



# Data science appliquée au climat

Arthur Charpentier (UQAM & Univ. Rennes)

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# Arthur Charpentier

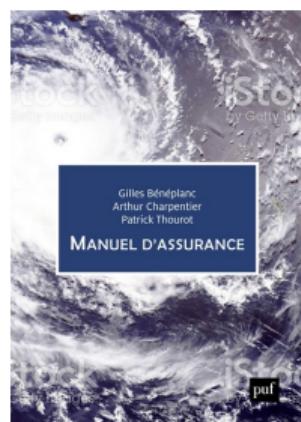
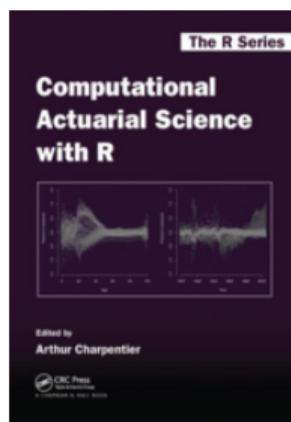
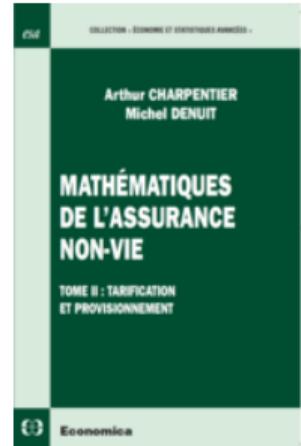
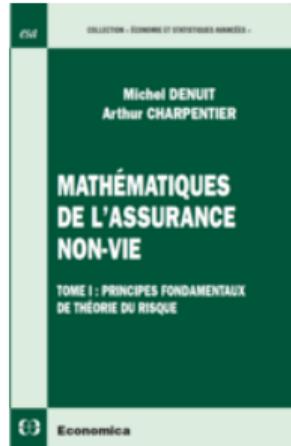
Université du Québec à Montréal

 @freakonometrics

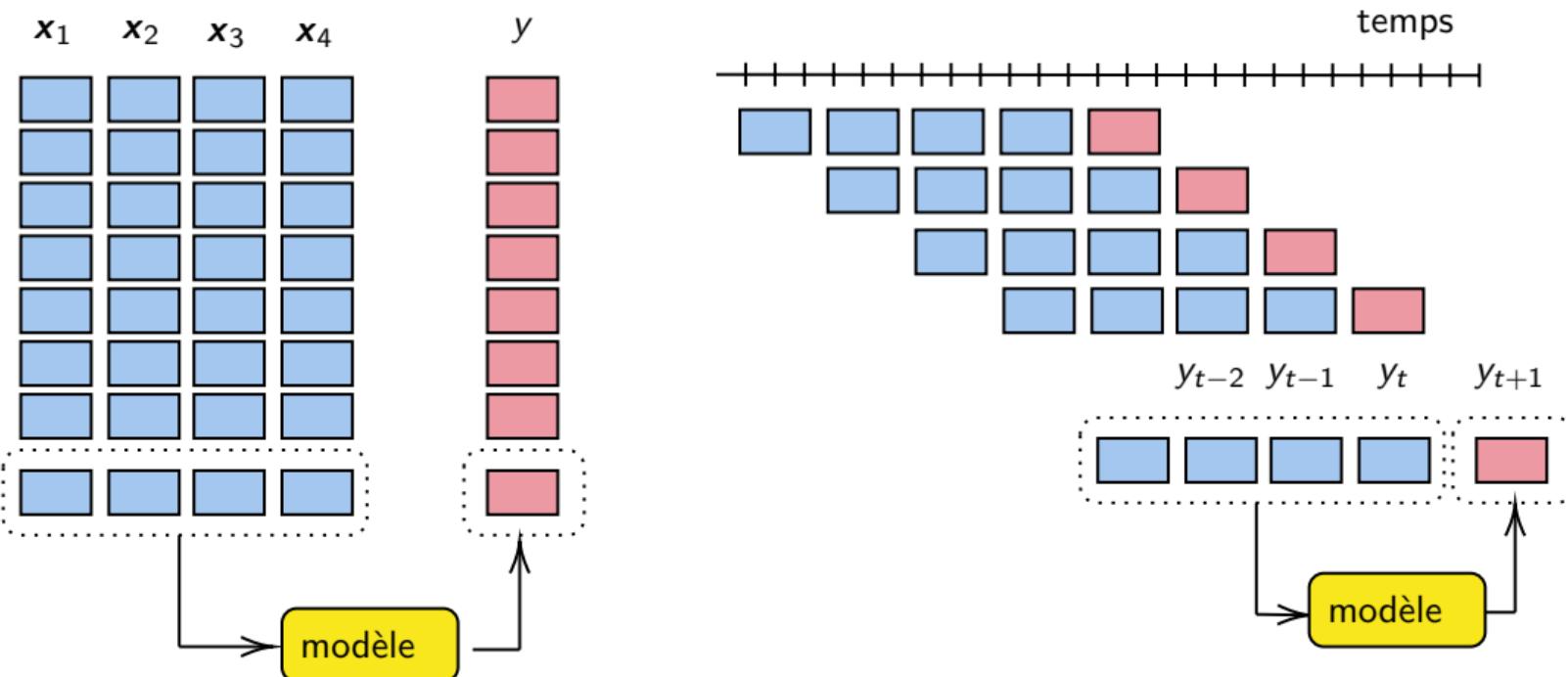
 freakonometrics

 [freakonometrics.hypotheses.org](https://freakonometrics.hypotheses.org)

