Application of Extreme Value Theory to hail risk assessment and management: a study in Spanish wine grapes insurance.

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Climate change risk and insurance sustainability

- A common belief is that climate change may be already affecting insurance companies, with the potential of damaging their solvency and even making them non-profitable businesses.
- For instance, in the USA some lines of business like fire in California are being abandoned by the insurance companies.
- Insurance companies are trying to assess the risk of climate change to study the sustainability of their businesses in the coming years:
    - How this change will affect their premiums, SCR, profits, etc?
- **This is the topic of our research**.

Objectives of our Research Project

- We aim to study the **sustainability of Spanish insurance lines of business facing the climate change risk**.
- To this aim, we need to find an objective measure of climate change to check (a) if there is any and (b) how it affects the lines.
  - We need an actuarial climate index playing as a proxy for climate change, hoping that it may be related to the evolution of insurance figures like severities, premiums, SCR, etc. of different lines of business.
  - So we can make conclusions on its past and future influence on the insurance business and its sustainability.
- We must choose a line of business and achieve two kinds of studies:
  - Has climate change, represented by the actuarial climate index, influenced in the past the insurance business?
  - How is climate change going to influence it in the future? Will the insurance business be sustainable?

Our progress: Iberian Actuarial climate Index (v 0.1)

- We have built the so-called *Iberian Actuarial Climate Index* (IACI) (see [1]).
- In its first version it consists of an imported American Actuarial Climate Index©, fed with Iberian data taken from ERA5-Land reanalysis dataset ([2]) and tide gauge data from the Permanent Service for Mean Sea Level (PSMSL) ([3])
- This index is made of six components: *warm temperature, cold temperature, precipitation, drought, wind speed, and see level*.
  - These components are standardized to a period of 30 years from 1961 to 1991.
  - So we can check if the IACI has been growing or decreasing through the next period 1992 to 2022

$$IACI = \frac{1}{6}(T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + S_{std}). \tag{1}$$

Our progress: Iberian Actuarial climate Index

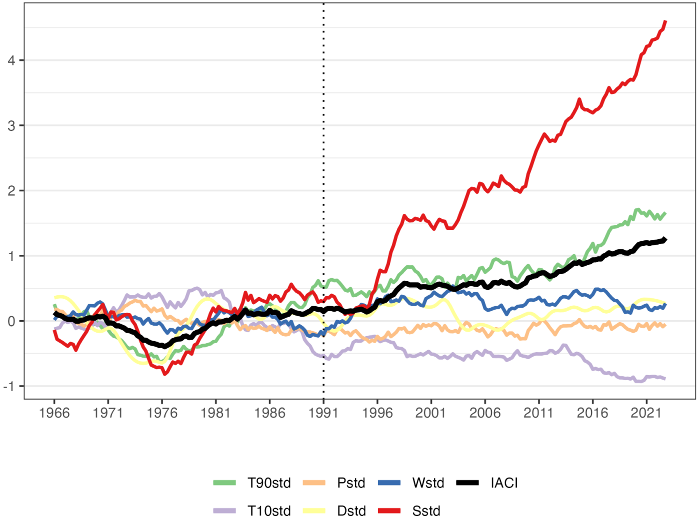


Figure: Iberian Peninsula: 5-year moving averages, IACI, and its 6 components

Our progress: Insurance lines of business and IACI: Crop insurance, Hail risk in wine grapes

- We are now studying a line of business in *Spanish crop insurance*: *wine grapes* all over Spain, facing the daunting *hail risk* which is very challenging because of:
  - Its extreme violence that causes profound damage to the crops.
  - Its extreme irregularity both in time and space.
  - Its extreme locality
- We aim to study hail risk and try to explain to what extent it is related to climate change...
- ... to assess the future sustainability of the line of business.
- This is done in a first step by **modeling extremes of hail risk**, related to the number of claims, severities, etc, because we think that **extreme figures will surrender their relationship to climate change (embodied by our IACI) better than common ones**.

