Extreme Value Analysis of Wind Droughts: A Hydrological Perspective

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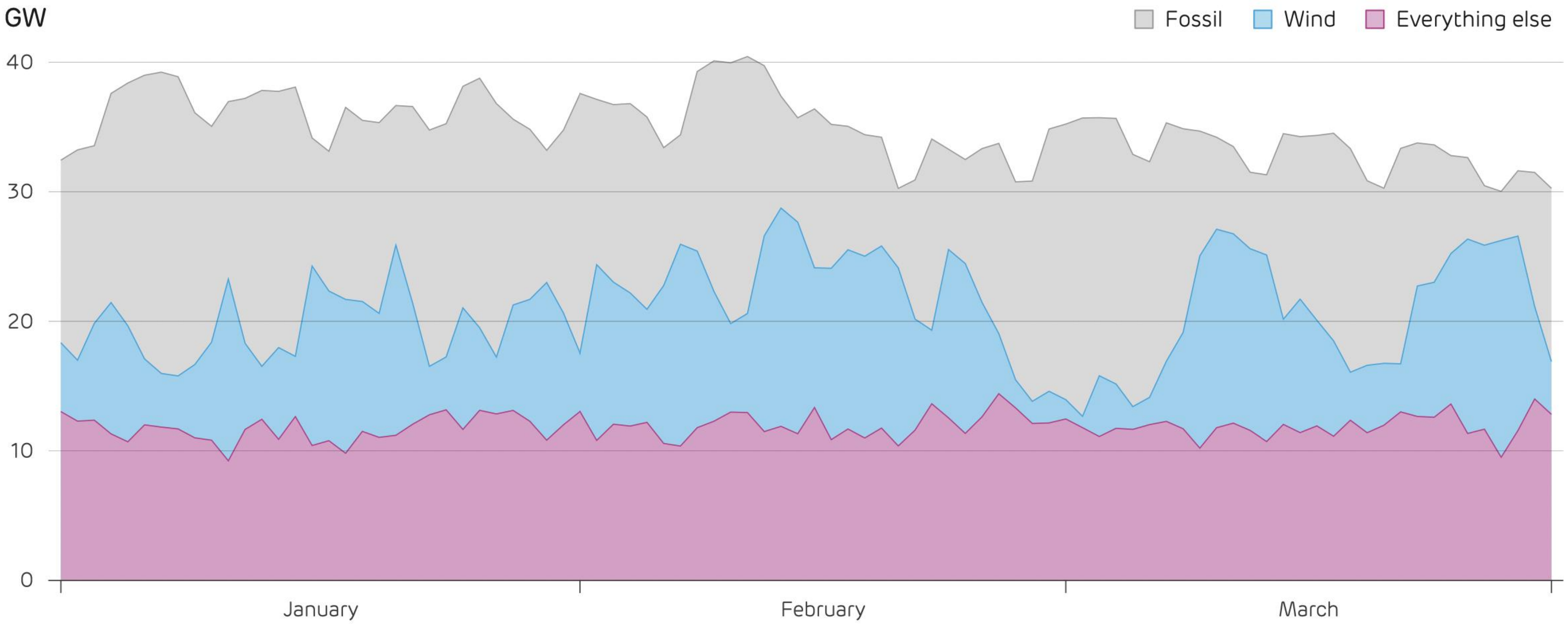
Motivation

- March 2021: longest “cold, calm” spell in over a decade
- Wind farms operated at 11% CF for 11 consecutive days
- “Biggest challenge in de-carbonising Britain’s electricity system” – BEIS

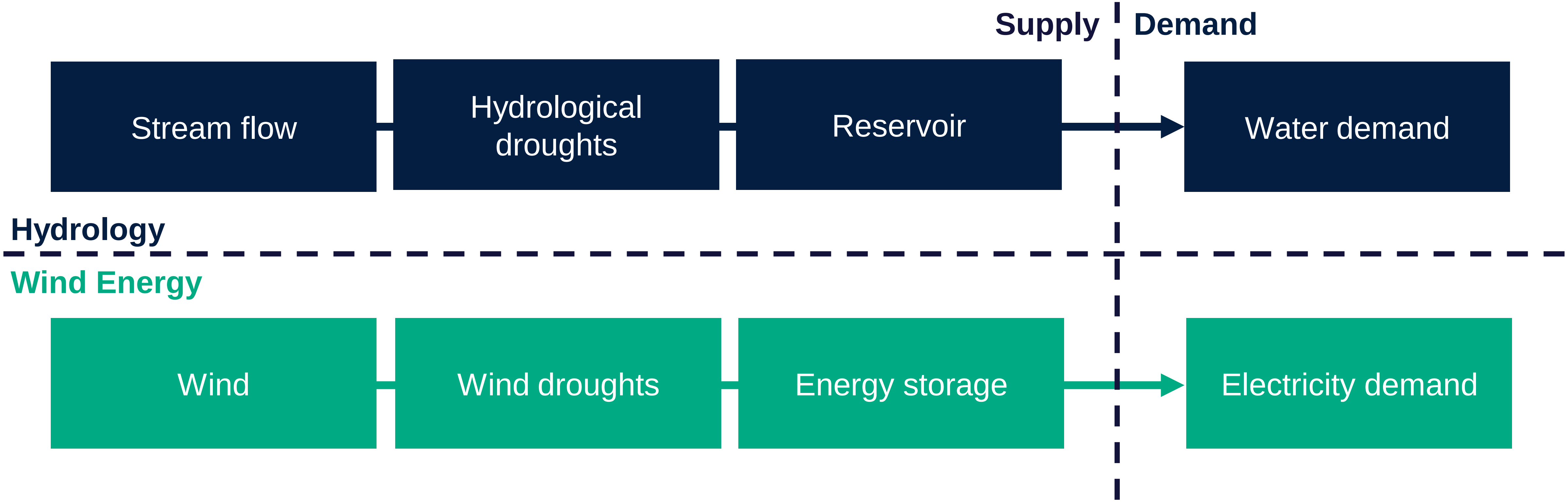


GB energy mix during a wind drought in 1Q2021 - BEIS (2021)

Background

Hydrology and wind energy analogy

- Both wind and stream flows are zero-limited, non-normally distributed, and non-stationary



Objective

Use insights from hydrological drought studies to quantify the risks associated with wind droughts in Great Britain.

1. Data
GB-aggregate wind CF modelling

2. Droughts Identification
Application of hydrological techniques to identify wind droughts

3. Extreme Value Analysis
Estimation of wind drought return periods

1. Data
1.1 Methods and validation

ERA5 10-m wind speed 1950-2021

Evaluation/correction - Potisomporn et al. (2023)