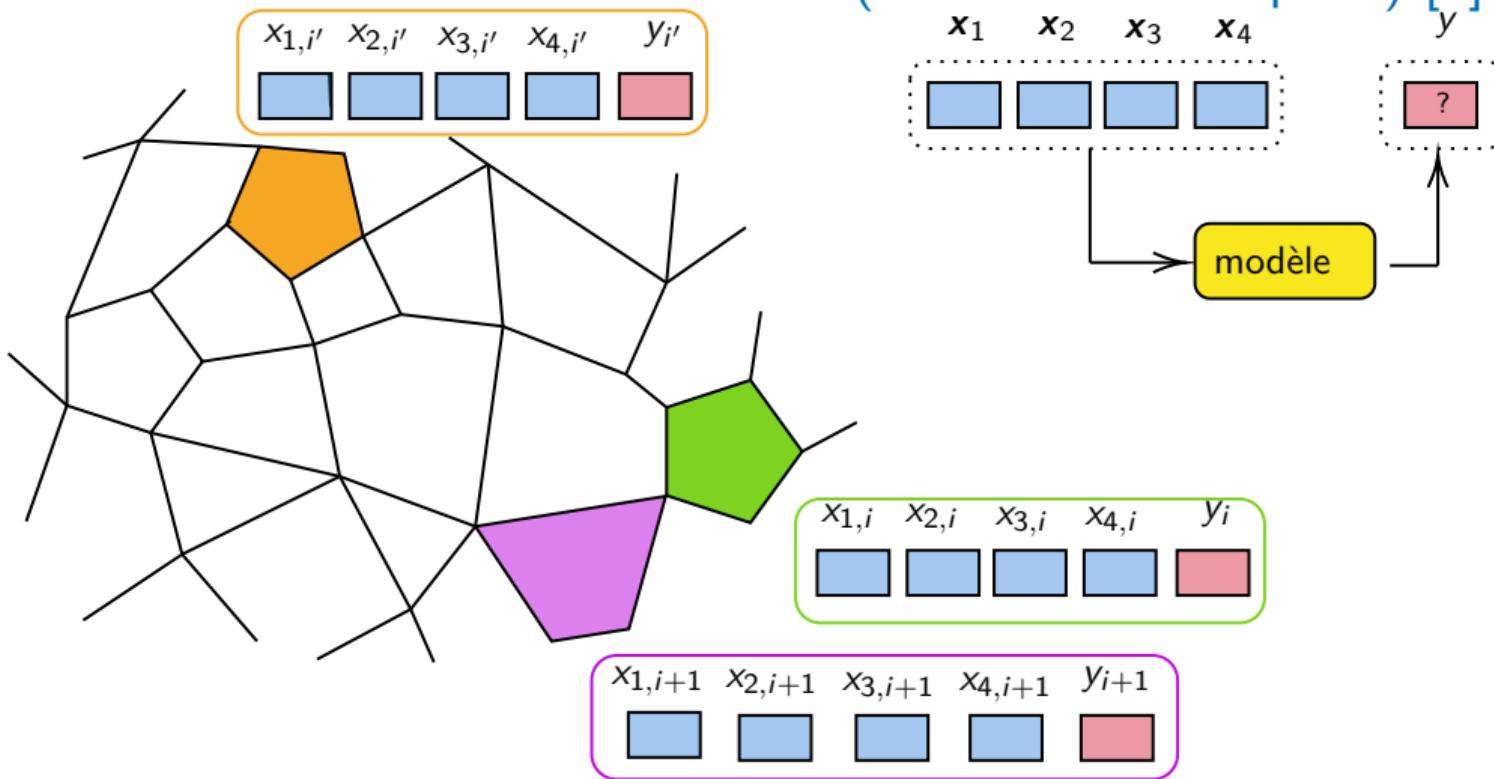
Modélisation prédictive, Science actuarielle,  
Économie mathématique, Risque, Inégalités,  
Économétrie, statistiques, apprentissage automatique  
Modélisation du climat, Extrêmes, Équité



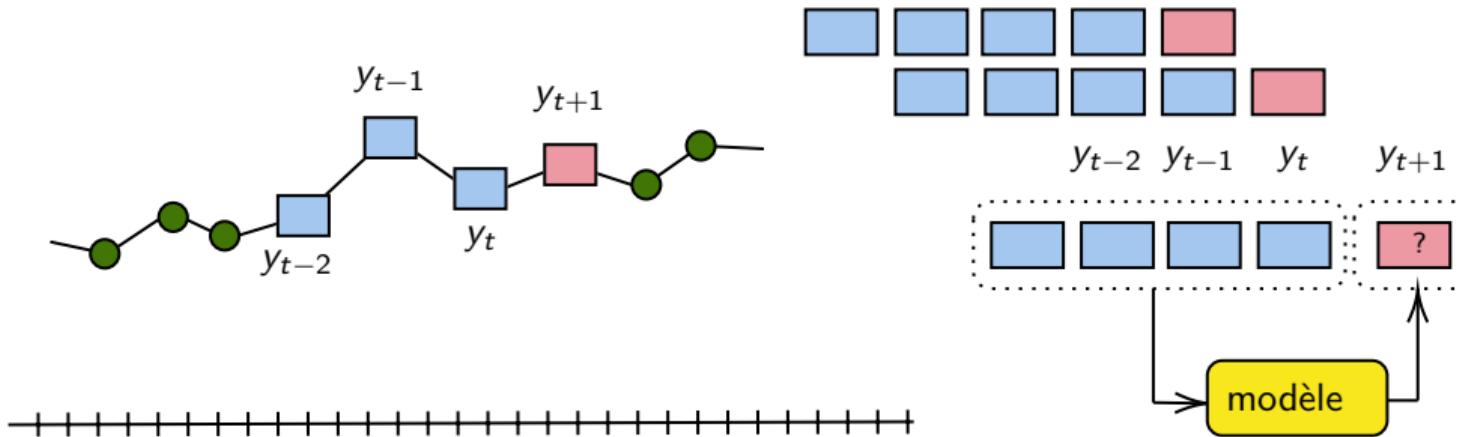
# Data science (individuel vs temporel) [1]



