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Flood Susceptibility Mapping for Houston, Texas
Using Fuzzy Logic and GIS-based SDSS with Chatbot Support

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Abstract

This study describes a flood susceptibility mapping application that was created for Houston, Texas, utilizing fuzzy logic that was incorporated into a Geographic Information System (GIS) framework. To evaluate flood-prone areas, the application makes use of a variety of environmental and hydrological raster layers, such as rainfall, elevation, soil type, river proximity, and land cover. Weights are allocated to various layers according to their impact on flood risk, and a fuzzy overlay technique is used to manage input data uncertainties. With the help of the application's intuitive PyQt5-built GUI, users can add raster data, conduct analysis, and view the finished flood susceptibility map. Tools for statistical analysis, a chatbot for customer service, and the creation of Web Map Services (WMS) for online display are extra features. The result is an engaging and educational decision support system aimed at enhancing flood risk management in the Houston area.

1.Introduction

Urban infrastructure and human life are seriously threatened by flooding, especially in areas like Houston, Texas, which are prone to flooding. For planning and mitigation to be effective, vulnerable zones must be accurately identified. The goal of this project is to create a GIS-based flood susceptibility application that models and visualizes flood risk areas by incorporating fuzzy logic concepts. The primary objective is to provide decision-makers with an easy-to-use tool for managing and comprehending flood susceptibility.

2. Literature Review

Flood susceptibility mapping has emerged as a critical tool in spatial decision support systems (SDSS) for urban planning and disaster risk reduction. The integration of Geographic Information Systems (GIS) with fuzzy logic provides an efficient means to assess spatial uncertainty and multi-criteria decision-making in flood-prone environments. Foundational work by Burrough and McDonnell [1] emphasizes the importance of GIS in modeling and analyzing environmental phenomena, laying the groundwork for combining geospatial data with advanced modeling techniques such as fuzzy logic.

The theory of fuzzy sets introduced by Zadeh [2] plays a pivotal role in handling the vagueness and imprecision inherent in environmental datasets. In flood risk modeling, fuzzy logic offers a structured approach to incorporating ambiguous variables like soil permeability, land use, and rainfall into a coherent analytical framework. By transforming quantitative inputs into fuzzy linguistic variables (e.g., “High Rainfall,” “Low Elevation”), models can more effectively mirror real-world complexity and stakeholder understanding.

Recent advancements have also explored the application of machine learning to enhance flood susceptibility assessments. Ait Naceur et al. [4] demonstrated how machine learning algorithms could be optimized to identify flood-prone areas in semi-arid zones with improved accuracy. Their work supports the integration of artificial intelligence with GIS tools to refine flood prediction outcomes. Similarly, Kherchouche et al. [5] employed an Analytical Hierarchy Process (AHP) alongside remote sensing and GIS data to assess flood susceptibility in Blida, Algeria, highlighting the value of multi-criteria evaluation and expert-driven weight assignment.

Comparative research by Tehrany et al. [3] underscores the significance of classification approaches in land use/land cover (LULC) mapping, particularly when using high-resolution satellite imagery. Their analysis showed that object-based classification methods outperform pixel-based techniques in accurately delineating features relevant to flood modeling, such as impervious surfaces and river buffers.

Overall, integrating GIS, fuzzy logic, and modern classification or machine learning techniques provides a robust framework for flood susceptibility mapping. These methodologies not only enhance spatial analysis but also support the development of user-friendly tools for decision-makers. The current study builds on these foundations by developing a PyQt5-based GUI application that combines fuzzy inference with environmental layers—such as rainfall, elevation, soil, river proximity, and LULC—to assess flood susceptibility across Houston, Texas.

3. Study Area

Houston, Texas, frequently experiences heavy rainfall and flooding due to its geographic location, urban sprawl, and extensive river systems. It is a good candidate for flood susceptibility analysis due to its low-lying terrain and high rate of impervious surface coverage.