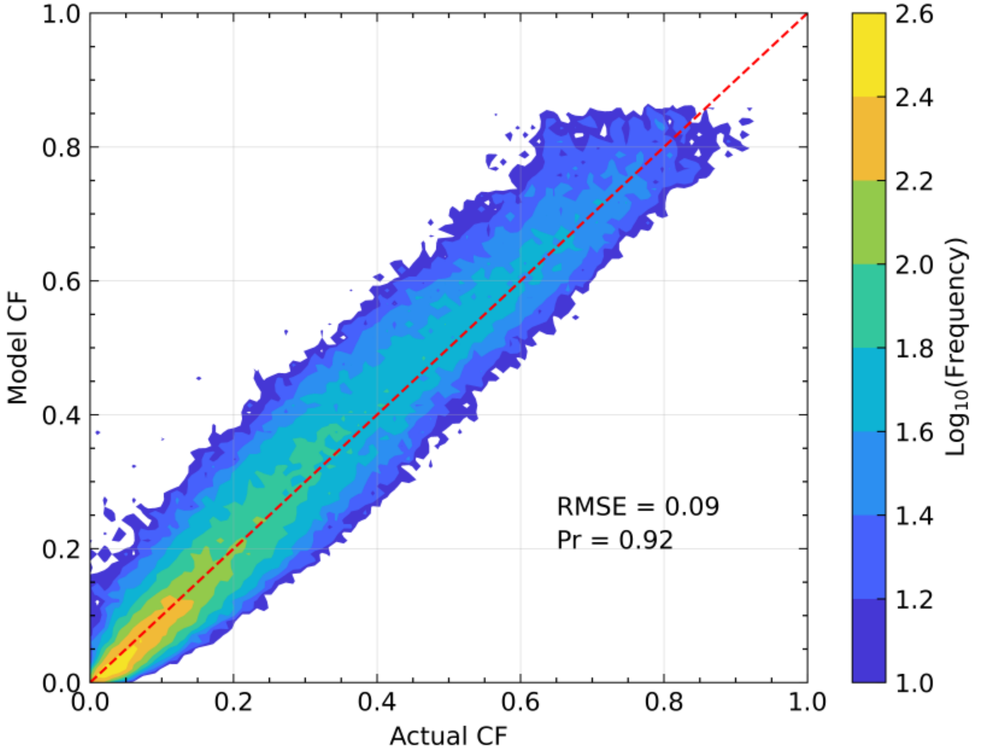
Interpolation of wind speed to wind farms

Extrapolation of wind speed to hub height

Conversion to power output

GB-aggregated CF time series

- Capacity factor validated against actual wind generation data from National Grid in the period 2010-2021



Validation of GB-aggregate CF against actual wind output from National Grid

2. Droughts identification
2.1 Runs analysis

Droughts definition

- *Runs Analysis* – Yevjevich (1975): Uninterrupted period during which a resource series remains below a certain threshold

- Commonly applied in wind energy [Cannon et al. (2016), Patlakas et al.(2017), Potisomporn & Vogel (2022)]

Issues

- Only considers constantly-below-threshold events

- *Mutually dependent droughts* do not satisfy the assumption of independence in an EVA

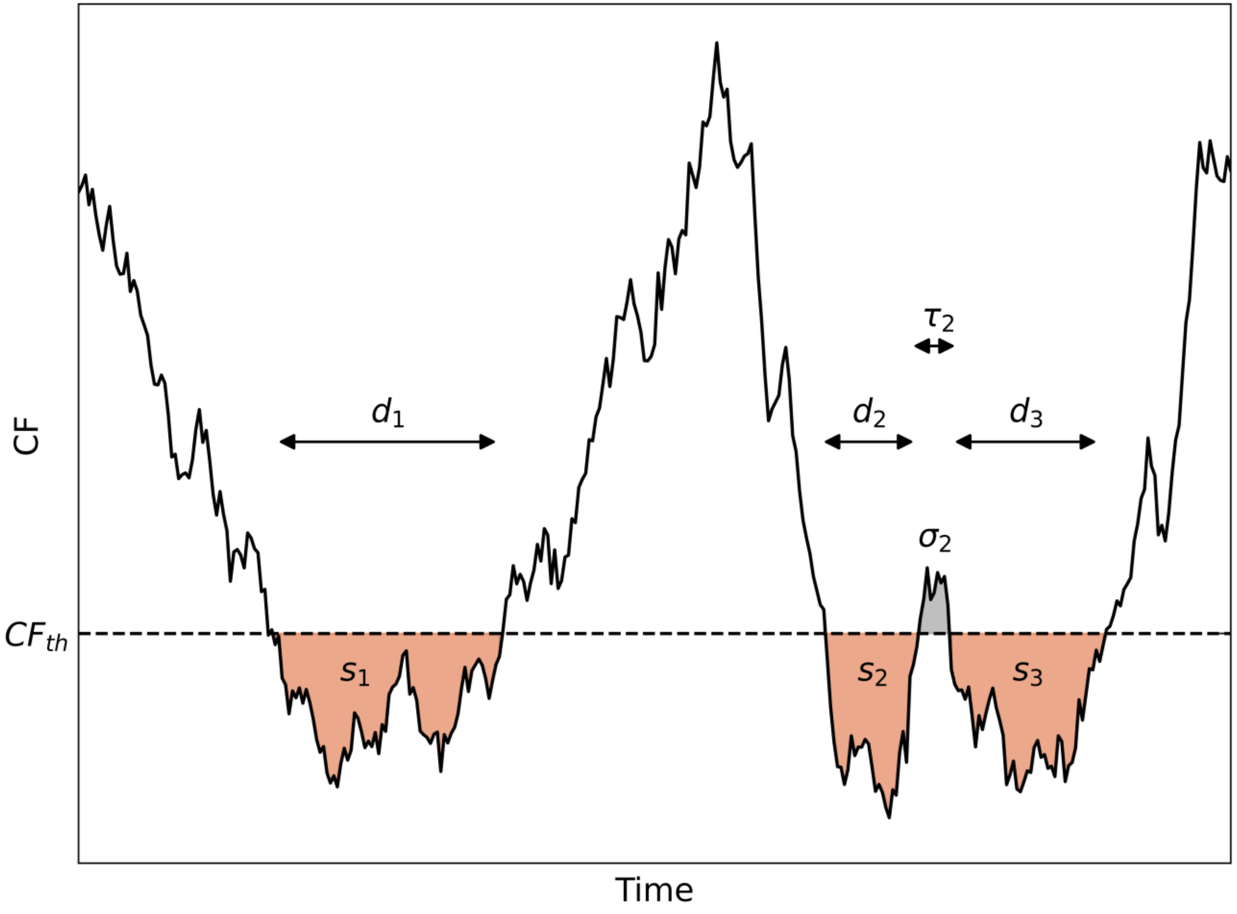


Illustration of drought events and characteristics

2. Droughts identification
2.2 Pooling procedures

Inter-Event Time (IET)
Events separated by $\tau < \tau_t$ are pooled

Moving Average (MA)
Apply runs analysis on a moving-average-filtered CF time series

Sequent Peak Algorithm (SPA)
Local maxima of zero-limited cumulative deficit series w defines drought duration

