Assessing drought induced subsidence risk in France under current and future climates (EGU24-1636)

EGU General Assembly 2024

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I Catalogue of historical SSWI footprints

Historical soil wetness index (SWI) is computed on high resolution (1km) monthly ERA5 Land data. Drought **Intensity** is broken down into three drought regimes, based on the Standardized SWI (SSWI, Vidal et Al 2010), expressed in number of standard deviations (std).

SSWI Value	<-1 std	<-1.5 std	<-2 std
Drought Regime	Moderate	Severe	Extreme

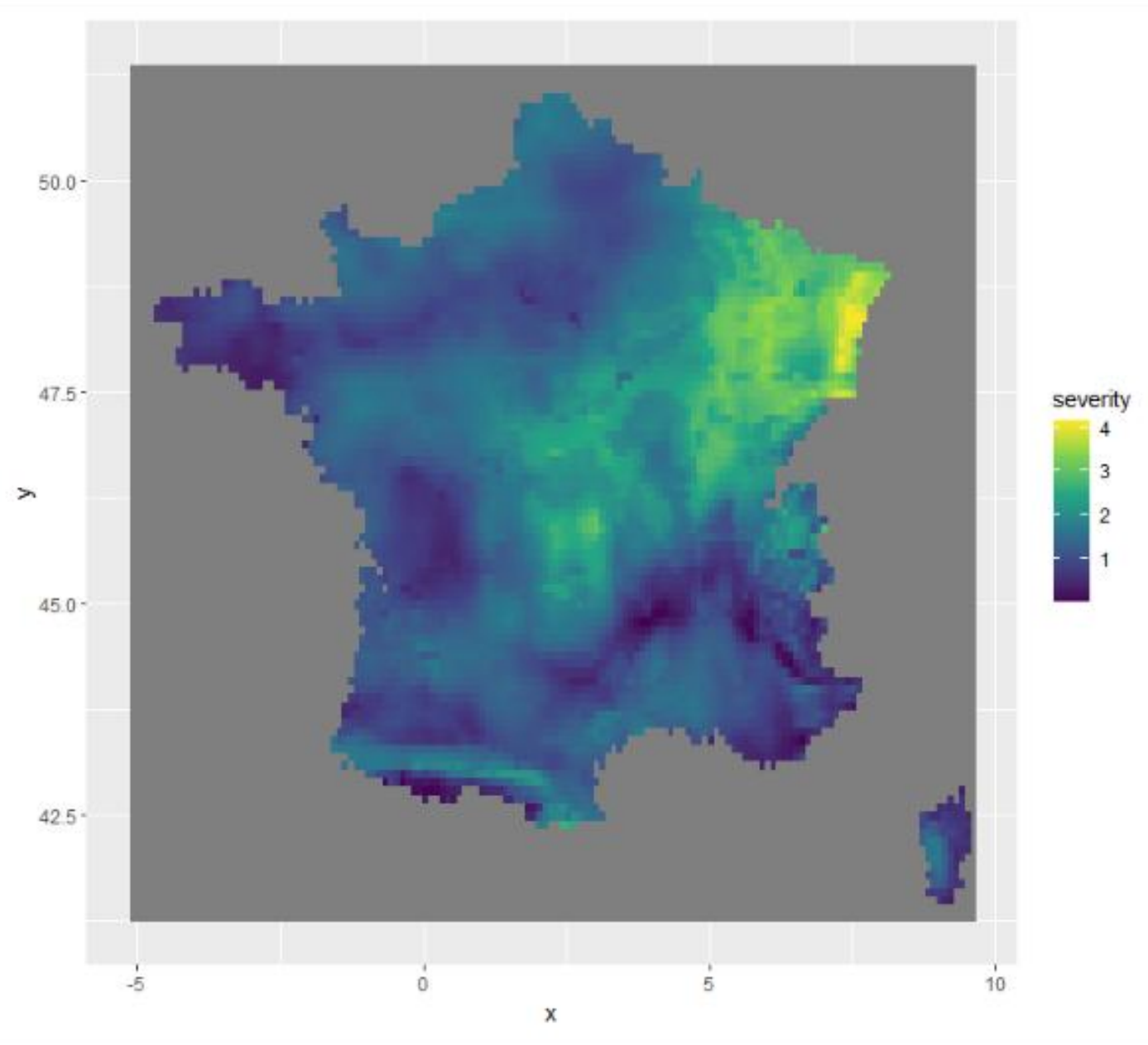
Yearly footprints of severity and durations are computed; the duration consist of the number of month a pixel as been under each regime of drought (and can extend beyond a year)

