COMPARING DIFFERENT SOLAR FLARE PREDICTION METHODS

Where are we, and how far can we go?

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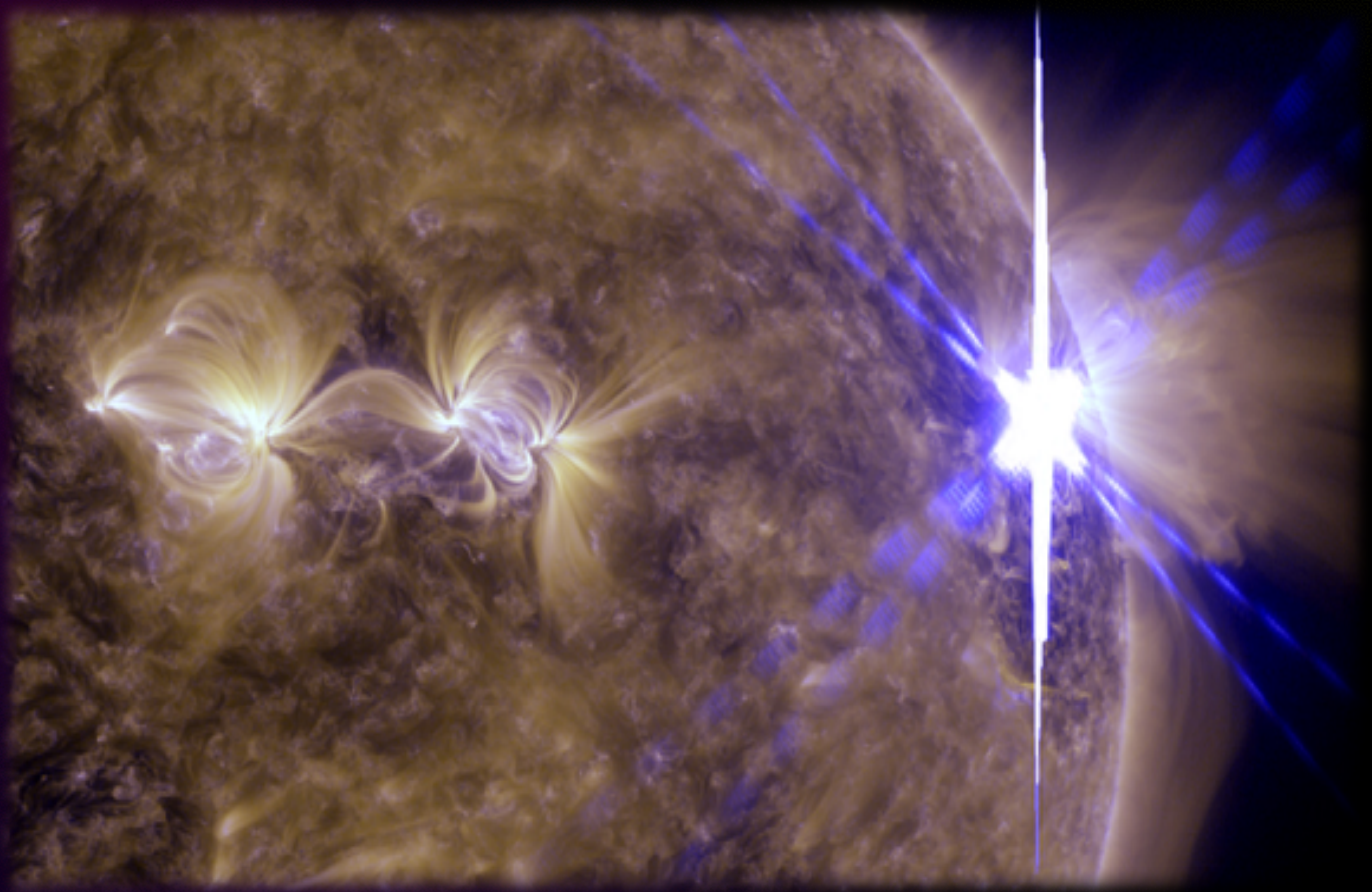
Oostende, Belgium, Nov 14 - 18, 2016

OUTLINE

- Why do we need flare prediction?
- The nature of flare occurrence - are flares random?
- Can flares be predicted? — different methods
- Recent trends in solar flare prediction
- Validation : process and intrinsics
- From a method to an operational forecasting service
- Conclusion

WHY PREDICT SOLAR FLARES?



WHY PREDICT SOLAR FLARES?

