Climate stress testing for mortgage default probability

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Embedding Sustainability in Credit Risk Assessment

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Agenda

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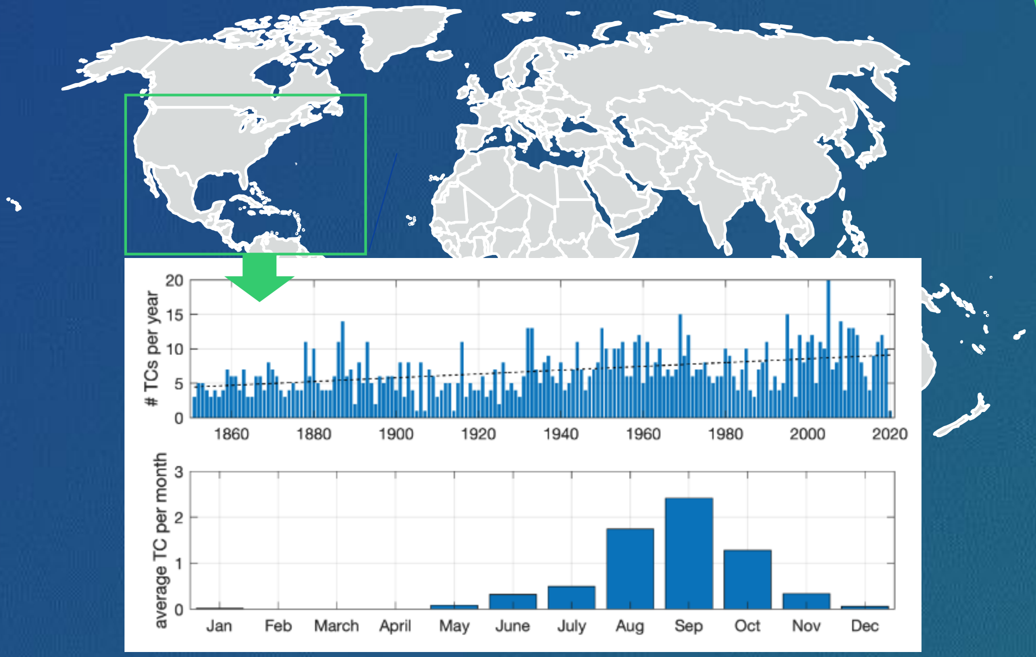
Introduction

Extreme weather events, such as tropical cyclones, floods, and heavy rains, occur more frequently and intensely **in the United States** than in the past owing to global warming (IPCC, 2023)

Policymakers, central banks, regulatory authorities, and **practitioners** have expressed **concerns** about the potential **risks** that extreme weather events may pose to **economic activity** and **asset values,** ultimately threatening **financial stability**

Trends of tropical cyclone activity in the U.S.



Stress testing

Stress testing exercises are an important tool for financial institutions to evaluate their portfolio vulnerability to **adverse scenarios**, especially **when outside the range of historical events**.

Climate stress testing involves assessing financial institutions' **resilience to climate-related risks**

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Literature review on climate stress testing

Focus

We focus on a climate stress testing framework for mortgage portfolios

The **real estate properties** used to **secure mortgages** can be threatened for their **location** by severe damage from acute weather events with cascading effects on the **mortgage default risk**.

Some examples from literature and practitioners

Author(s)	Some main features	Some main limitations
Wong and Ho (2023)	The PD and the LGD are estimated by designing predetermined and hypothetical extreme weather events.	The scenarios are not designed using science-based climate or statistical models
Caloia and Jansen (2021)	The design of the stressed flood depth scenario derived from guidance from a Dutch government expert group on flood incidence and related inundation depths.	The scenarios are not designed using science-based climate or statistical models
Federal Reserve Board (2023)	The first exercise of climate stress tests for the six largest U.S. Banks. One of the goals is to evaluate the impacts of extreme events on residential real estate assets of the mortgage portfolio (PD). The FRB recommended that banks consider including tropical cyclone events with a return period of 1-in-100 years and 1-in-200 years in the Northeastern U.S.	No larger return period events are considered No uniform scenarios