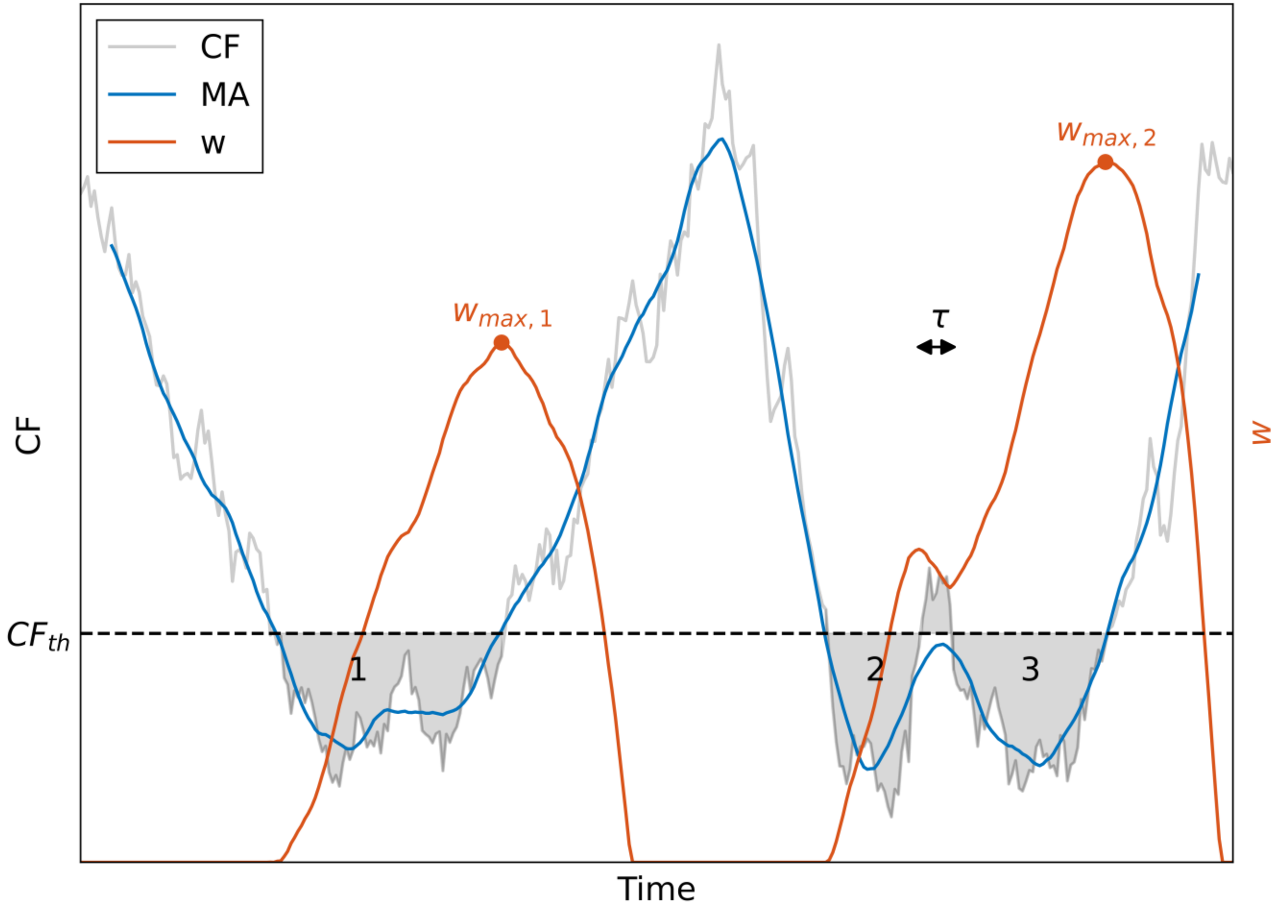
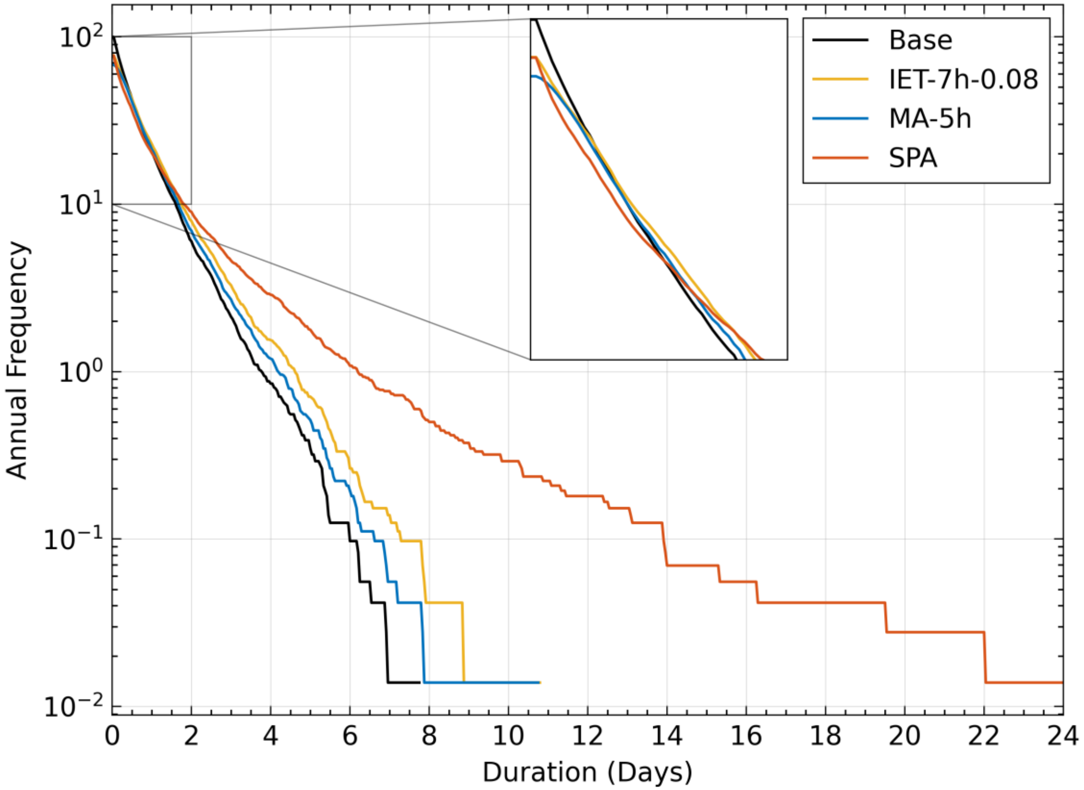
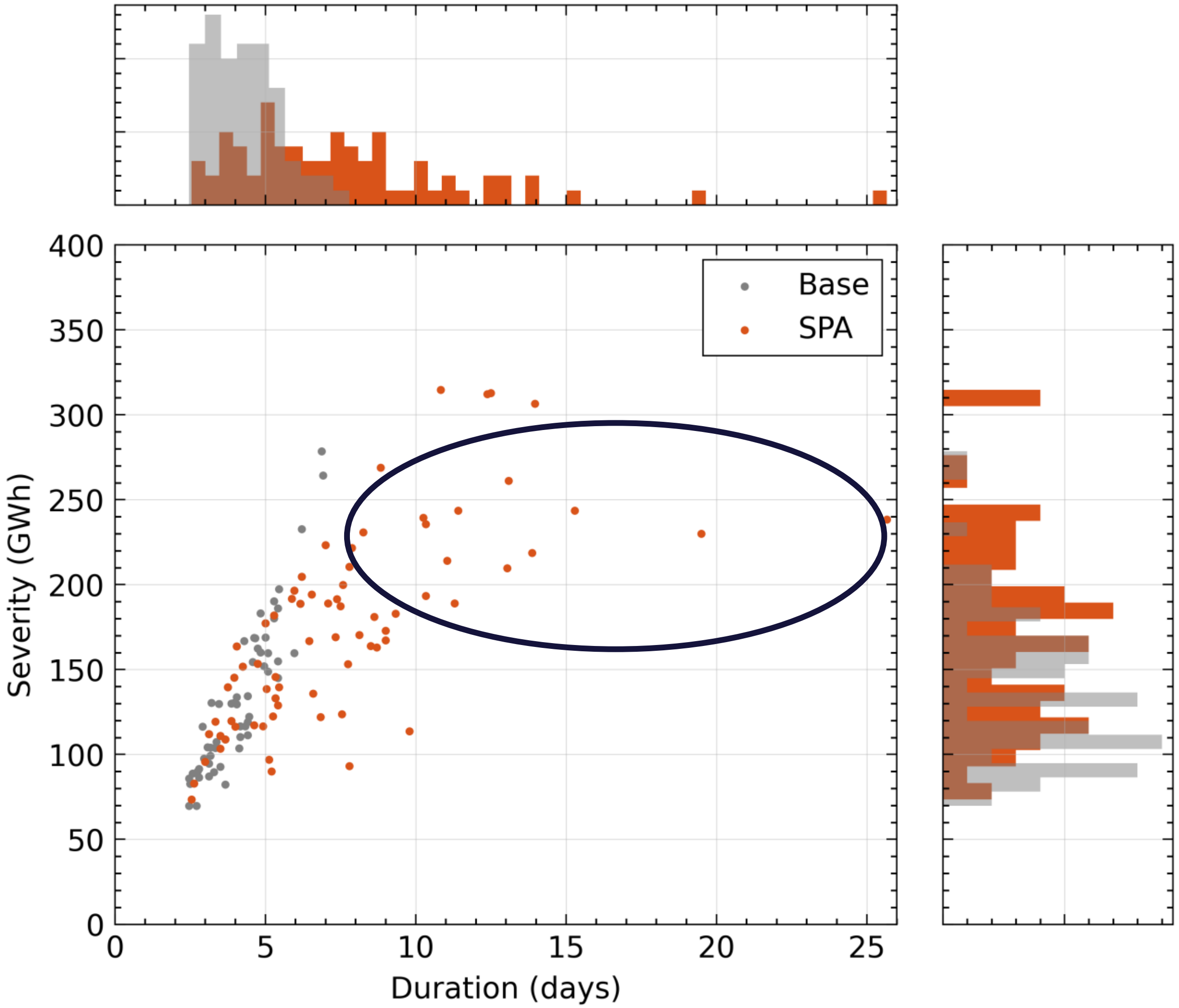