solar flare — t_0

arrival of "hard" (X-, γ)-ray photons — t_0+ 8 min

arrival of first flare-accelerated particles — ~ t_0+ 20 min

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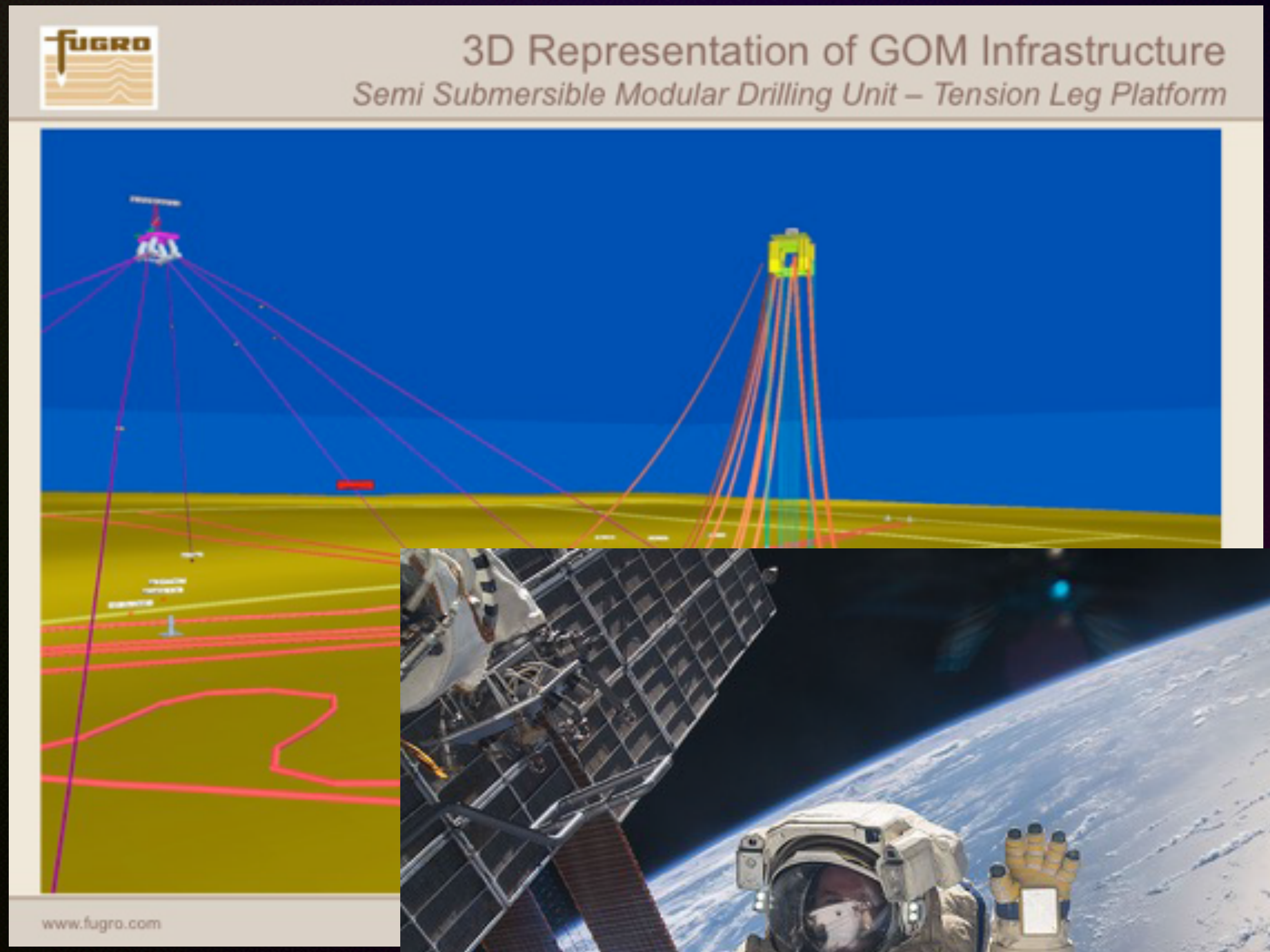