Lack of a common framework

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Purpose

This study aims to **overcome some of these limitations** by proposing a methodology for **assessing the change in the default probability** of mortgage loans affected by extreme weather events (tropical cyclones) with **large return periods, such as up to 1-in-1,000 years**

Moreover, we aim to address the following two research questions:

- The first is whether the **default risk** in different geographical areas shows **heterogeneous exposure to tropical cyclones**.
- The second research question is focused on **insurance coverage** to understand if and to what extent it **contributes to mitigating the effects of physical risk** on mortgage defaults.

For the empirical analysis, we apply the suggested climate stress testing framework to a **portfolio of mortgages** provided by Freddie Mac in **Louisiana**, a U.S. state affected by **devastating hurricanes in the last decades** (e.g., Hurricane Katrina in August 2005; Hurricane Laura in August 2020; and Hurricane Ida in August 2021)

Methodological framework

We designed a climate stress testing framework based on the following steps:

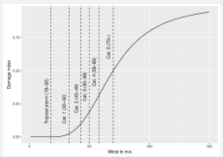
Model workflow

Data source collection and data management

- **Data collection** (loan-month observations, flood risk index, flood insurance, etc)
- Mapping of **historical tropical cyclone events** and estimation of the **damages** using a power function (Emanuel, 2011)

Tropical cyclone tracks

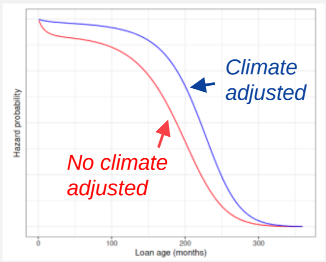
Damage function



Estimation of a credit scoring model

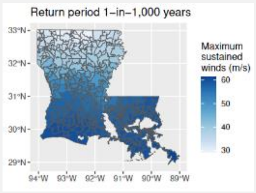
- Estimation of a **dynamic credit scoring model based on survival analysis** – including weather events and flood insurance coverage
- **Predictive accuracy** assessment (out-of-time and out-of-sample)

Hazard function



Scenario of damages by return period

- Design of the **tropical cyclone scenario** by return periods



Wind speed scenario

- Estimation of the **index of damage** by return periods (proxy for the property damage fraction in the zone)

Stress testing

- **Climate damage-adjusted LTV**
- Evaluation of the **stressed PD** under extreme weather events scenarios **with or without flood insurance coverage**

PD – stressed scenario

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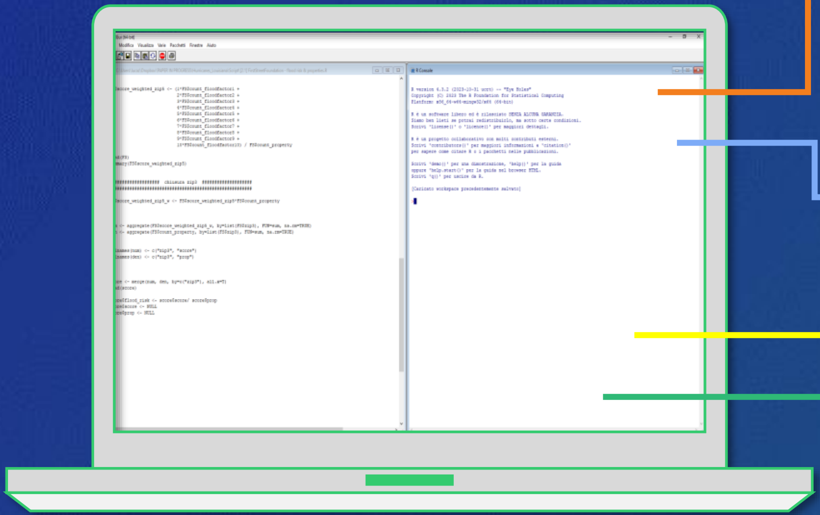
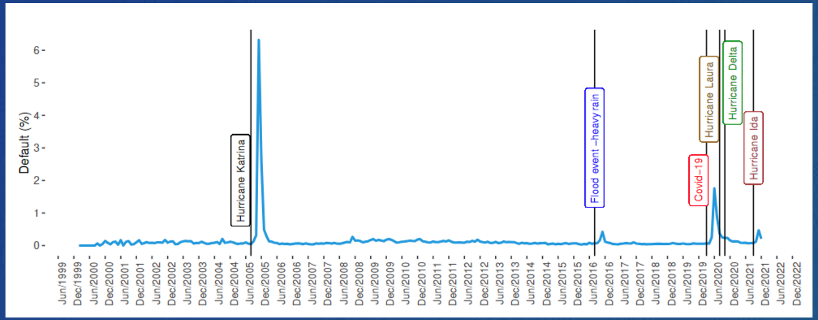
Data collection

