Catastrophic Climate Risks and Insurance

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Workshop on Impacts of Climate Change
on Economics, Finance, and Insurance, September 2022

September 17, 2022

Published & on-going work on climate related risks

- Flood (Hurst / Gumbel, 2008)
  doi: 10.1002/env.909
- Windstorm dynamics (2006)
  doi: 10.1007/s00477-005-0029-y
- Insurability of climate risks (2008)
  doi: 10.1057/palgrave.gpp.2510155
- Public intervention ? (2014)
  doi: 10.1016/j.jpubeco.2014.03.004
- Earthquake dynamics (2015)
  doi: 10.1007/s10950-015-9489-9
- Heat wave and return period (2011)
  doi: 10.1007/s10584-010-9944-0
- Floods & fairness (2021)
  doi: 10.1057/s41288-021-00233-7
- Subsidence & heat waves (2022)
  doi: 10.5194/nhess-2021-214
- Wildfires (2022)
  ICAG-CSRS Conference 2022
- Public intervention with RL (2022)
  arXiv: 2207.01010

Flood Risk in France, and solidarity [1]

[1] France Info. "Seine-et-Marne : la ville de Thoméry se remet progressivement des inondations". In: (2018). URL: http://tinyurl.com/mtc9tprm.

Flood Risk in France, and solidarity [2]

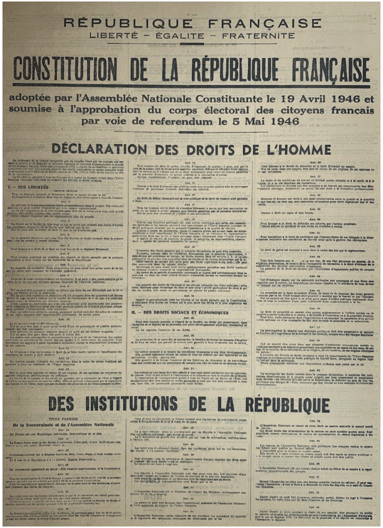
On fairness & solidarity

- French Constitution (1946)

  12. *La Nation proclame la solidarité et l'égalité de tous les Français devant les charges qui résultent des calamités nationales.*

- 82-600 Law (1982)

  régime d'indemnisation des catastrophes naturelles


RÉPUBLIQUE FRANÇAISE

LIBERTÉ – ÉGALITÉ – FRATERNITÉ

CONSTITUTION DE LA RÉPUBLIQUE FRANÇAISE

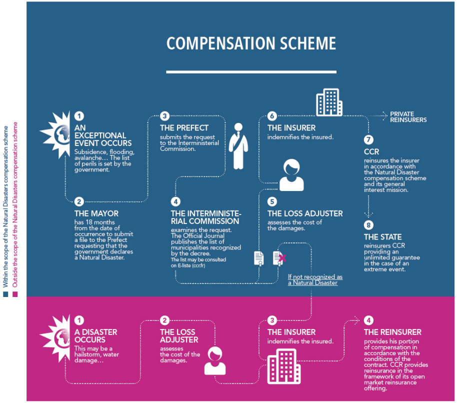
adoptée par l'Assemblée Nationale Constituante le 19 Avril 1946 et soumise à l'approbation du corps électoral des citoyens français par voie de referendum le 5 Mai 1946

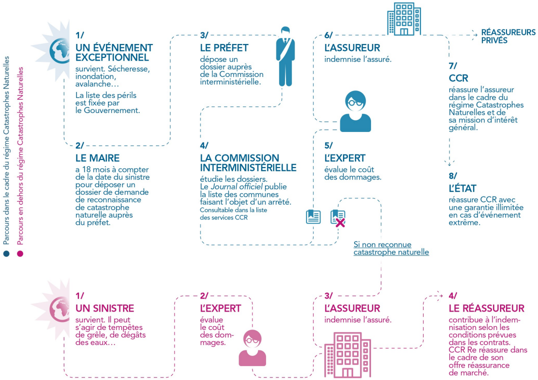
DÉCLARATION DES DROITS DE L'HOMME

DES INSTITUTIONS DE LA RÉPUBLIQUE

[1] A. Charpentier, L. Barry, and M. James. "Insurance against Natural Catastrophes: Balancing Actuarial Fairness and Social Solidarity". In: *Geneva Papers on Risk & Insurance* (2021). DOI: 10.1057/s41288-021-00233-7.

Flood Risk in France, and solidarity [3]



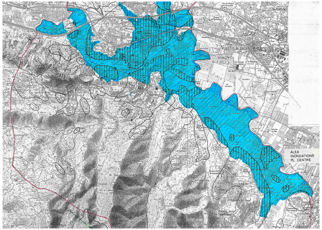


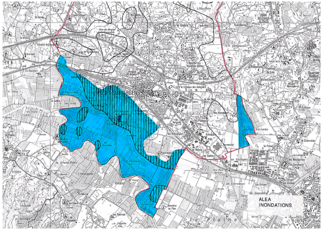
source: https://www.ccr.fr/en/-/indemnisation-des-catastrophes-naturelles-en-france

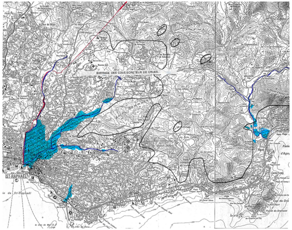
Flood Risk in France, and solidarity [4]

Two different flood perils : overflow vs. coastal

PPRIs (plan de prévention du risque inondation) in Roquebrune-sur-Argens, Puget and Saint-Raphaël. The plain area (in blue) is the risky area.