Illustration of each pooling procedure

2. Droughts identification
2.3 Pooled events



Frequency-duration curve of wind droughts as identified by each pooling procedure



Duration of wind droughts plotted against severity for unpooled droughts and SPA-pooled droughts

3. Extreme value analysis
3.1 Methods

GB-aggregated CF time series

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Runs analysis + Pooling procedure

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Extreme value series extraction (AMS/PDS)

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Extreme value distribution fitting

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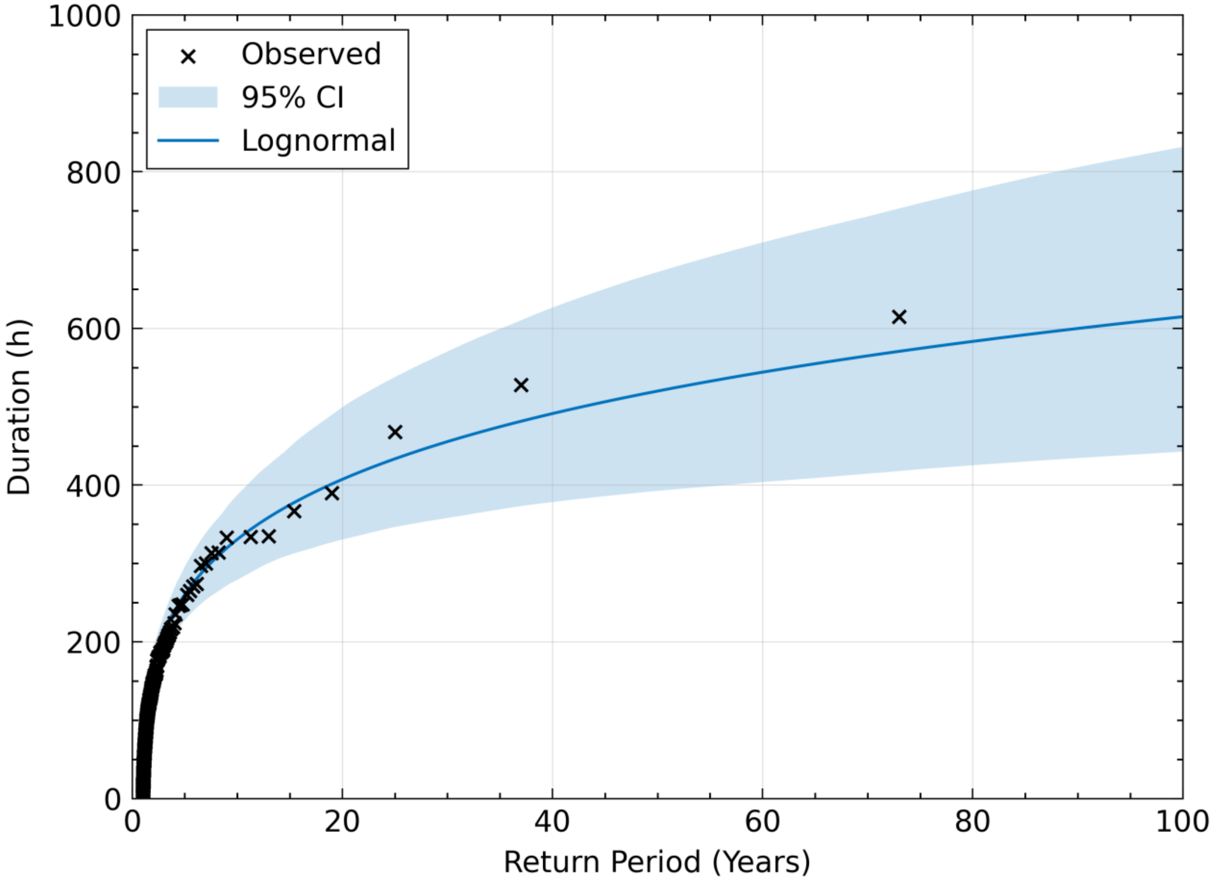
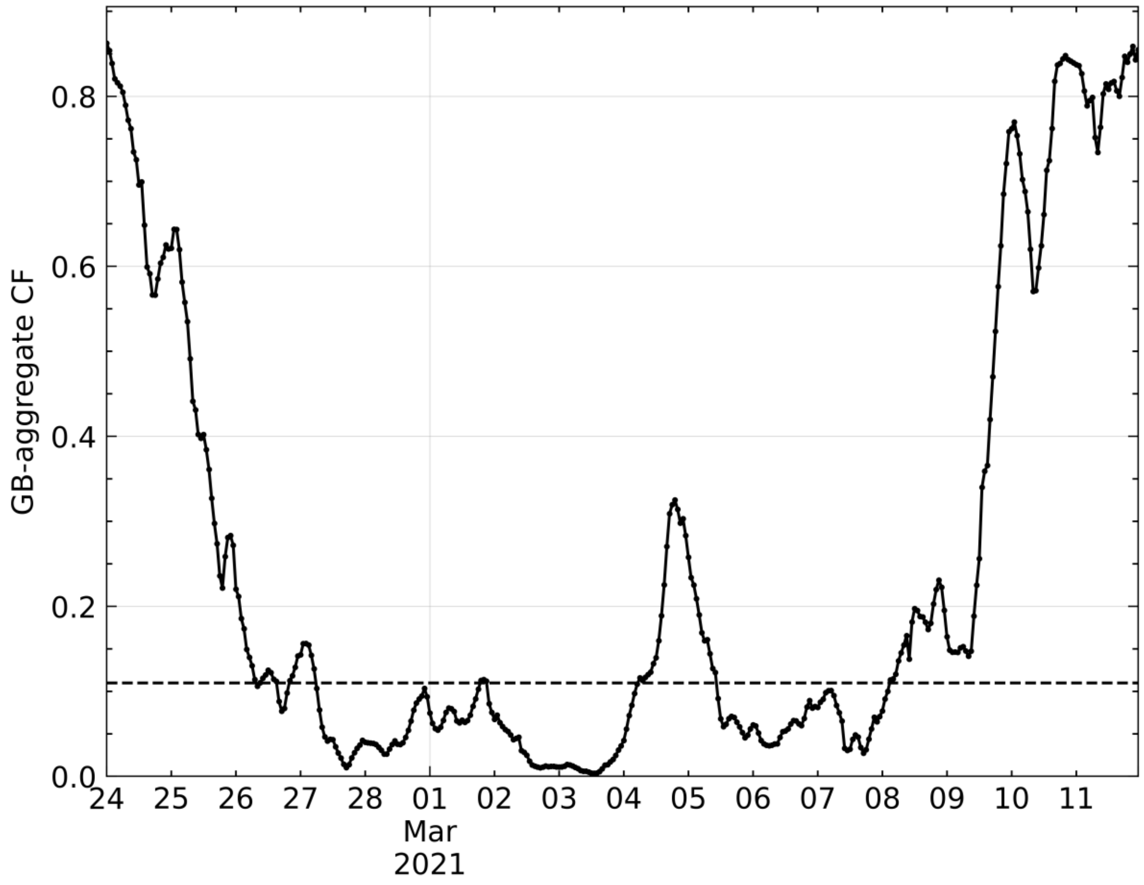
Return period and uncertainty



