

Executive Summary

Flooding is one of the most frequent and costly disasters in the United States, affecting all 50 states and causing billions of damage each year.

This project aims to provide accurate flood information using our model to identify affected areas and support decision-making. While models have limitations, integrating the latest satellite data helps validate and improve accuracy, ensuring dependable results for researchers and responders.

Background

On average, floods lead to over **\$8–10 billion in annual losses** and impact thousands of communities nationwide.^[1] With flood events becoming more frequent and widespread, there is a growing need for timely and reliable data.

From sudden flash floods to large-scale river flooding, these events damage homes, roads, and infrastructure, and can displace thousands of people. In recent years, places like **Texas Hill Country, Louisiana**, and parts

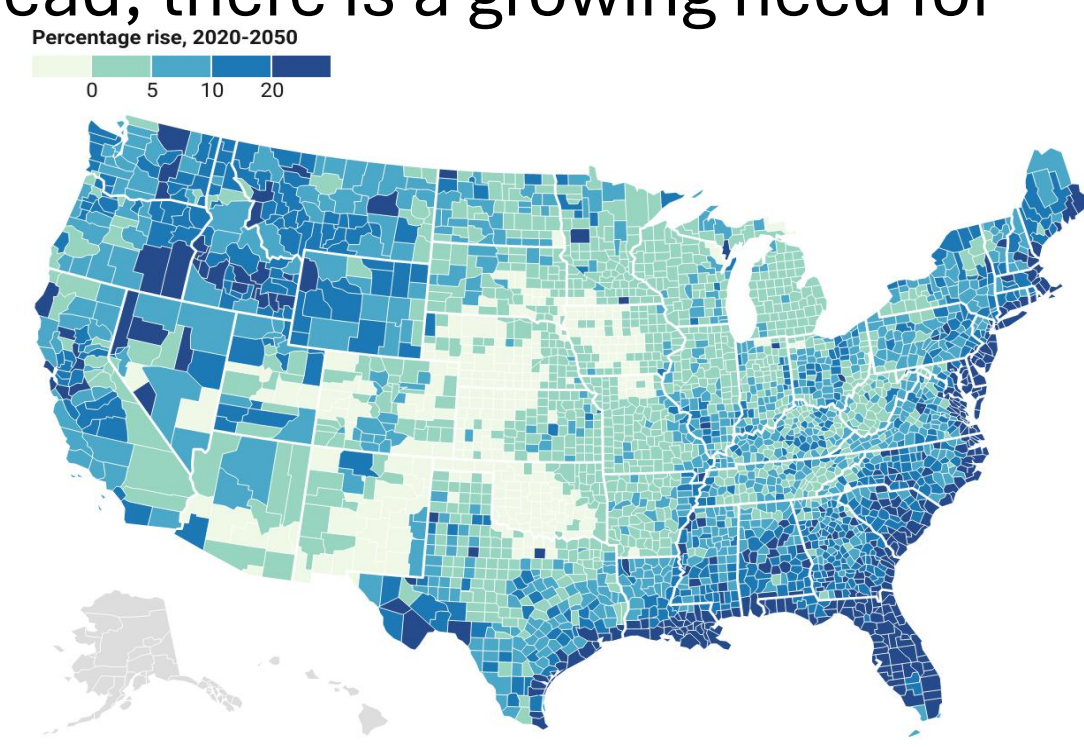


Figure 1: Flood Damage measured in 2020 (US dollars)



Figure 2: Visual Summary of Flood Disaster Impacts in Texas

of the **Midwest** have experienced severe flooding that led to emergency declarations, rescue operations, and widespread disruption of daily life. These events highlight how quickly flooding can turn into a national or regional emergency.

To respond effectively, decision-makers and researchers rely on data to understand which areas are affected and how severe the

situation is. However, the tools used to predict and map flooding are not always perfect—they can sometimes miss areas or incorrectly estimate how far water has spread.^[2]

Our work focuses on improving confidence in these tools by checking how well they perform through our model. By comparing predicted flood areas with actual observations, we can see where the model works well and where it needs improvement. This helps ensure that the information provided to emergency responders, planners, and researchers is more reliable, ultimately supporting better decisions during flood events.