## Data science (individuel vs temporel) [2]

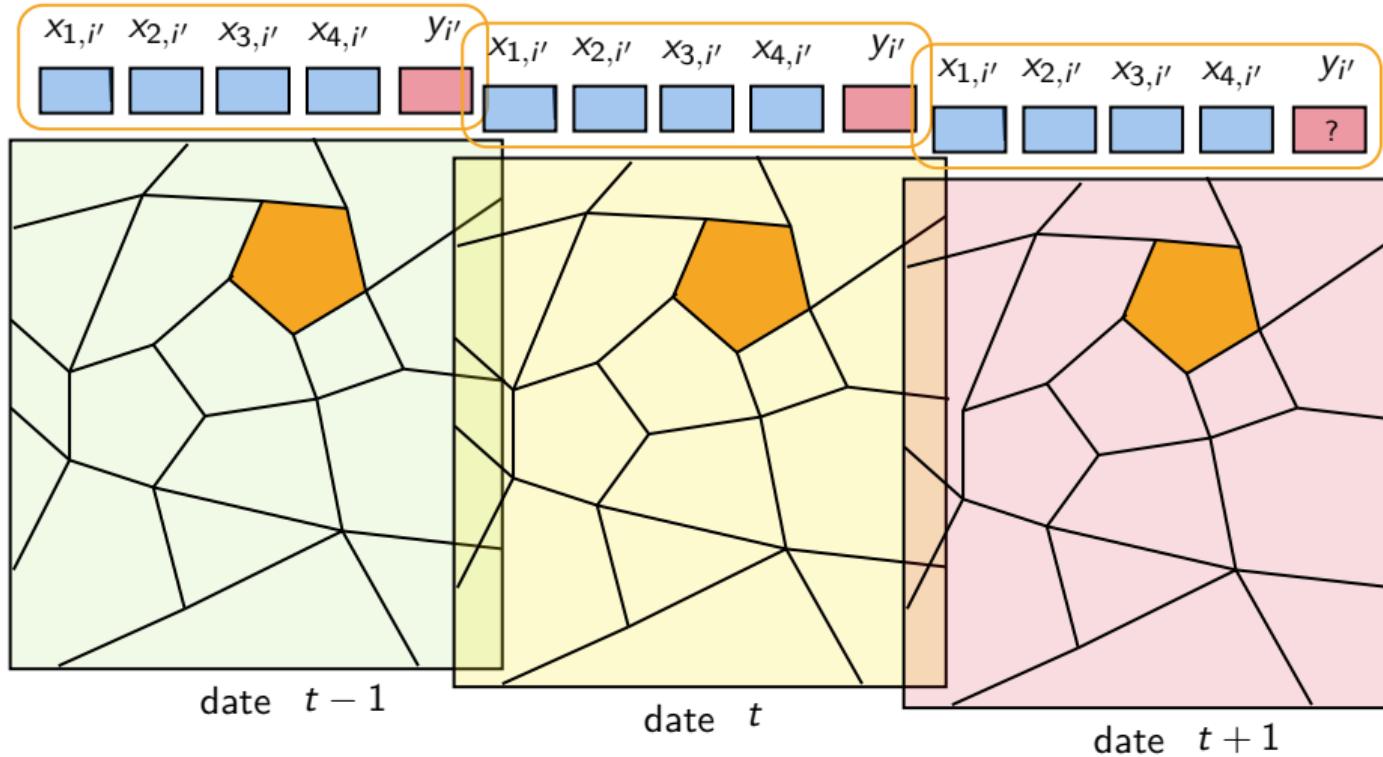


## Data science (individuel vs temporel) [3]

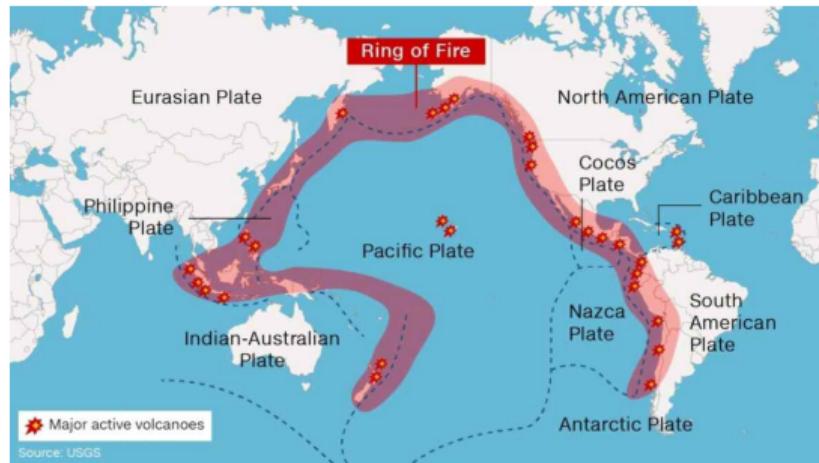
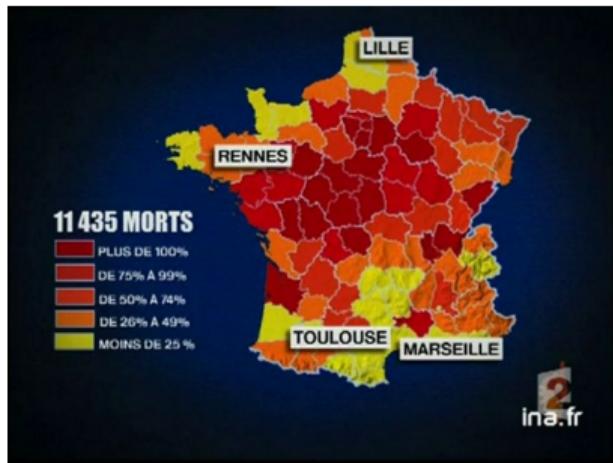


On suppose que la dynamique liant  $y_{t+1}$  et son passé se réplique dans le temps  
Mais il est aussi possible de mélanger données spatiales et temporelles...

## Data science (individuel vs temporel) [4]



# La dynamique des catastrophes naturelles [1]



- [1] A. Charpentier. "On the return period of the 2003 heat wave". In: *Climatic change* 109.3 (2011), pp. 245–260.
- [2] A. Charpentier and D. Sibaï. "Dynamic flood modeling: combining Hurst and Gumbel's approach". In: *Environmetrics* 20.1 (2009), pp. 32–52.

# La dynamique des catastrophes naturelles [2]



IRIS is a university research consortium dedicated to monitoring the earth and exploring its interior through the collection and distribution of geophysical data.

IRIS programs contribute to heliocentric research, education, earthquake hazard mitigation, and the verification of the Comprehensive Test Ban Treaty.

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This figure was produced in cooperation with University of Arizona, University of California, Berkeley, University of California, San Diego, Purdue University, and the US Geological Survey.

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## How are Earthquakes Located?

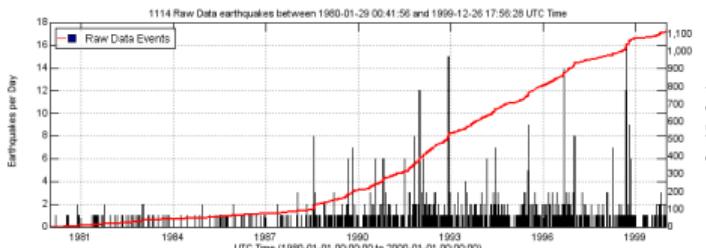
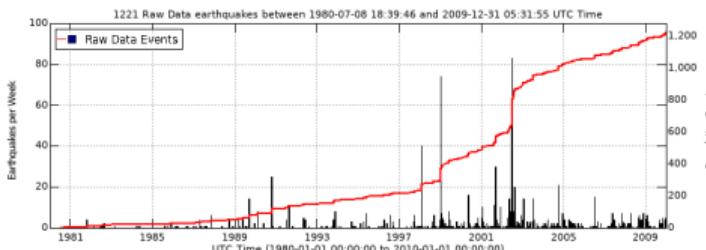
We can locate earthquakes using a simple fact: an earthquake creates different seismic waves (P waves, S waves, etc.) The different waves each travel at different speeds and therefore arrive at a seismic station at different times. P waves travel the fastest, so they arrive first. S waves, which travel at about half the speed of P waves, arrive later. A seismic station closer to the earthquake records P waves and S waves in quick succession. With increasing distance from the earthquake the time difference between the arrival of the P waves and the arrival of the S waves increases.