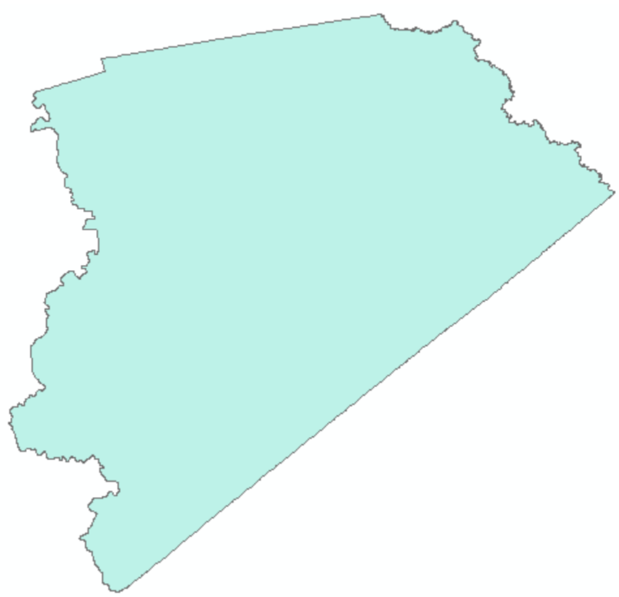

Figure 1:Houston_Texas

4. Data Sources and Parameters

The analysis incorporates the following raster layers:

- **Rainfall**: Represents precipitation levels in the region.

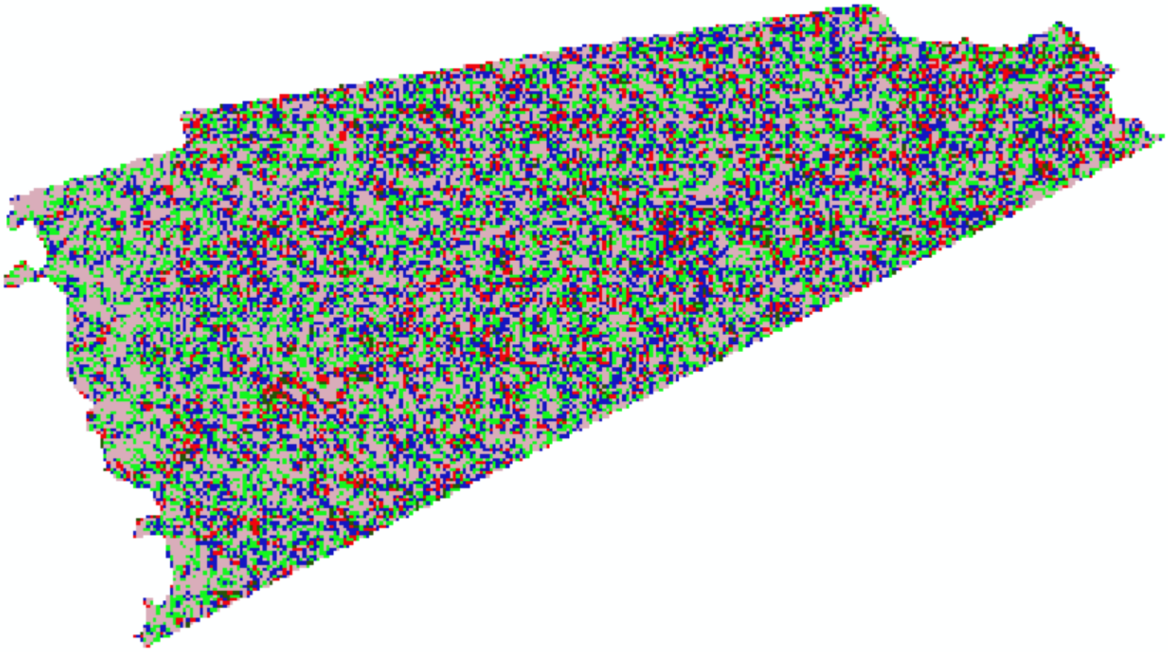

Figure 2:Rainfall_Layer

- **Soil Type**: Indicates permeability and drainage capacity.