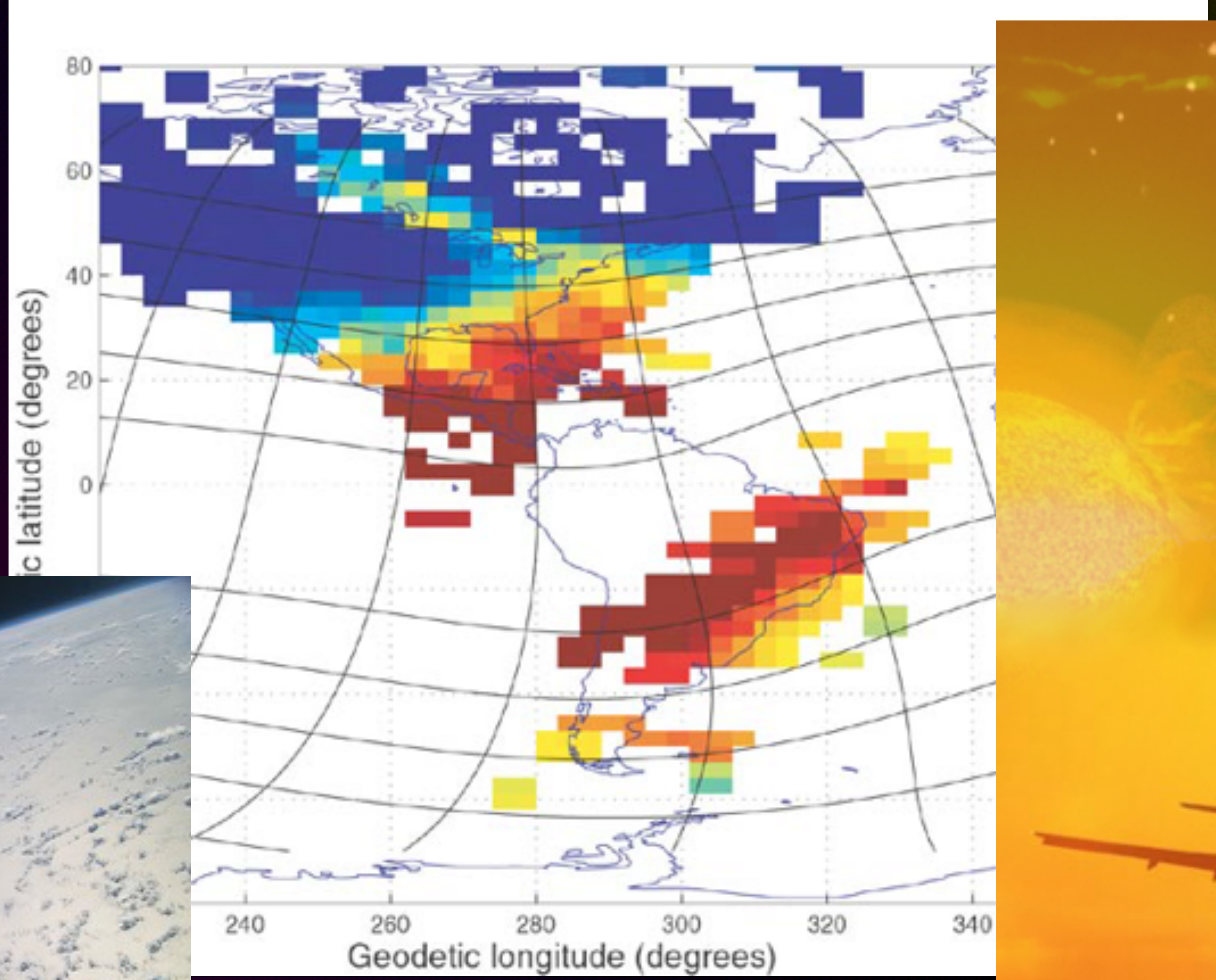
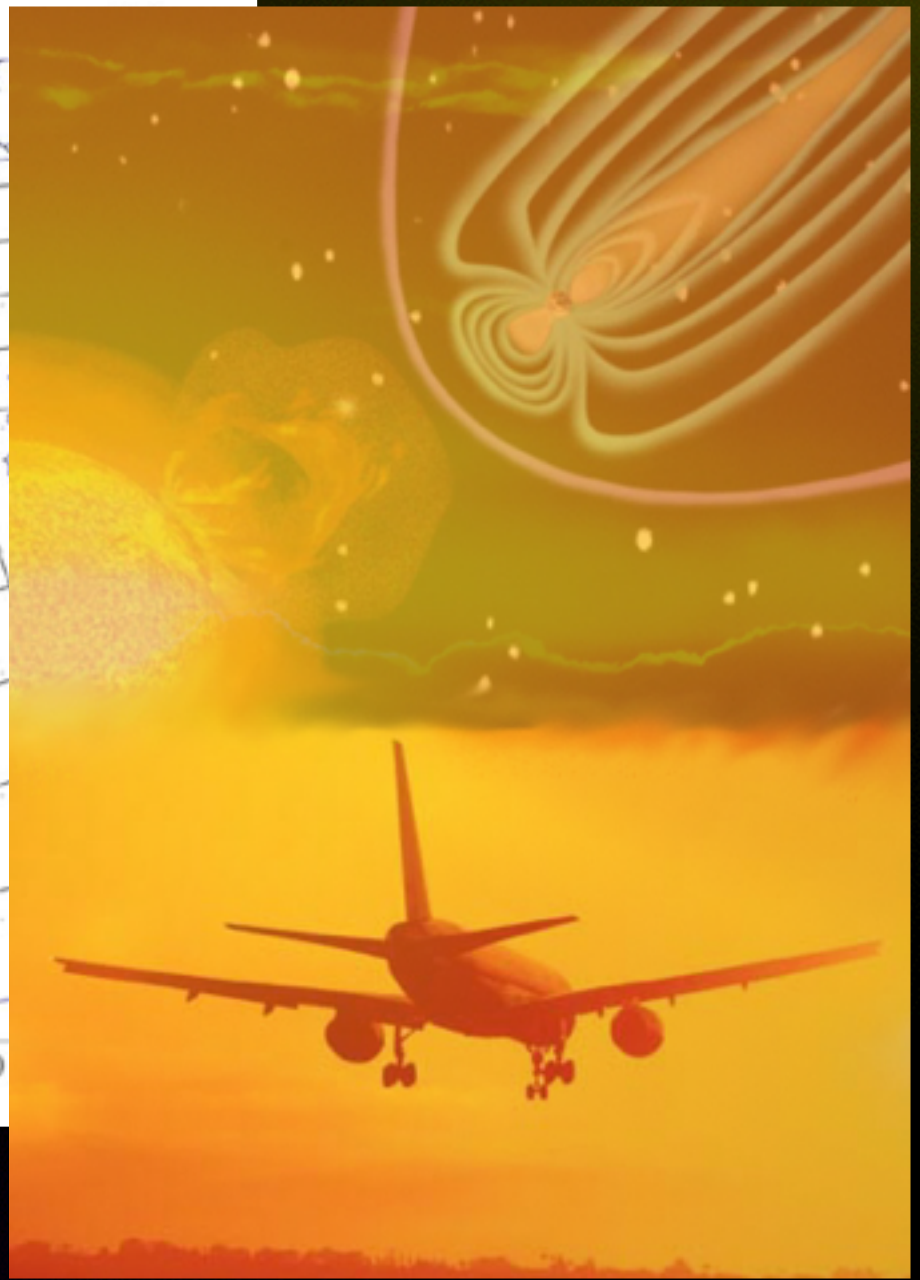
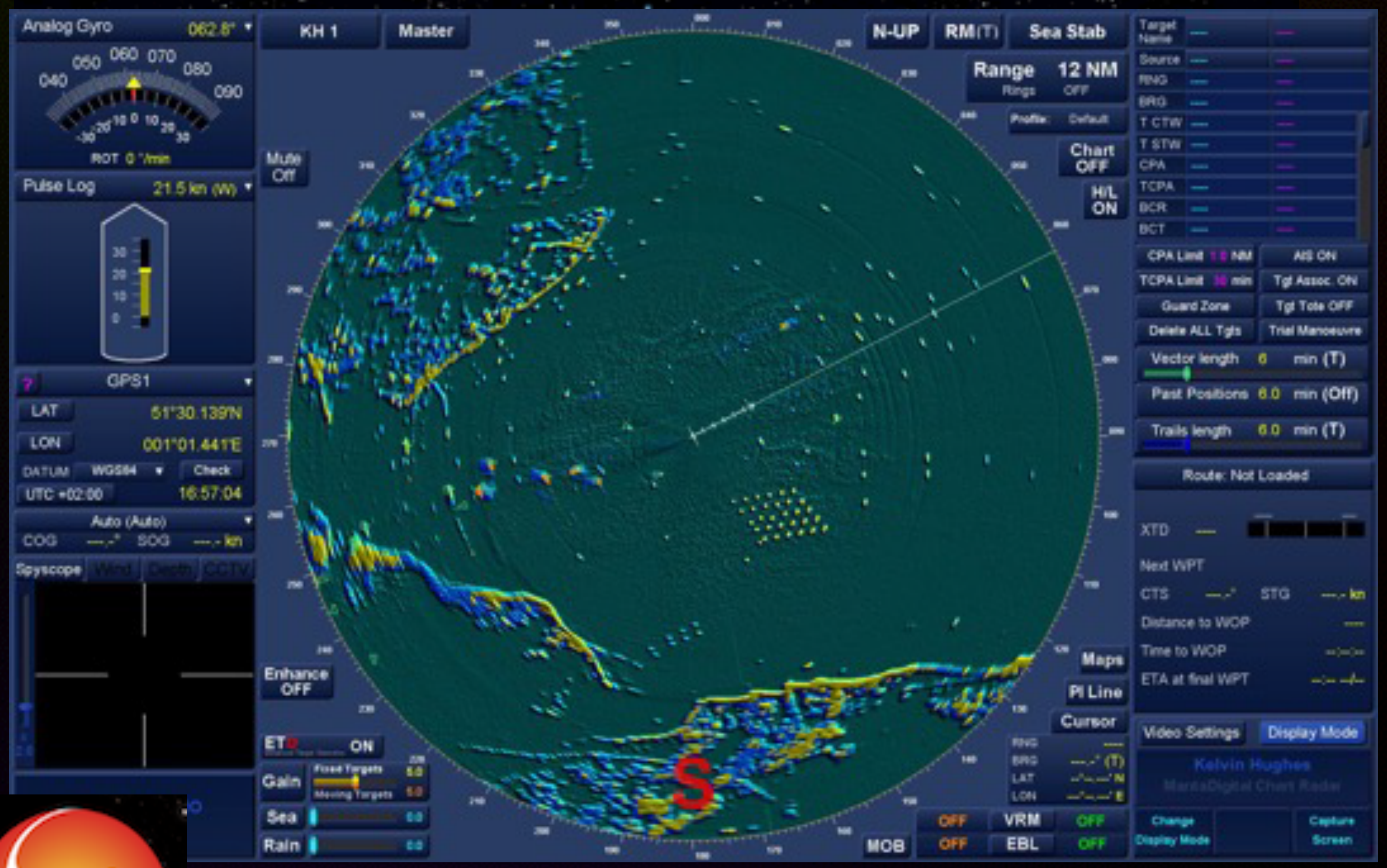
No early warning time for flare photons - slim window for particulate in worst case!