Return period and the 95% confidence interval for AMS CF0.1 by SPA – Potisomporn et al. (2023)

3. Extreme value analysis
3.2 Revisiting March 2021 event



March 2021 event

"A wind drought with a duration of 11 days corresponding to 0.11 CF threshold"

AMS-CF0.1	Return Period (y)
Base	100
IET	20
MA	30
SPA	3

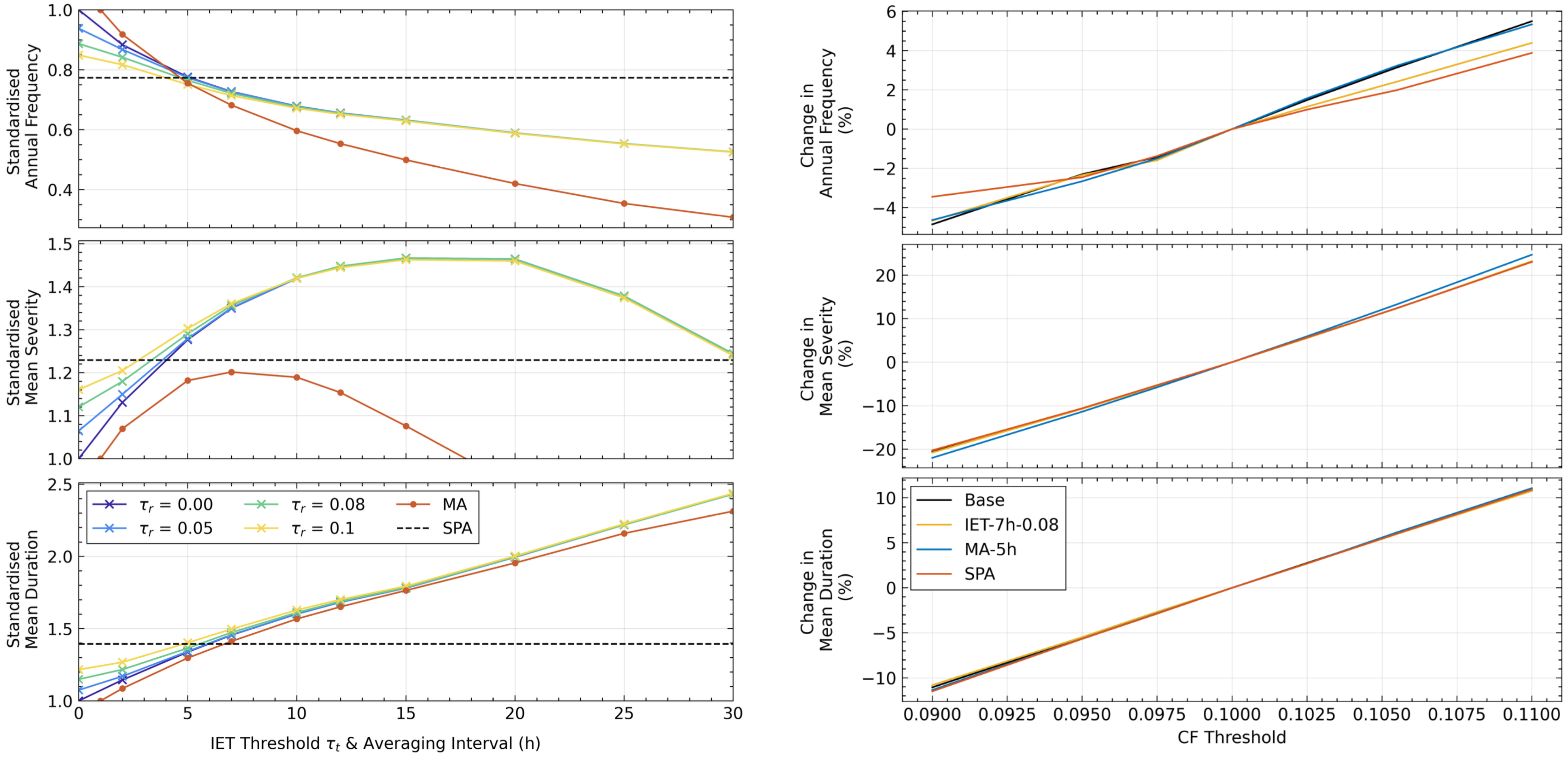
Conclusions

- Analogy between hydrological and wind droughts are useful
- Pooling drought events can give us new perspectives on wind droughts
- Failure to consider mutually dependent droughts can lead to an underestimation of the risk of wind droughts
- Further details on extreme value analysis – Potisomporn et al. (2023)