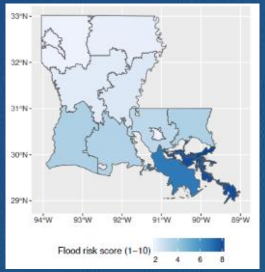


Freddie Mac single family loan-level data (3-digit zip level)

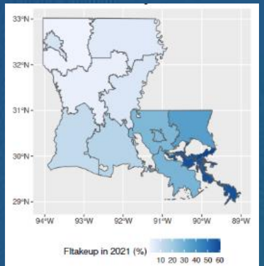


National Oceanic and Atmospheric Administration

First Street Foundation



National Flood Insurance Program (NFIP)



We aggregate the metrics of weather events, damage index, flood risk, and insurance coverage from 5-digit to 3-digit zip code level. We consider using the #properties as a measure for weighing.

Bureau of Labor Statistics

Federal Housing Finance Agency

Housing price index at the three-digit zip code level

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Model of credit scoring

Methodology

The dependent variable of a credit scoring model is

$$Y_{it} = \begin{cases} 1 & Y^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases}$$

mortgage default based on the 90+ day delinquency

The model is defined as

$$Y^*_{it} = \alpha + \phi(d)^\top \beta_0 + \boldsymbol{z}_{iot}^\top \beta_1 + \boldsymbol{x}_{it-k}^\top \beta_2 + \boldsymbol{w}_{it-k}^\top \beta_3 + \boldsymbol{c}_{it-k}^\top \beta_4 + \epsilon_{it}$$

Hazard function | Static and time-varying variables | Weather and insurance variables

We estimate the model using a logit link function (Bellotti and Crook, 2013)

Results from survival models

	Base model		Base model+Climate-related variables	
Variables	Estimates	Std. Error	Estimates	Std. Error
Intercept	-4.9471***	0.3179	-6.4038***	0.3199
Loan age	-0.0061	0.0069	-0.0086	0.0069
Loan age (squared)	0.0001**	0.0000	0.0001*	0.0000
Loan age (log)	1.3245***	0.2442	0.9445***	0.2433
loan age (log squared)	-0.1599**	0.0639	-0.0578	0.0638
Occupacy type (Base: Primary residence)				
Investment property	0.2286***	0.0418	0.2396***	0.0415
Second home	-0.0331	0.0697	-0.0436	0.0699
Nr. of units	0.3259***	0.0297	0.2280***	0.0308
Mortgage characteristics				
FICO score	-0.0102***	0.0001	-0.0092***	0.0002
LTV_{t-3}	0.0149***	0.0008	0.0196***	0.0008
Spread IR_{t-3}	0.0267**	0.0126	0.0951***	0.0127
DTI	0.0185***	0.0009	0.0177***	0.0009
Loan motivation (Base: Purchase)				
Refinance - cash out	0.2900***	0.0257	0.2979***	0.0259
Refinance - no cash out	0.1692***	0.0251	0.1791***	0.0252
Nr. of borrowers	-0.4601***	0.0206	-0.4707***	0.0207
Macroeconomics + insurance				
Unemployment rate_{t-3}	0.2685***	0.0045	0.2856***	0.0046
FItakeup_{t-3}			-0.0229***	0.0006
Tropical cyclones damages + major flood event + flood risk				
Flood event 2016_{t-3}			2.0452***	0.0863
Damage index_{t-3}			0.1404***	0.0026
Flood risk			0.2270***	0.0049
Deviance explained (%)	6.43		9.02	
Loan-month observation (Nr.)	6,742,194		6,742,194	