For any given year, the historical SSWI footprint F is defined by:

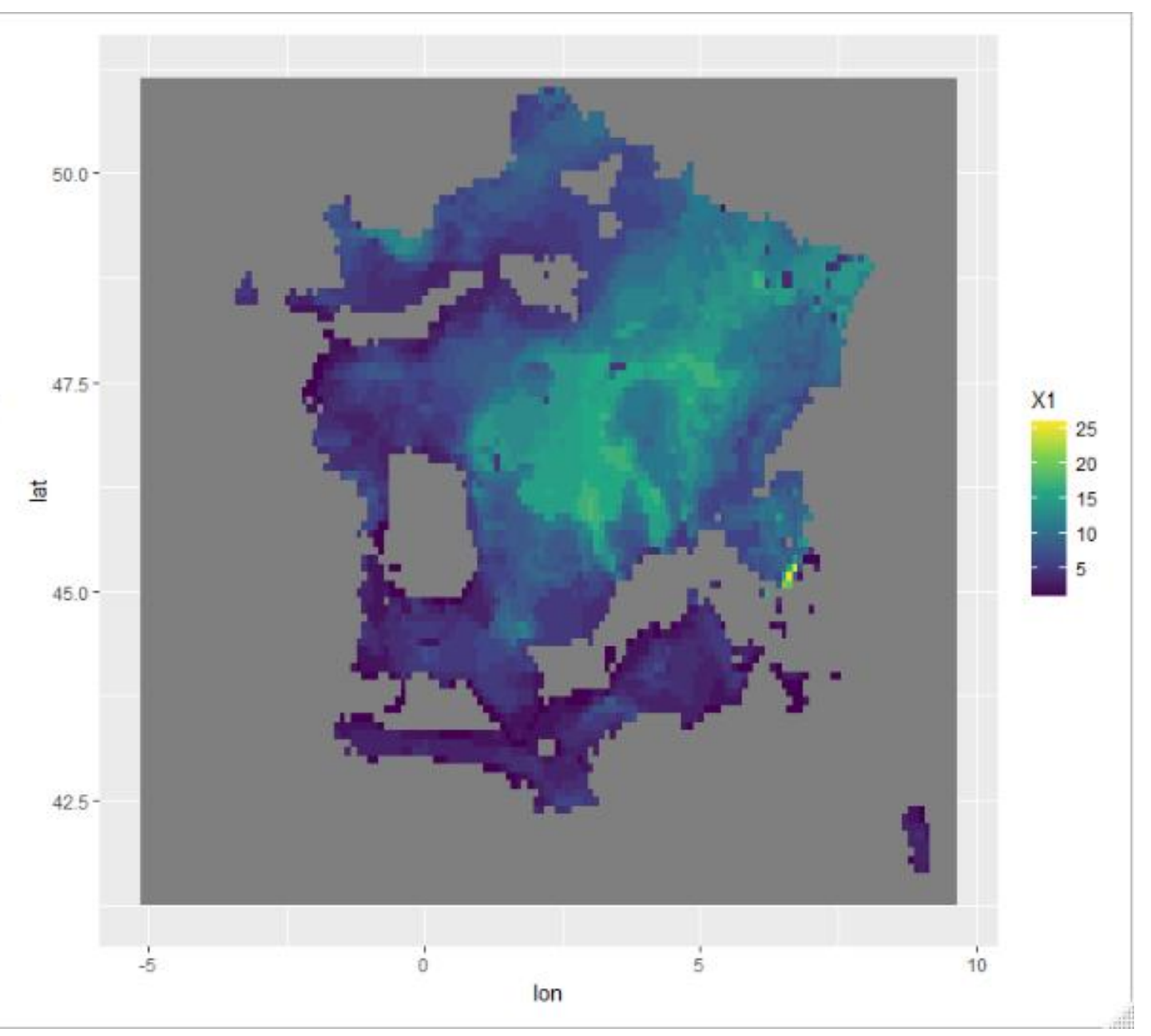
$$\mathrm{F}(x, y, year) = \max_{0 \leq i \leq 12} 1/3 \sum_{k}^{2} SSWI(i-k)$$

For each pixel (x,y) and each year, H provides one drought intensity value (denoted by **I)**, and three duration values (**d1**,**d2** and **d3**) accounting for long lasting droughts.

