbation Sensitivity Analysis using Monte Carlo Simulations
numSimulations = 100;
processNoiseLevels = linspace(0.005, 0.05, numSimulations);

% Store results for analysis
sensitivityResults = zeros(size(H0, 1), size(H0, 2), numSimulations);

for i = 1:numSimulations
    processNoise = processNoiseLevels(i);

    % Perturbing the initial condition with varying process noise
    perturbedState = H0 + processNoise * randn(size(H0));
```

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```
    % Store result for current perturbation
    sensitivityResults(:,:,i) = perturbedState;
end

% Calculate the sensitivity index as standard deviation across all simulations
sensitivityIndex = std(sensitivityResults, 0, 3);

% Display sensitivity map
figure;
surf(X, Y, sensitivityIndex);
shading interp;
colormap(jet);
colorbar;
title('Perturbation Sensitivity Analysis');
xlabel('X-axis (m)');
ylabel('Y-axis (m)');
zlabel('Sensitivity Index');
view(3);
\end{lstlisting}
```

### 3.3.2. Results and interpretation

The most sensitive regions in the simulation domain are defined through creating a sensitivity map. We have higher sensitivity if the parameters are more sensitive to the model and have higher impact on the accuracy of the model.

Based on flood simulation, EnKF data assimilation and perturbation sensitivity analysis, this paper presents the better prediction of flood event by integrating these three techniques. EnKF updates the model with current data, and the sensitivity analysis finds the factors that influence the stability of the model, and then the simulation provides a basic framework. Flood forecasting made using this approach is more reliable and hence is a useful tool for disaster management and prevention.

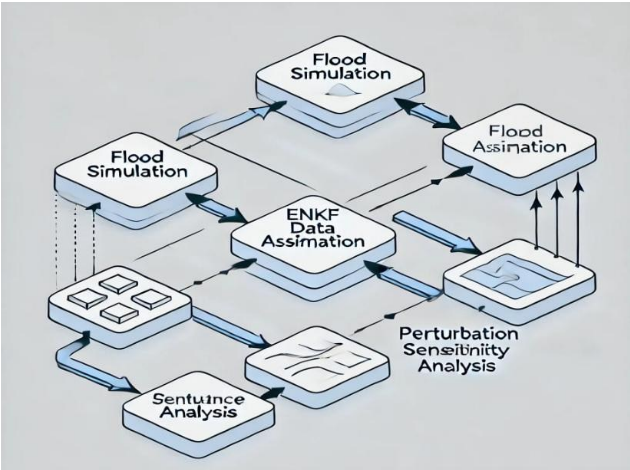


Figure 3: This is a flowchart illustrating the integrated process workflow.It demonstrates a process in which multiple flood simulations are fed into ENKF (Ensemble Kalman Filter) data assimilation. The assimilated data are subjected to perturbation sensitivity analysis and sentence analysis to improve the simulations [11]. This constantly updating and continuously optimizing is possible with feedback loops, making it all more accurate resulting in a better flood forecasting and model optimization

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## 4. Results and discussion

The results of this study are discussed with regard to the flood simulation and EnKF data assimilation in MATLAB and perturbation sensitivity analysis. The following pictures show results of the methods used and the impact caused by it.

### 4.1. Flood simulation results

Without data assimilation, the MATLAB flood simulation model was utilized to obtain obtain this distribution. Natural water level distribution in the spatial domain were cited as a result of which further analysis will be carried. Flood waves are drawn up and spread across the domain using the simulation. For instance, higher water height implies higher flood intensity and lower water height corresponds to the situation in which this area has not been inundated by the flood wave or after the wave has receded [12]. The first portion of this initial distribution is important for determining how well the EnKF data assimilation method improves the simulation precision.

