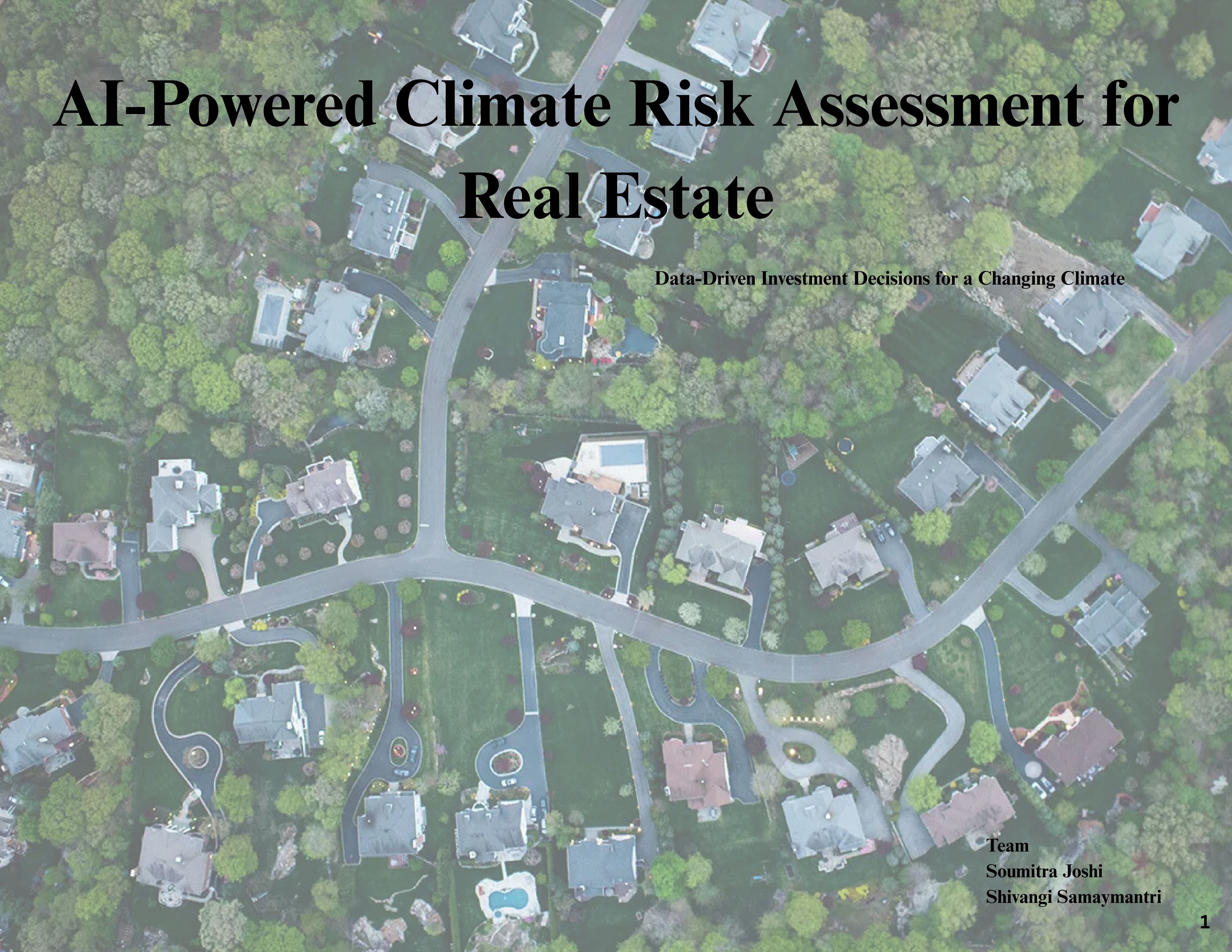

# AI-Powered Climate Risk Assessment for Real Estate

Data-Driven Investment Decisions for a Changing Climate

**Team**
**Soumitra Joshi**
**Shivangi Samaymantri**

# Overview

The project brings together real estate, disaster, and climate data to help understand and predict how climate risk impacts property prices across the United States. For each city and month, the data combines housing market trends, disaster history, and weather patterns. The analysis looks for patterns-such as whether more disasters or extreme weather in an area lead to a change in home prices or sales. Building on this, an interactive application lets users select a city and state to view recent housing price trends and get a prediction for the next 1 year. The application uses real-time data and machine learning to provide clear, visual insights that help homebuyers, investor,s and policymakers to understand both current market conditions and the possible impact of climate risks on real estate decisions.