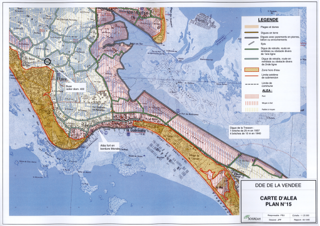


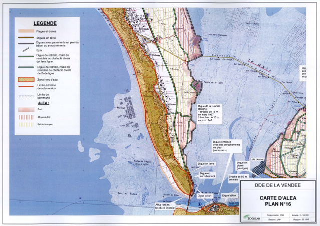


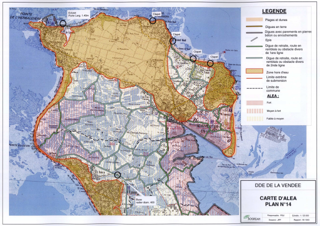
Areas clearly identified as risky, from documented (historical) floods.

Flood Risk in France, and solidarity [5]

PPRLs (plan de prévention des risques littoraux) in Vendée. The dashed area is the risky area. Areas with possible coastal risk.





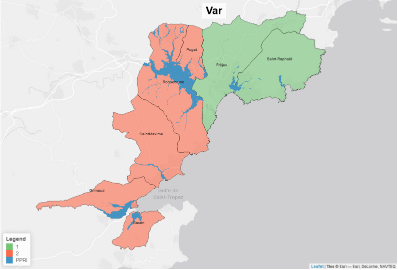


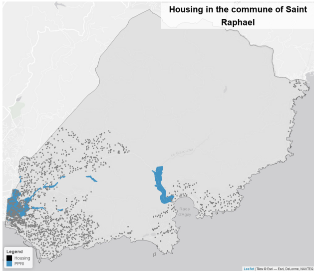
See https://github.com/freakonometrics/floods

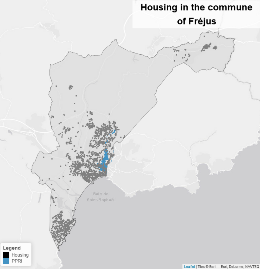
Flood Risk in France, and solidarity [6]

10% of households represent 73.6% of the losses... who lives in those risky areas ?

"ventes de biens fonciers" dataset, https://cadastre.data.gouv.fr/dvf, 2014-2018,



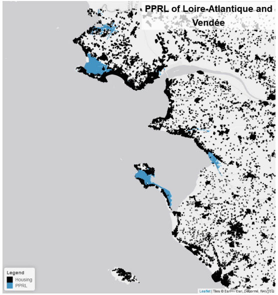


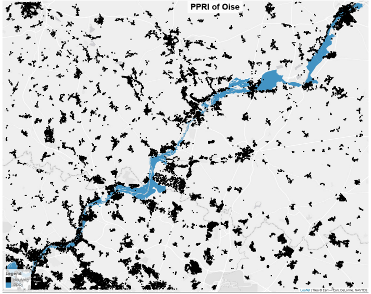


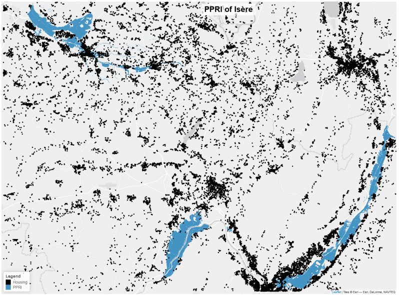
(possible bias on those 5-year notarial transactions...)

Flood Risk in France, and solidarity [7]

E.g. in 4 “departements” (Loire-Atlantique, Vendée, Oise, Isère)







- sold houses / apartments, ■ PPRI-PPRL areas

Flood Risk in France, and solidarity [8]

Table 1: coastal risk areas vs. Table 2: overflow / non-costal risk areas

			Average Price	Difference (%)	Maximum Price	Number	Proportion (%)	Welch t test
Vendée	Non risky	Apartments	4293		21840	329	9%	
		Houses	2928		65909	2795	74%	
	Risky	Apartments	3302	-23%	9773	39	1%	1.0
		Houses	10253	+250%	71483	637	17%	-60.1
Pays-Loire	Non risky	Apartments	4399		79913	8411	37%	
		Houses	3019		75472	12678	55%	
	Risky	Apartments	6784	+54%	68478	1001	4%	-8.6
		Houses	3245	+7%	22895	765	3%	-2.7

Table 1: Prices (€ per m^2) of houses sold (2014-2018) for Vendée - Western part of France, with PPRL (coastal risk). The *Difference* is the relative difference between average prices (per m^2) between the risky and the non-risky zones, either for apartments or houses.

Flood Risk in France, and solidarity [9]

			Average Price	Difference (%)	Maximum Price	Number	Proportion (%)	Welch t value
Var	Non risky	Apartments	5392			9874	53%	
		Houses	5957			6913	37%	
	Risky	Apartments	4190	-22%		1471	8%	6.4
		Houses	4172	-30%		226	1%	5.2
Haute Loire	Non risky	Apartments	2399		38333	3403	27%	
		Houses	1314		20625	8857	69%	
	Risky	Apartments	2163	-11%	28125	319	2%	1.6
		Houses	1247	-5%	7432	272	2%	0.9
Seine et Marne	Non risky	Apartments	6260		79710	82133	44%	
		Houses	3356		79167	98824	53%	
	Risky	Apartments	4333	-30%	40000	2177	1%	8.0
		Houses	2693	-20%	54096	1784	1%	7.5

Flood Risk in France, and solidarity [10]

			Average Price	Difference (%)	Maximum Price	Number	Proportion (%)	Welch t value
Isère	Non risky	Apartments	4960		79800	27982	52%	
		Houses	2429		69375	24600	45%	
	Risky	Apartments	3252	-3%	35714	885	2%	6.1
		Houses	2543	+5%	14067	435	1%	-1.2
Oise	Non risky	Apartments	6170		79963	24613	34%	
		Houses	3126		78214	44737	62%	
	Risky	Apartments	5725	-7%	50000	1385	2%	2.1
		Houses	2866	-8%	62184	1640	2%	4.6

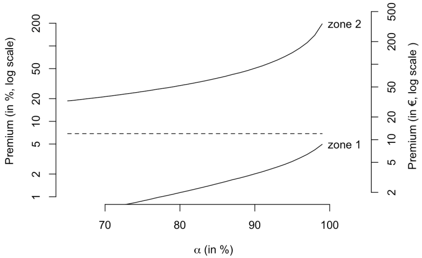
Table 2: Prices (€ per m^2) of houses sold (2000-2020) for several départements in France, with PPRI (overflow risk, or non-costal).