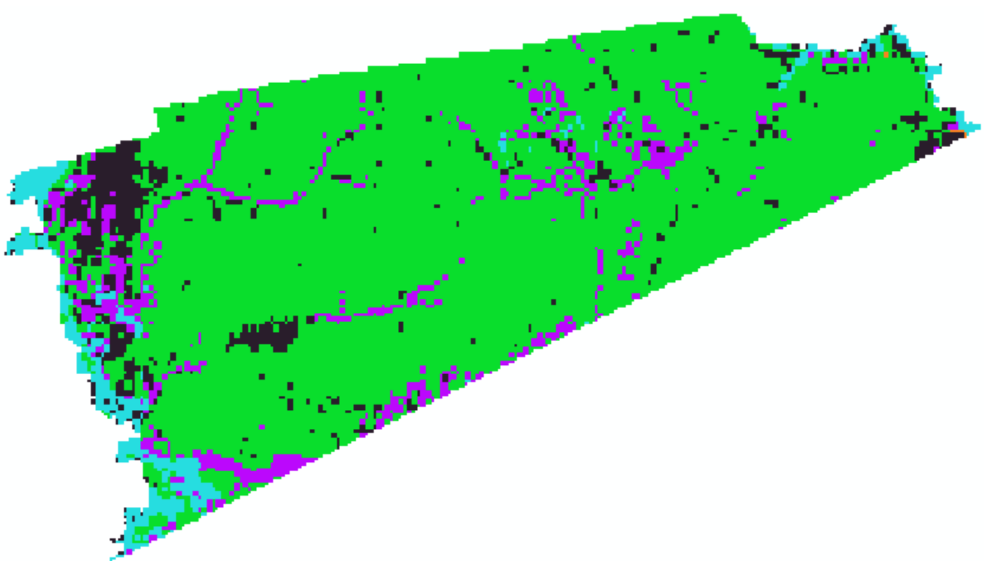

Figure 3:Soil_Layer

- **River Proximity**: Calculated distance from river bodies.

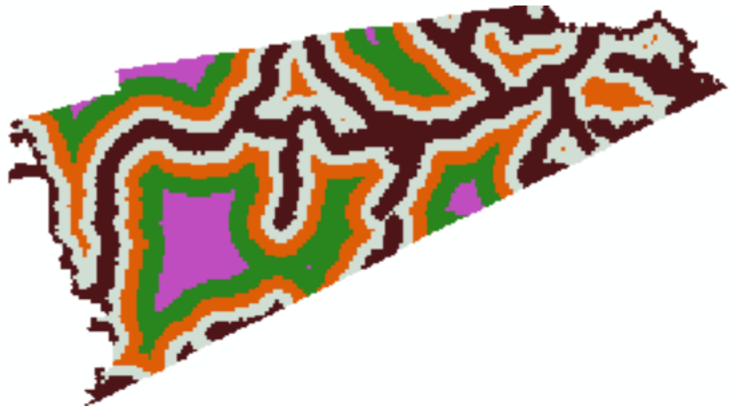

Figure 4:River_Layer

- **Land Use/Land Cover (LULC)**: Represents surface types (e.g., built-up areas, vegetation).

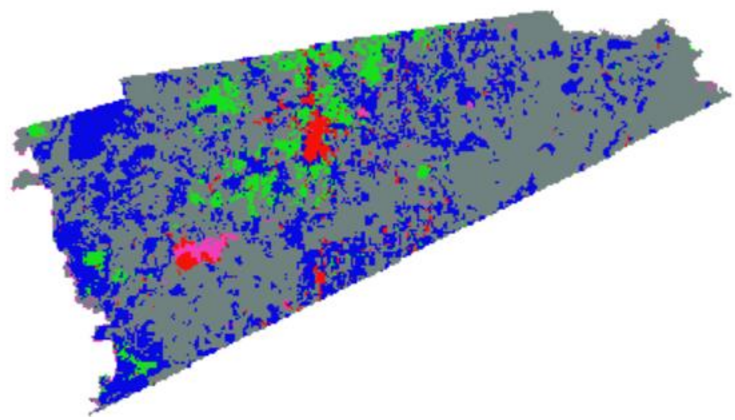

Figure 5:LULC_Layer

These layers are loaded into the application via a PostGIS-connected database or file upload. Raster preprocessing includes normalization and resolution alignment.