Although modern techniques are more complex, we have illustrated the basic concept using an example of an earthquake near Mexico and seismic stations in North America. The following two steps show how we determine distance from the seismograms and estimate the location using three stations.

**Step 1.** The time between the arrival of the P wave and the arrival of the S wave (S-P time) is measured at each station. The S-P time indicates the distance to the earthquake similar to how the time interval between the flash of light and the sound of thunder indicates the distance to a thunderstorm. In our example, station TEIG (with an S-P time of 1.5 minutes) is closest to the earthquake, and station SSPA (with an S-P time of 5 minutes) is farthest away.

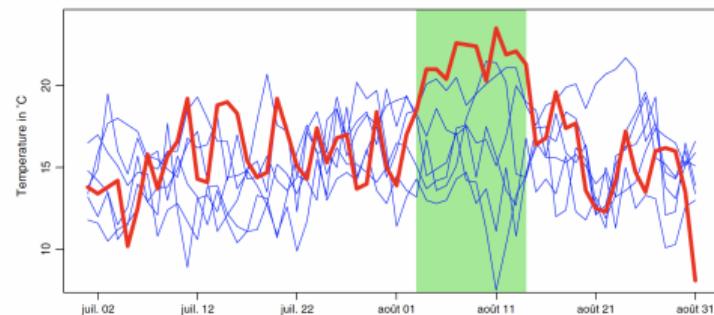
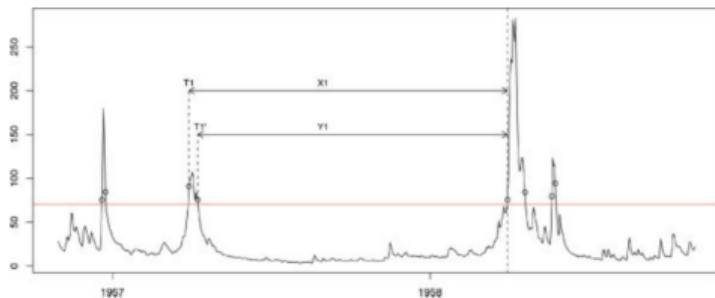
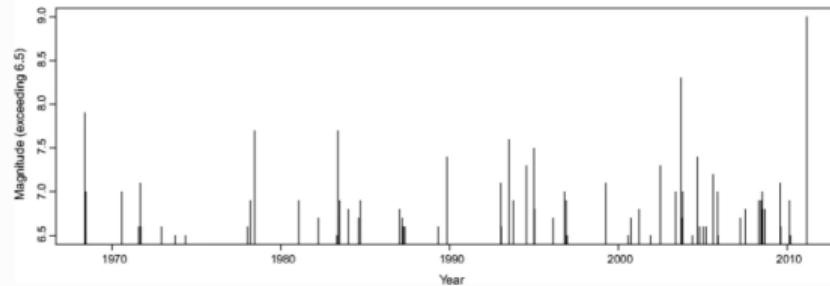
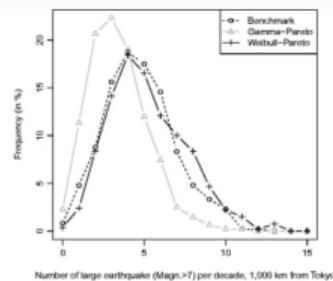
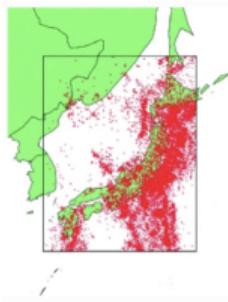
From observing and analyzing many earthquakes, we know the relationship between the S-P time and the distance between the station and the earthquake. We can therefore convert each measured S-P time to distance. A 1 minute interval of 1.5 minutes corresponds to a distance of 900 kilometers, 3 minutes to 1800 kilometers, and 5 minutes to 3300 kilometers.

**Step 2.** Once we know the distance to the earthquake for three stations, we can determine the location of the earthquake. For each station we draw a circle around the station with a radius equal to its distance from the earthquake. The earthquake occurred at the point where all three circles intersect.



# La dynamique des catastrophes naturelles [3]

*"seismic gap hypothesis"* / dynamique des inondation / persistance de la température



## Les inondations France [1]



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

# Les inondations France [2]

- [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.