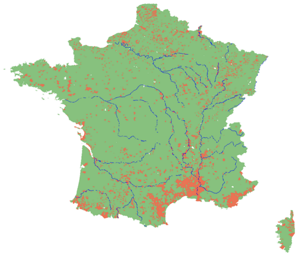
Flood Risk in France, and solidarity [11]

2 zone model, $\alpha \in [0\%, 100\%]$,

- zone 1, proportion α, less risky
- zone 2, proportion $1-\alpha$, more risky

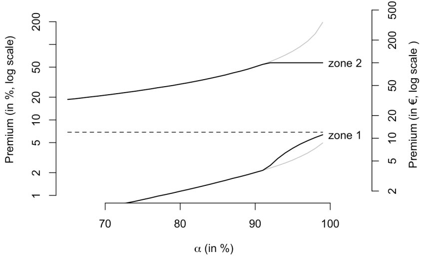
so called "*Will Rogers phenomenon*",
When the Okies left Oklahoma and moved to California, they raised the average intelligence level in both states.





$\alpha = 90\%$, less risky,
26.4% of losses, 3.5€

$1-\alpha = 10\%$, more risky,
73.6% of losses, 88.5€



Flood Risk in France, and solidarity [12]

		Uniform			Two-Zone Model		
		Country	Region	Municipality	$\alpha = 95\%$	$\alpha = 90\%$	$\alpha = 80\%$
Var	Frejus	12.0€	30.6€	15.7€	5.1€	3.5€	52.1€
	Grimaud	12.0€	30.6€	84.3€	142.3€	88.5€	52.1€
	Puget	12.0€	30.6€	133.0€	142.3€	88.5€	52.1€
Pays Loire	Assérac	12.0€	3.6€	6.7€	5.1€	3.5€	2.0€
	Mesquer	12.0€	3.6€	10.2€	5.1€	3.5€	2.0€
	Le Croisic	12.0€	3.6€	25.9€	5.1€	88.5€	52.1€
Vendée	Talmont-Saint-Hilaire	12.0€	10.7€	4.8€	5.1€	3.5€	2.0€
	Noirmoutier-en-l'Île	12.0€	10.7€	8.5€	5.1€	3.5€	2.0€
	La Faute-sur-Mer	12.0€	10.7€	275.1€	142.3€	88.5€	52.1€

Table 3: Comparing premiums, in €, in nine cities, in Var, Pays-de-Loire and Vendée.

Flood Risk in France, and solidarity [13]

		Uniform			Two-Zone Model		
		Country	Region	Municipality	$\alpha = 95\%$	$\alpha = 90\%$	$\alpha = 80\%$
Var	Fréjus	6.9%	17.5%	9%	2.9%	2.0%	29.8 %
	Grimaud	6.9%	17.5%	48.2%	81.3%	50.6%	29.8 %
	Puget-sur-Argens	6.9%	17.5%	76.1%	81.3%	50.6%	29.8 %
Pays Loire	Assérac	6.9%	2%	3.8%	2.9%	2.0%	1.1 %
	Mesquer	6.9%	2%	5.8%	2.9%	2.0%	1.1 %
	Le Croisic	6.9%	2%	14.8%	2.9%	50.6%	29.8 %
Vendée	Talmont-Saint-Hilaire	6.9%	6.1%	2.7%	2.9%	2.0%	1.5 %
	Noirmoutier-en-l'Île	6.9%	6.1%	4.9%	2.9%	2.0%	1.1 %
	La Faute-sur-Mer	6.9%	6.1%	157.2%	81.3%	50.6%	29.8 %

Table 4: Comparing premiums, in percent of the household premium, in nine cities, in Var, Pays-de-Loire and Vendée.

Flood Risk in France, and solidarity [14]

		Hierarchical Model $\gamma = 20\%$			Hierarchical Model $\gamma = 40\%$		
		$\beta = 10\%$	$\beta = 20\%$	$\beta = 50\%$	$\beta = 10\%$	$\beta = 20\%$	$\beta = 50\%$
Var	Fréjus	14.7%	13.7%	12%	12.7%	12.0%	10.7 %
	Grimaud	17.8%	21.5%	27.7%	15.1%	17.8%	22.5 %
	Puget-sur-Argens	20.1%	27.1%	38.8%	16.8%	22.0%	30.8 %
Pays Loire	Assérac	3.2%	3.4%	3.7%	4.1%	4.2%	4.5 %
	Mesquer	3.3%	3.8%	4.5%	4.2%	4.5%	5.1 %
	Le Croisic	4.0%	5.6%	8.1%	4.7%	5.9%	7.8 %
Vendée	Talmont-Saint-Hilaire	6%	5.6%	4.9%	6.2%	5.9%	5.4 %
	Noirmoutier-en-l'Île	6.2%	6.0%	5.8%	6.3%	6.2%	6.0 %
	La Faute-sur-Mer	18.3%	36.5%	66.7%	15.5%	29.1%	51.7 %

Table 5: γ: national, $(1-\gamma)(1-\beta)$: département, $(1-\gamma)\beta$: municipality.

