

Climate data and machine learning integration for evaluating flood insurance risk patterns

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Flood events, exacerbated by **climate variability**, pose significant challenges to flood risk management and the insurance industry in the United States.

To enhance flood risk modeling strategies, this study explores **spatial correlations** between different areas and applies **machine learning** to predict regions prone to high flood insurance claims by integrating hydrological, meteorological, and socio-economic data.

We combine the **FEMA NFIP Redacted Claims dataset**, detailing over 2.5 million flood-related insurance claims, with the US-CAMELS streamflow dataset, offering rich hydrological insights across numerous catchments in the USA (Papoulakos, 2025).

A key focus is the influence of climate indices, such as the **El Niño-Southern Oscillation (ENSO)**, on flood patterns. Using the Oceanic Niño Index (ONI) as a quantitative metric, we explore the spatiotemporal relationship between ENSO phases, streamflow variability, and flood insurance claims.

Keywords: Flood insurance claims, Streamflow extremes, Climate variability, Machine Learning, FEMA

Influence of ENSO on Flood Insurance Claims:

Insights from National and California Perspectives

The Pearson correlation analysis between the maximum annual ENSO index and insurance claims by state reveals **spatial variability**.

In California, the correlation coefficients indicate a **moderate positive relationship** — meaning that stronger El Niño events tend to be associated with higher numbers of insurance claims.

This finding is **consistent with previous studies**, such as Hoell et al. (2015), which reported that "the strongest El Niño events greatly increase the likelihood for above-average precipitation across the state," leading to elevated flood risks.

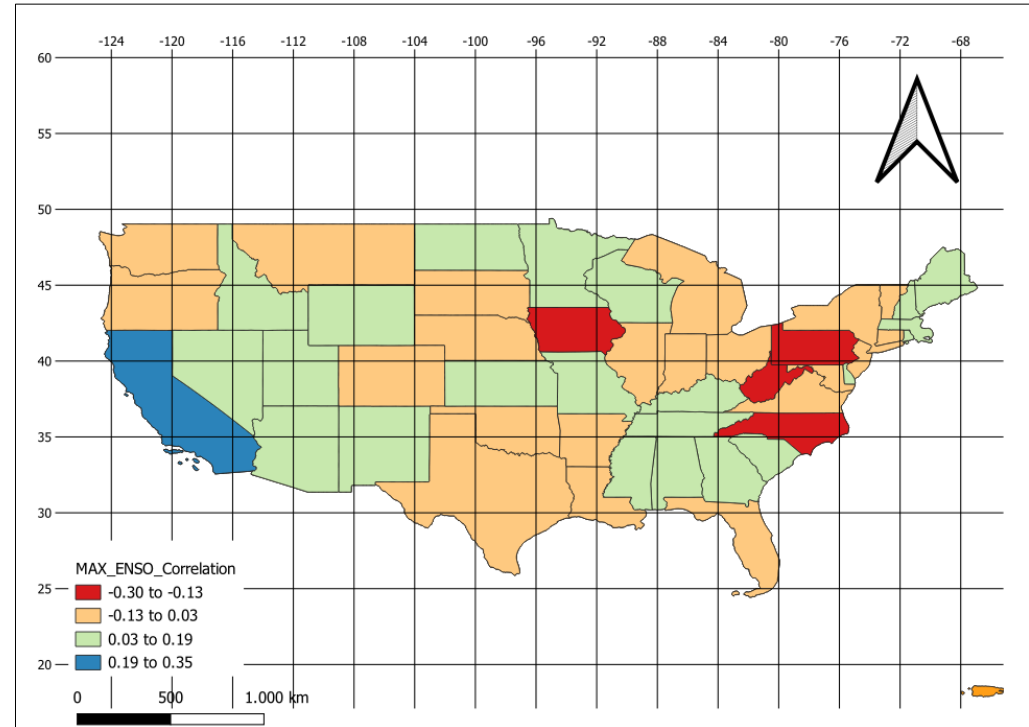


Fig. 1 Pearson Correlation Between Maximum Annual ENSO Index and FEMA's Aggregated Annual Insurance Claims by State.

Influence of ENSO on Flood Insurance Claims:

Insights from National and California Perspectives

The Pearson correlation analysis between the maximum annual ENSO index and insurance claims by County in California state reveals **spatial variability**.

These higher correlations suggest a notable relationship between strong **El Niño events** and increased **insurance claims** due to flooding.