Hail risk in wine grapes: database

Our database supplied by the Spanish crop insurance coinsurance pool **Agroseguro** consists of

- 7,547,292 registers with 18 columns...
- ...describing 893,144 policies...
- ...over 33 years from 1990 to 2022...
- ...49 provinces...
- ...and 240 districts...

...giving a fine complete description of the Spanish market during the last 33 years. Very relevant for our extremes analysis are the following columns:

- Severities (€)
- Value of Production (Insured sum) (€)
- These two give rise to the Loss Cost: Severities/VP.
- Production (t.)
- VP/Production= Indemnity /t.

Yearly Claim Number

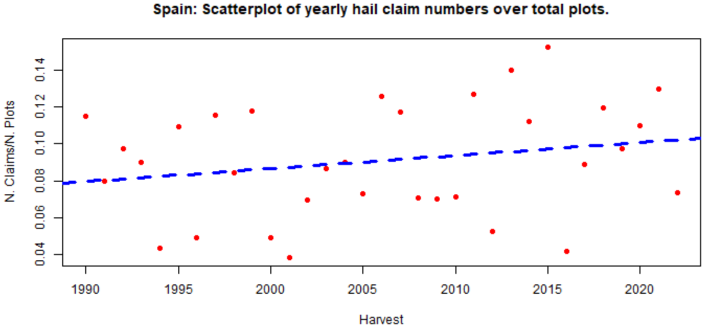


Figure: Yearly normalized claim numbers, 1990-2022

Monthly Claim Numbers

Column1	Column2	Column3	Column4	Column5	Column6	Column7	Column8
month	1990	1991	1992	1993	1994	1995	1996
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	2	0	6	4	3	8	9
4	413	62	0	609	824	1206	633
5	3152	622	3210	2574	2054	1784	772
6	552	288	2469	5624	2461	1709	1881
7	2052	3355	4783	2994	640	1521	2787
8	4182	571	6825	3718	2015	10005	1965
9	4932	7070	1873	1800	606	1812	1182
10	0	25	45	135	16	5	63
11	0	1	0	0	0	0	0
12	0	0	0	0	0	0	0

Figure: Monthly claim numbers, 1990-2022

- We can conclude that, when studying yearly figures of hail risk, we should better seasonalise the AICI to the months running from April to September.

Monthly Claim Numbers vs Monthly IACI

Column1	Column2	Column3	Column4	Column5	Column6
	.	Linear.Regression	Quantile.Regression..0.9.	Quantile.Regression..0.95.	Quantile.Regression..0.99.
(Intercept)	Intercept	0.0021*	0.0118***	0.0223***	0.0478***
aci_monthly_9022$ACI	IACI	0.0111***	0.0217***	0.0291***	0.0334**

Figure: (Normalized) Monthly claim numbers versus Monthly IACI 1990-2022

- This proves that IACI is somewhat explaining the monthly hail claim numbers.

Monthly Claim Numbers vs Monthly IACI

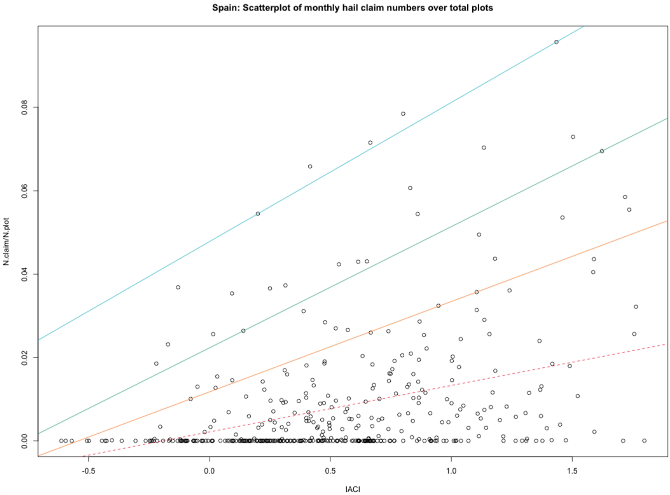
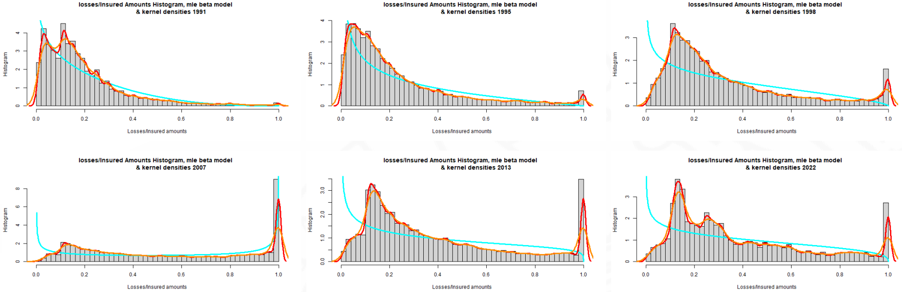