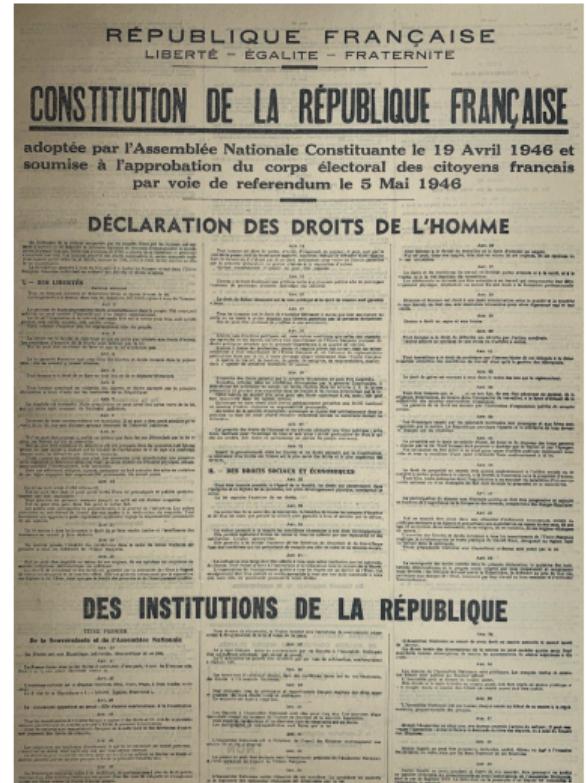
Sur la solidarité du système

## ➤ Constitution Française (1946)

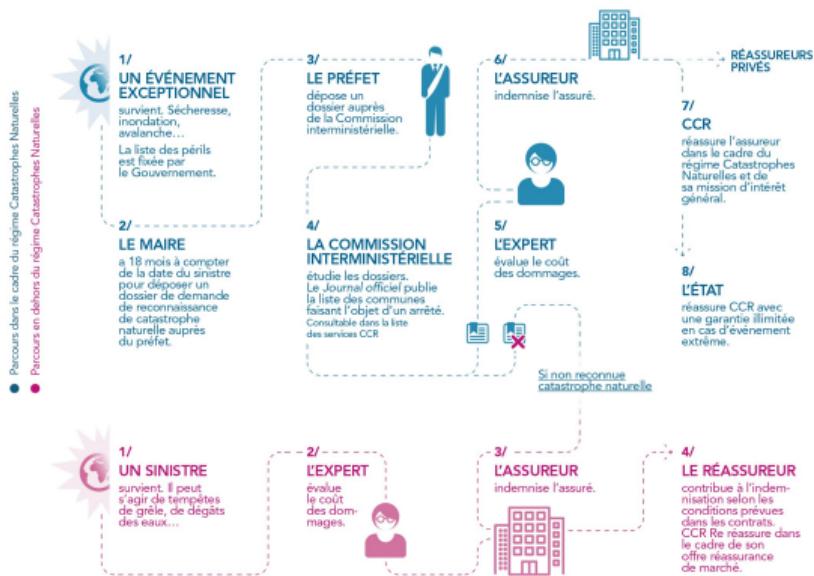
12. *La Nation proclame la solidarité et l'égalité de tous les Français devant les charges qui résultent des calamités nationales.*

## ➤ 82-600 Law (1982)

régime d'indemnisation des catastrophes naturelles



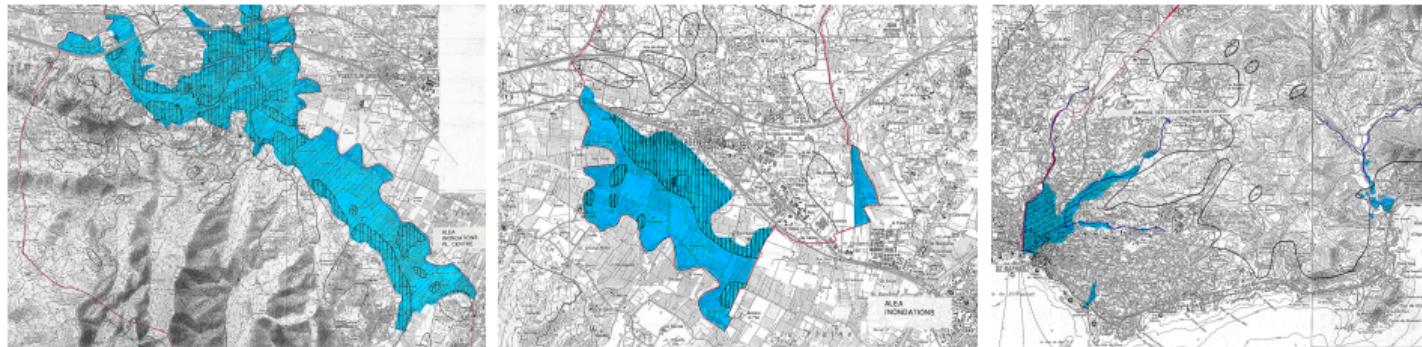
# Les inondations France [3]



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

## Les inondations France [4]

Deux types d'inondation analysées ici: par débordement (de rivière) et costale  
PPRIs ([plan de prévention du risque inondation](#)) à Roquebrune-sur-Argens, Puget et Saint-Raphaël. Les zones bleues sont reconnues comme "à risque" (sur la base d'évènements passés)



# Les inondations France [5]



## Procès tempête Xynthia : deux élus condamnés à des peines de prison



- [1] France 3. "Tempête Xynthia: la responsabilité de La Faute-sur-Mer pourrait être alourdie". In: (2019).

## Les inondations France [6]

PPRLs (plan de prévention des risques littoraux) en Vendée. L'aire hachurée est la zone à risque.

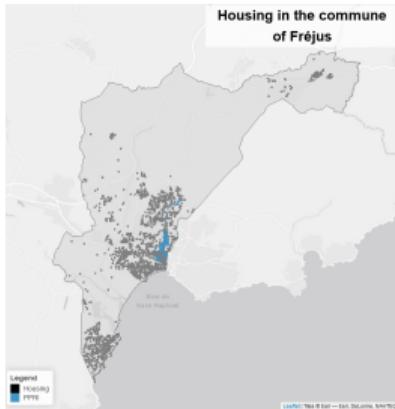
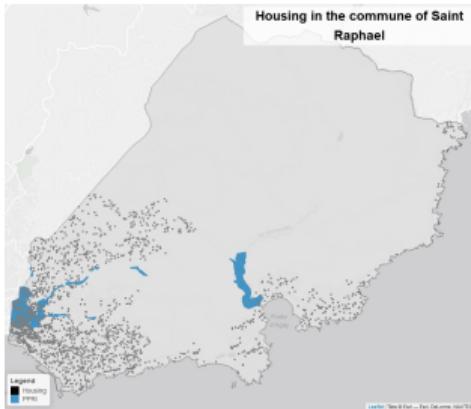
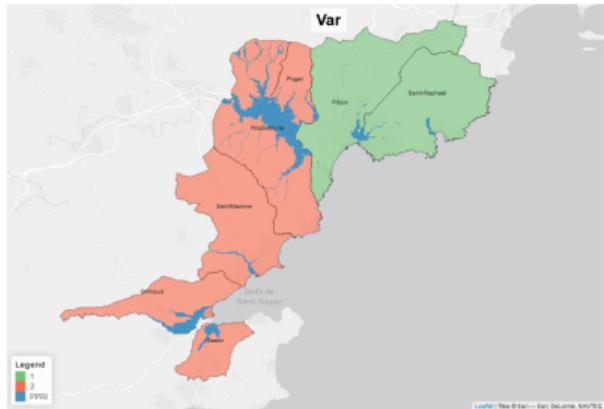


Voir aussi <https://github.com/freakonometrics/floods>

## Les inondations France [7]

10% des polices d'assurances concentrent 73.6% des pertes... qui vit dans les zones à risque ?