5. Methodology

The application employs fuzzy logic to account for uncertainty in spatial data. The methodology involves:

- **Data Normalization**: Raster layers are rescaled to a 0-5 range.
- **Weight Assignment**: Users assign relative importance (weights) to each layer.
- **Fuzzy Membership Functions**: Each criterion is categorized into five fuzzy sets (Very Low to Very High) with Gaussian membership curves.
- **Fuzzy Overlay**: Weighted fuzzy layers are combined using gamma operator logic.

- **Defuzzification**: The output is transformed into a final map showing susceptibility levels from 1 (Very Low) to 5 (Very High)

6. Application Design

The desktop GUI application is built using PyQt5 and features:

- **Layer Management**: Upload, view, and toggle raster layers.
- **Statistical Tools**: Histogram, scatter, and box plots for exploratory analysis.
- **Map Display**: Interactive plotting using Matplotlib.
- **Fuzzy Rules Info Panel**: Display of membership functions and rule descriptions.

➢ Following is the set off fuzzy rules we applied:

❖ RAINFALL
❖ Higher rainfall increases flood risk. Direct relationship:
❖ VL (0-1): Minimal rainfall, low flood risk
❖ L (1-2): Light rainfall
❖ M (2-3): Moderate rainfall
❖ H (3-4): Heavy rainfall
❖ VH (4-5): Intense rainfall, high flood risk
❖ ELEVATION
❖ Lower elevation increases flood risk. Inverse relationship:
❖ VL (4-5): High elevation, low risk
❖ L (3-4): Moderately high elevation
❖ M (2-3): Medium elevation
❖ H (1-2): Low elevation
❖ VH (0-1): Very low elevation, high risk
❖ LULC
❖ Built-up areas increase flood risk. Direct relationship:
❖ VL (0-1): Forest/dense vegetation
❖ L (1-2): Mixed vegetation
❖ M (2-3): Agricultural land
❖ H (3-4): Sparse vegetation

- ❖ VH (4-5): Built-up/impervious areas
- ❖ SOIL
- ❖ Less permeable soils increase flood risk. Direct relationship:
- ❖ VL (0-1): Sandy/high permeability
- ❖ L (1-2): Sandy loam
- ❖ M (2-3): Loam
- ❖ H (3-4): Clay loam
- ❖ VH (4-5): Clay/low permeability
- ❖ RIVER_DISTANCE
- ❖ Closer to rivers means higher flood risk. Inverse relationship:
- ❖ VL (4-5): Far from river
- ❖ L (3-4): Moderately far
- ❖ M (2-3): Medium distance
- ❖ H (1-2): Close to river
- ❖ VH (0-1): Very close to river