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Model of credit scoring – predictive accuracy

Out-of-time

Model	Base model+	AUC	H	KS	F-score	ACC
Survival model	No climate-related variables	0.6912	0.1016	0.2971	0.0055	77.0132
	Climate-related variables	**0.7117**	**0.1280**	**0.3263**	**0.0063**	**81.0094**
Binomial model (link = Logit)	No climate-related variables	0.6736	0.0885	0.2729	0.0051	75.2346
	Climate-related variables	0.6997	0.1164	0.3127	0.0060	79.0430
Binomial model (link = Probit)	No climate-related variables	0.6744	0.0896	0.2770	0.0051	74.6558
	Climate-related variables	0.7005	0.1175	0.3103	0.0058	77.0727

The training sample encompasses loans observed from 2000 to 2020. The test sample looks one year ahead (2021)

Out-of-sample

Model	Base model+	AUC	H	KS	F-score	ACC
Survival model	No climate-related variables	0.7630	0.1956	0.3955	0.0068	69.4748
	Climate-related variables	**0.7967**	**0.2576**	**0.4414**	**0.0076**	**72.2825**
Binomial model (link = Logit)	No climate-related variables	0.7559	0.1864	0.3826	0.0066	69.1860
	Climate-related variables	0.7869	0.2472	0.4258	0.0074	72.0425
Binomial model (link = Probit)	No climate-related variables	0.7565	0.1870	0.3833	0.0065	68.3752
	Climate-related variables	0.7902	0.2539	0.4308	0.0073	71.3284

The average predictive accuracy measures are derived from five-fold out-of-sample cross-validation, with each test sample size constituting one-fifth of the ID loans

- **Models incorporating climate-related variables** (extreme events, risk exposure, and mitigation risk measures) **outperform those that exclude them.**
- The **survival model outperforms the logit and probit models** without duration time.
- These findings not only validate the existing literature on the enhanced predictive accuracy of credit risk when integrating climate-related variables but also underscore the growing **preference for survival models over traditional scoring models** (such as logit and probit models)

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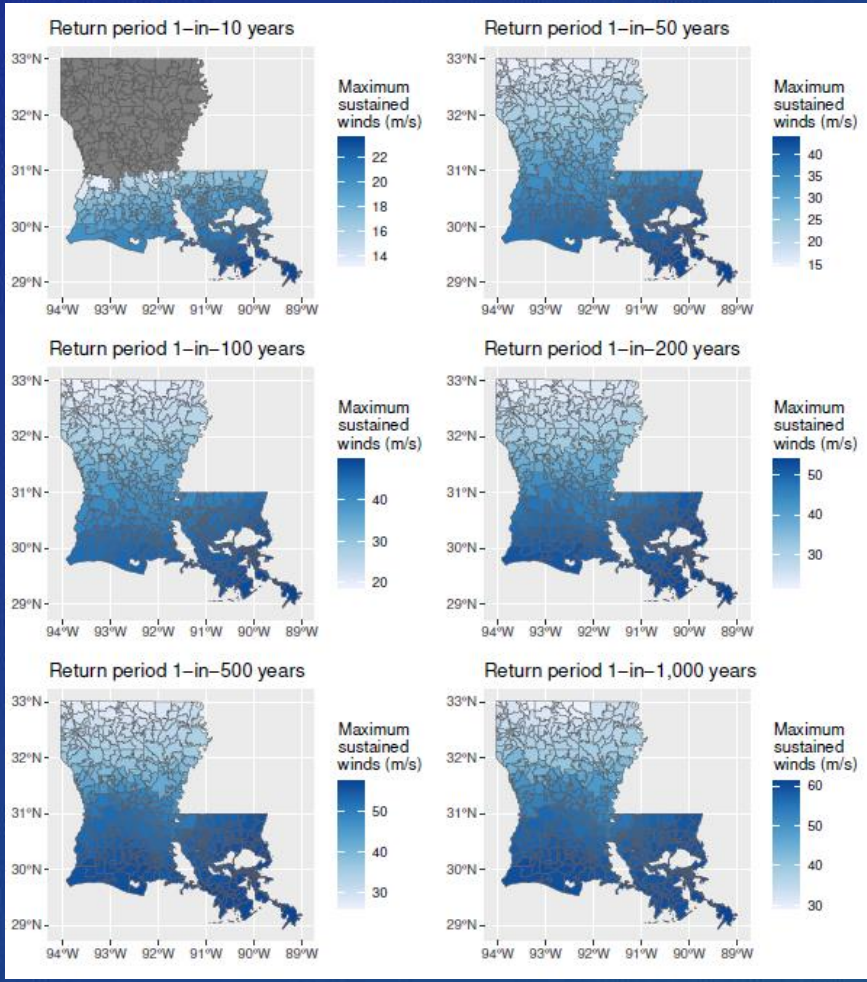
Design of scenarios – tropical cyclone wind speed