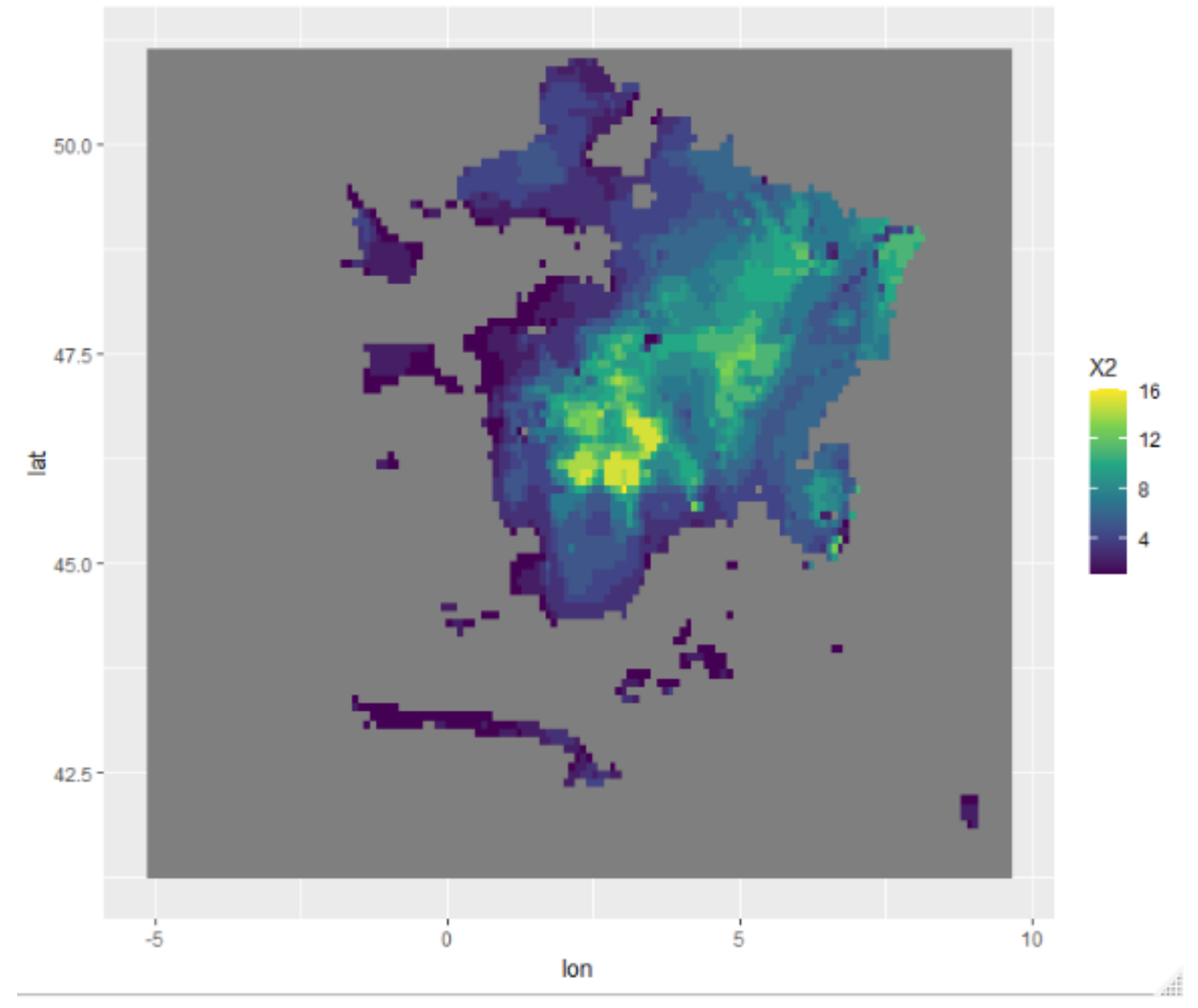
2019 Intensity I



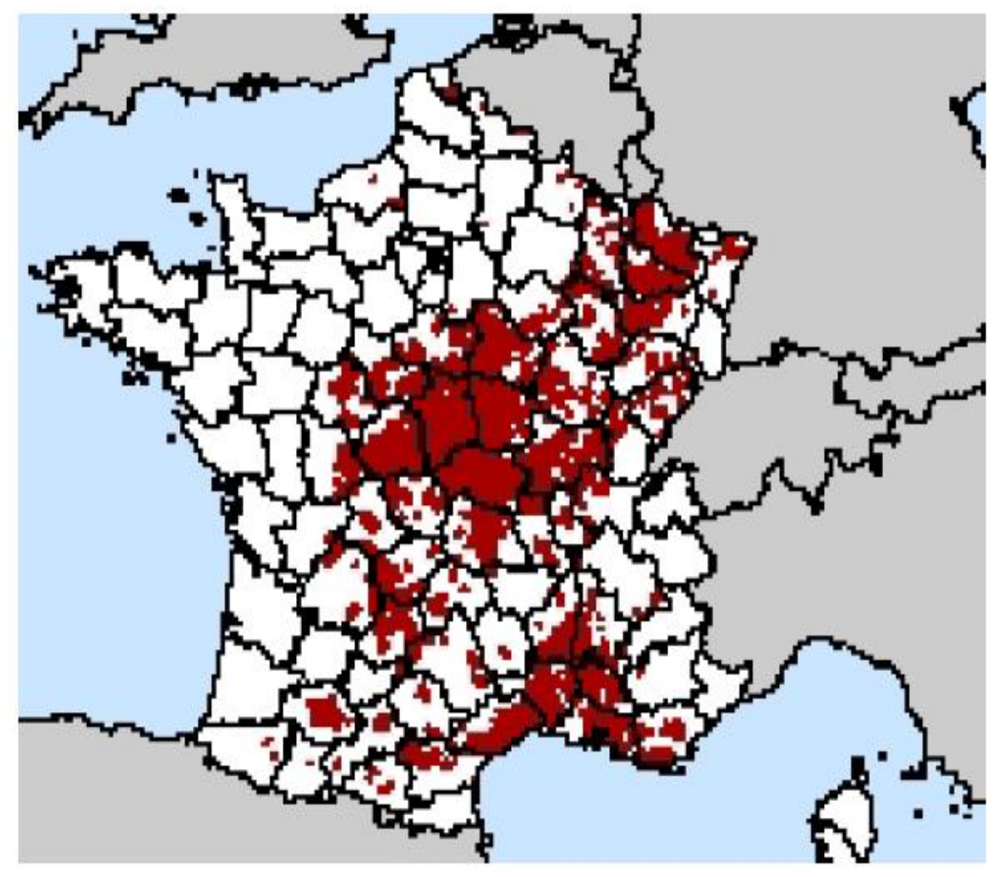
2019 Duration d1



2019 Duration d2



2019 Losses (CCR)



II Catalogues of stochastic SSWI footprints

Based on $\mathrm{F}(x, y, .)$, two sets of footprints are derived, based on a methodology shown in Marie Shaylor et Al., EGU24-8646 (NH13.1).

1. $F^{s}_{current}$(x , y , .) is a stochastic footprint catalogue in the current climate (1980-2021)
2. F^{s}_{future}(x , y , .) is a stochastic footprint catalogue in the future climate (2060-2100)