Figure: Monthly claim numbers versus Monthly IACI 1990-2022: linear (red) and quantile regressions Q90(orange), 95(green), 99(cyan)

Yearly Loss Costs Histograms



Loss Costs: Proportion of 1's

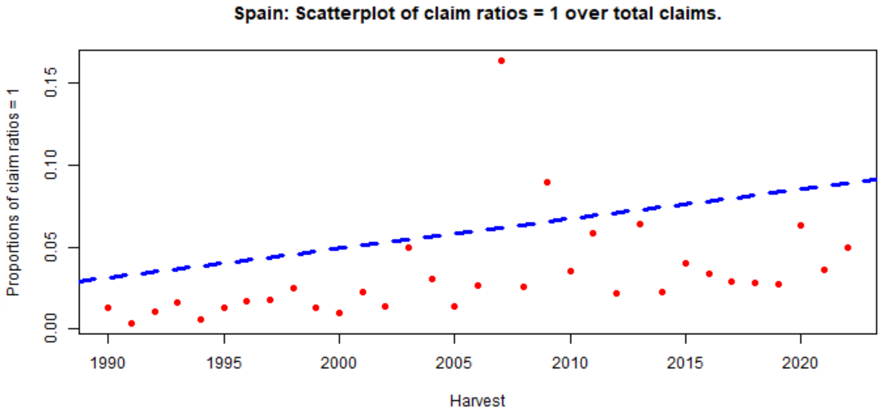


Figure: Proportions (relative to total) of LC=1

Loss Costs: monthly Proportion of 1's vs Monthly IACI

Column1	Column2	Column3	Column4	Column5
.	Linear.Regression	Quantile.Regression..0.9.	Quantile.Regression..0.95.	Quantile.Regression..0.99.
Intercept	0.0001	0.0004***	0.0006*	0.0025***
IACI	0.0005***	0.0008***	0.0012***	0.0041***

Figure: Monthly Proportions (relative) of LC=1 vs Monthly IACI

- This proves that the IACI is somewhat explaining the monthly number of LC=1.

Scatterplot of Monthly Number of LC=1 vs Monthly IACI

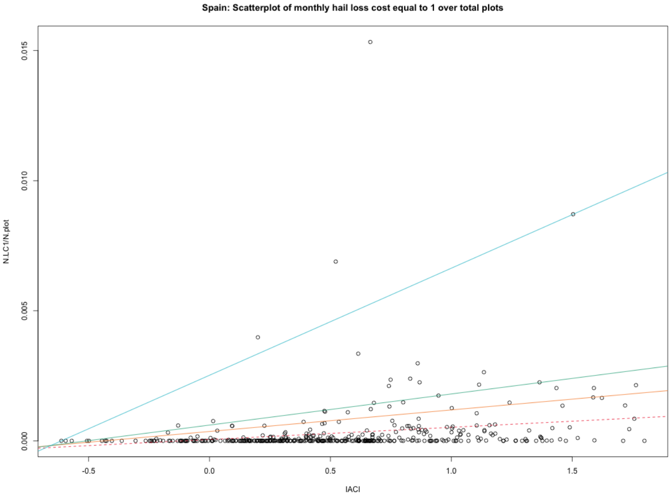


Figure: Monthly number of LC=1 versus Monthly IACI 1990-2022: linear (red) and quantile regressions Q90(orange),95(green),99(cyan)