Figure 3: Observed Flood Impacts Across Different Landscapes

Experimental Setup

The Height Above Nearest Drainage (HAND) model uses elevation data to estimate how high a location is relative to the nearest stream, allowing for rapid flood mapping without complex simulations.^[3] However, its performance varies with terrain, land cover, and hydrologic conditions. To evaluate HAND, we compiled 100 flood events (2001–2018) across 28 U.S. states and compared them to 50 HAND-generated flood predictions.^[4]

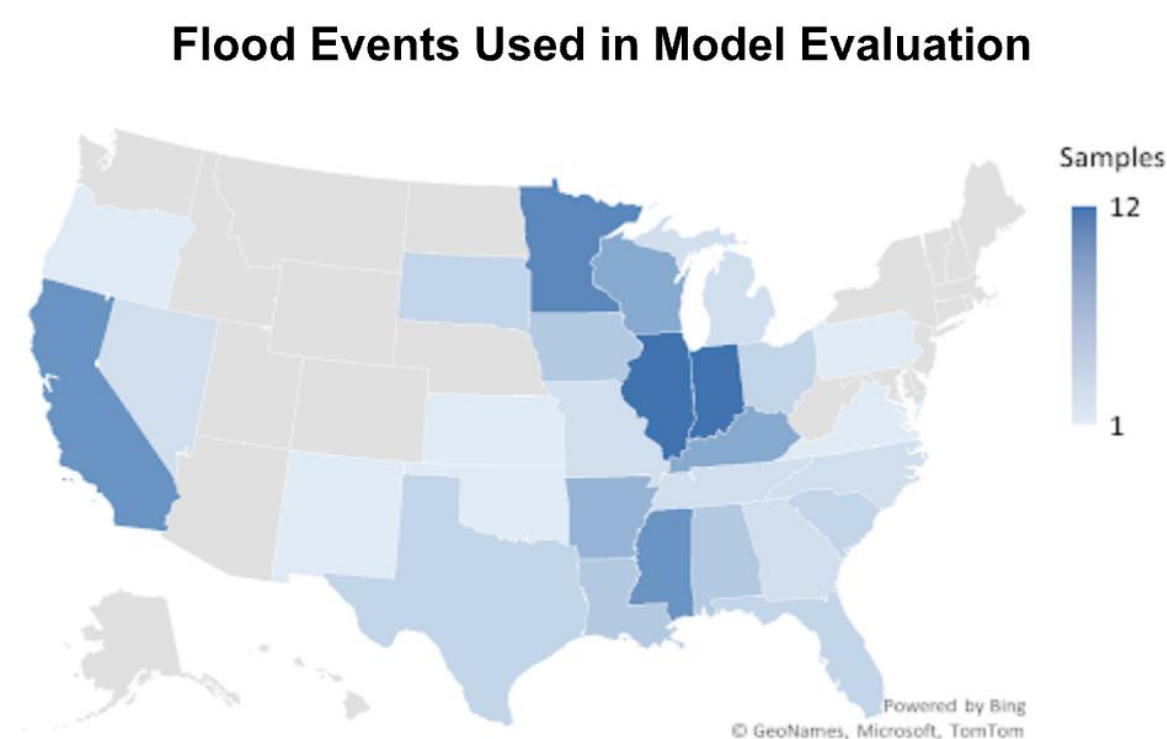


Figure 4: Samples taken from regions across the United States

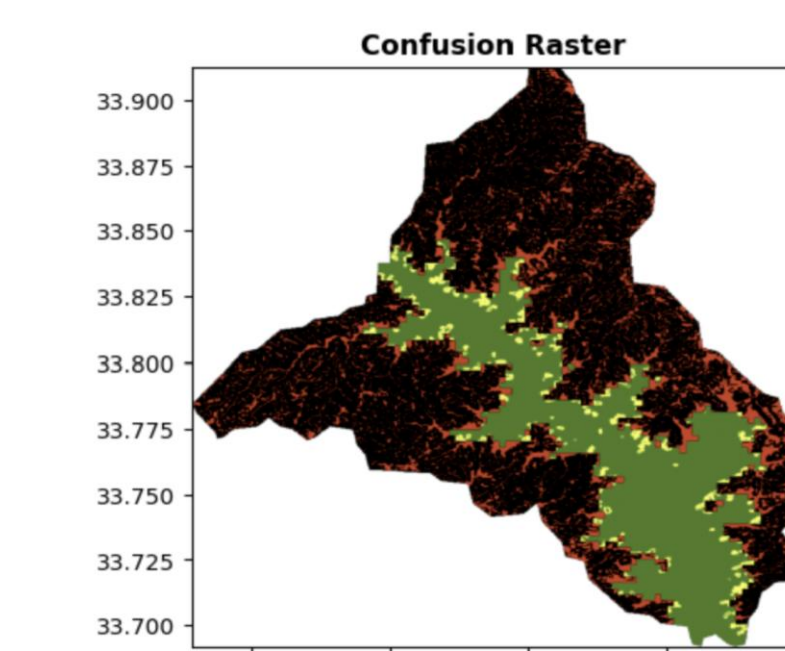


Figure 5a: Confusion raster showing TP, TN, FP, FN.

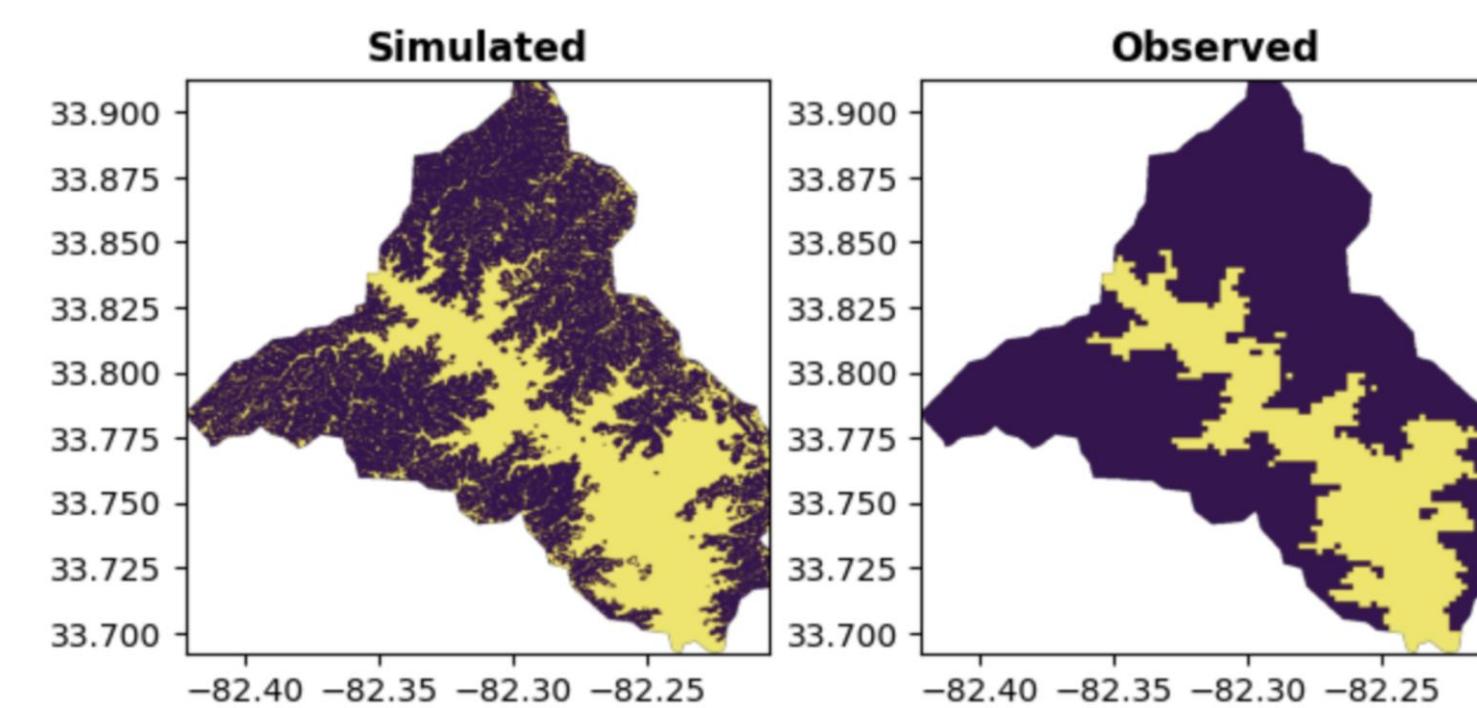


Figure 5b: Comparison of simulated (our model) vs observed (satellite data)



Our model produced the first publicly available flood data within hours of the catastrophic July 4 Texas Hill Country disaster, and was highlighted in national news. Scan here to view.