- We considered using the **Synthetic Tropical cyclOne geneRation Model** (STORM) proposed by Bloemendaal et al. (2020) to generate wind speed scenarios for tropical cyclones.
- As elaborated in Meiler et al. (2022), the scenarios obtained from **STORM incorporate a greater number of high-impact events** (specifically, Hurricanes categories 3-5) compared to alternative solutions (e.g., CLImate ADAptation (CLIMADA) platform and the Columbia HAZard model). This unique feature enables us **to generate the most severe scenarios of tropical cyclones**, facilitating a thorough evaluation of their impact on mortgage defaults.
- **Coastal zones** have emerged as the areas **most affected by severe tropical cyclones**

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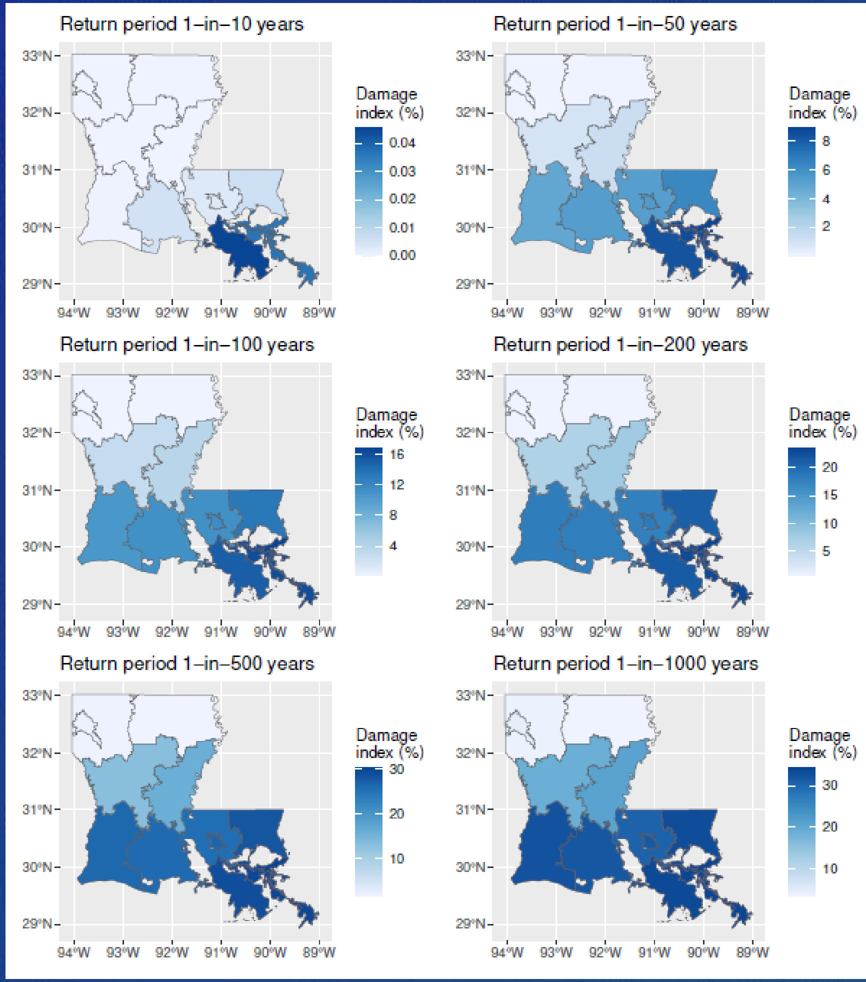
Design of scenarios – damage index