Quantiles of Loss Cost

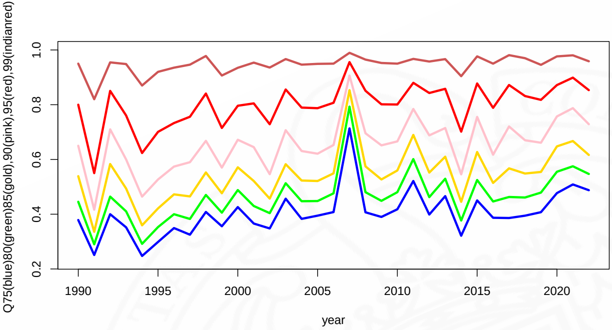


Figure: Quantiles 0<LC<1, 99(indianred), 95(red), 90(pink), 85(gold), 80(green), 75(blue), 1990-2022

Loss Cost: Sample Mean Excesses Q75, 80, 85, 95, 97.5, 99

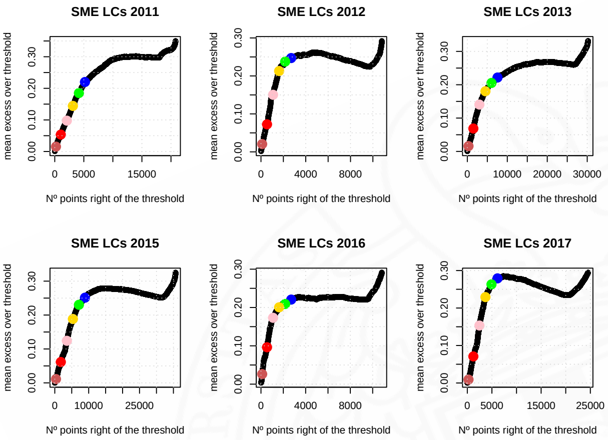


Figure: Examples of Sample Mean Excesses 2011-2017. Thresholds at Quantiles 99(indianred), 95(red), 90(pink), 85(gold), 80(green), 75(blue) 0<LC<1

Loss Cost: Q95 GPD fit (Weibull)