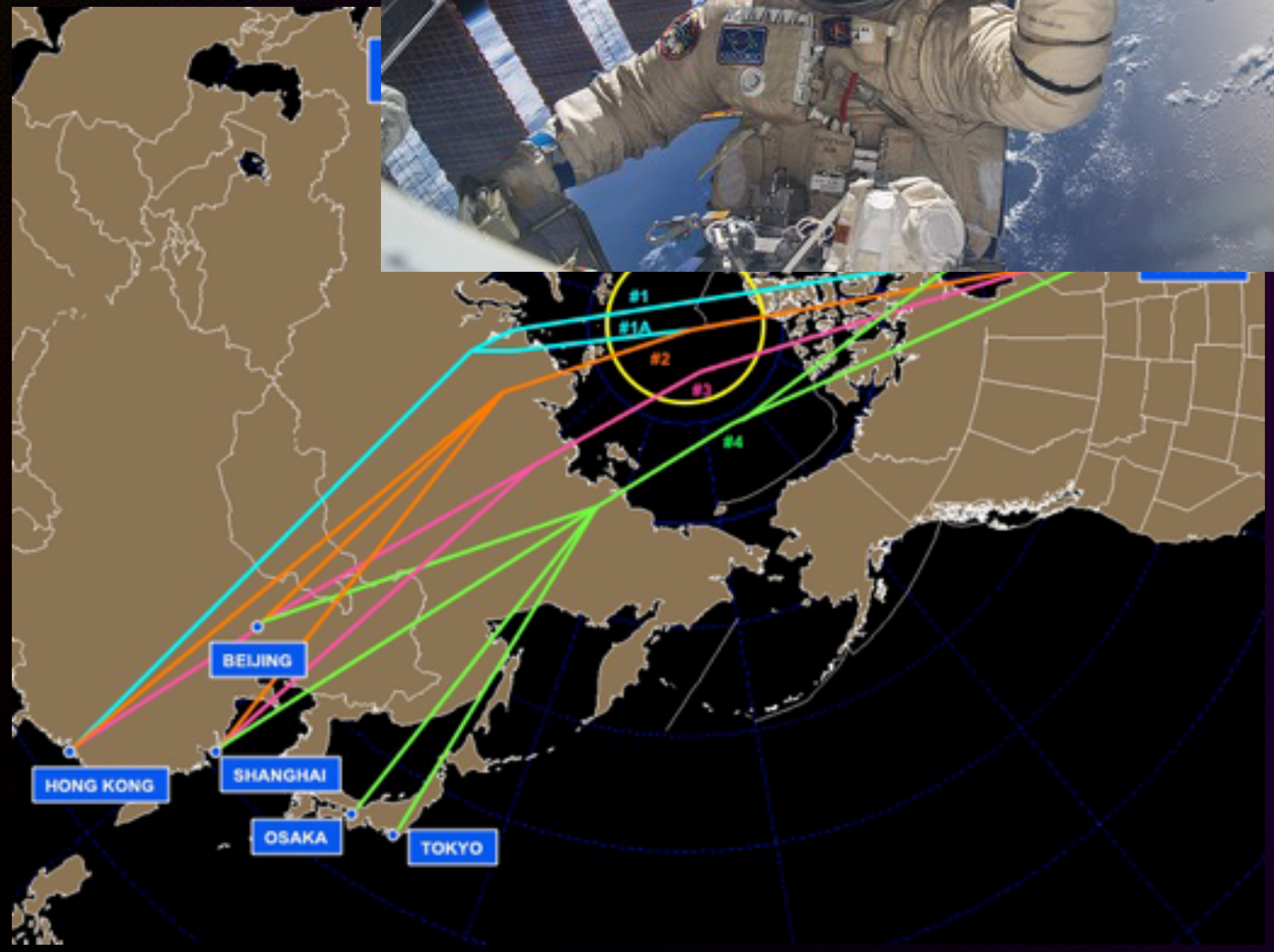
MAJOR FLARE REPERCUSSIONS: EVERYTHING UNDER THE SUN



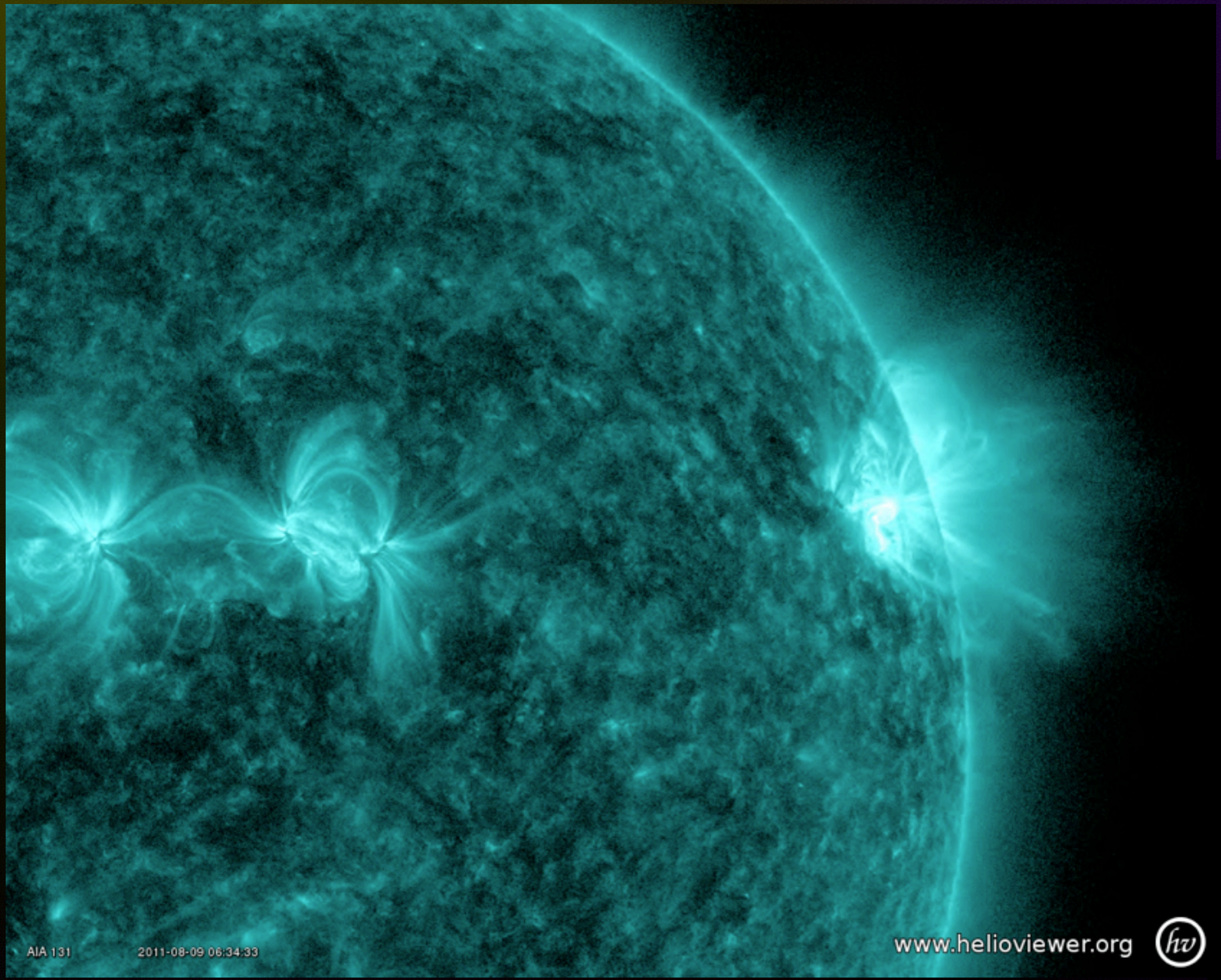


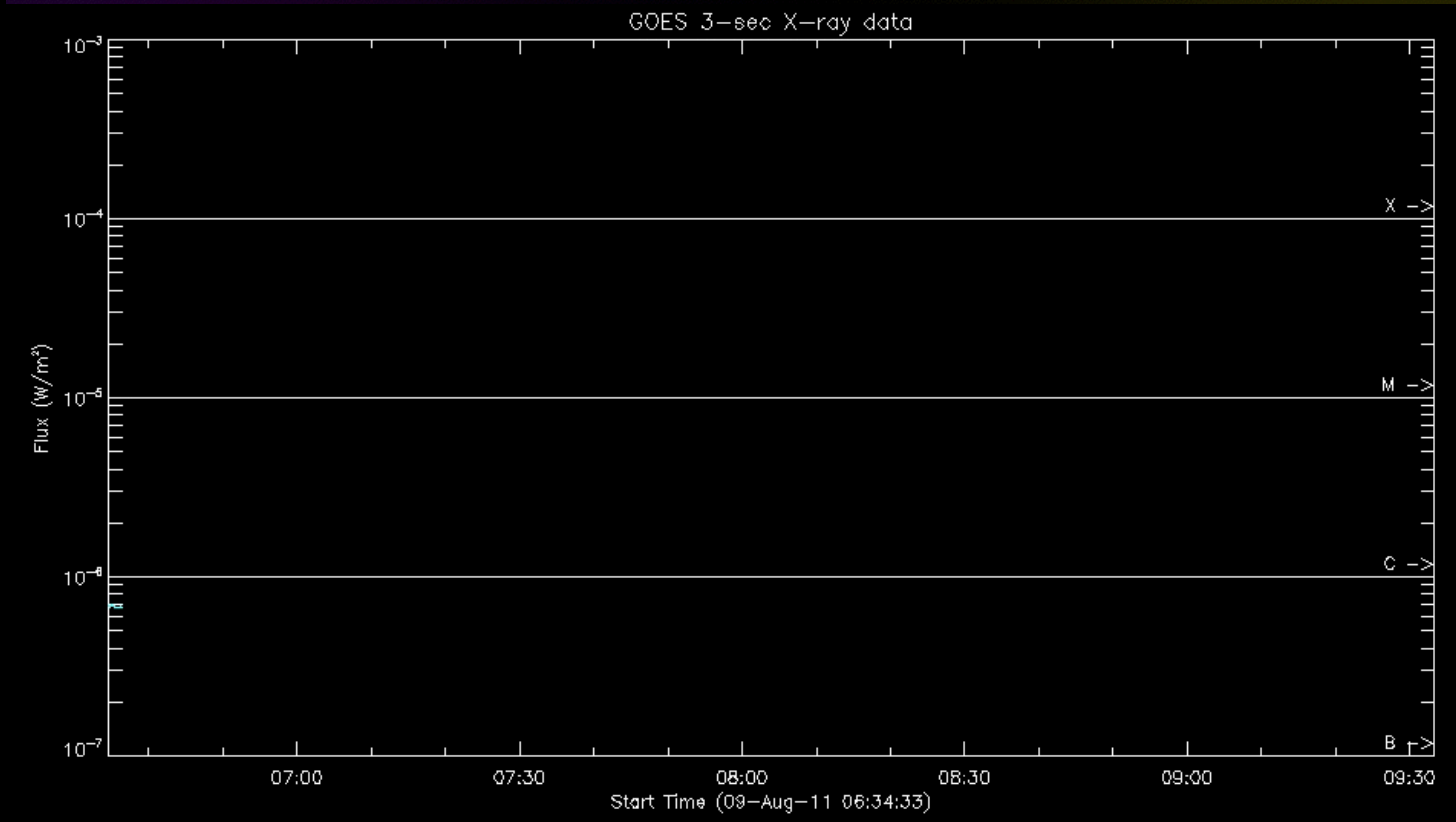






A PHENOMENOLOGY DEFINITION …