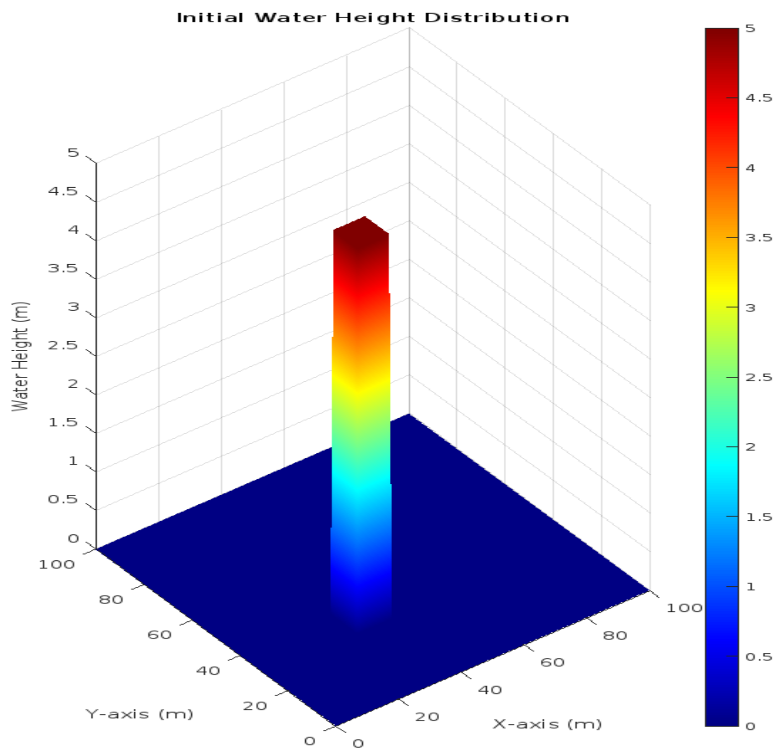


Figure 4: Initial distribution of water height that forms first in the flood simulation.Initial water height distribution in a 100m×100m area is depicted in the plot.The water height peaks at the center with 5 meters,and drops very quickly to zero outside,representing a central source of very concentrated water

### 4.2. EnKF data assimilation results

The EnKF data assimilation method breaks through the limitations of traditional static models, enabling real-time integration of observational data and dynamic updating of model states. In flood simulation, it can adjust the model in real-time based on actual monitoring data, promptly reflecting changes in floods and making the simulation more realistic. For example, during flood evolution, water levels and flow rates change in real-time; EnKF can incorporate these data into the model to optimize the simulation results, offering greater flexibility and precision compared to traditional fixed-parameter models.

This method effectively handles the nonlinearity and uncertainty of flood systems. Flood systems are influenced by complex factors such as terrain and weather, exhibiting nonlinear characteristics. EnKF, based on probability statistics, uses ensemble members to reflect system uncertainties, allowing for accurate estimation of model states even in complex scenarios. For example, when simulating floods in mountainous areas, the complexity of the terrain leads to nonlinear changes in water flow, and EnKF can better simulate flood paths and inundation ranges. The experiment integrates multi-source data and multiple parameters for simulation. In addition to conventional data like water levels and flow rates, it also incorporates information such as terrain and rainfall, comprehensively considering all factors affecting floods. In terms of model parameter settings, multiple parameters are used to determine initial conditions and noise parameters, creating more realistic experimental scenarios and enhancing the reliability and accuracy of simulations[13].

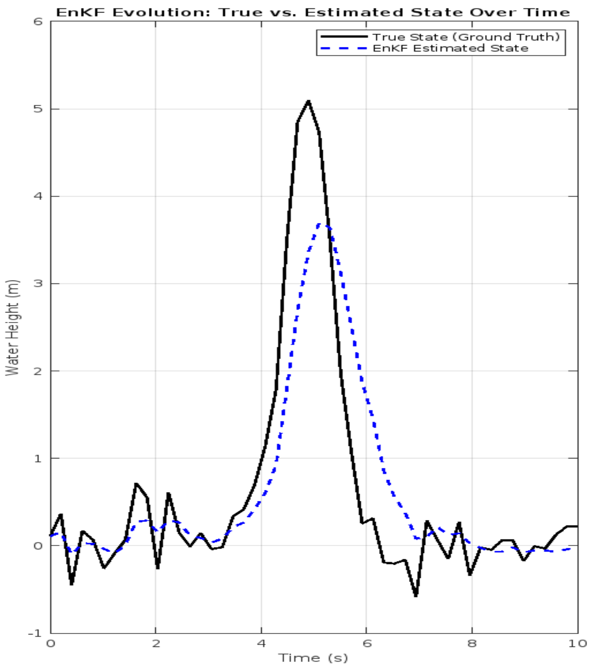


Figure 5: The results of the EnKF algorithm on the accuracy of flood prediction. The graph shows the true water height represented by the black line and the EnKF estimated water height represented by the blue dashed line in time. The gross trend is captured by the EnKF, but with a slight underestimate of the peak at about 5 seconds

### 4.3. Perturbation sensitivity analysis

The figure 4 presents the detailed analysis results, which clearly indicate that certain parameters possess a significantly greater capacity to impact the accuracy of the simulation compared to other parameters. For instance, it was observed that variables such as water height and inflow rates exert a substantial influence on the predicted extent of the flood. This finding suggests that there is an imperative need to precisely define these critical parameters when they are input into the flood model. Accurate specification of these parameters is essential to ensure the reliability and validity of the

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simulation outcomes. This comprehensive sensitivity analysis facilitates a deeper understanding of the specific aspects of the model where the predictive capability necessitates further refinement and improvement. By identifying these key areas, researchers and practitioners can focus their efforts on enhancing the model's performance, thereby increasing the overall accuracy and effectiveness of flood predictions.