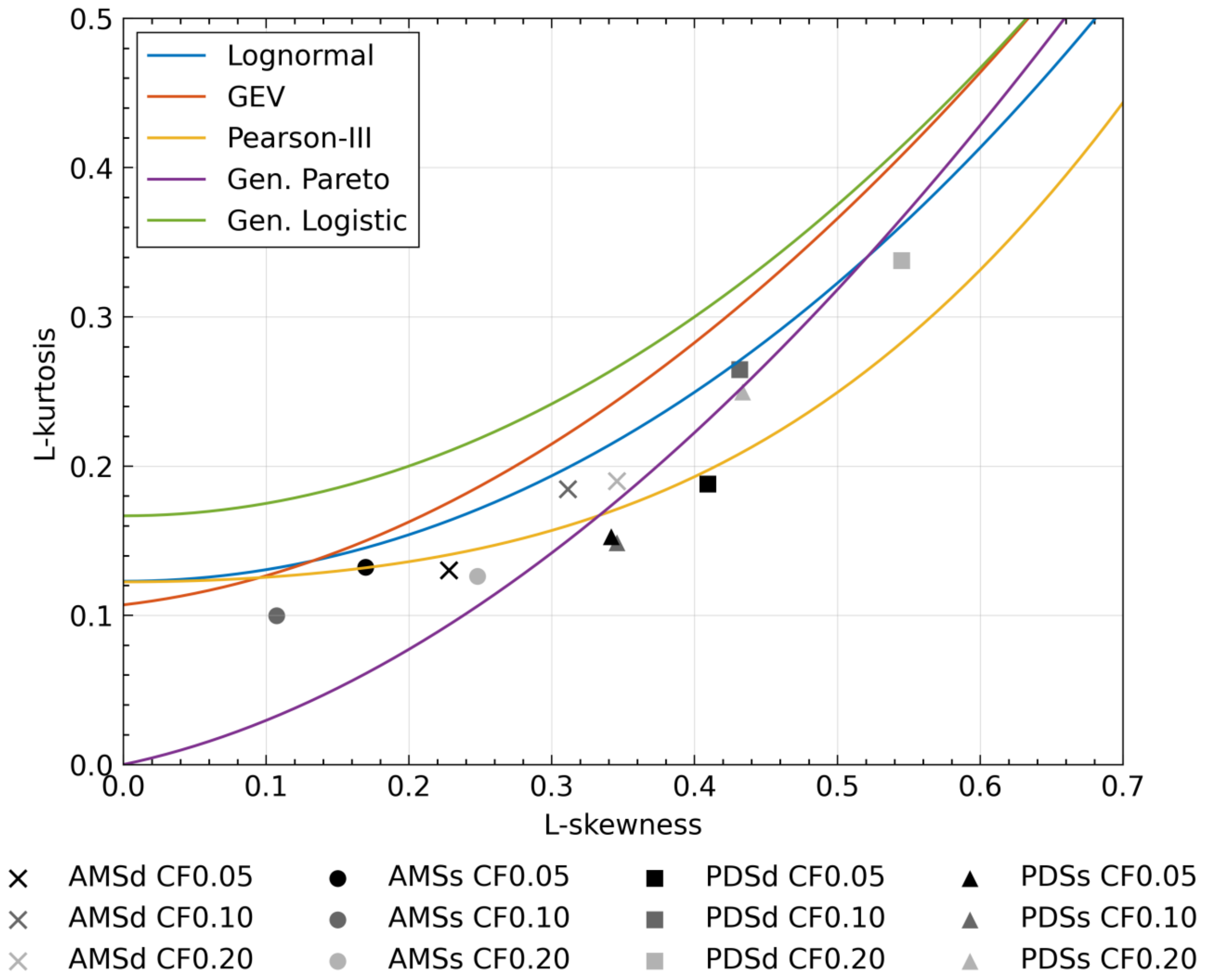
Thank you

Appendices

Sensitivity of pooling procedures



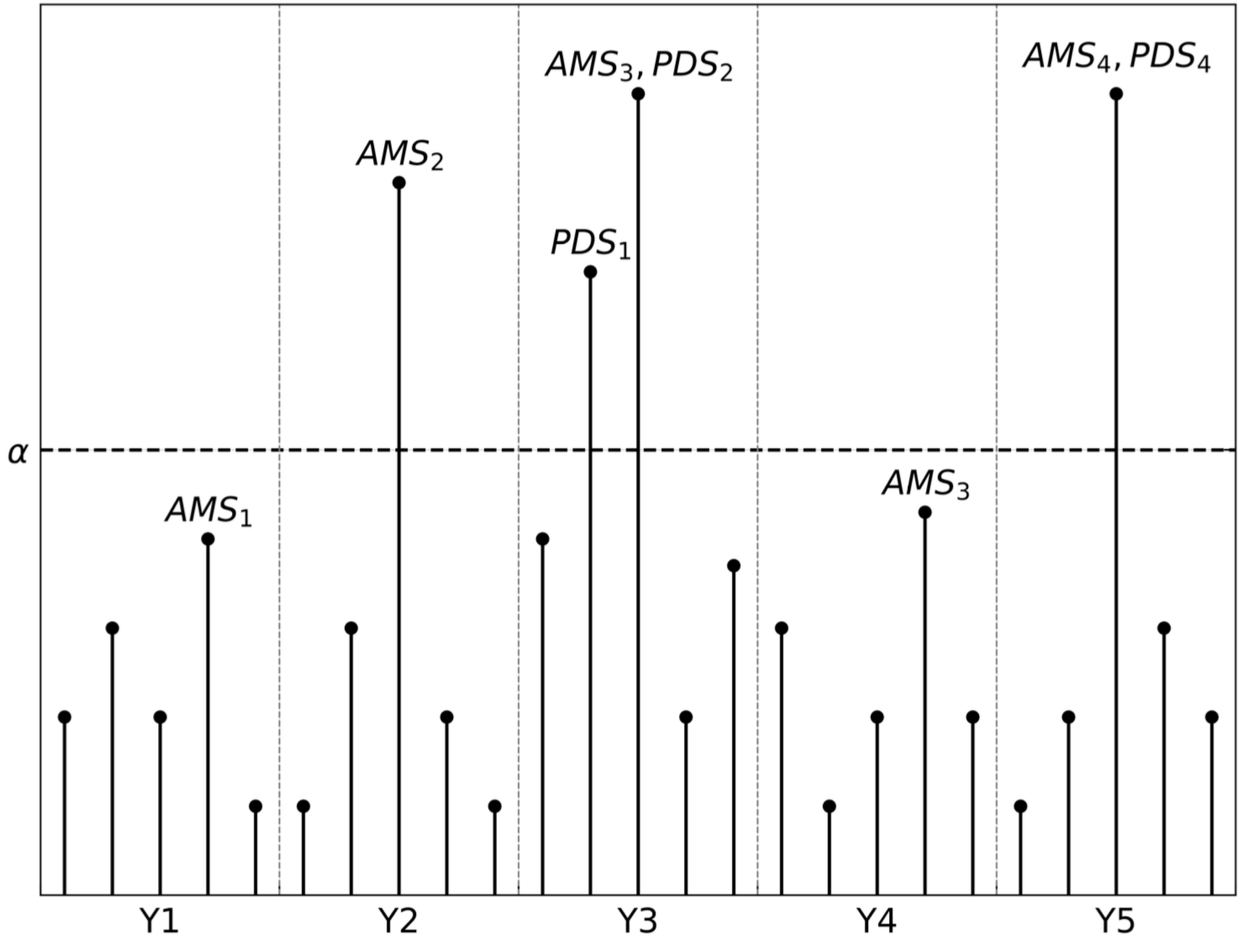
Distribution evaluation: L-moment ratios diagram



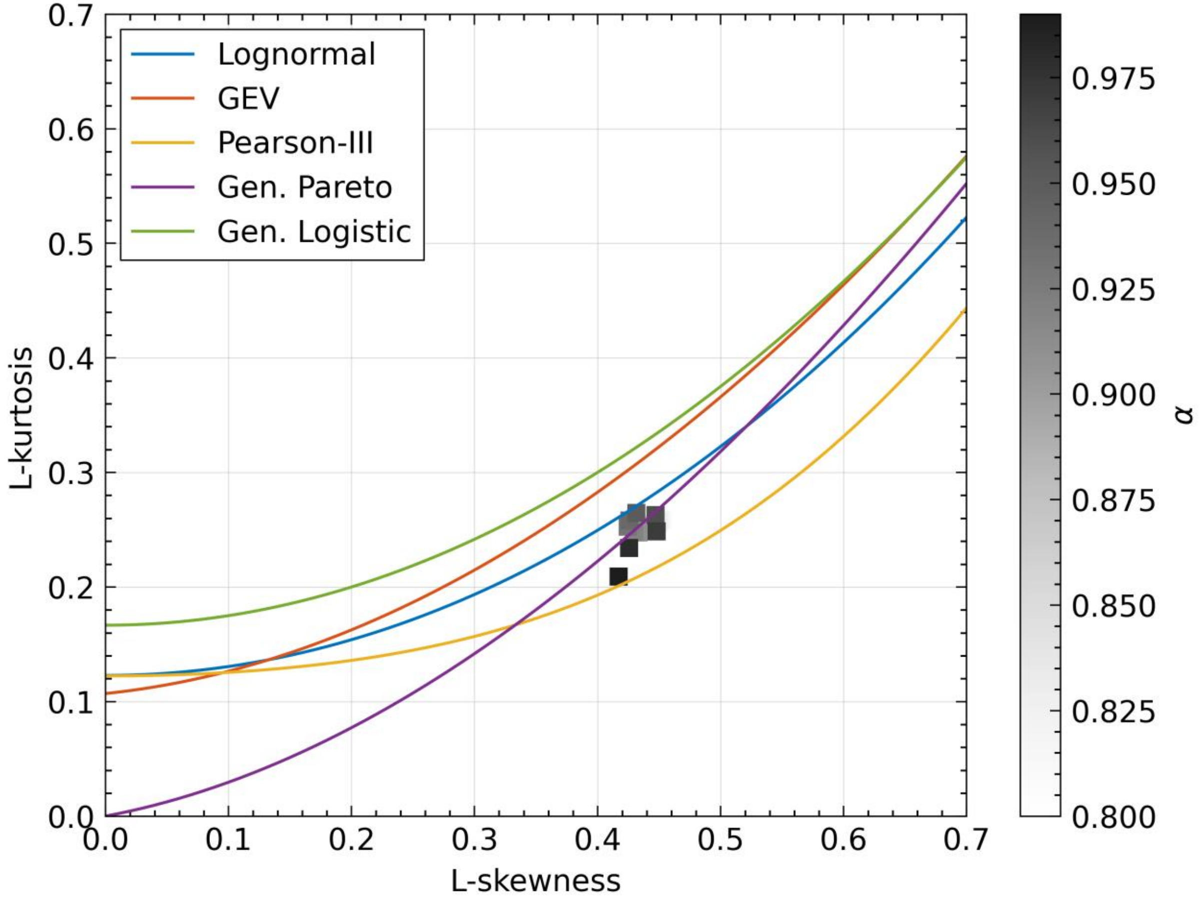
Distribution evaluation: CvM test and AIC