A sudden commencement of enhanced, localized electromagnetic emission extending over practically the entire range of the electromagnetic spectrum. Typically measured in 1 - 8 Å SXR

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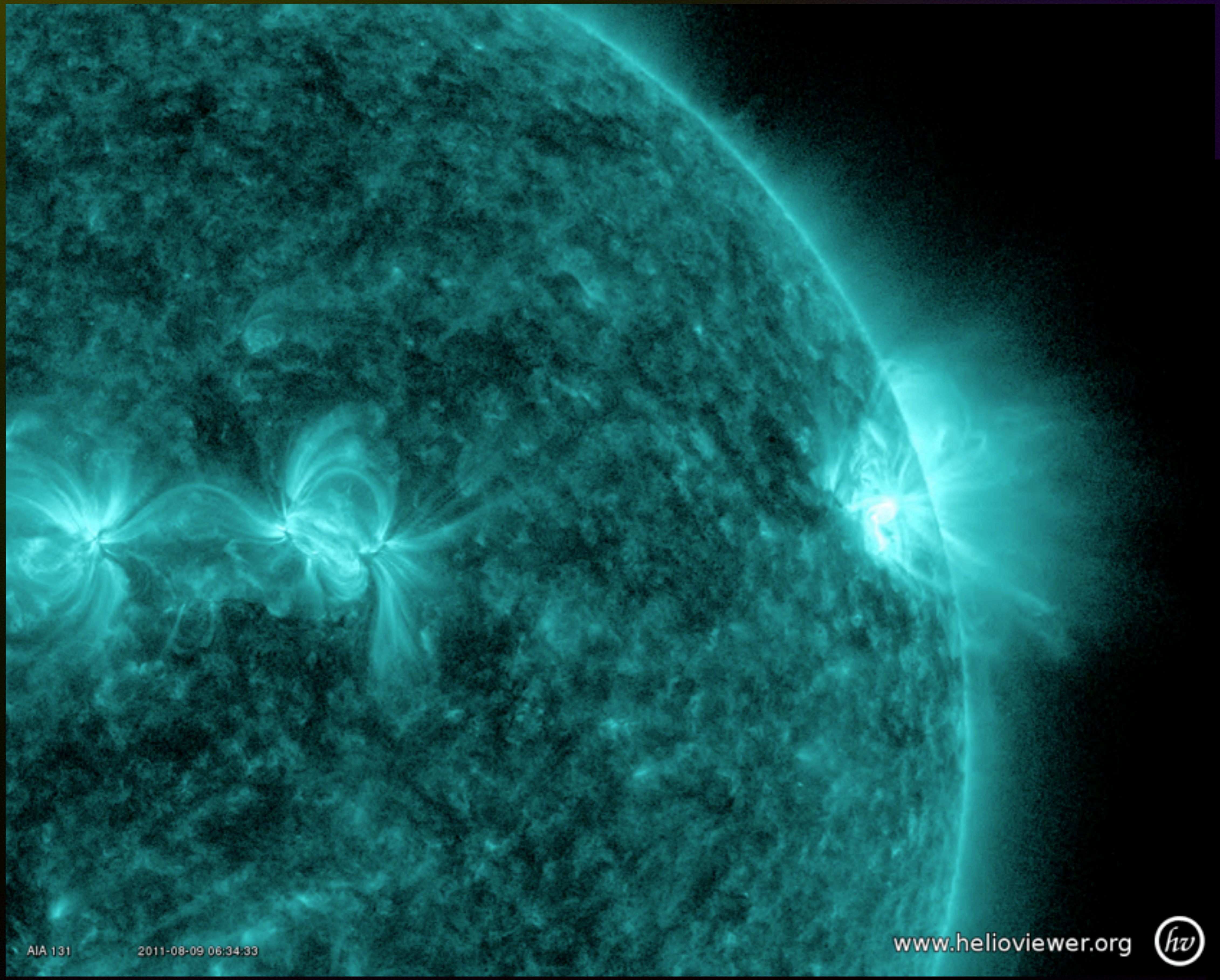