# Data Sources

This project combines three key datasets to provide a detailed analysis of real estate and climate risks across U.S. cities and regions. It uses **Redfin's** monthly housing market data to track local trends in home sales, prices, and inventory. **FEMA** disaster records are integrated to measure the frequency and type of natural disasters in each area and period, allowing for the calculation of local disaster risk scores. To assess weather impacts, the project includes monthly climate variables, such as temperature, rainfall, and humidity-using a synthetic **NOAA**-based dataset where official city-level data was unavailable. By merging these sources, the project enables a comprehensive study of how market activity, disaster exposure, and weather patterns interact to shape real estate risk and value.

# Workflow

The ClimateWise System Architecture begins by collecting data from three main sources: **FEMA** disaster records, **NOAA** weather statistics, and **Redfin** real estate market data. These datasets are merged and cleaned so that each city and month includes complete information on disasters, weather, and housing trends. The data processing stage also creates new features and calculates risk scores for every location and time period. Once prepared, the data powers a range of analysis components, including price prediction, market trend analysis, climate risk assessment, disaster mapping, and real-time news feeds. Users interact with the system through an intuitive dashboard, where they can select locations and view tailored insights. Throughout, a live news ticker provides ongoing updates on real estate and climate events, ensuring users always have the most current information for informed decision-making.