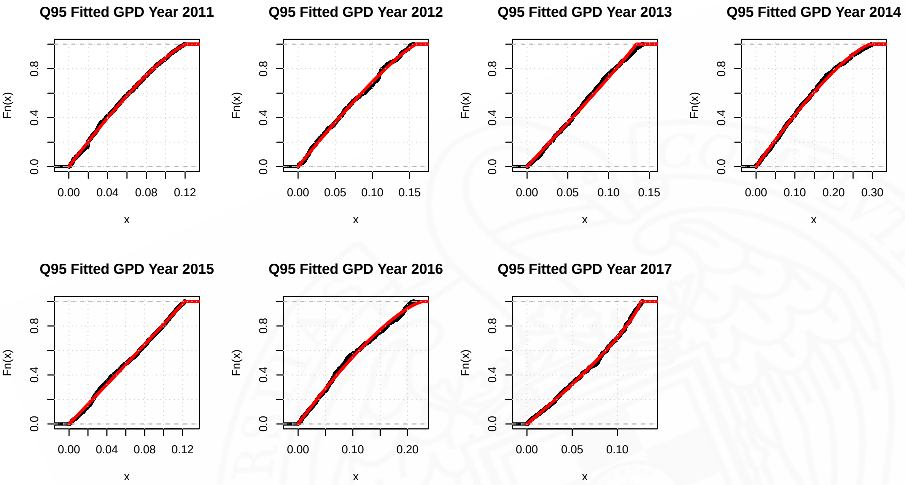


Figure: GPD fit threshold Q95

Loss Cost: Q95 GPD fit (Weibull) estimation and KS test

year	umbral95	xi95.pwm	beta95.pwm	p.value.pwm	Reject.pwm
1990	0.65	-1.46544875592543	0.248170581487054	0	REJECT
1991	0.4163	-0.413674040738434	0.228559967799281	0.30173	
1992	0.71	-1.15652425649822	0.151280289500379	3.5e-05	REJECT
1993	0.6	-1.07309360321229	0.245883812223042	2.7e-05	REJECT
1994	0.4642	-0.553837052283552	0.228508122534426	0.849768	
1995	0.5269	-0.630815003576852	0.210256432333941	0.247735	
1996	0.574	-0.568257605204079	0.182024793528587	0.256607	
1997	0.59	-0.811280662509331	0.209346315482224	0.151059	
1998	0.668	-1.33398914032729	0.207986237084787	0.046389	
1999	0.5702	-0.701921502497346	0.201566183021964	0.616235	
2000	0.672	-0.686066604163168	0.143189835487887	0.369396	
2001	0.645	-0.866368736902906	0.171282552781591	0.986532	
2002	0.5462	-0.708346243055975	0.205948334014132	0.218194	
2003	0.7069	-0.91345139860357	0.130794185078013	0.786963	
2004	0.6308	-1.06865550468177	0.208105088846583	0.027149	REJECT
2005	0.621	-0.590483265594092	0.146690693052717	0.212956	
2006	0.6528	-0.98391806158506	0.179238782065469	0.442257	
2007	0.9063	-0.811738910155709	0.0368214458135687	0.409379	
2008	0.6957	-1.22642712218663	0.164375822857294	0.000788	REJECT
2009	0.6515	-1.07106208168404	0.198132664639635	0.01942	REJECT
2010	0.666	-0.621920124312438	0.139172175488472	0.092904	
2011	0.7845	-0.784178216139079	0.0954918282826129	0.206492	
2012	0.688	-0.836680079246663	0.13319427396131	0.565594	
2013	0.7148	-1.0518018315307	0.140925924407017	0.033881	REJECT
2014	0.5457	-0.755789664800543	0.223053724387618	0.304598	
2015	0.7554	-1.01959574083368	0.124302944521672	0.212135	
2016	0.6173	-0.728239997741395	0.166362869317639	0.421745	
2017	0.7205	-1.29575054902485	0.162688072647408	0.247742	
2018	0.6702	-0.932362358615414	0.162935753883393	0.015165	REJECT
2019	0.6611	-0.930597365483386	0.158508524510063	0.080074	
2020	0.7571	-1.03497972320945	0.130767517955038	0.259004	
2021	0.7874	-0.872123406502152	0.093211767734822	8e-06	REJECT
2022	0.7288	-0.695434139617782	0.108299048693977	0.294509	

Figure: Q95 threshold GPD fit. Estimation and KS test

Yearly Severities > 0: Quantiles 99, 97.5, 95, 90, 85, 80, 75

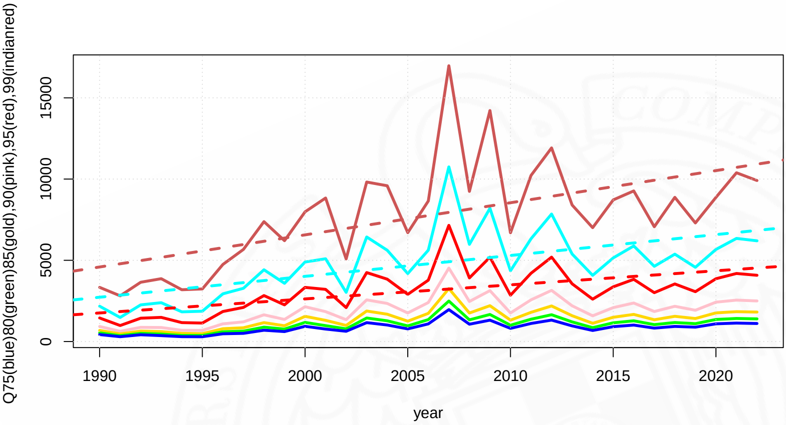


Figure: Yearly quantiles of severities > 0: Q99(indianred), 97.5(cyan), 95(red), 90(pink), 85(gold), 80(green), 75(blue)