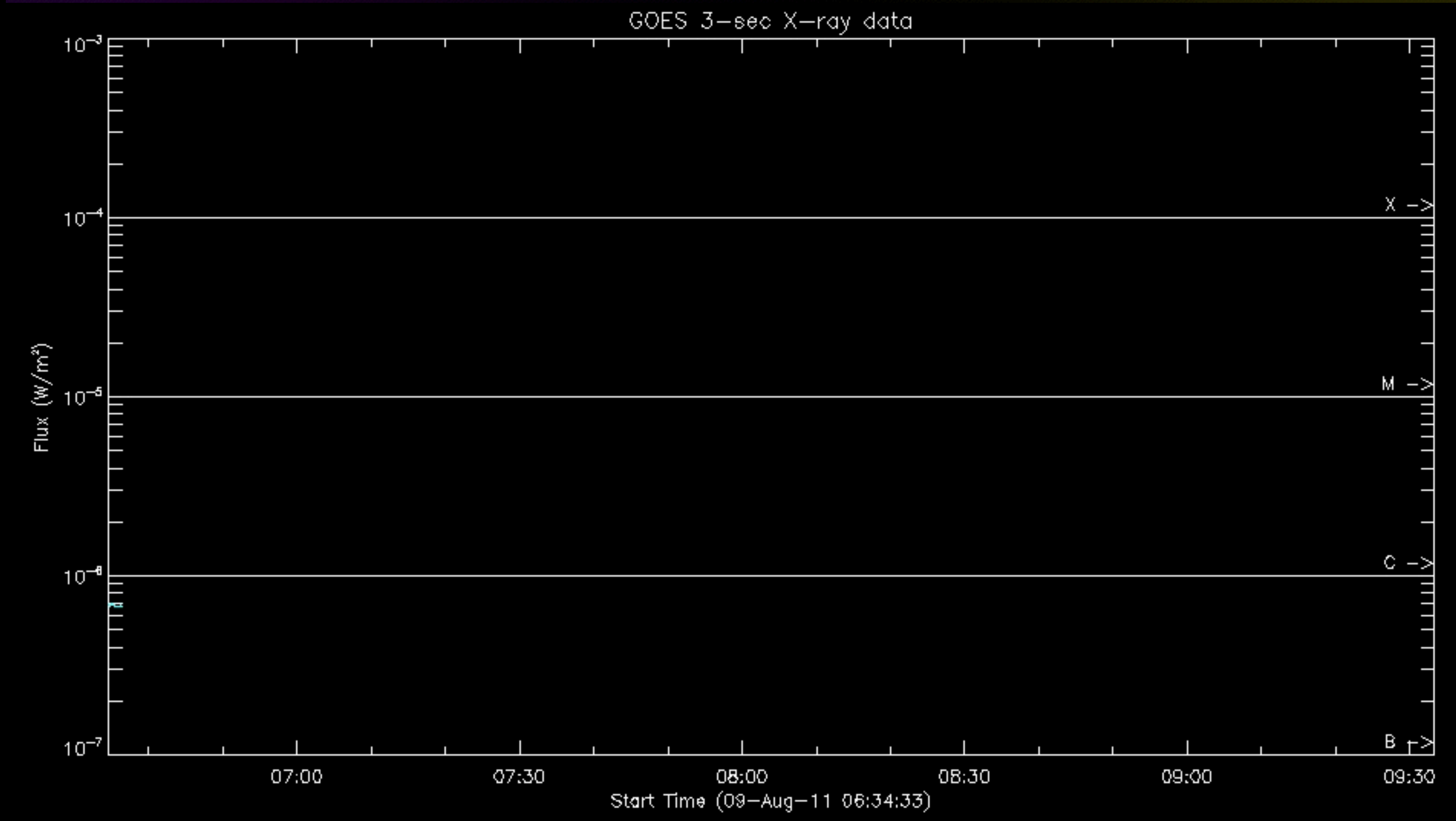

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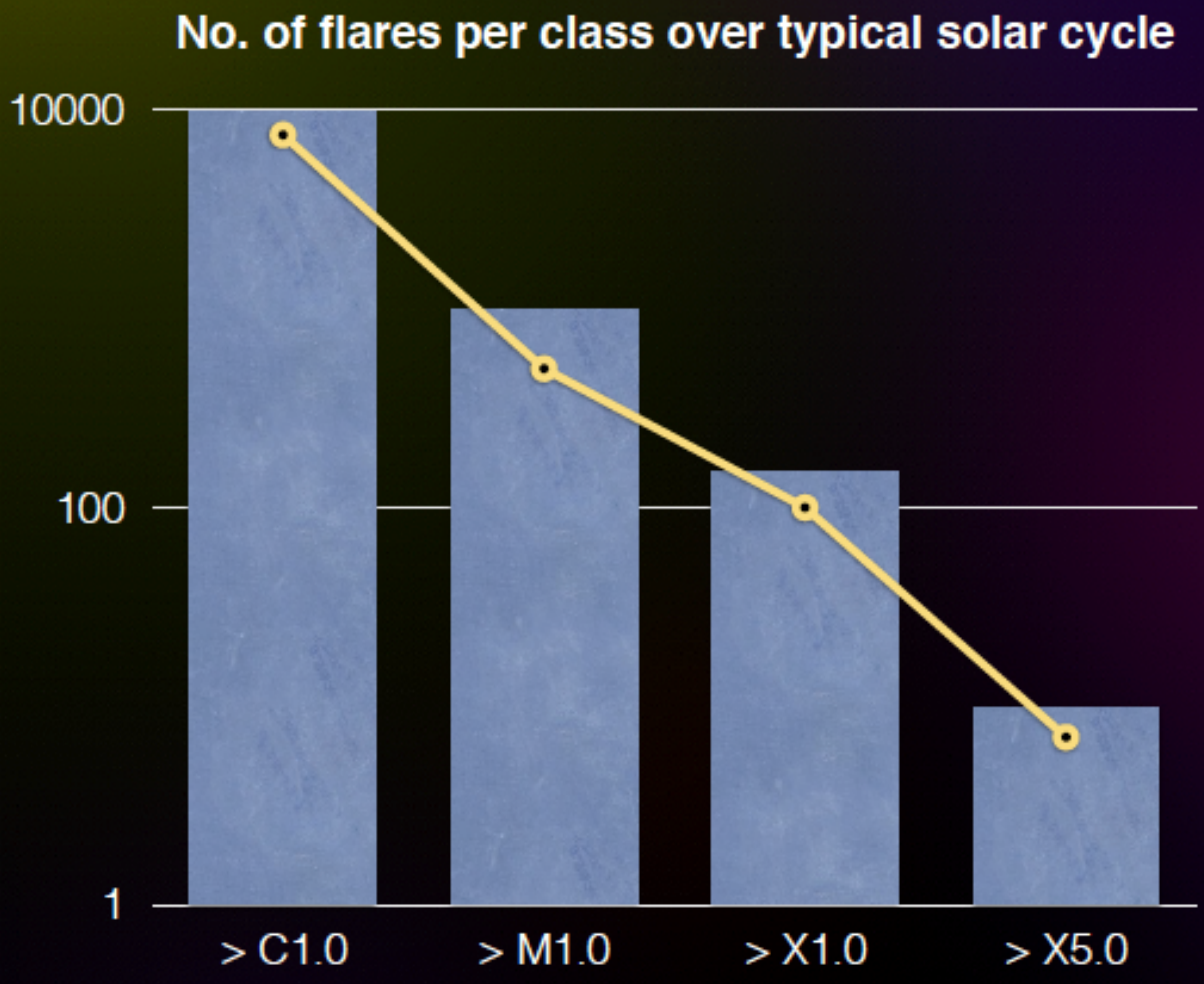