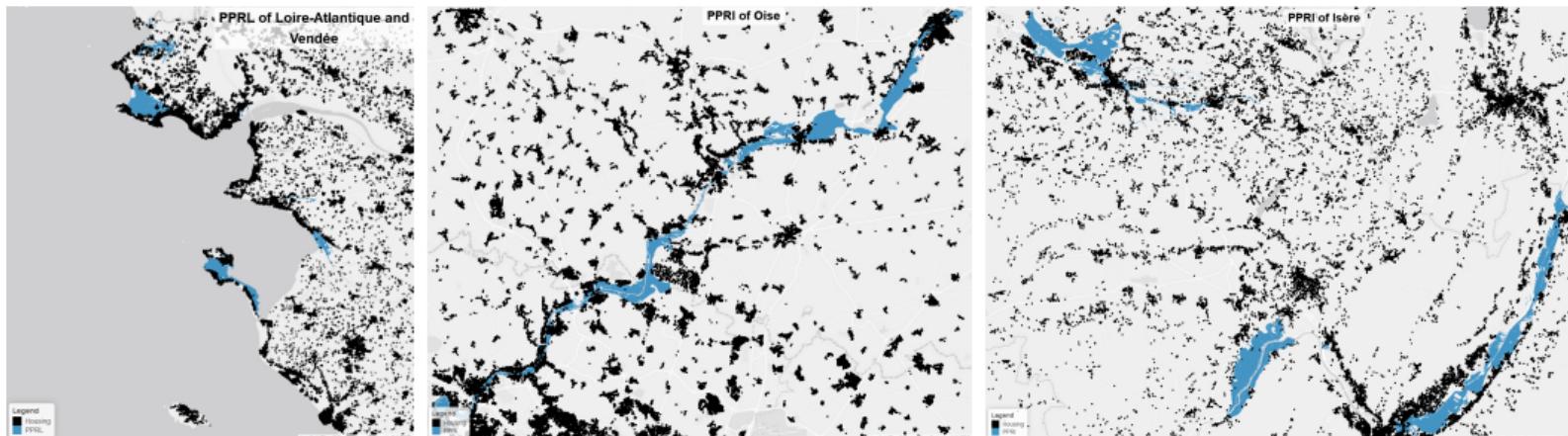
Base des “ventes de biens fonciers”, <https://cadastre.data.gouv.fr/dvf>, 2014-2018,



(biais possible, 5 ans de transactions notariales)

## Les inondations France [8]

E.g. dans 4 départements (Loire-Atlantique, Vendée, Oise, Isère)



- maison & appartement vendu, ■ PPRI-PPRL

## Les inondations France [9]

			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
	Non risky	Apartments	4399		79913	8411	37%	
		Houses	3019		75472	12678	55%	
Pays-Loire	Risky	Apartments	6784	+54%	68478	1001	4%	-8.6
		Houses	3245	+7%	22895	765	3%	-2.7

**Table 1:** Prices ( $\text{€ per } m^2$ ) 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.

## Les inondations France [10]

			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

## Les inondations France [11]

		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%
		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).

## Risque de sécheresse (subsidence) en France [1]



- [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](https://doi.org/10.5194/nhess-22-2401-2022).
- [2] France Bleu. "La sécheresse coûte de plus en plus cher en assurances". In: (2019). URL: <http://tinyurl.com/yeqr67xu>.

## Risque de sécheresse (subsidence) en France [2]

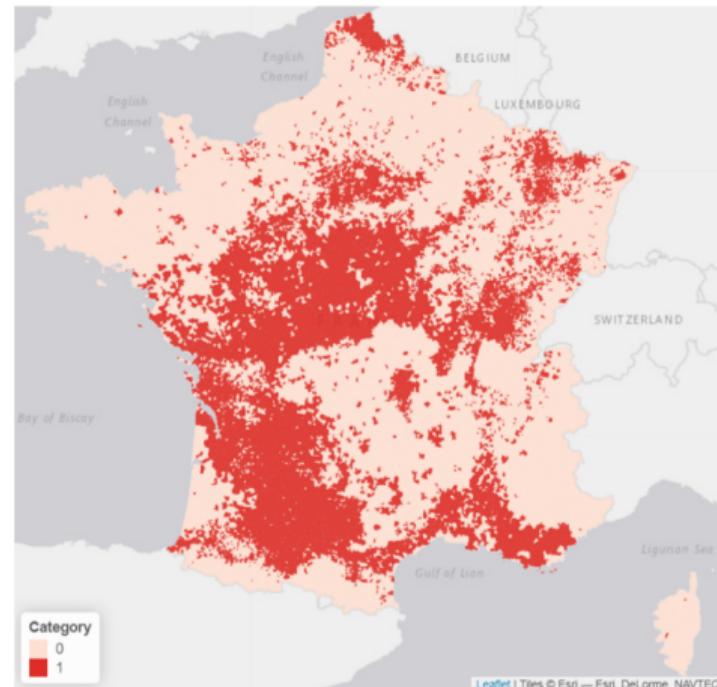
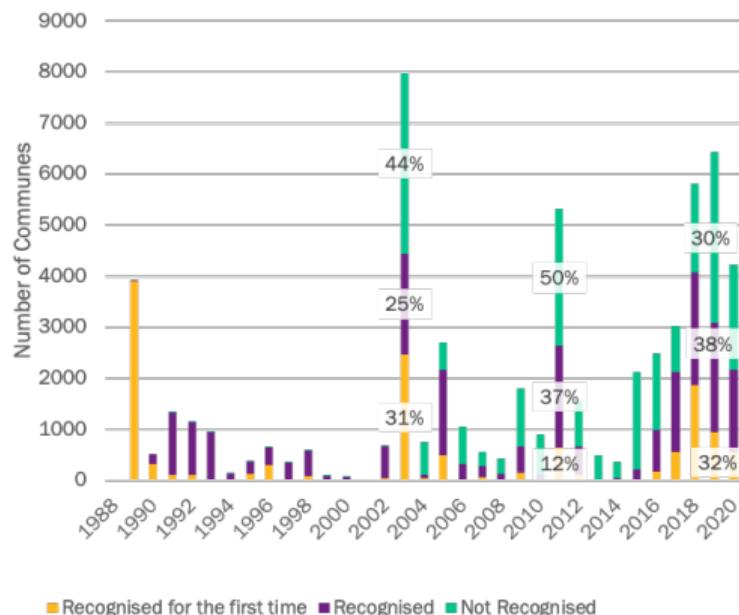
- [1] A. Charpentier, M. R. James, and H. Ali. "Predicting Drought and Subsidence Risks in France". In: *Natural Hazards and Earth System Sciences* 22 (2022), pp. 2401–2418. DOI: [10.5194/nhess-22-2401-2022](https://doi.org/10.5194/nhess-22-2401-2022).

"La subsidence est causée par le retrait et le gonflement des sols argileux."