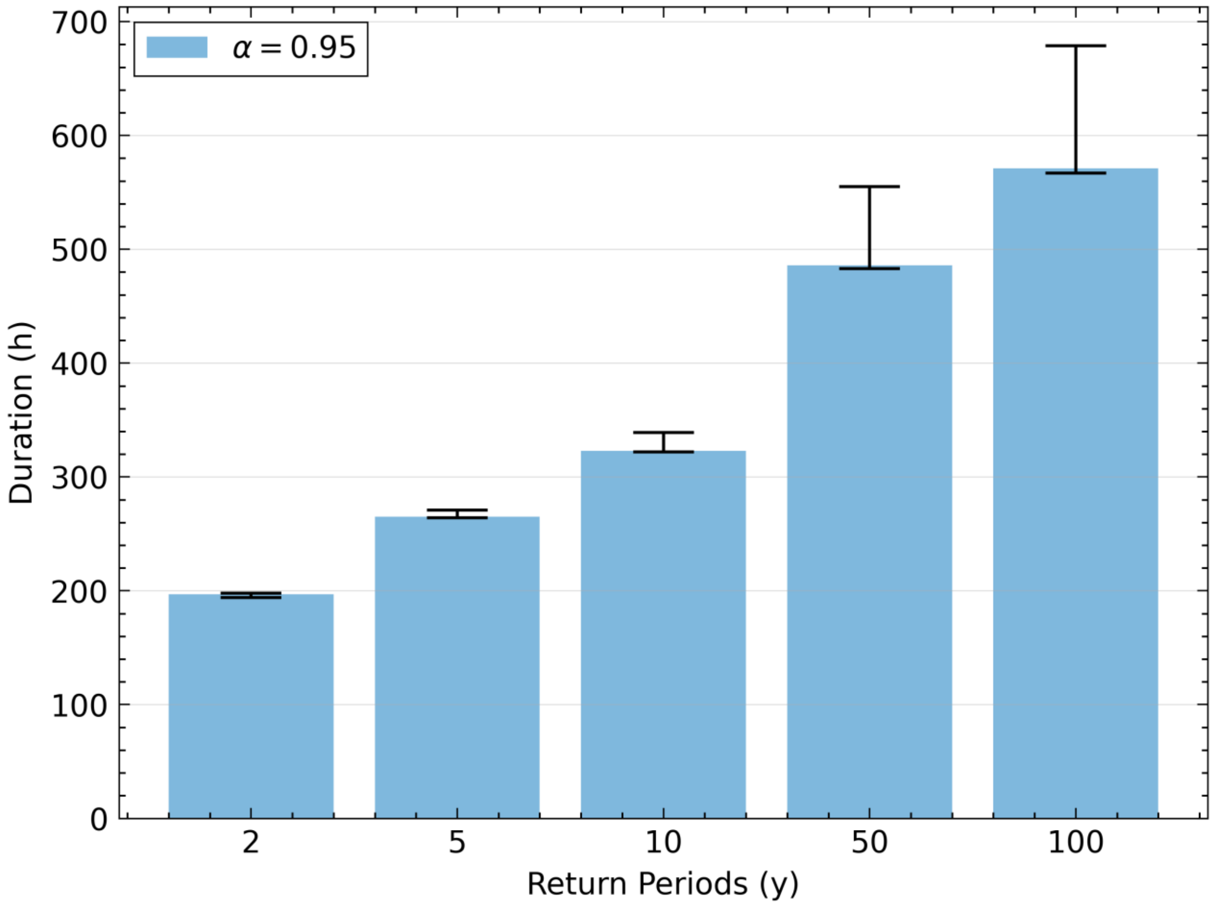
θ_{CF}	Distribution	D_{AMS} p-value	D_{AMS} AIC	D_{PDS} p-value	D_{PDS} AIC	S_{AMS} p-value	S_{AMS} AIC	S_{PDS} p-value	S_{PDS} AIC
0.05	**Lognormal**	0.814	711.2	0.622	1626.4	0.368	605.7	0.344	1387.8
	GEV	0.708	712.9	0.325	1641.2	0.338	606.5	0.260	1404.2
	Pearson-III	0.947	**709.3**	0.569	**1524.9**	0.444	**604.8**	0.849	**1358.3**
	Gen. Pareto	0.501	710.7	0.437	1632.7	0.112	611.5	0.647	1396.6
	Gen. Logistic	0.638	715.4	0.001	1730.7	0.362	606.9	0.010	1454.1
0.1	**Lognormal**	0.983	**835.0**	0.537	2770.8	0.860	787.9	0.386	2733.8
	GEV	0.920	836.4	0.477	2785.8	0.000	1051.1	0.219	2755.3
	Pearson-III	0.966	835.4	0.244	2796.6	0.869	**787.0**	0.683	**2710.2**
	Gen. Pareto	0.398	839.9	0.675	**2765.2**	0.259	789.9	0.637	2723.4
	Gen. Logistic	0.555	844.9	0.001	2898.9	0.784	788.6	0.002	2829.1
0.2	**Lognormal**	0.942	1081.0	0.864	3674.0	0.000	1273.7	0.676	3767.7
	GEV	0.835	1083.9	0.738	3689.4	0.000	1325.3	0.482	3784.7
	Pearson-III	0.952	**1080.3**	0.002	3661.9	0.752	**1056.7**	0.113	**3745.0**
	Gen. Pareto	0.815	1081.1	0.728	**3672.6**	0.001	1070.5	0.909	3753.7
	Gen. Logistic	0.282	1098.4	0.000	3949.0	0.460	1063.1	0.000	3911.7

AMS vs PDS



PDS sensitivity to truncation level α





Return period calculations

Return Period

$$T_A = \frac{\lambda}{1 - F(x)}$$

Confidence interval by bootstrapping

1. Sample (with replacement) from the extreme value series
2. Fit the best-fit candidate distribution to the sample
3. Calculate return period
4. Repeat n times and obtain the 95% confidence interval