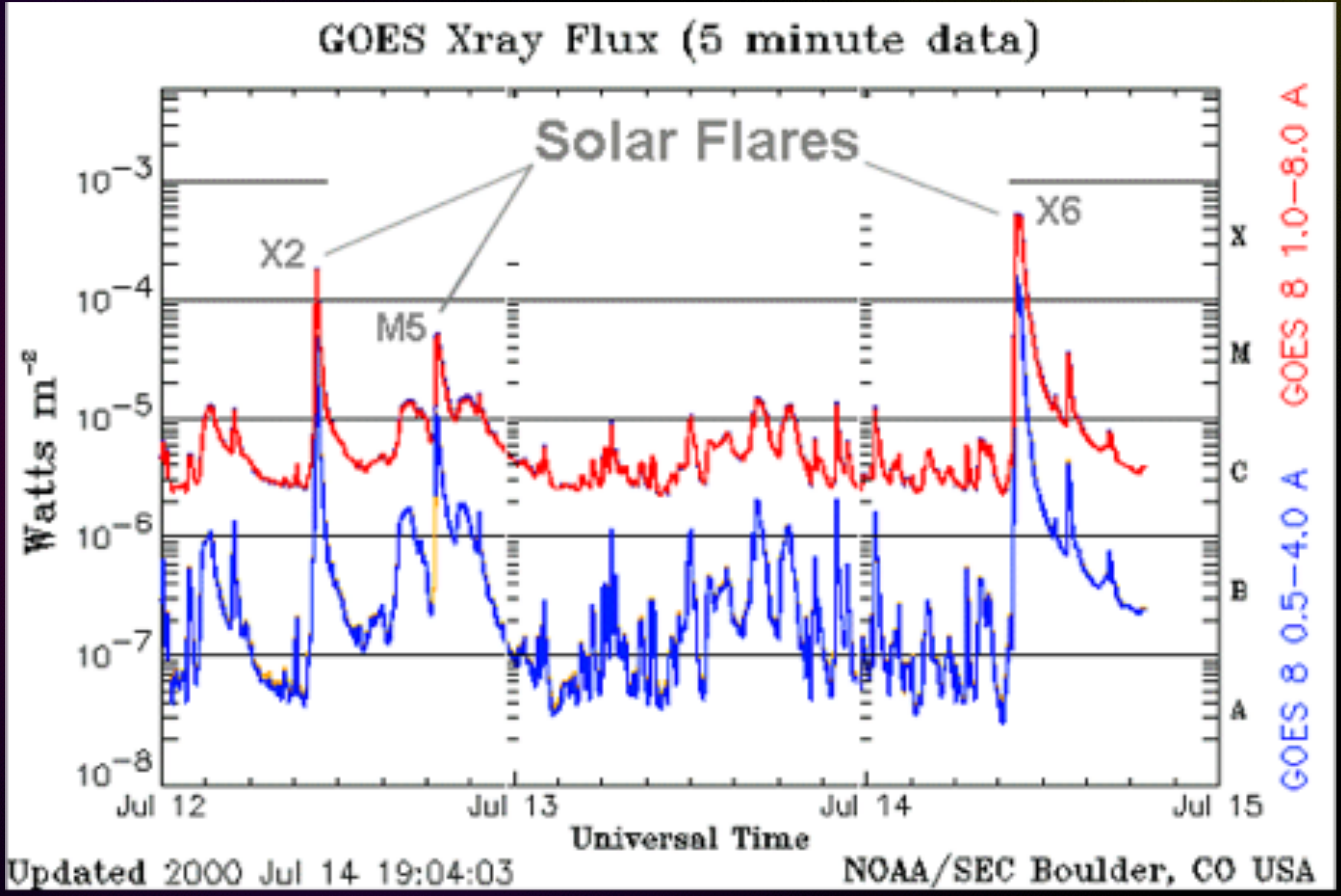
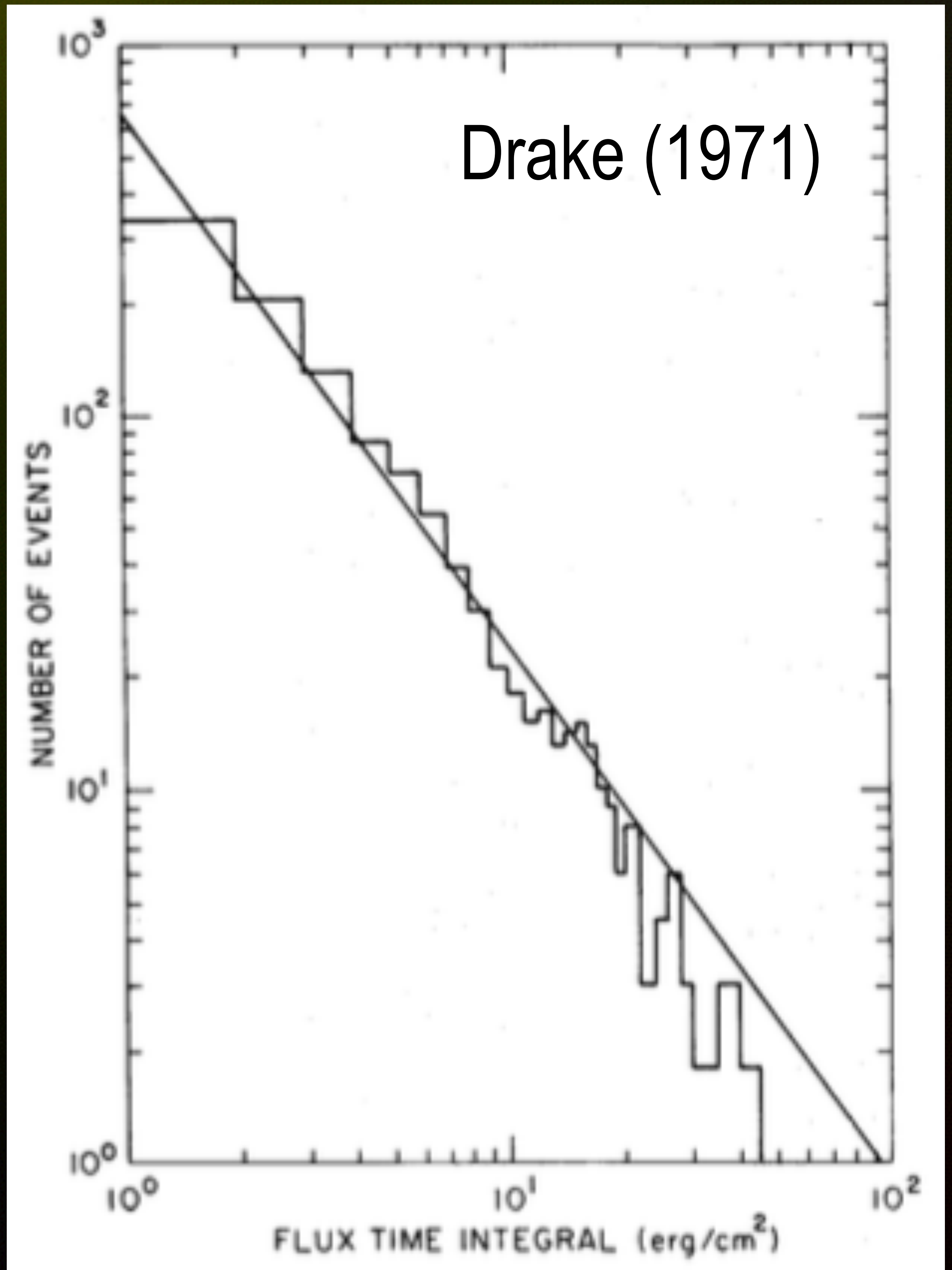
… AND STATISTICAL BEHAVIOR