Flood Risk in France, and solidarity [15]

- Tradeoff: risk vs. welfare / wealth
- Prevention cannot be done at the individual level, even cities...
- Hierarchical approach: city / region / country
- too small granularity might cause market failure, Charpentier & Le Maux (2014)

[1] A. Charpentier, L. Barry, and M. James. "Insurance against Natural Catastrophes: Balancing Actuarial Fairness and Social Solidarity". In: *Geneva Papers on Risk & Insurance* (2021). DOI: 10.1057/s41288-021-00233-7.

[2] A. Charpentier and B. Le Maux. "Natural catastrophe insurance: How should the government intervene?" In: *Journal of Public Economics* 115 (2014), pp. 1–17.

Subsidence Risk in France [1]

[1] France Bleu. "La sécheresse coûte de plus en plus cher en assurances". In: (2019). URL: http://tinyurl.com/yeyr67xu.

Subsidence Risk in France [2]

Joint work with Hani Ali (Willis Re) and Molly James (EURIA / ACPR).

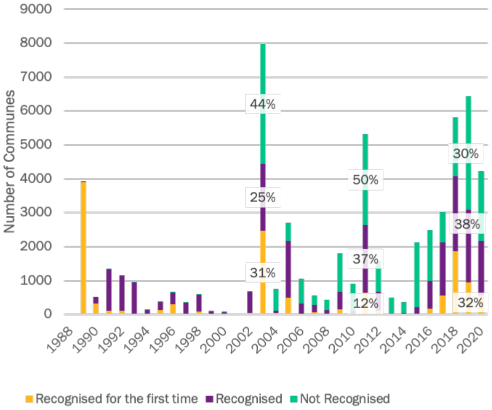
[1] A. Charpentier, M. R. James, and H. Ali. "Predicting Drought and Subsidence Risks in France". In: *Natural Hazards and Earth System Sciences* 22 (2022), pp. 2401–2418. DOI: 10.5194/nhess-22-2401-2022.

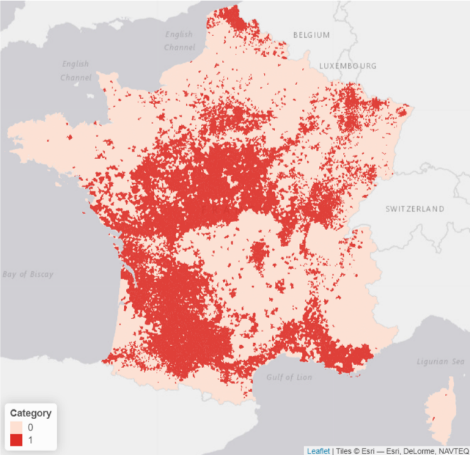
"*Subsidence is caused by the shrinkage and swelling of clay soils*"

- Geotechnical factor: Area of municipalities at medium or high risk $> 3\%$. (categories based on clay concentration in the soil and historical statements)
- Meteorological factor: Standardized soil moisture index (SSWI), if an indicator of the season is lower than a return period of 25 years, then the whole season is eligible for the commune concerned.

Subsidence Risk in France [3]

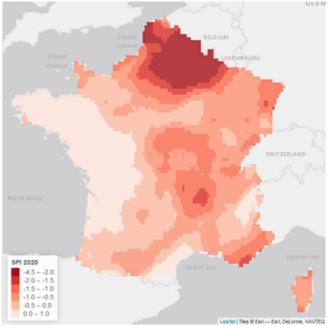
Data 1989-2018

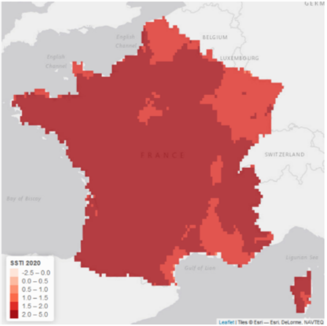


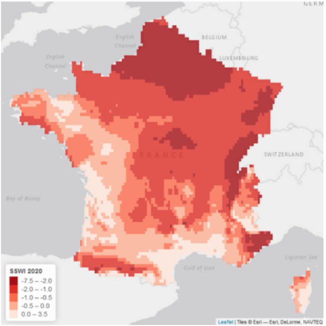


Subsidence Risk in France [4]

Indicators 2020: ESPI (precipitation) ESSTI (soil temperature) & ESSWI (soil humidity), ERA5-Land 9 km $\times$ 9 km