- **Facteur géotechnique:** Superficie des communes à risque moyen ou élevé > 3%. (catégories basées sur la concentration d'argile dans le sol et les relevés historiques)
- **Facteur météorologique:** Indice standardisé d'humidité du sol (SSWI), si un indicateur de la saison est inférieur à une période de retour de 25 ans, alors toute la saison est éligible pour la commune concernée.

# Risque de sécheresse (subsidence) en France [3]

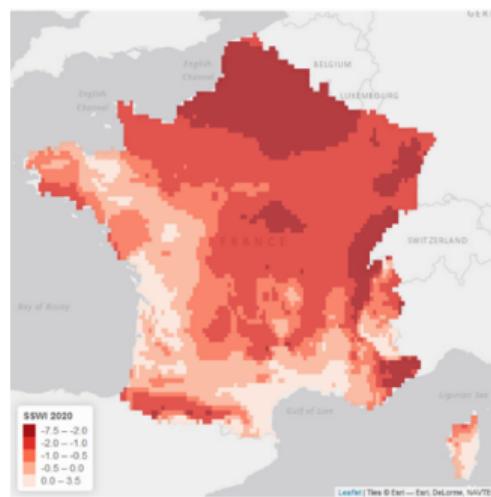
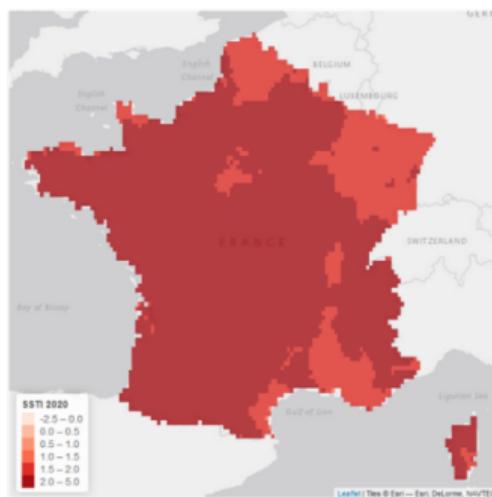
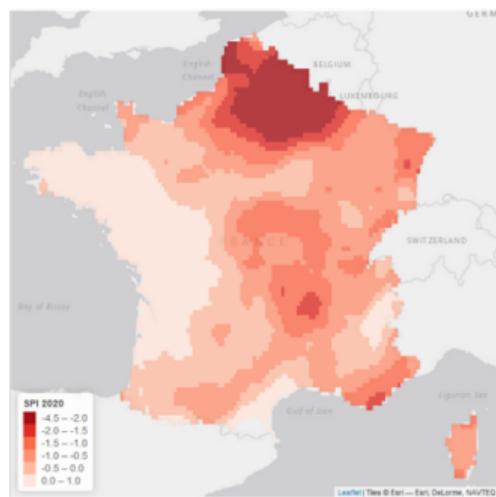
Données 1989-2018



Leaflet | Tiles © Esri — Esri, DeLorme, NAVTEQ

## Risque de sécheresse (subsidence) en France [4]

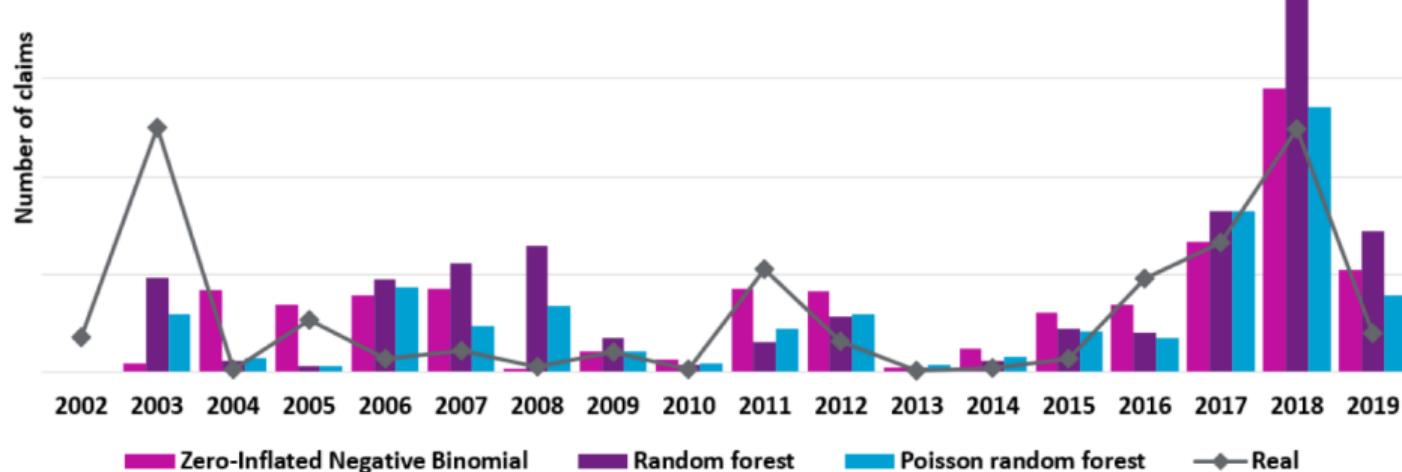
Indicateurs 2020: **ESPI** (précipitations) **ESSTI** (température du sol) & **ESSWI** (humidité du sol), ERA5-Land 9 km × 9 km



(via ESDAC (European Soil Data Centre) pour la concentration des sols)