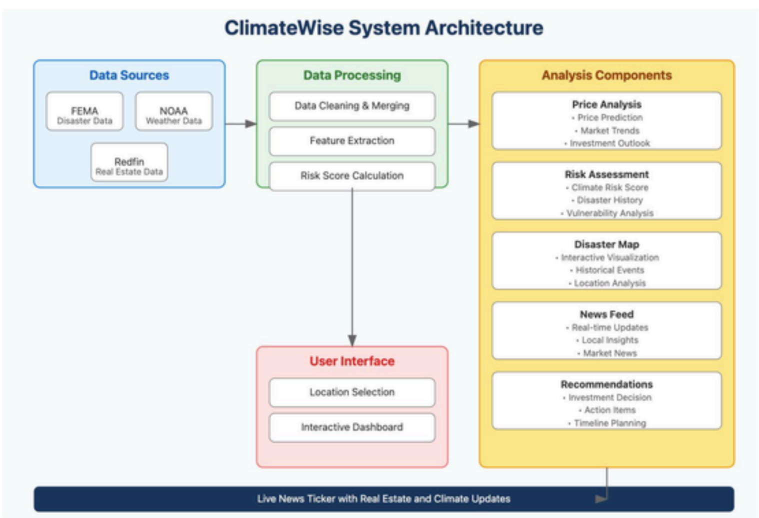


**Figure - 1: Workflow for ClimateWise System Architecture**

# Key Findings

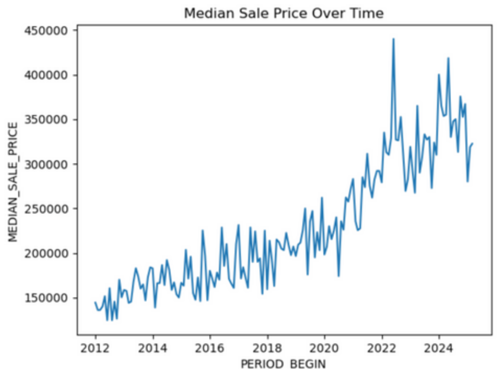


**Figure-2: Median Sale Price Over Time**

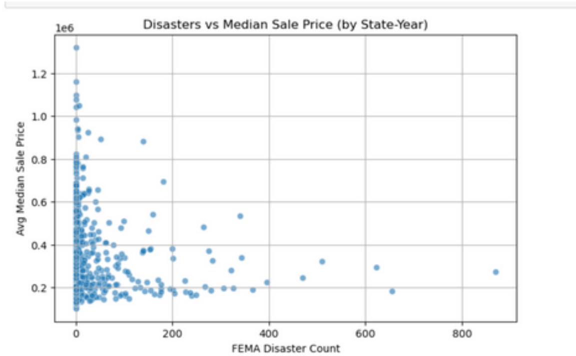


**Figure-3: Disaster vs Median Sale Price**

According to Figure 2, the median sale price of homes has shown steady growth from 2012 to 2025, more than doubling over this period and highlighting the overall strength of the housing market. Figure 3 reveals that in most states and years, there are only a few disasters, and home prices can vary widely, but as the number of disasters increases, average home prices tend to flatten or even decline. The highest home prices are typically found in areas with very few disasters, while frequent disasters keep property values from reaching top levels. Together, these figures show that while the housing market has generally grown stronger over time, regions with more frequent disasters see much less price growth, emphasizing the impact of disaster risk on long-term property values.

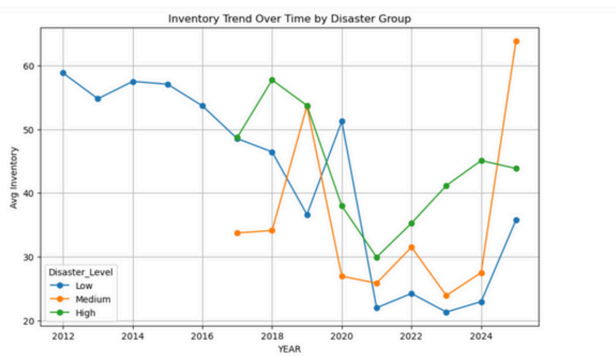


**Figure - 4: Inventory Trends Over Time by Disaster**

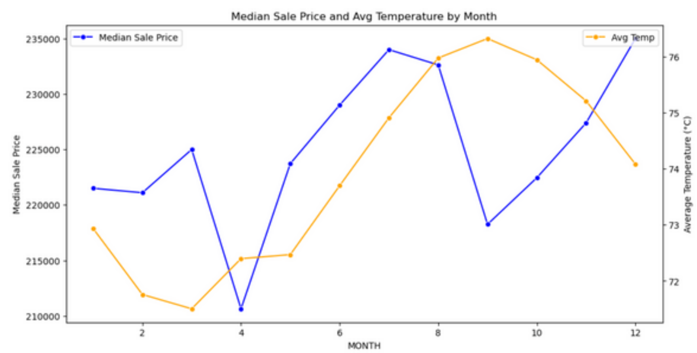


**Figure 5: Median Sale Price and Average Temperature by Month**

The analysis in Figure 4 shows that the number of homes for sale (inventory) is much more unpredictable in regions with medium or high disaster risks, with sharp rises and falls from year to year. This makes the housing market in these areas less stable and more challenging for both buyers and sellers. In contrast, areas with lower disaster risks tend to have steadier inventory trends and fewer sudden changes, offering more predictability for those looking to buy or sell a home. Figure 5 highlights that both median home sale prices and average temperatures follow a clear seasonal pattern, rising during the warmer months and peaking in late summer or early fall. This suggests that the housing market is more active and prices are higher when the weather is warmer, likely because more people are buying and selling homes during these months. Together, these figures show how both disaster risk and seasonal weather patterns can impact the stability, availability, and pricing of homes in the market, making it important to consider these factors when making real estate decisions