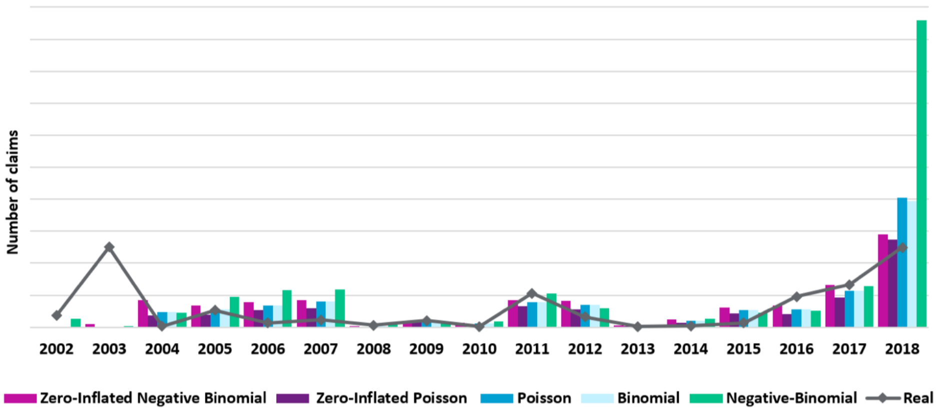






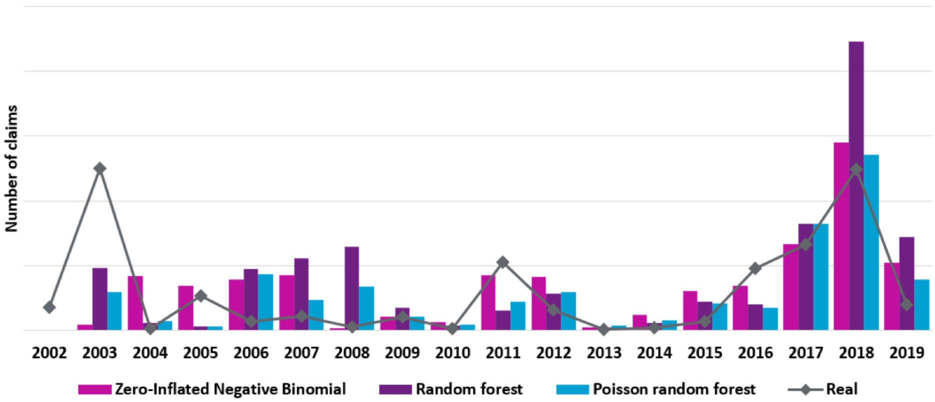
(via ESDAC (European Soil Data Centre) for soil concentration)

Regression models for frequencies: binomial, Poisson, negative binomial & zero-inflated Poisson, zero-inflated negative binomial,



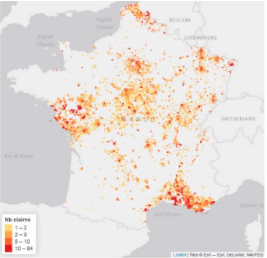
Subsidence Risk in France [6]

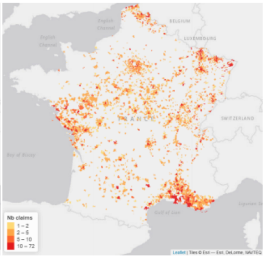
Random forest models for frequencies

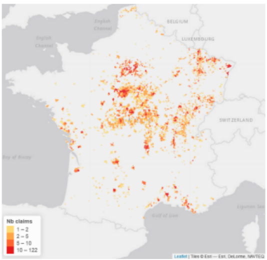


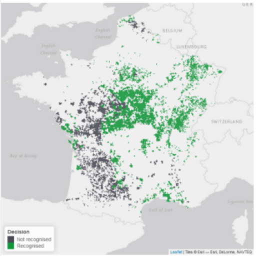
Subsidence Risk in France [7]

2017, random forest Poisson, zero inflated, observed, Nat Cat recognition



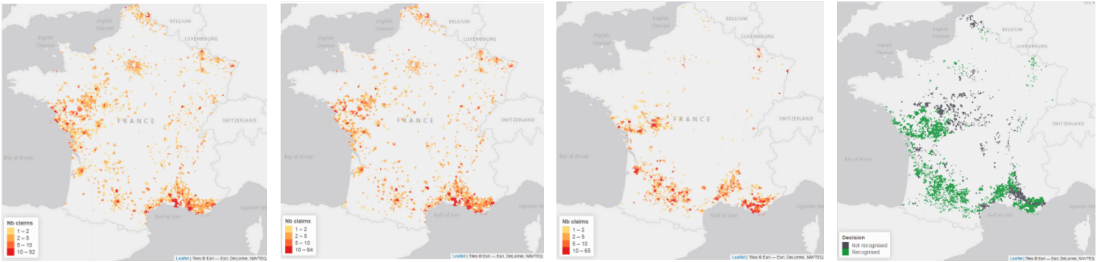






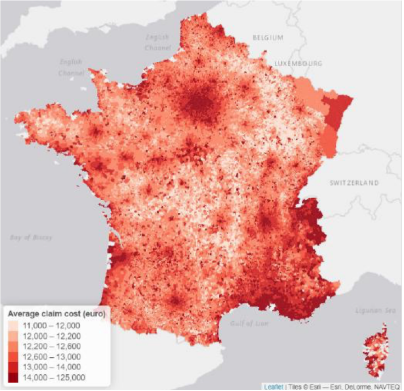
Subsidence Risk in France [8]

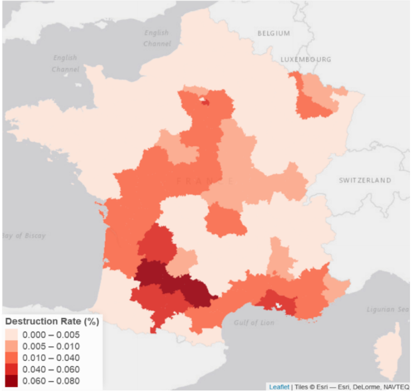
2018, random forest Poisson, zero inflated, observed, Nat Cat recognition



Subsidence Risk in France [9]

Models for costs and destruction rates

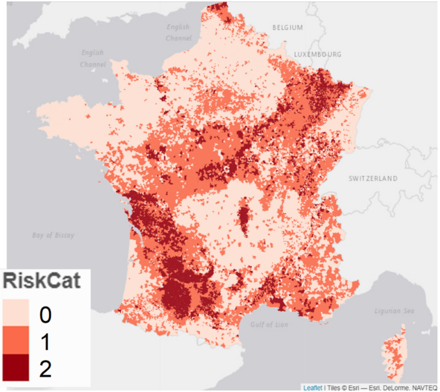




Subsidence Risk in France [10]