Methods/ Test Plan

```
PC = (TP+TN)/(TP+TN+FP+FN)
H = TP/(TP+FN)
CSI = TP/(TP+FN+FP)
B = (TP+FP)/(TP+FN)

print(f"Proportion Correct (PC): {PC:.2f}")
print(f"Hit Rate (H): {H:.2f}")
print(f"Critical Success Index (CSI): {CSI:.2f}")
print(f"Bias (B): {B:.2f}")

Proportion Correct (PC): 0.79
Hit Rate (H): 0.06
Critical Success Index (CSI): 0.06
Bias (B): 0.11
```

```
def getCMRaster():
    # Read Observed data, this will be our reference for dimensions
    Obs_array = obs_src.read(1)
    Obs_profile = obs_src.profile

    # Initialize an empty array for the simulated data with the same shape as Obs_array
    Sim_array = np.empty(Obs_array.shape, dtype=Sim_src.dtypes[0])

    # Reproject the simulated data to match the observed data's spatial properties
    reproject(
        source=Sim_src.read(1),
        destination=Sim_array,
        src_transform=Sim_src.transform,
        src_crs=Sim_src.crs,
        dst_transform=Obs_profile['transform'],
        dst_crs=Obs_profile['crs'],
        resampling=Resampling.nearest # Nearest neighbor resampling is generally preferred for categorical data
```

Figure 6: Codes of one of our sample demonstrating methods to test the data

Model performance was evaluated using key measures including **Proportion Correct (overall accuracy)**, **Hit Rate (ability to detect floods)**, **Critical Success Index (overall prediction quality considering errors)**, and **Bias (tendency to over- or under-predict flooding)**. Together, these indicate how reliably the model represents real flood conditions and where it can be improved.