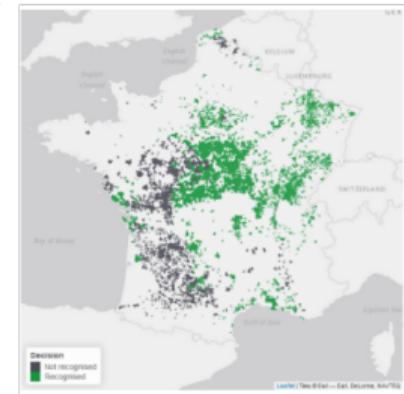
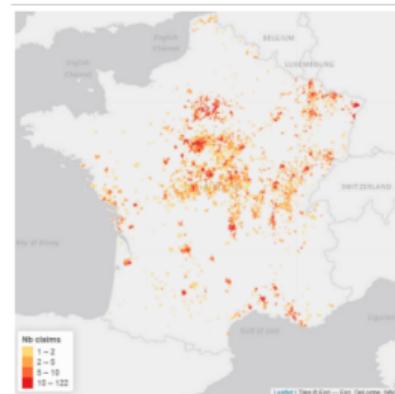
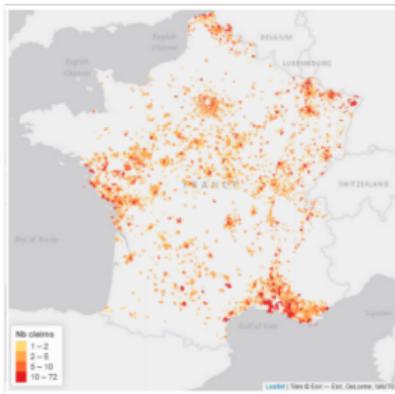
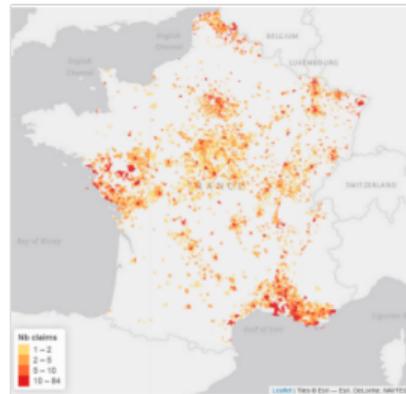
## Risque de sécheresse (subsidence) en France [5]

Quelques prédictions de fréquence de sinistre par différents modèles



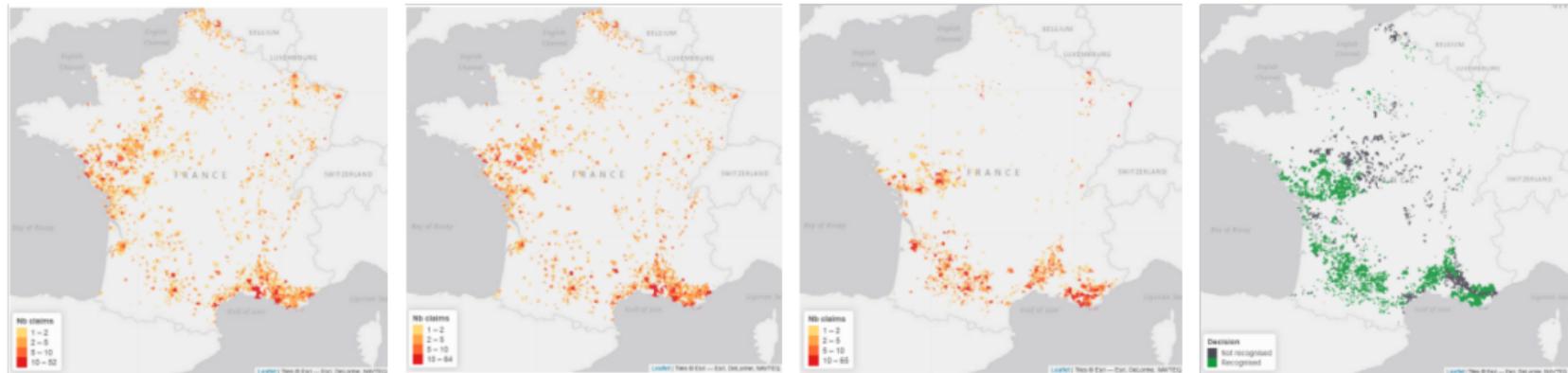
# Risque de sécheresse (subsidence) en France [6]

2017, random forest Poisson, zero inflated, observé, arrêté Nat Cat



# Risque de sécheresse (subsidence) en France [7]

2018, random forest Poisson, zero inflated, observé, arrêté Nat Cat

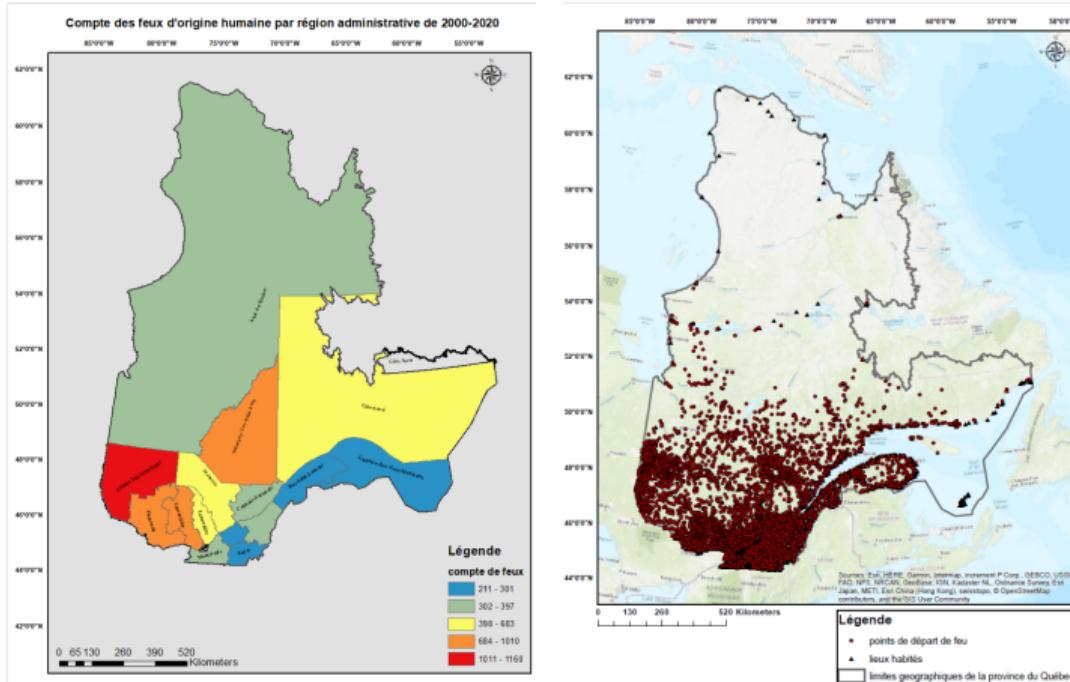


# Feux de forêt ("wildfire") au Québec (Canada) [1]



- [1] A. Benchallal, Y. Bouroubi, and A. Charpentier. "Human-caused wildland fire occurrence prediction over the province of Quebec using machine learning algorithms and free geospatial datasets". In: 10th International Conference on Agro-Geoinformatics and 43rd Canadian Symposium on Remote Sensing (2022).
- [2] France Info. "Canada : le "dôme de chaleur" provoque de violents incendies à Lytton". In: (2021).

## Feux de forêt ("wildfire") au Québec (Canada) [2]



# Feux de forêt (“wildfire”) au Québec (Canada) [3]