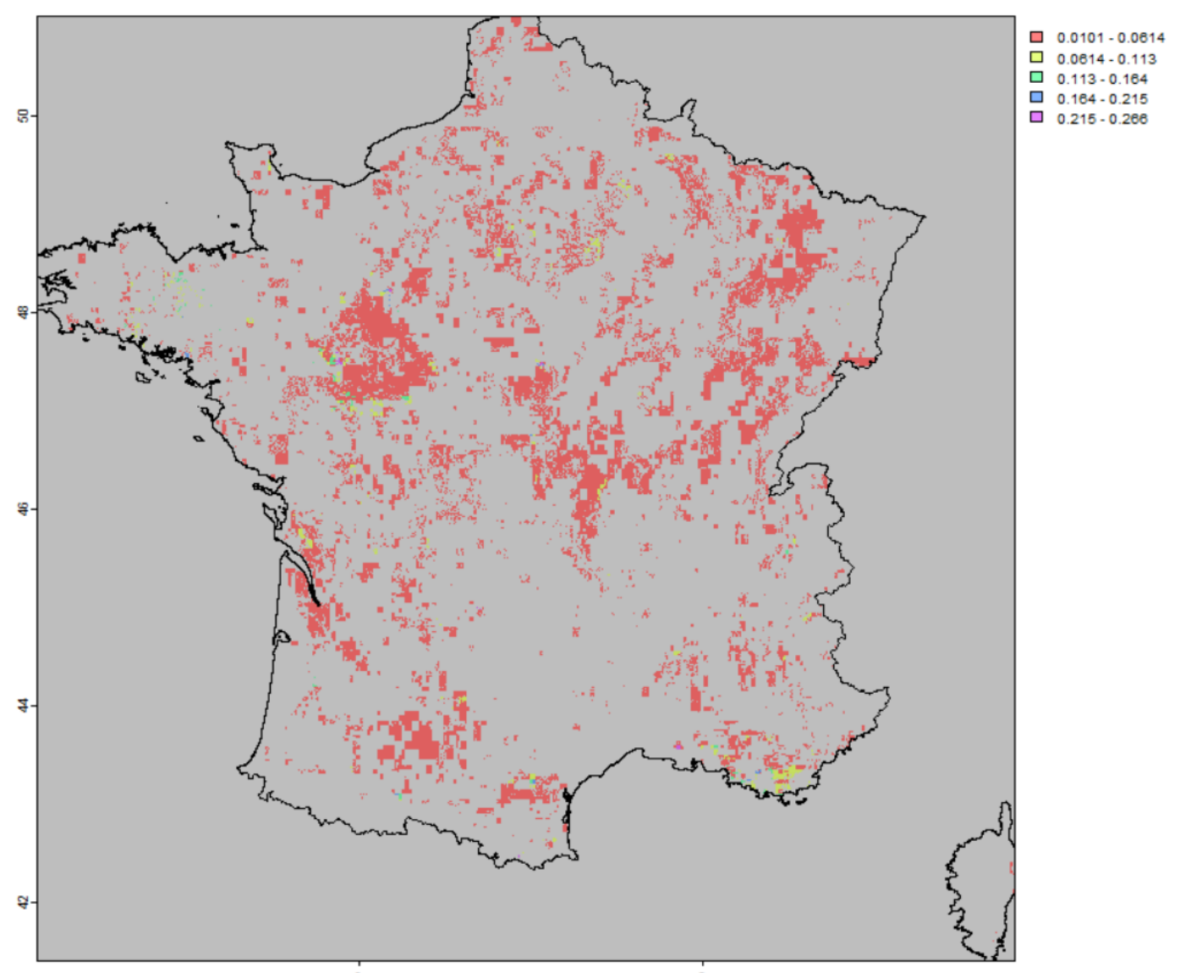
III Chance of loss

Y | X

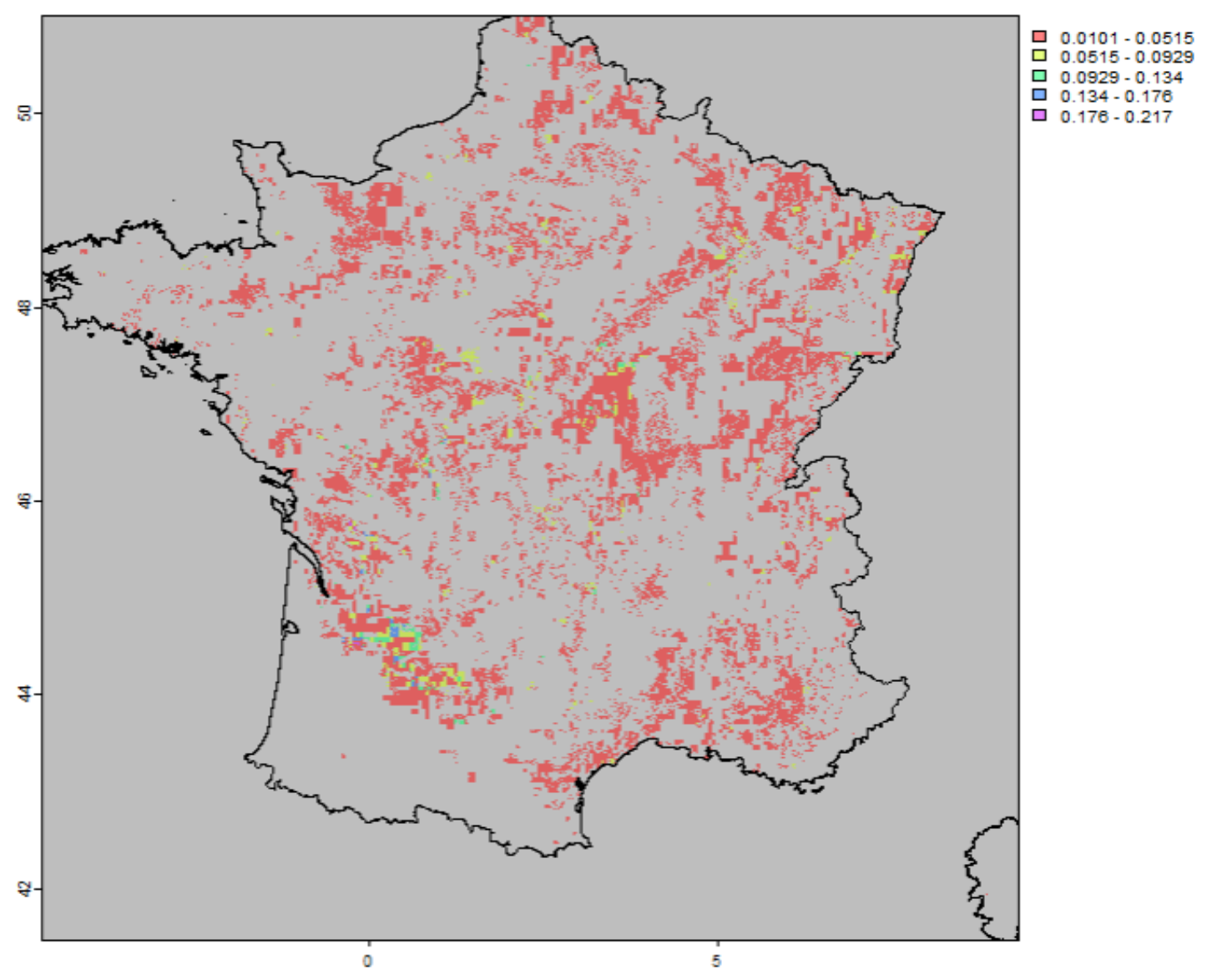
Score		Claim yes / no	I	d1	d2	BRGM level
0.01		0	-1	10	5	1
0.03	⬅	0	-2	20	10	2
0.04		1	-3	30	20	3

1. We fit a Random Forest classification algorithm on a learning database formed by $\mathrm{F}(x, y, .)$ intersected with building level exposure and claim databases. The learning database is highly unbalanced (approx 1/1000) as a subsidence claim is a rare event at building level.
   We use the classification probabilities to estimate the claim occurrence probabilities.
2. We define the threshold, consistently with internal events losses
3. We apply the fitted algorithm to $F^{s}_{current}$(x , y , .) and F^{s}_{future}(x , y , .) with the same thresholding hypotheses.

Extreme event (99.5 quantile) – current climate



Extreme event (99.5 quantile) – future climate



IV Exposure and vulnerability hypotheses

(i) The **exposure** data used is resampled from a representative insured portfolio in France, at building level and filtered on low-rise buildings (<5 storeys).
(ii) For every building generating a claim according to the algorithm from III ,the insured loss equals its value multiplied by a 8% factor (**Destruction Rate**)