Yearly Severities > 0: Sample Mean Excesses coloured thresholds Q75, 80, 85, 95, 97.5, 99

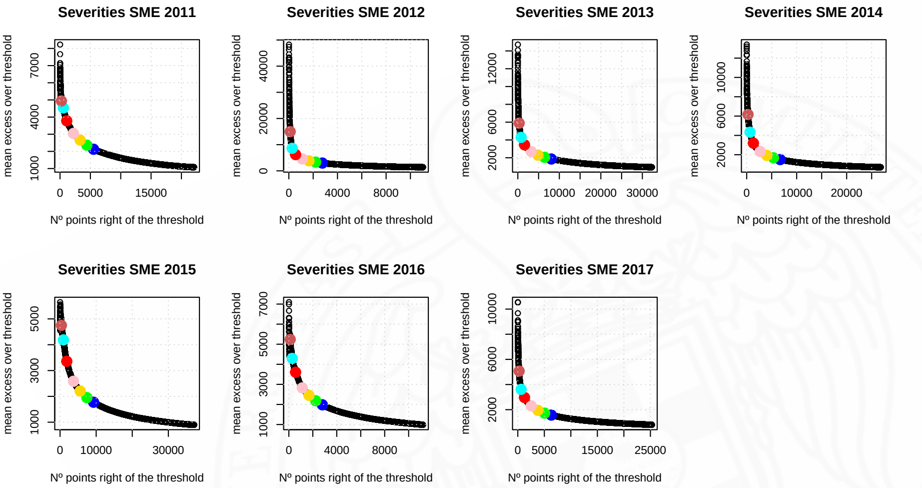


Figure: Thresholds Quant 99(indianred), 95(red), 90(pink), 85(gold), 80(green), 75(blue)

Yearly Severities > 0: Q95 GPD fit (Fréchet)