Experimental Results

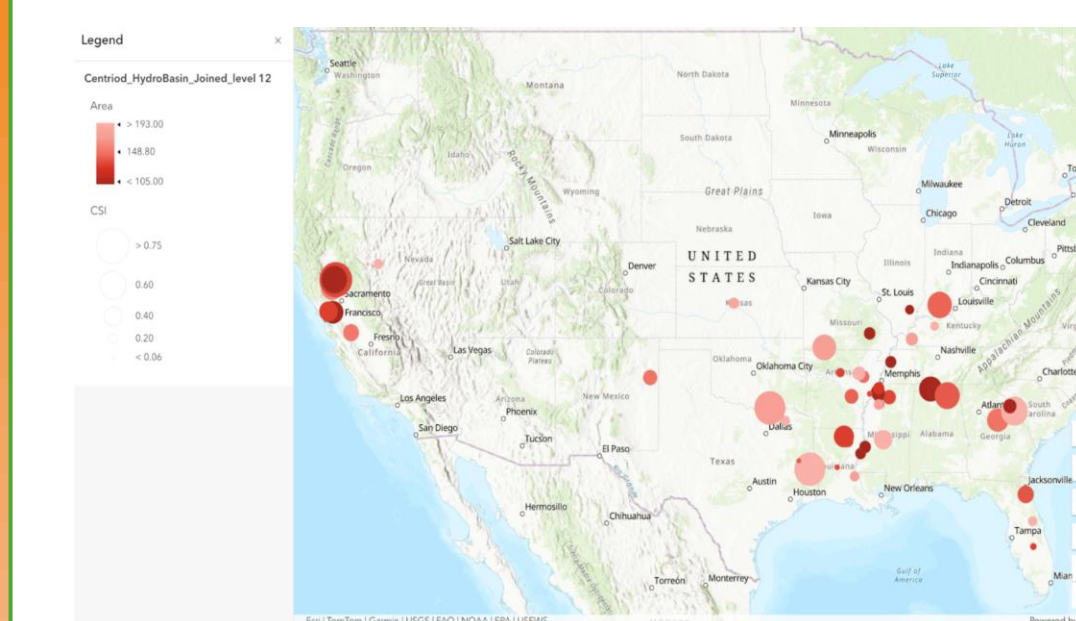


Figure 7: Bubble map representing Area vs CSI

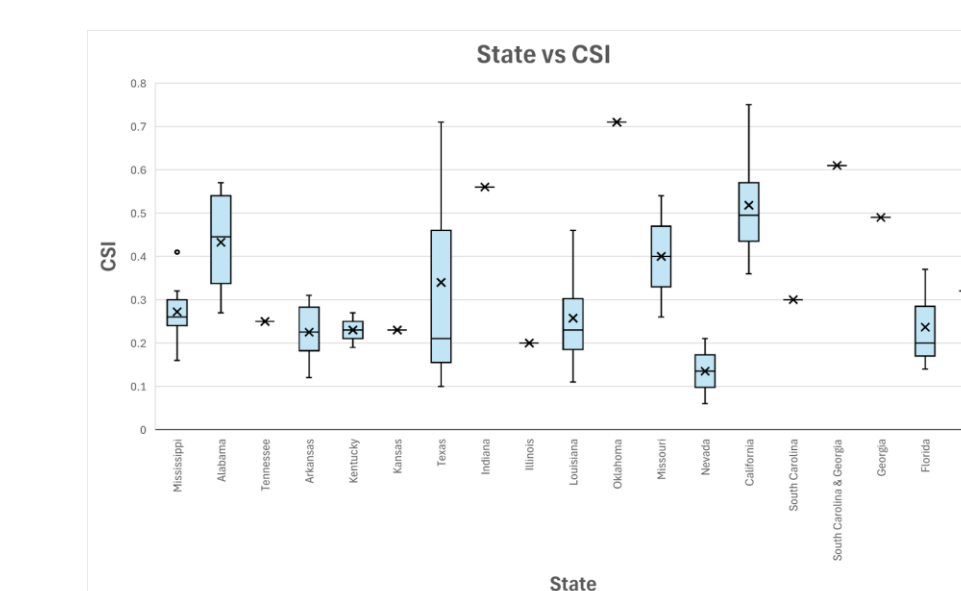


Figure 9: Box plot representing inclusive quartile

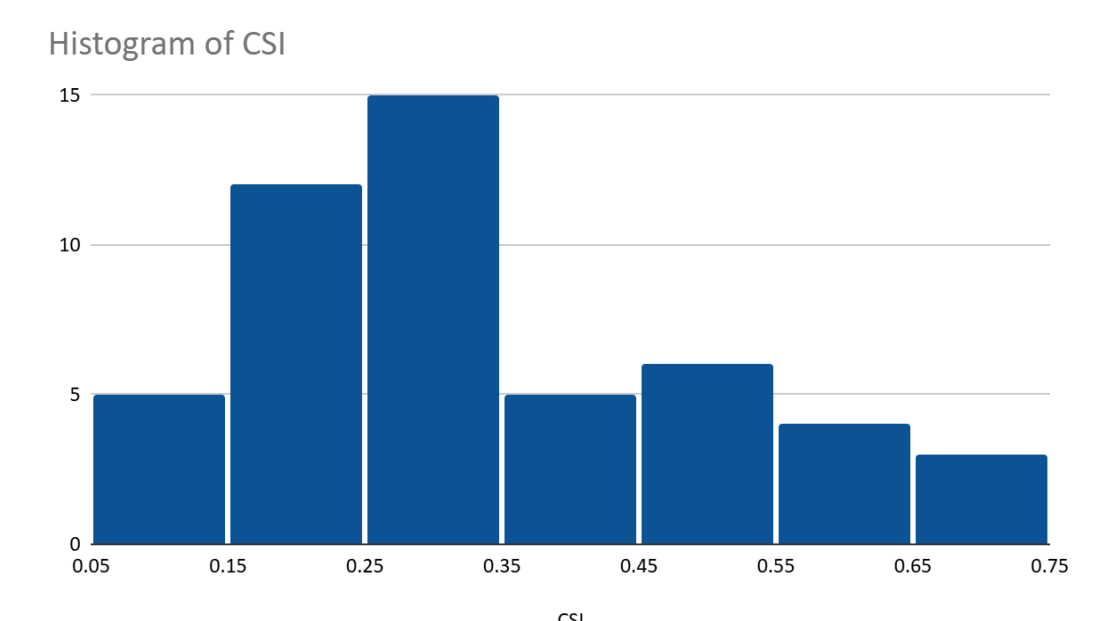


Figure 8: Histogram chart - CSI itself is very variable

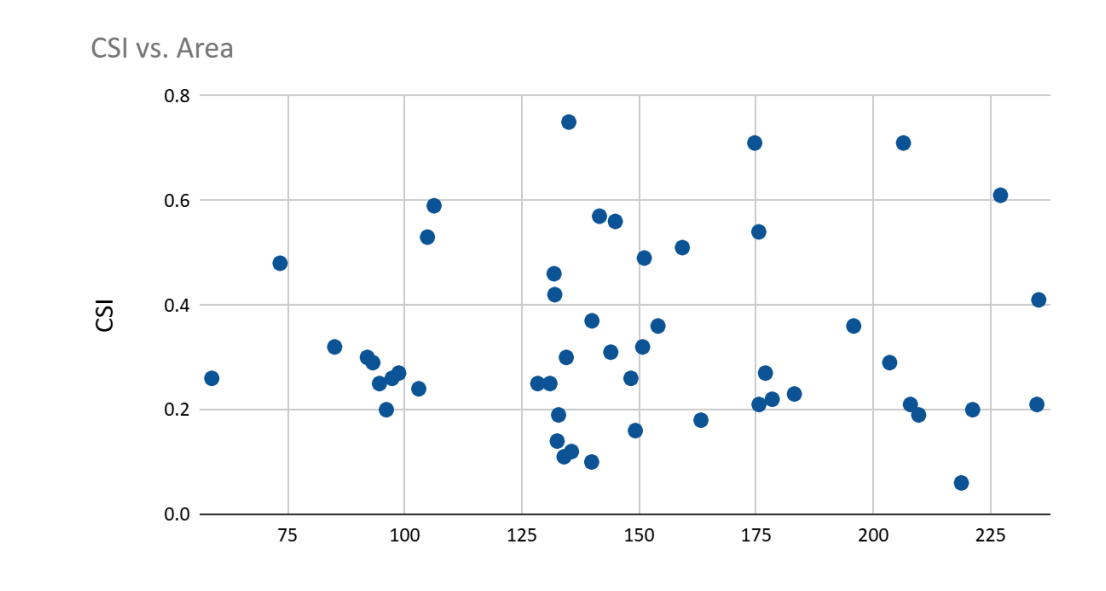


Figure 10: Scatter plot - Performance is inconsistent

The analysis of 50 flood events shows significant spatial variability in model performance across the United States. The geo bubble map highlights regional differences with no clear national pattern. CSI values range from **0.06 to 0.75**, with most between **0.2–0.4**, indicating overall moderate performance, as shown in the histogram. The box plot emphasizes the **variability in CSI across locations**, showing that performance is not consistent regionally. The scatter plot shows **no strong relationship between flood area and CSI**, suggesting that model performance is more influenced by regional characteristics than by area alone. Overall, the results show that model performance varies by region, highlighting the need for location-specific improvements.

Conclusions

This study shows that the model is an efficient tool for large-scale flood mapping but exhibits strong regional variability in performance. Analysis of 50 flood events reveals wide differences in accuracy across states, climate zones, and terrain types, with both overprediction and underprediction observed. These results highlight the importance of regional context and suggest that incorporating additional hydrologic information could improve flood predictions at national scales.

References

- [1] National Oceanic and Atmospheric Administration (NOAA) <https://www.nationalacademies.org/read/25381/chapter/5>
- [2] Rajib, A., Liu, Z., Merwade, V., Tavakoly, A. A., & Follum, M. L. (2020). Towards a large-scale locally relevant flood inundation modeling framework using SWAT and LISFLOOD-FP. *Journal of Hydrology*, 581, 124406. <https://doi.org/10.1016/j.jhydrol.2019.124406>
- [3] Zheng, X., D'Angelo, C., Maidment, D. R., & Passalacqua, P. (2022). Application of a Large-Scale Terrain-Analysis-Based Flood Mapping System to Hurricane Harvey. *JAWRA Journal of the American Water Resources Association*, 58(2), 149–163. <https://doi.org/10.1111/1752-1688.12987>
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- [5] Dartmouth Flood Observatory (DFO), https://floodobservatory.colorado.edu/wiki/Main_Page