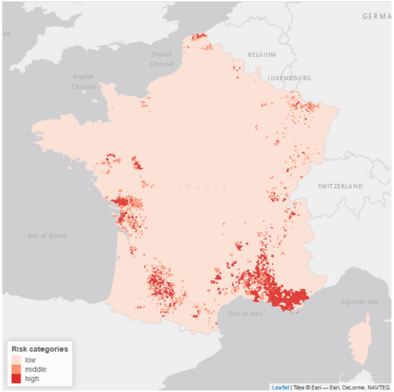
Risk map

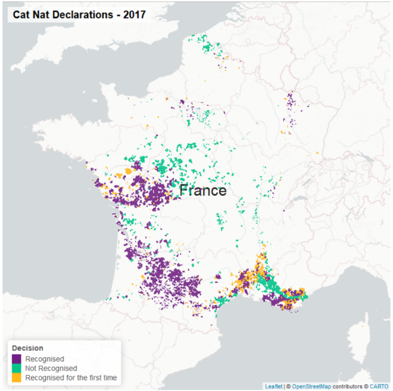
zone 0: 41% contracts, 0% losses
zone 1: 47% contracts, 67% losses
zone 2: 12% contracts, 33% losses



Subsidence Risk in France [11]

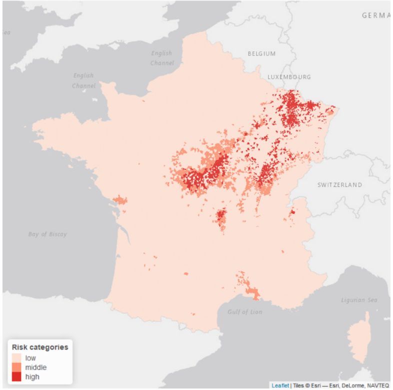
Risk map for 2017

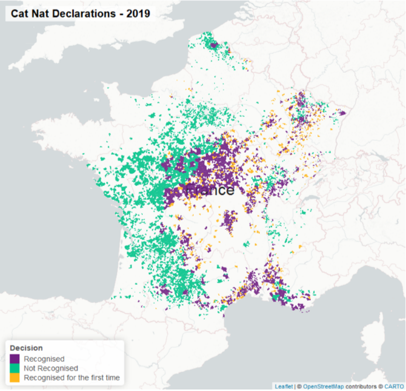




Subsidence Risk in France [12]

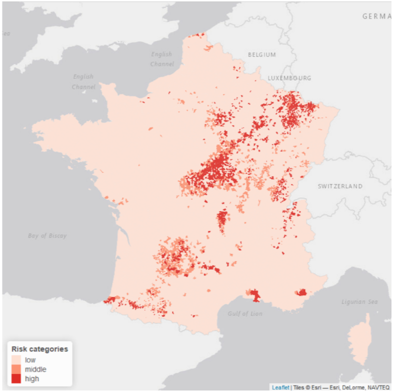
Risk map for 2019

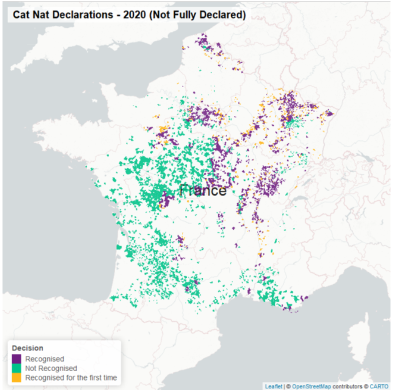




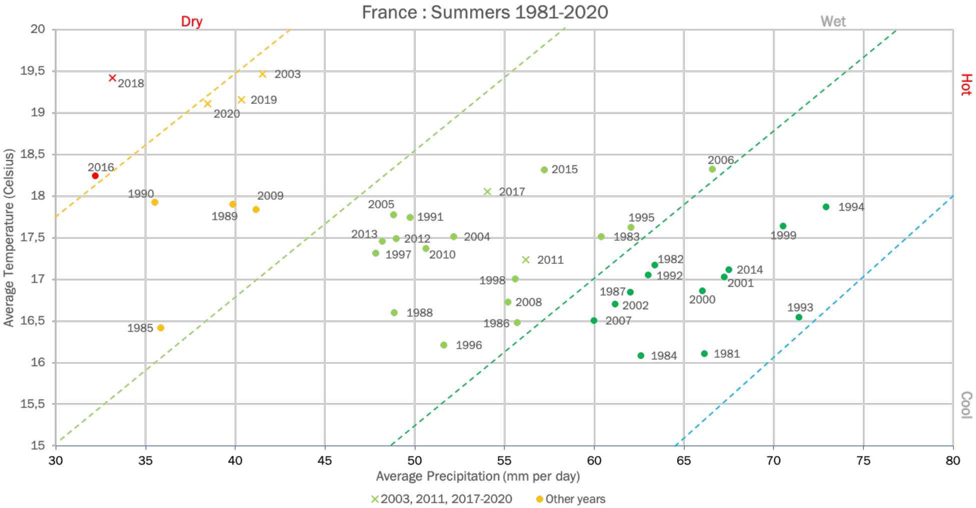
Subsidence Risk in France [13]

Risk map for 2020





Subsidence Risk in France [14]



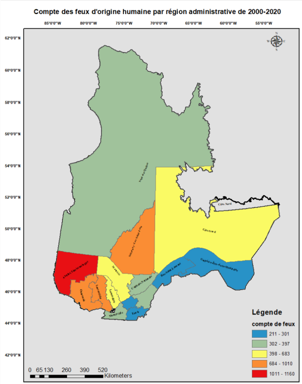
Subsidence Risk in France [15]