- The **damage index is at the five-digit ZIP code** level. As the information on mortgages is provided at the three-digit ZIP code level, **we compute a weighted average to obtain the wide damage index at the three-digit ZIP code** level using the number of properties provided by First Street Foundation

- Consistently with the wind speed scenarios, **the most substantial damage is expected in coastal areas**. This occurs when hurricanes intensify by absorbing heat from warmer ocean waters via air-sea heat fluxes, making landfall on the mainland with heightened energy levels

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From damage index to climate-adjusted LTV

Damages from tropical cyclones, encompassing wind speed, heavy rain/flooding, and storm surges, **affect the value of the impacted properties**.

The decline in property value contributes to a rise in the loan-to-value (LTV) ratio, consequently elevating the probability of default on mortgages. For a damage index with return period *rp*, **we estimate a simplified climate damage-adjusted LTV ratio** associated with each mortgage *i* as follows:

Scoring model

Scenario tropical cyclones

$$\text{Climate damage-adjusted LTV}_{i,t} = \frac{\text{UPB}_{i,t}}{\text{value of property}_{i,t} - \text{potential damage}_{i,rp}}$$

Mortgage-ending balance of loan

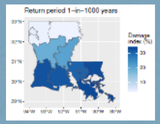
$$\text{value of property}_{i,t} = \text{value of property}_{i,t0} \times \frac{\text{HPI}_{i,s,t}}{\text{HPI}_{i,s,t0}}$$

Value of the property at the mortgage origination (t0)

House price index (3 digit zipcode)

$$\text{potential damage}_{i,t} = \text{value of property}_{i,t} \times \text{damage index}_{s,rp}$$