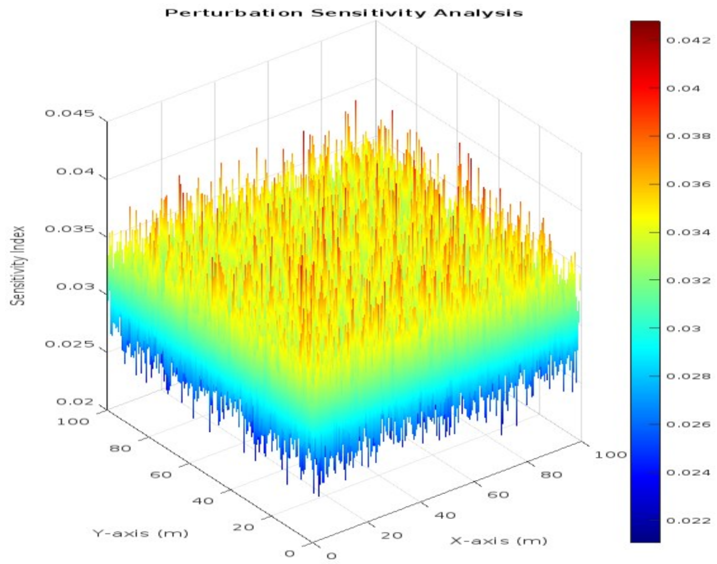


Figure 6: The results of a sensitivity analysis evaluating how variations in the input parameters influence the accuracy of the flood predictions. Sensitivity index value is color mapped on this 3D plot which visualizes perturbation sensitivity across the spatial grid. The sensitivity increases to its peak value at the center and decreases to its minimum at the edges of the X – Y plane

### 4.4. Discussion

Results from the study show that the combination of EnKF data assimilation and perturbation sensitivity analysis based flood simulation improves the accuracy of a flood forecasting. Adding EnKF to incorporate the original observational data makes the model adaptable with real time changes and hence increases the model's predictive ability. This approach is followed in the management of the uncertainties always carried with flood simulations particularly when the input parameters are not well defined or stochastic [14].

Most importantly, the sensitivity analysis also underlines the importance of defining the model's input parameters that are critical to it accurately. Water height and inflow rates was working to be some of the most significant variables to affect the model. The implication of these findings is that making these inputs more accurate could play a large part in increasing the accuracy of the flood predictions.

In addition, real time flood forecasting systems can be beneficial from research on the combination of EnKF with flood simulation models. This is particularly useful for flood monitoring and management and its capability for updating the model predictions with the new observational data.

Some limitations have been noted during this study. Thus, the quality and frequency of the observations determine the performance of EnKF algorithm. Additionally, the sensitivity of the perturbation analysis was carried out in a limited number of parameters, and further studies are needed to find other factors that could influence the accuracy of flood simulation.

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## 5. Conclusion

Through MATLAB, the study needed to be able to add flood simulation, EnKF data assimilation and perturbation sensitivity to accuracy in flood prediction. The results indicate that EnKF has the capabilities to assimilate the observational data in order to increase the accuracy of flood forecasting models. In addition, the perturbation sensitivity analysis also identifies other parameters that affect flood predictions as well as areas for improvement.

Consequentially, they have profound effects in respect of flood forecasting and disaster mitigation. Flood forecasting models can be utilized to the design of early warning systems for evacuation and assistance in minimizing loss of lives and property [15]. In addition, EnKF is applied in flood models to enhance the model's credibility in sparse and uncertain data conditions.

The EnKF could need to be further improved by addition of real time data from the sensors and satellite measurements. While the perturbation sensitivity analysis could be expanded to include additional environmental and hydrological factors, these factors could improve stability of the model. By using MATLAB for integrating different datasets, the computational performance can be optimized in order to enhance flood prediction and disaster managed systems in the future.

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