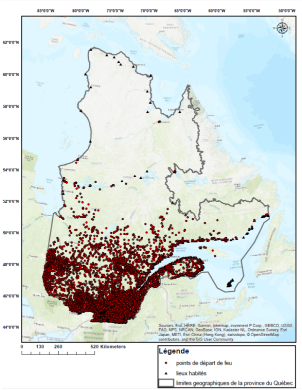
- Quite good in predicting which municipality will claim a loss
- More difficult to understand which one will be recognize by the government
- "*It is considered abnormal if the indicator presents a return period greater than or equal to 25 years*"
- Difficult task in the context of climate change

[1] A. Charpentier, M. R. James, and H. Ali. "Predicting Drought and Subsidence Risks in France". In: *Natural Hazards and Earth System Sciences* 22 (2022), pp. 2401–2418. DOI: 10.5194/nhess-22-2401-2022.

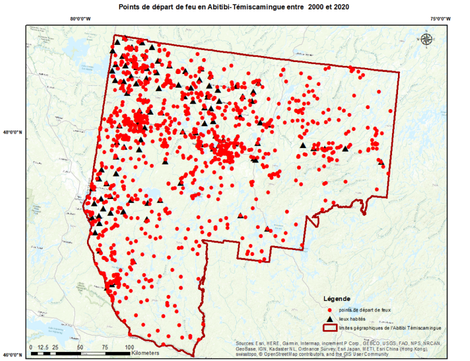
Wildfire in Québec (Canada) [1]

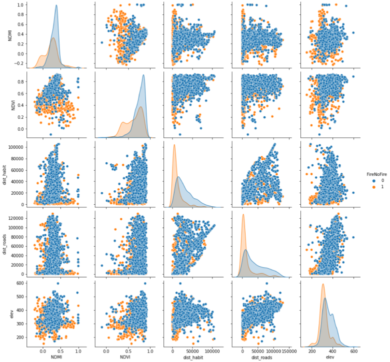
Joint work with Amirouche Benchallal (UQAM) and Yacine Bouroubi (Sherbrooke).





Wildfire in Québec (Canada) [2]

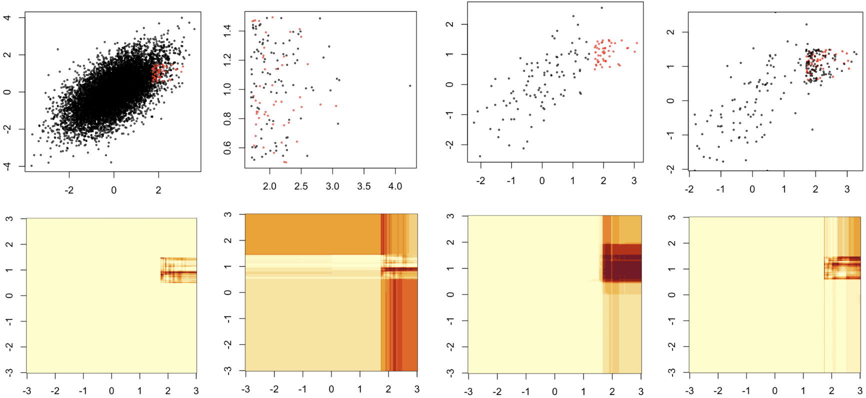




[1] A. Benchallal, Y. Bouroubi, and A. Charpentier. “Human-caused wildland fire occurrence prediction over the province of Quebec using mahine learning algorithms and free geospatial datasets”. In: 10th International Conference on Agro-Geoinformatics and 43rd Canadian Symposium on Remote Sensing (2022).

Wildfire in Québec (Canada) [3]

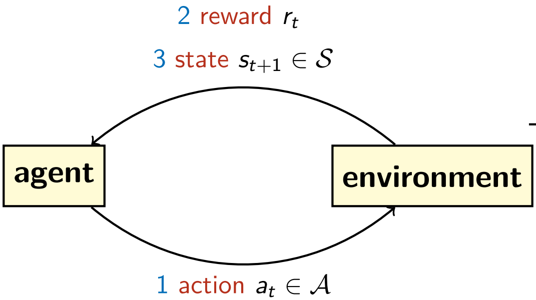
Theoretical issues on creating a balanced from largely unbalanced data

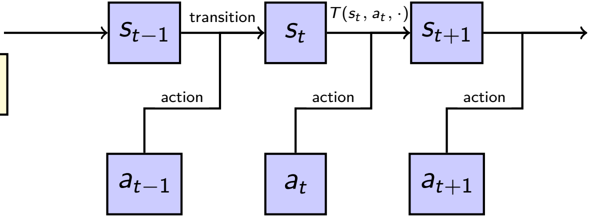


[1] David Hand. *Dark Data: Why What You Don't Know Matters*. Princeton University Press, 2020.

On Government Intervention [1]

Joint work with Nouri Sakr (Columbia) and Mennatalla Mohamed Hassan (American University in Cairo).





[1] M. Hassan, N. Sakr, and A. Charpentier. "Government Intervention in Society Under Catastrophe Risk: A Reinforcement Learning Approach". In: ArXiv 2207.01010 (2022).

On Government Intervention [2]

For governments, the reward is the Marginal Value of Public Funds ($MVPF$) (similar to social cost-benefit approaches),

$$MVPF = \frac{\text{Willingness to pay for policy by beneficiaries } (WTP)}{\text{Net cost of Government Spending } (G)}$$

[1] Amy Finkelstein and Nathaniel Hendren. "Welfare analysis meets causal inference". In: *Journal of Economic Perspectives* 34.4 (2020), pp. 146–67.