In Trinity County, California, we observe a significant **negative correlation** (represented in red on the map), supported by previous studies (National Research Council , 1997), which indicates that in the Trinity and Klamath basins, peak flows are largely influenced by **snowmelt** rather than just **rainfall**.

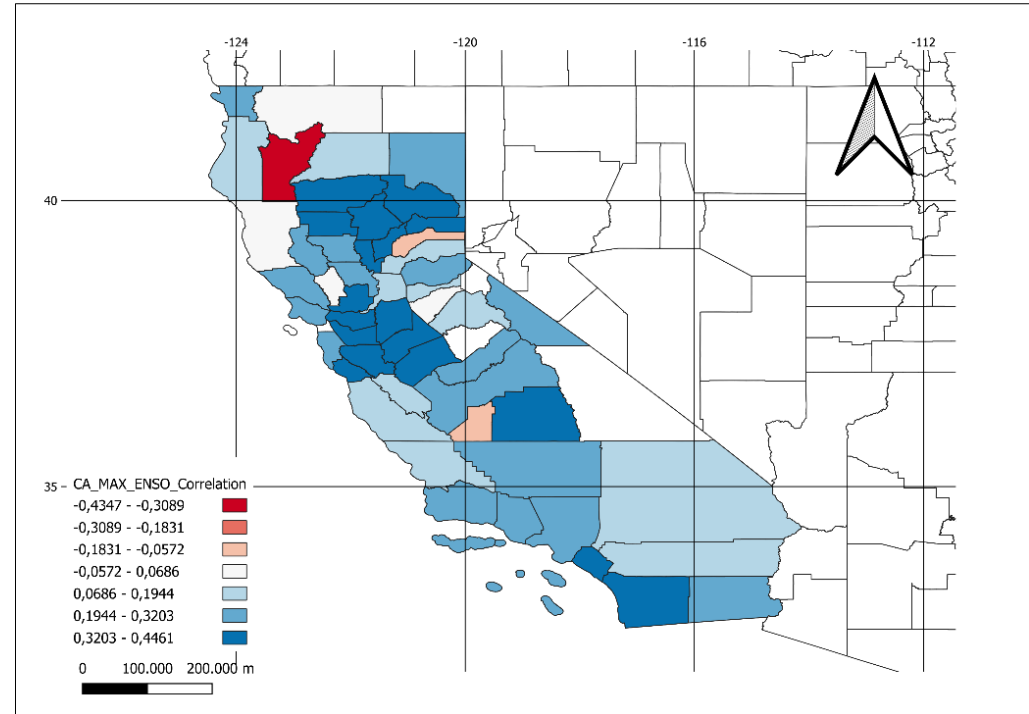


Fig. 2 Pearson Correlation Between Maximum Annual ENSO Index and FEMA's Aggregated Annual Insurance Claims by County (California).

Influence of ENSO on Flood Insurance Claims:

Insights from National and California Perspectives

As shown in the chart, the interplay between insurance claims and the Maximum ENSO Index reveals a **notable trend**, particularly during El Niño years.

These years often bring intense **storms**, heavier-than-normal **rainfall**, and in some cases, severe **flooding**, which can strain local infrastructure and lead to significant **damage claims**.

This **aligns** with findings from Pielke and Landsea (1999), who noted that El Niño events can have a significant impact on **weather patterns**, including increased hurricane activity and associated damage.