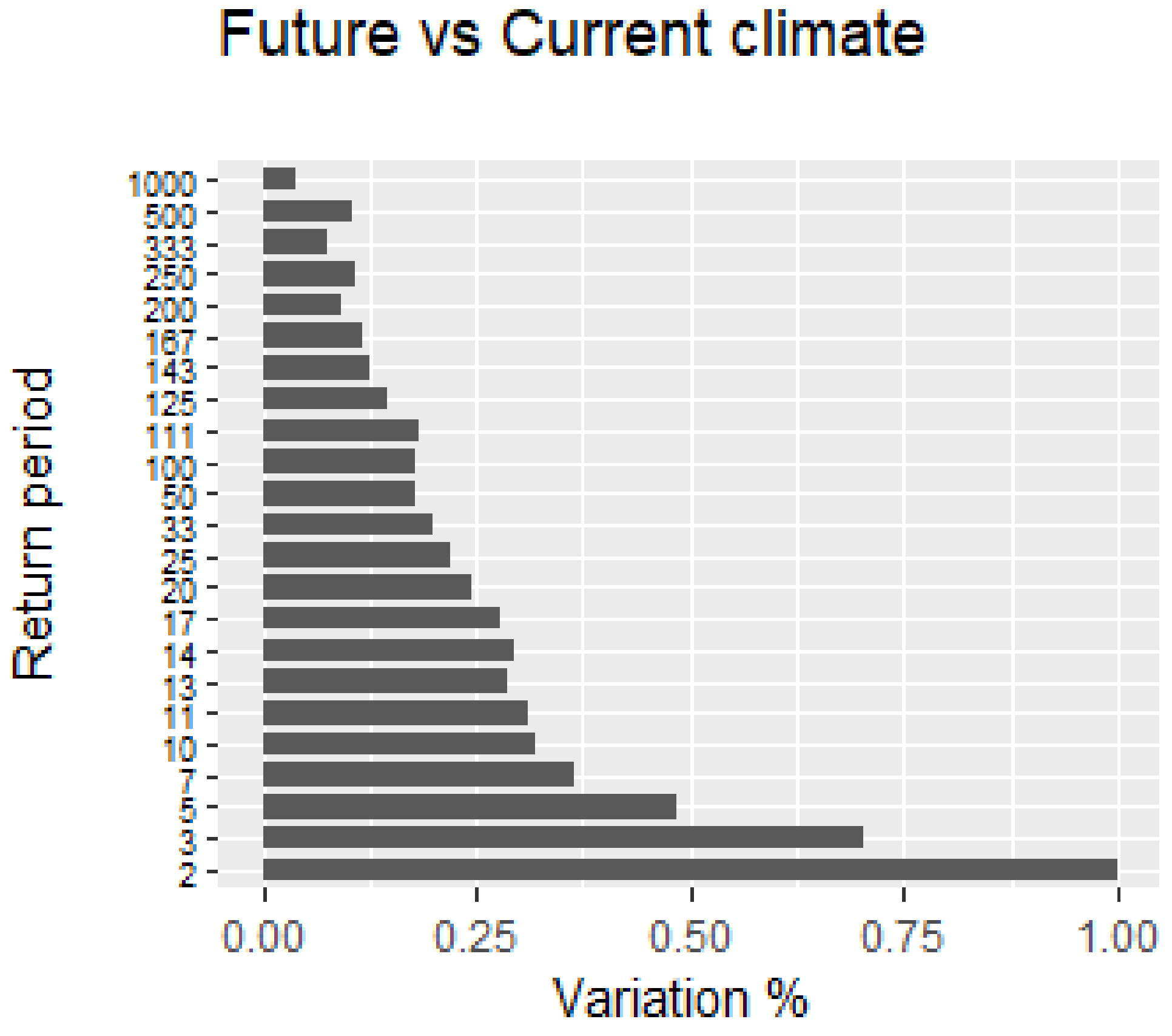
Average claim cost (MRN,2018)	Chosen average building value	Destruction Rate
26K€	[300-350]K€	8%

V Results and findings

(i) 99.5% quantile (200 year return period) destruction rates are of 1/10 000 order, whereas leading perils in European countries such as Flood and Windstorm can produce destruction rates proportional to 1/1000. However, AAL (Average Annual Loss) subsidence destruction rates are of the same order as leading perils.

(ii) Lowest return periods are the most impacted by climate change. The 99.5% OEPs show a variation of **9.5%** while the AALs show a **49%** variation between current and future climate.

However, results on highest return period shall be taken with cautious as they are strongly affected by the number of historical years considered in the modeling, and by the sampling hypotheses used in this study.



VI Conclusions

We have presented a stochastic model to evaluate drought induced subsidence risk in France.

Subsidence risk is much less costly for higher return periods compared to other perils, but being of similar order regarding annual average loss, it can be seen as a recurrent and material peril. Since lowest return periods appear to be the most impacted by climate change, that conclusion is expected to remain valid in a future climate.

The methodology can be applied to any country where soil and building-level claim data is available. The type of index can be changed to reflect other drought impacts (agricultural, fluvial). The identified challenges to improve the model are the potential French law changes, the data resolution, and the addition of key predictor variables.

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