[2] Nathaniel Hendren and Ben Sprung-Keyser. "A unified welfare analysis of government policies". In: *The Quarterly Journal of Economics* 135.3 (2020), pp. 1209–1318.

The government can take various actions

- Offer government-provided insurance
- Ease Insurer Solvency Requirements
- Subsidies on insurance premiums
- Increase premium regulations
- Increase Reinsurance Funds
- Increase Disaster Prevention

On Government Intervention [3]

Those actions have some impact on decisions of individuals-policyholders and insurance companies (multiple feedbacks)

- individuals behaviors
  - dynamic consumption-saving-wealth approach,
  - disaster impact their wealth and their risk perception
  - individual's optimism and amnesia biases
  - if not compulsory, they can purchase insurance, or not
- insurer behaviors
  - initial capital, can add loading to risk premiums
  - possible bias in risk perception

On Government Intervention [4]

We discuss stylized facts on catastrophe markets,

- Free catastrophe insurance markets generate inadequate coverages
- Purchases of catastrophe insurance tend to increase right after the society witnesses a catastrophe experience and while the memory is still there
- Policyholders tend to cancel their insurance coverages as the memory of past catastrophe fades and the time since the last catastrophe exceeds 5 years
- After a catastrophe experience, many insurers respond by restricting supply and raising premium rates
- Many insurers exit the market right after a catastrophe experience. For example, many private insurers cut their terrorism insurance supply right after 9/11 attacks
- Many individuals are willing to purchase catastrophe insurance but they are unable to find insurance at an affordable price

On Government Intervention [5]

Algorithm 1 Sequence of events in a single episode of the environment

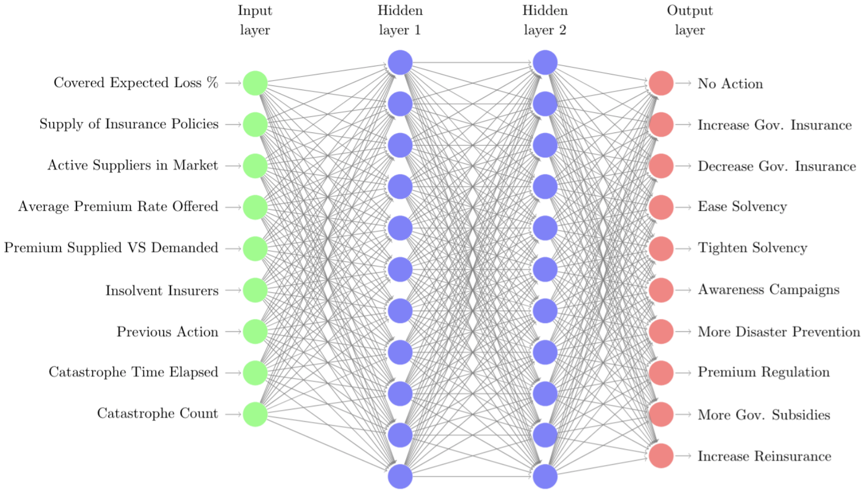
for each time-step $t \in T$ **do**
    A Bernoulli trial is run with θ as probability of catastrophe
    if Bernoulli trial was successful **then**
        Catastrophe occurs in society
        Every individual in the population loses a share of their wealth due to catastrophes
        Individuals who are catastrophe-insured file claims to their insurance companies
        Insurers pay claims to their customers or exit market if insolvent
    end if
    Every individual updates their catastrophe risk perception based on personal assessment
    Every individual plans their optimal consumption and saving for time-step t and time-step $t+1$
    Every individual determines their catastrophe insurance demand and attempts to buy, renew, or cancel catastrophe insurance policies accordingly
    Each insurer collects premiums from clients who were subscribed with them for a year
    Each insurer updates catastrophe loss model and evaluates financial position, deciding whether to stay or leave the market accordingly
end for

On Government Intervention [6]

Algorithm 2 Government Policy Learning Process (Q-learning)

for each episode $\in$ training episodes **do**
    Government agent observes the state of the environment after algorithm in Section 2.2 is played
    Government intervenes via exploration or exploitation in an ϵ-greedy strategy
    if Government agent chooses to **explore then**
        Government intervenes by taking a random action from its action space
    end if
    if Government agent chooses to **exploit then**
        Government intervenes by choosing the action that has the highest Q-value
    end if
    Government observes the reward/penalty associated with the action taken.
    Government updates the Q-value of the chosen action by Equation (32).
end for

On Government Intervention [7]



References

[1] A. Benchallal, Y. Bouroubi, and A. Charpentier. "Human-caused wildland fire occurrence prediction over the province of Quebec using mahine learning algorithms and free geospatial datasets". In: 10th International Conference on Agro-Geoinformatics and 43rd Canadian Symposium on Remote Sensing (2022).

[2] A. Charpentier, L. Barry, and M. James. "Insurance against Natural Catastrophes: Balancing Actuarial Fairness and Social Solidarity". In: *Geneva Papers on Risk & Insurance* (2021). DOI: 10.1057/s41288-021-00233-7.

[3] A. Charpentier, R. Élie, and C. Remlinger. "Reinforcement Learning in Economics and Finance". In: *Computational Economics* (2021). DOI: 10.1007/s10614-021-10119-4.

[4] A. Charpentier, M. R. James, and H. Ali. "Predicting Drought and Subsidence Risks in France". In: *Natural Hazards and Earth System Sciences* 22 (2022), pp. 2401–2418. DOI: 10.5194/nhess-22-2401-2022.

[5] M. Hassan, N. Sakr, and A. Charpentier. "Government Intervention in Society Under Catastrophe Risk: A Reinforcement Learning Approach". In: ArXiv 2207.01010 (2022).