Scenario damage index by RP



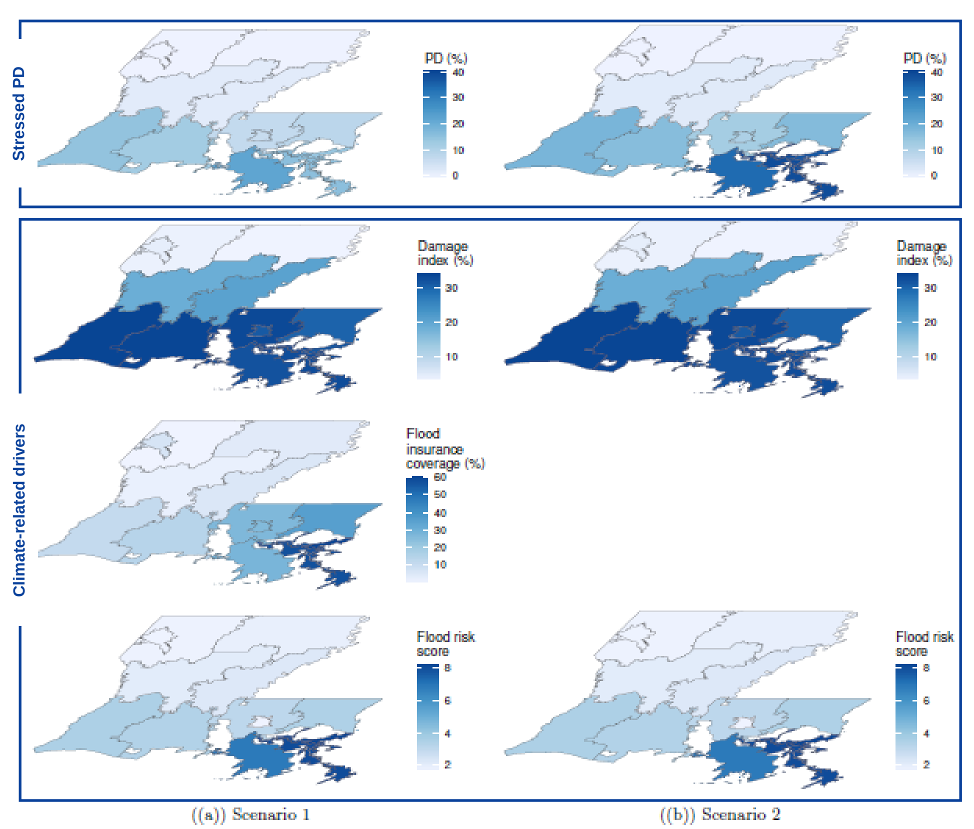
Stressed mortgage PD

Stress test for mortgage PD

Scenario	Scenarios predicted PD (%) with current (%) of insurance coverage on flood risk				
	Mean	$P50^{th}$	$P95^{th}$	$P97^{th}$	$P99^{th}$
Baseline	0.0782	0.0574	0.2091	0.2491	0.3507
RP 1-in-10 years	0.0784	0.0575	0.2097	0.2497	0.3520
RP 1-in-50 years	0.2055	0.1354	0.6106	0.7527	1.0979
RP 1-in-100 years	0.5858	0.3565	1.8987	2.3584	3.4035
RP 1-in-200 years	1.6604	1.0700	5.3277	6.5459	9.1542
RP 1-in-500 years	4.9574	3.4922	15.0860	18.0101	23.8237
RP 1-in-1,000 years	9.9810	7.7341	28.1505	32.1224	39.9288

Scenario	Scenarios predicted PD (%) without an insurance coverage on flood risk				
	Mean	$P50^{th}$	$P95^{th}$	$P97^{th}$	$P99^{th}$
RP 1-in-10 years	0.1760	0.1129	0.5324	0.6648	0.9774
RP 1-in-50 years	0.5306	0.2565	1.9356	2.4174	3.5373
RP 1-in-100 years	1.5782	0.6815	6.1391	7.6390	10.9140
RP 1-in-200 years	4.2422	2.0653	15.9236	19.2984	26.1142
RP 1-in-500 years	10.9998	6.7615	36.5067	42.1965	51.5627
RP 1-in-1,000 years	19.3382	14.8431	54.2235	59.8746	68.3952

Scenarios of default probability for various return periods of tropical cyclone wind speeds



The mean probability of default is computed at the three-digit zip code level in Scenarios 1 and 2. **Scenario 1 includes flood insurance coverage**, while **Scenario 2 excludes it**. The analysis focuses on a tropical cyclone event with a return period of 1-in-1,000 years

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Conclusions

We apply the proposed climate stress test framework to a mortgage portfolio in Louisiana, a region frequently affected by major tropical cyclones in the U.S.

Main findings:

- We found that damage from **tropical cyclones with larger return periods** significantly **increased the default probability**.
- The effects of tropical cyclones on the **default risk** of mortgage loans are **spatially heterogeneous**.
- The findings highlight the crucial role of **flood insurance in mitigating default risk** in high-risk flooding locations

Implications for a wider group of stakeholders:

- ***Financial institutions and regulators*** can use our proposal to **identify mortgage loans that are most vulnerable** to extreme climate events. This would support lenders in adopting a more reliable approach for **prudential risk management**.
- Lenders can share their default risk assessment with ***borrowers*** who would be able to make more **informed decisions on the risk of buying a property in risky areas** and potentially purchase **insurance to mitigate losses** from catastrophic events.
- ***Policymakers*** can consider these findings to **allocate public funds** in a more effective way **to protect homeowners** living in high-risk areas.

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Confidentiality

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