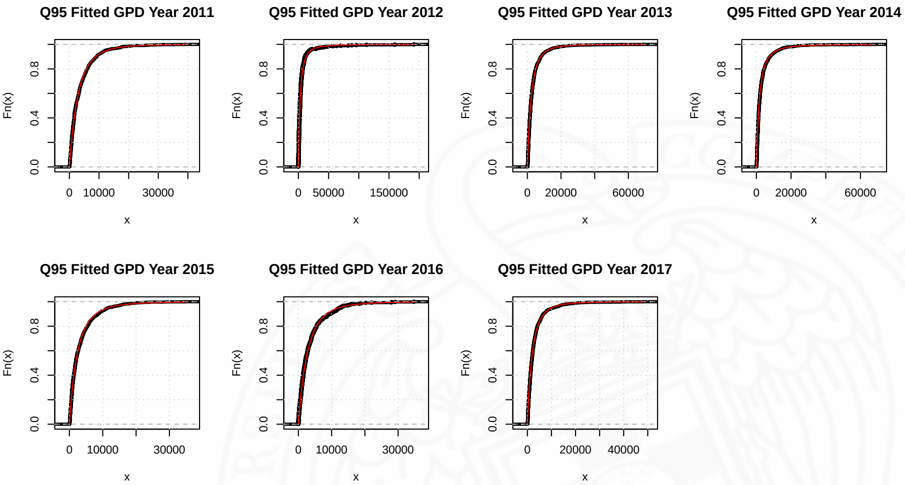


Figure: GPD fit threshold Q95

Yearly severities > 0: Q95 GPD fit (Fréchet) estimation and KS test

year	umbral95	xi95.mle	beta95.mle	mean95	variance95	p.value.mle	Reject.mle
1990	1449.85	0.346914774173718	936.30345058508	1433.66196869707	6713210.33559691	0.869818	NO
1991	986.11	0.609724734650946	580.608460355912	1487.68961783071	NA	0.638294	NO
1992	1437.59	0.372982377746188	1029.46717695373	1641.84727895415	10611372.0268774	0.460067	NO
1993	1487.47	0.338677160425753	1140.11892249884	1723.99750057451	9211861.72345814	0.759932	NO
1994	1166.15	0.50175311289551	811.564527691301	1628.84013667927	NA	0.389073	NO
1995	1137.93	0.327309419852016	943.133107374458	1402.03109008451	5691367.69324385	0.535566	NO
1996	1849.14	0.277462941924584	1387.90512210279	1920.8774229514	8290237.37869755	0.886971	NO
1997	2101.13	0.420837012191159	1536.81868359327	2653.51674043872	44472494.5753129	0.496156	NO
1998	2829.87	0.381918014961386	2063.21234272264	3338.08846183042	47182618.8192955	0.707742	NO
1999	2257.66	0.312631625971279	1769.02599448077	2573.62145440641	17675147.7534989	0.382865	NO
2000	3332.94	0.340206616245534	2110.24046682829	3198.33529524083	32008048.207119	0.744959	NO
2001	3211.49	0.604492552316425	2213.22262100288	5595.9063071135	NA	0.708006	NO
2002	2089.86	0.47978273495234	1213.34352914092	2332.37843236471	134538206.303768	0.83645	NO
2003	4245.02	0.262240666574071	2886.89959952857	3913.06415077488	32200778.0461116	0.998026	NO
2004	3840	0.407805944416208	2347.06958503786	3963.34539819737	85190453.1476856	0.309305	NO
2005	2904.39	0.311126099271554	1709.36527129912	2481.39067177834	16300027.8022564	0.981544	NO
2006	3777.2	0.328591308805408	2382.98122805675	3549.22606649145	36745527.8471313	0.871657	NO
2007	7151.25	0.35998650018702	4657.35243684355	7276.95968632613	189103701.95427	0.688342	NO
2008	3916.4	0.333517357947797	2614.19881393096	3922.38094285762	46206235.2904886	0.797415	NO
2009	5191.9	0.377359616050179	3886.55550370253	6242.05497087666	158851631.919988	0.60231	NO
2010	2851.2	0.29190881530133	1911.8511498363	2700.00699224902	17516450.2252944	0.957375	NO
2011	4203.52	0.209187106935646	3007.01128003775	3802.43077270246	24858732.4118314	0.11892	NO
2012	5194.2	0.487642502194866	3051.75385522016	5956.29783558051	1435463896.72038	0.645636	NO
2013	3554.76	0.320881676066556	2358.27891906201	3472.55969387322	33661187.0932691	0.974034	NO
2014	2608.65	0.454027708076791	1829.48531753665	3350.87575798437	122121041.563503	0.964238	NO
2015	3368	0.280437396565319	2460.06678007576	3418.83634354141	26617560.9167362	0.083827	NO
2016	3828.75	0.242805163721484	2758.33463082552	3642.83338801182	25798020.0629754	0.888456	NO
2017	3007.62	0.305307663481765	2068.63194840292	2977.76704831782	22772074.0133418	0.729749	NO
2018	3545.22	0.358256240236467	2360.25093693225	3677.87127030569	47715458.8798342	0.465099	NO
2019	3069.5	0.394904384726742	1928.79839944745	3187.59275519855	48340492.3534414	0.757197	NO
2020	3866.08	0.319739753423401	2374.77383239495	3490.97840766966	33803710.1198493	0.674814	NO
2021	4189.68	0.298941602444452	2913.27997595365	4155.54536699322	42944133.413696	0.518225	NO
2022	4078.14	0.296066343271861	2822.46822731706	4009.5656747481	39416291.4499928	0.68553	NO

Work still in progress...

- Once the severity extremes are modeled, we want to calculate yearly risk measures for those GPD: quantiles, CVaR at some probability levels.
- Then run models to check if these figures are explained by the Seasonal (April to September) IACI...
- ...as done with the monthly number of hail claims and the monthly number of Loss Costs $=1$.
- We also have to run the same program for **Monthly** severities > 0.

References

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