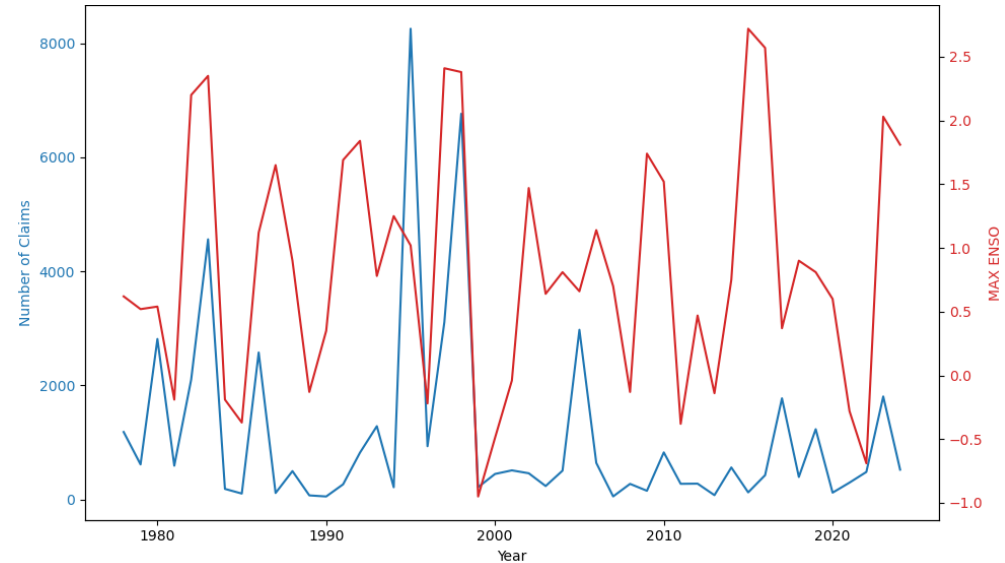


Fig. 3 The interplay between Flood Insurance Claims and Maximum ENSO Index in California (1980–2024)

Input features for Machine Learning model

Spatial Distribution of Transportation and Hydrographic Networks

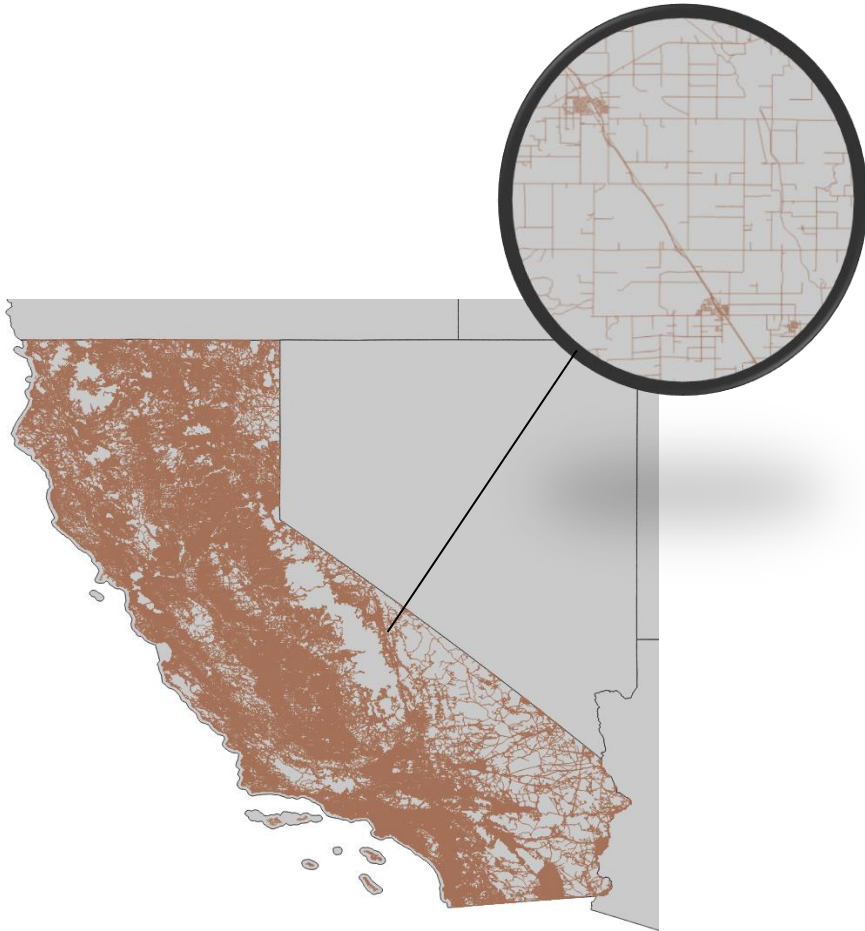


Fig. 4 Spatial distribution of Transportation networks in CA.