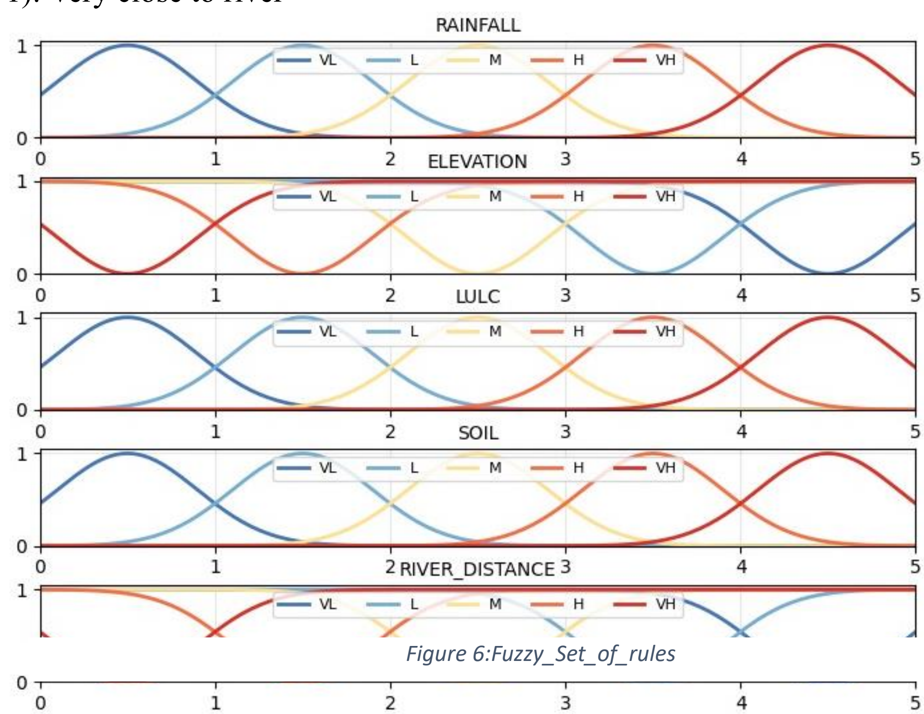

Figure 6:Fuzzy_Set_of_rules

- **Report Generation**: PDF export summarizing input data and final results.
- **Chatbot**: AI assistant for user queries.

The following diagram illustrates the workflow of the application:

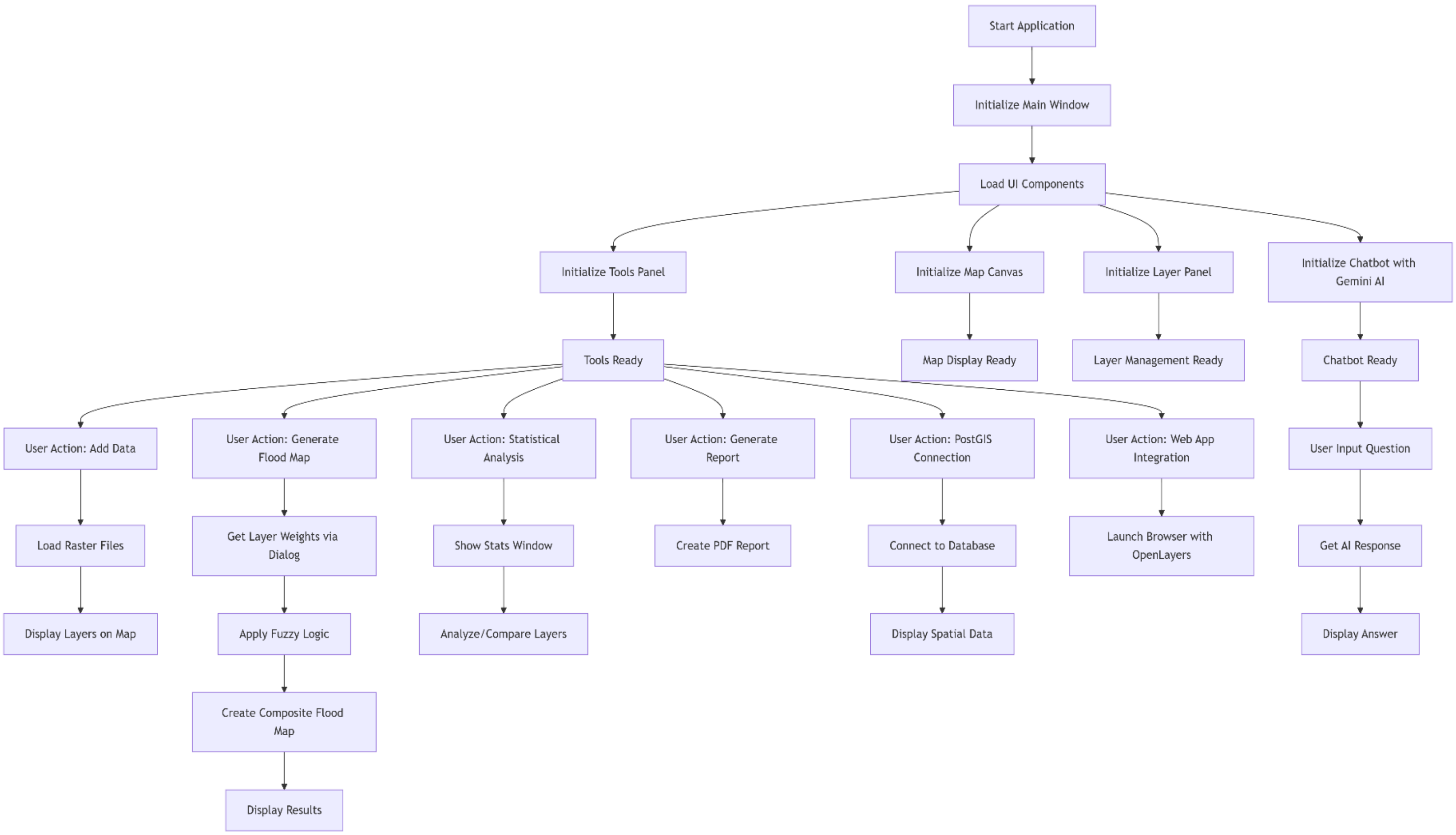

Figure 7:Fuzzy Logic Workflow Diagram

7.Web Integration

The application supports WMS generation using Flask, allowing flood maps to be visualized on a web platform. This incorporates spatial data into larger decision-making systems and improves accessibility for stakeholders.

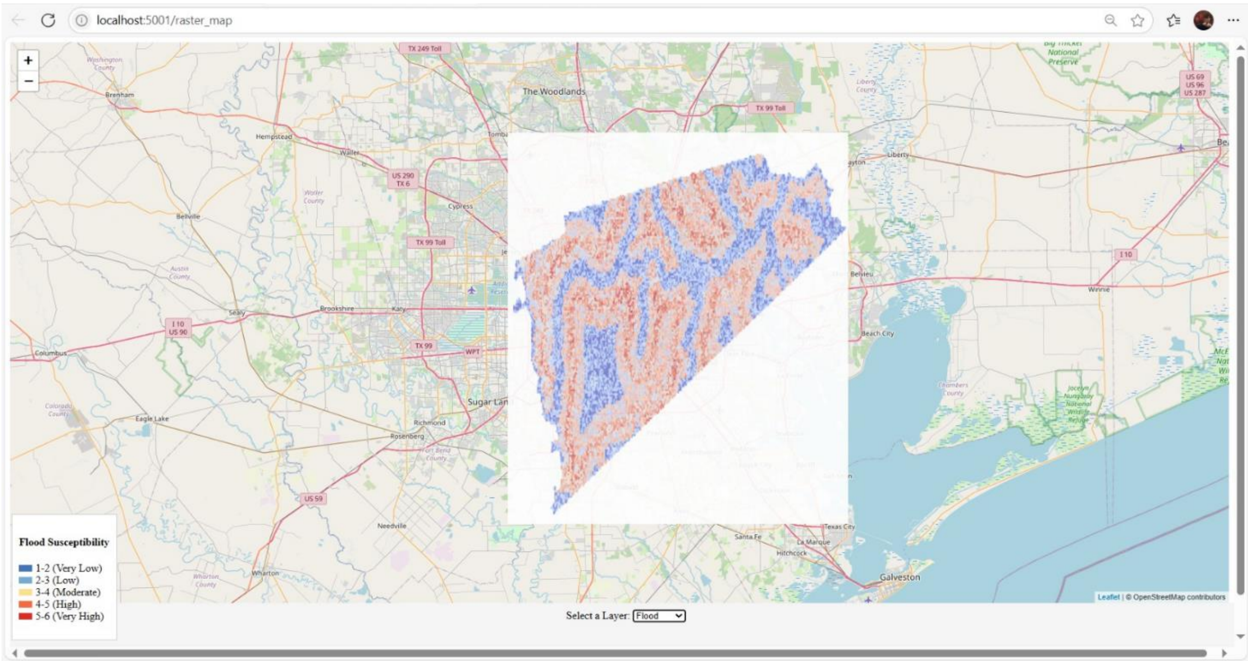

Figure 8: WMS of MAP

8.Results

The final flood susceptibility map categorizes the region into five zones. Areas near rivers with low elevation and impermeable soils display higher flood risks. In this analysis, the user assigned the highest weight to the river proximity layer, considering it the most influential factor for flood vulnerability. Other layers such as rainfall, soil, elevation, and land use were given sequential weights ranging from 1 to 5. This prioritization emphasized regions close to rivers in the resulting map. The resulting flood susceptibility map, shown below, visually reflects this decision, with higher risk zones appearing more prominently around river corridors:

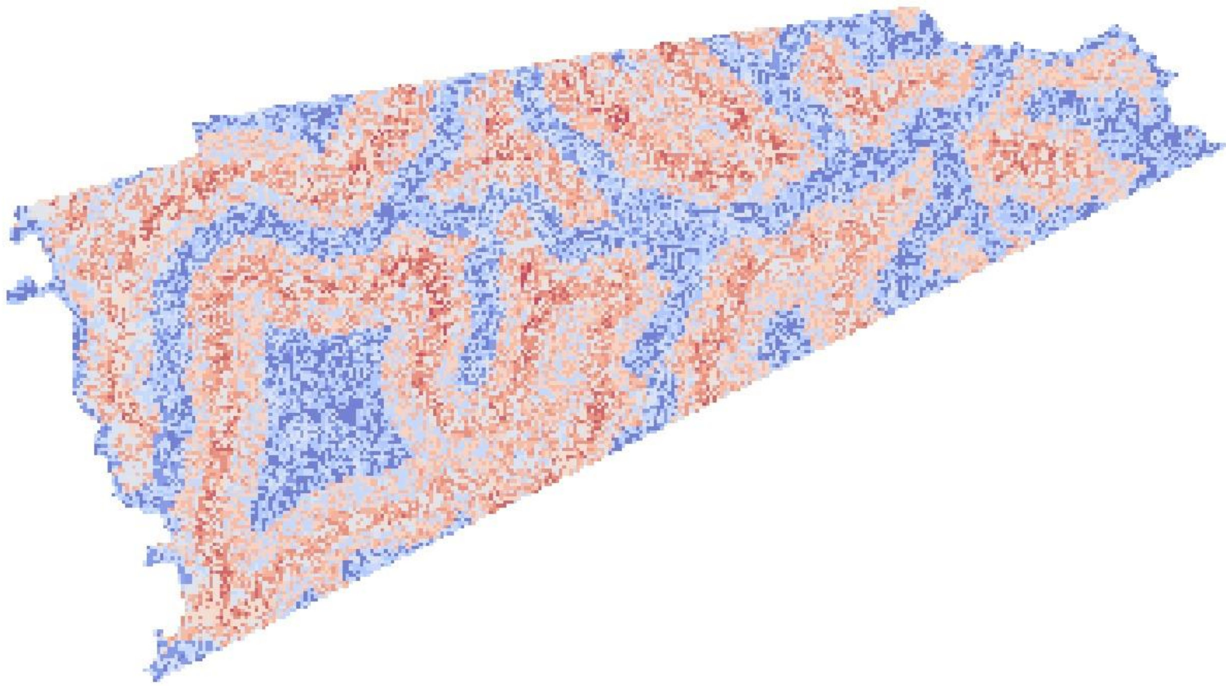

Figure 9:Flood Susceptibility Map of Houston

9.Conclusion

The flood susceptibility application for Houston, Texas, successfully integrates fuzzy logic and GIS to provide a flexible and informative tool for risk assessment. Its features, including statistical analysis, AI assistance, and WMS output, support a robust decision-making environment. Future enhancements could involve real-time data integration and mobile compatibility.

10. Future Recommendations

- **Real-time Data Integration**: To enable real-time flood forecasting, include dynamic data feeds for river flow and rainfall.
- **Mobile Application Development**: For field accessibility, expand the desktop tool into a mobile platform.
- **Machine Learning Enhancement**: To increase accuracy, test hybrid models that combine machine learning algorithms with fuzzy logic.

- **Crowdsourced Validation**: To verify model results, incorporate flood events that the community has reported.
- **Policy Integration**: For a proactive response, connect outputs to emergency planning systems.

11. References

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