# Prediction

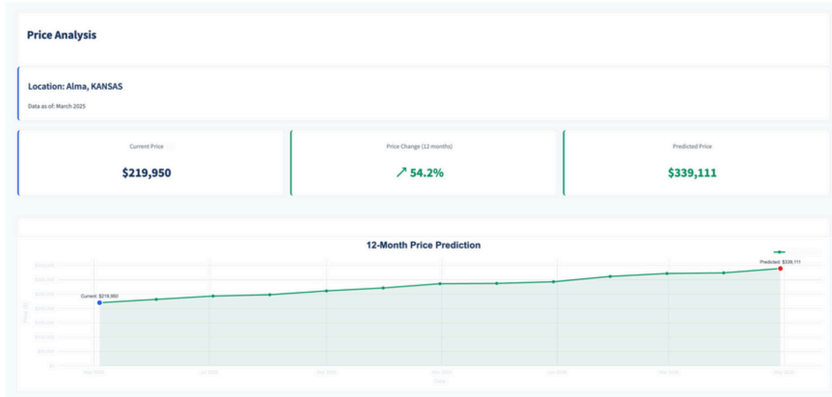

**Figure 6: Investment Opportunity Analysis: Bullhead City Market Trends**

Our 12-month price prediction uses advanced machine learning to analyze historical data from Redfin, specifically tracking monthly patterns and price trends in Alma's market. By incorporating FEMA disaster records and weather data, we assess climate risks that may impact property values. The model factors in supply-demand indicators like inventory levels and homes sold to predict market movement. We calculate annual growth rates based on recent price changes, adjusting for seasonal variations and local economic conditions. This comprehensive approach generates our month-by-month forecast, projecting a 54.2% increase to $339,111 by March 2026.

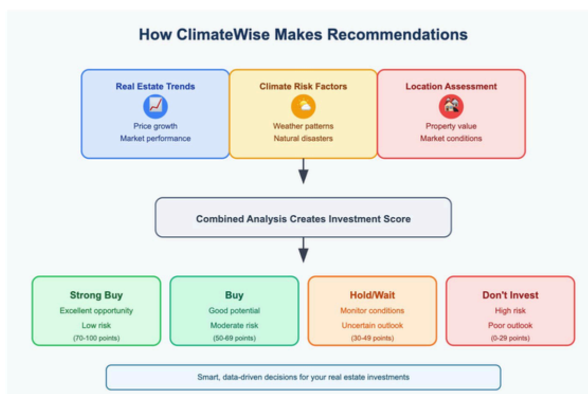

**Figure 7: The Impact of Disasters and Seasons on Home Values and Inventory**

ClimateWise helps you make smart real estate investment decisions by analyzing three key areas: real estate trends, climate risk factors, and location assessments. It looks at price growth, weather patterns, potential natural disasters, property value, and local market conditions. These insights are combined to generate an investment score that falls into one of four categories—Strong Buy (low risk, excellent opportunity), Buy (moderate risk, good potential), Hold/Wait (uncertain outlook, monitor conditions), or Do not Invest (high risk, poor outlook). This approach ensures you get clear, data-driven recommendations tailored to your investment goals.

# Challenges

- **Data Integration and NOAA Hourly Coverage:** One of the most significant challenges in this project was merging datasets from multiple sources with varying formats and timeframes. Obtaining hourly NOAA weather data for every city in our dataset proved particularly difficult, as the NOAA API does not consistently provide hourly historical data for all locations. This forced us to implement a fallback system that generates estimated weather patterns based on regional averages when specific city data is not available.
- **FEMA API Rate Limitations:** The FEMA Disaster Declarations API imposes a strict limitation of 1,000 records per call, which significantly impacted our ability to retrieve comprehensive disaster data for the entire United States. With over 20,000 disaster records needed for our analysis, we had to implement a pagination system with rate limiting and multiple API calls, creating delays in data collection and increasing the risk of incomplete datasets during peak server load times.
- **Data Quality and Missing Values:** Ensuring data quality across different sources presented another major hurdle. Redfin's market data had inconsistencies in city name formatting, missing values for certain properties, and temporal gaps in some locations. We had to develop robust data cleaning algorithms to standardize city and state names, impute missing values using location-based averages, and interpolate missing time periods to maintain data integrity.
- **Scalability and Performance Issues:** Processing and analyzing such large datasets (5+ million real estate records) while maintaining a real-time response for users required significant optimization. Initial implementation resulted in slow load times and memory issues. We had to implement data caching and develop efficient algorithms for calculating risk scores without compromising accuracy.

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