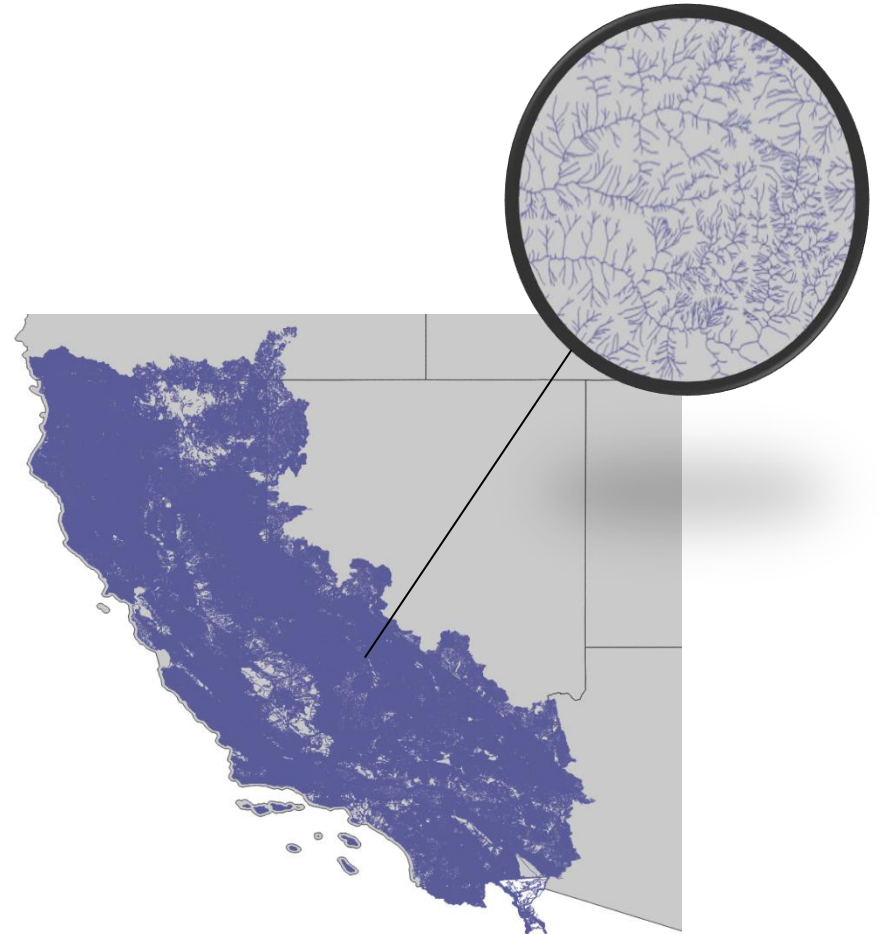


Fig. 5 Spatial distribution of Hydrographic networks in CA.

Machine Learning Workflow for Predicting Flood Claims

state	countyCode	countyName	yearOfLoss	Num_Claims	Total_PolicyCount	Mean_Claims Per_Policy	hydro_density (km/km ²)	transport_density (km/km ²)	ENSO_avg (index)
NJ	34001.0	Atlantic	1978	63	63	1.0	2,597	25,521	-0,369
NJ	34001.0	Atlantic	1979	157	157	1.0	2,597	25,521	-0,022
NJ	34001.0	Atlantic	1980	206	206	1.0	2,597	25,521	-0,002
NJ	34001.0	Atlantic	1981	24	24	1.0	2,597	25,521	-0,456
NJ	34001.0	Atlantic	1982	18	18	1.0	2,597	25,521	0,832
NJ	34001.0	Atlantic	1983	31	31	1.0	2,597	25,521	0,307
NJ	34001.0	Atlantic	1984	1073	1073	1.0	2,597	25,521	-0,664
NJ	34001.0	Atlantic	1985	935	935	1.0	2,597	25,521	-0,755
NJ	34001.0	Atlantic	1986	19	19	1.0	2,597	25,521	0,060

Table 1 Input Data for Machine Learning Model.



Machine Learning Model



state	countyCode	countyName	yearOfLoss	Prediction (Num_Claims)
NJ	34001.0	Atlantic	2026	33
NJ	34001.0	Atlantic	2027	97
NJ	34001.0	Atlantic	2028	85

Table 2 Output Data from Machine Learning Model.

Integrating **climate data** with **machine learning** provides a powerful framework to uncover complex spatiotemporal patterns of flood risk and insurance claims.

Stronger El Niño events are moderately linked to increased flood insurance claims in California, reflecting **spatial variability** in climate impacts and confirming established precipitation-flood risk patterns.

El Niño years tend to coincide with increased insurance claims, suggesting that **ENSO** may influence **storm intensity** and **flood-related impacts**.

The combined use of **physical** and **socio-economic** information enhances our ability to predict, understand, and manage flood-related impacts.

Such approaches can support more **resilient** and equitable insurance systems and contribute to effective **climate adaptation** strategies in vulnerable communities.

References

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