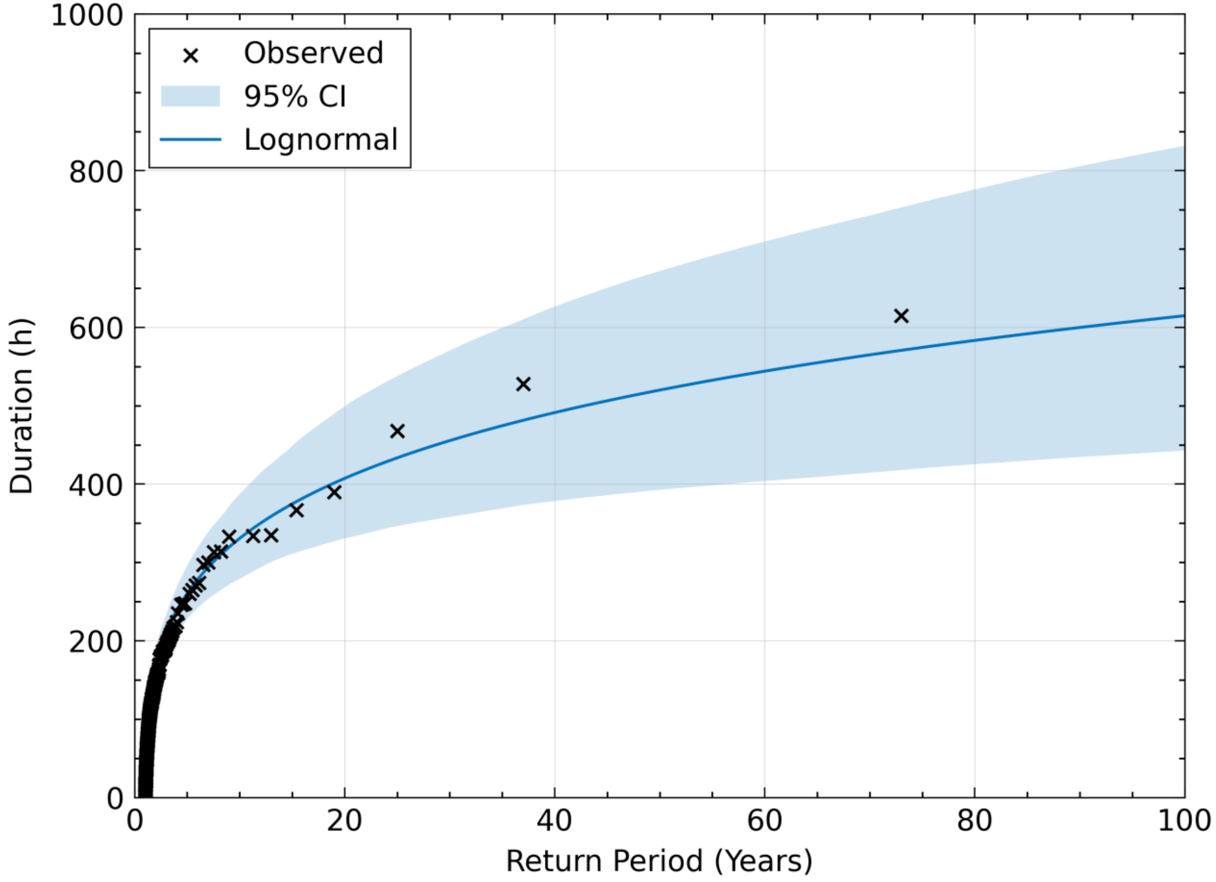
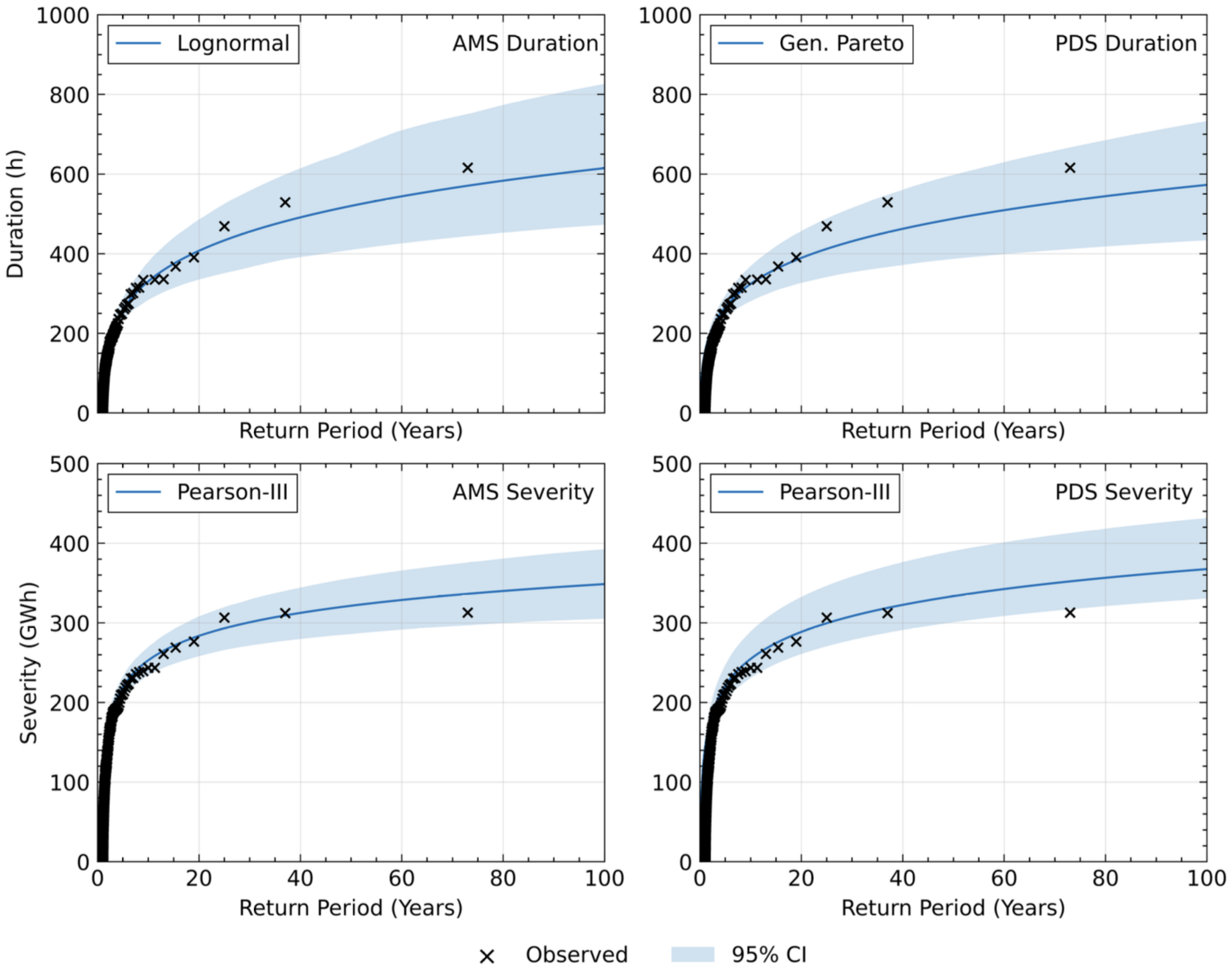


Figure x: Return period and the 95% confidence interval for AMSd CF0.1

Return period results: CF threshold = 0.1



Return period results: Other CF thresholds

θ_{CF}	T (y)	D_{AMS} (h)			D_{PDS} (h)			S_{AMS} (GWh)			S_{PDS} (GWh)		
		Fit	0.025	0.975	Fit	0.025	0.975	Fit	0.025	0.975	Fit	0.025	0.975
0.05	**2**	79	62	88	89	83	96	39	35	43	44	39	51
	5	116	101	133	127	111	142	55	50	62	56	48	68
	10	142	122	163	167	139	194	66	58	76	65	56	80
	50	198	160	245	306	227	391	89	73	108	87	72	110
	100	221	161	281	391	278	520	98	79	121	96	79	123
0.1	**2**	173	154	195	198	183	214	165	149	181	176	157	199
	5	260	223	300	266	235	298	219	201	237	221	194	258
	10	331	273	391	324	277	379	253	227	274	255	223	303
	50	520	391	683	488	373	644	321	272	370	334	290	410
	100	615	445	854	573	418	809	349	291	409	368	319	457
0.2	**2**	699	421	819	684	605	777	870	736	964	926	734	1105
	5	1244	849	1615	1127	938	1365	1271	1099	1450	1224	948	1493
	10	1643	1190	2284	1616	1261	2093	1544	1331	1794	1452	1111	1805
	50	2551	1888	3766	3605	2394	5582	2137	1793	2641	1987	1483	2564
	100	2938	2164	4439	5050	3124	8480	2383	1974	3018	2218	1642	2889