"Active" solar conditions over a 3-day period in July 2000

NATURE OF FLARE OCCURRENCE



Flare occurrence number vs. integrated photon flux

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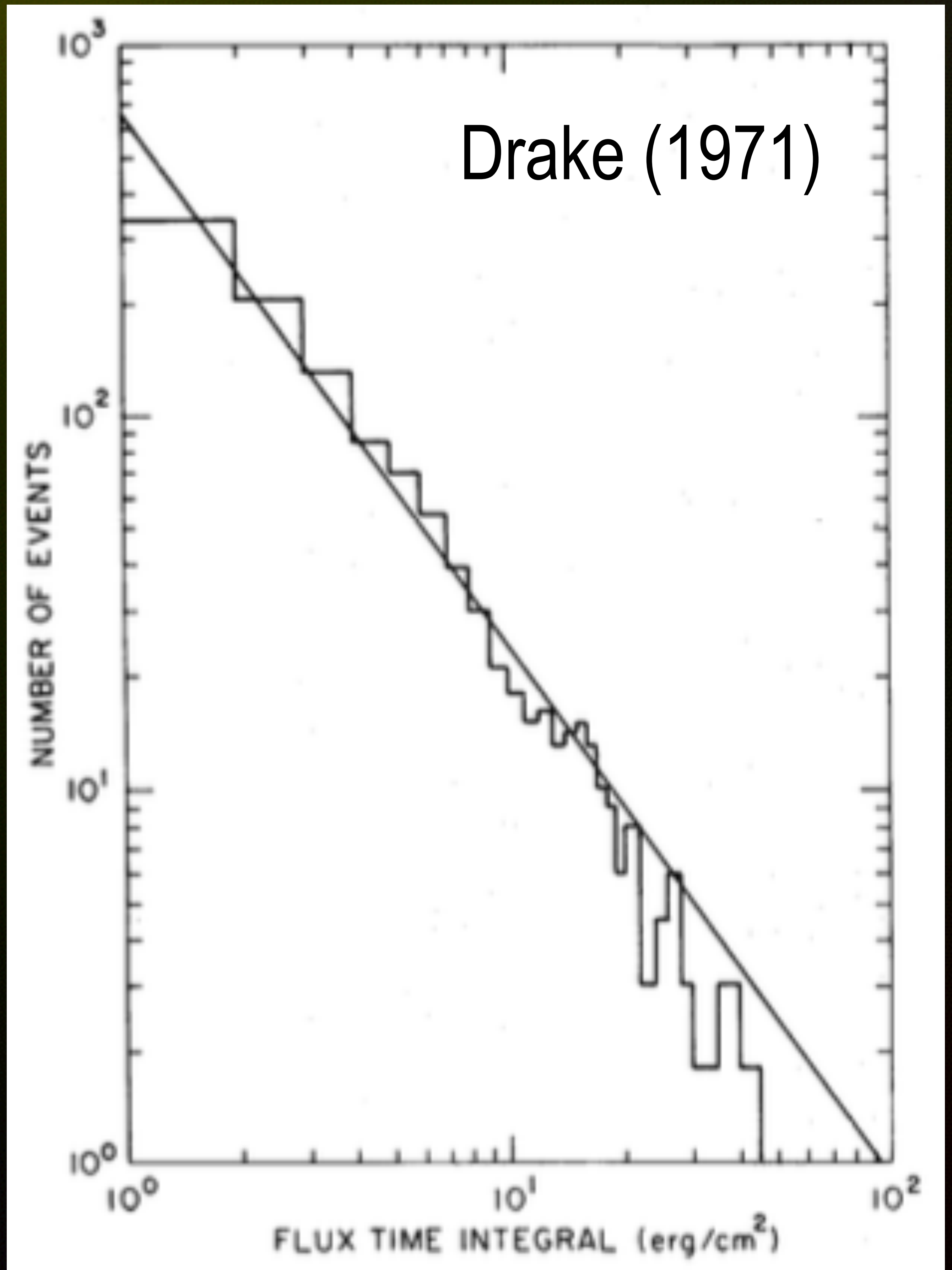

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- Stochastic relaxation (storage and release) processes
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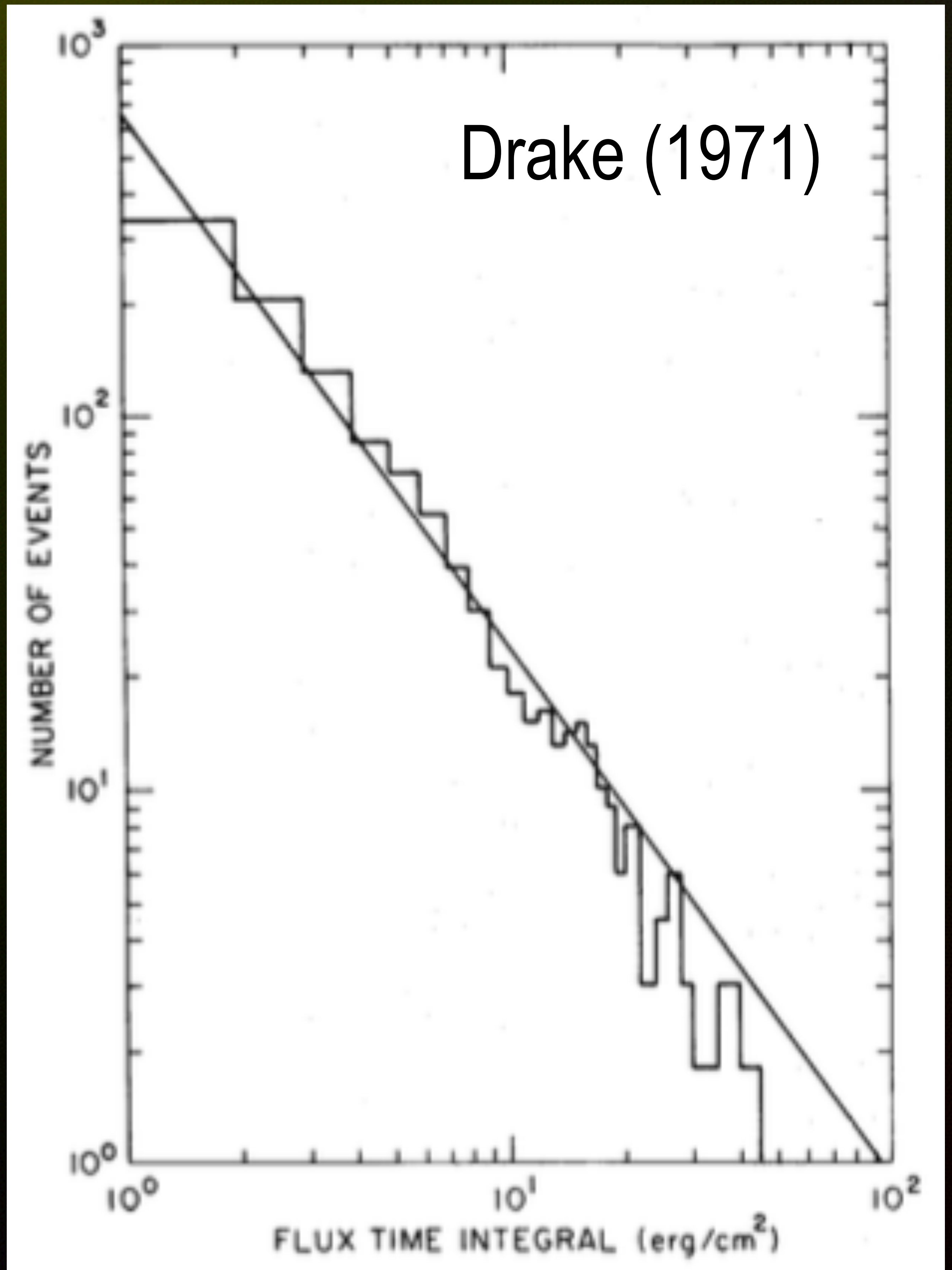

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Power-law distribution of flare size later attributed to the concept of self-organized criticality (1990s)

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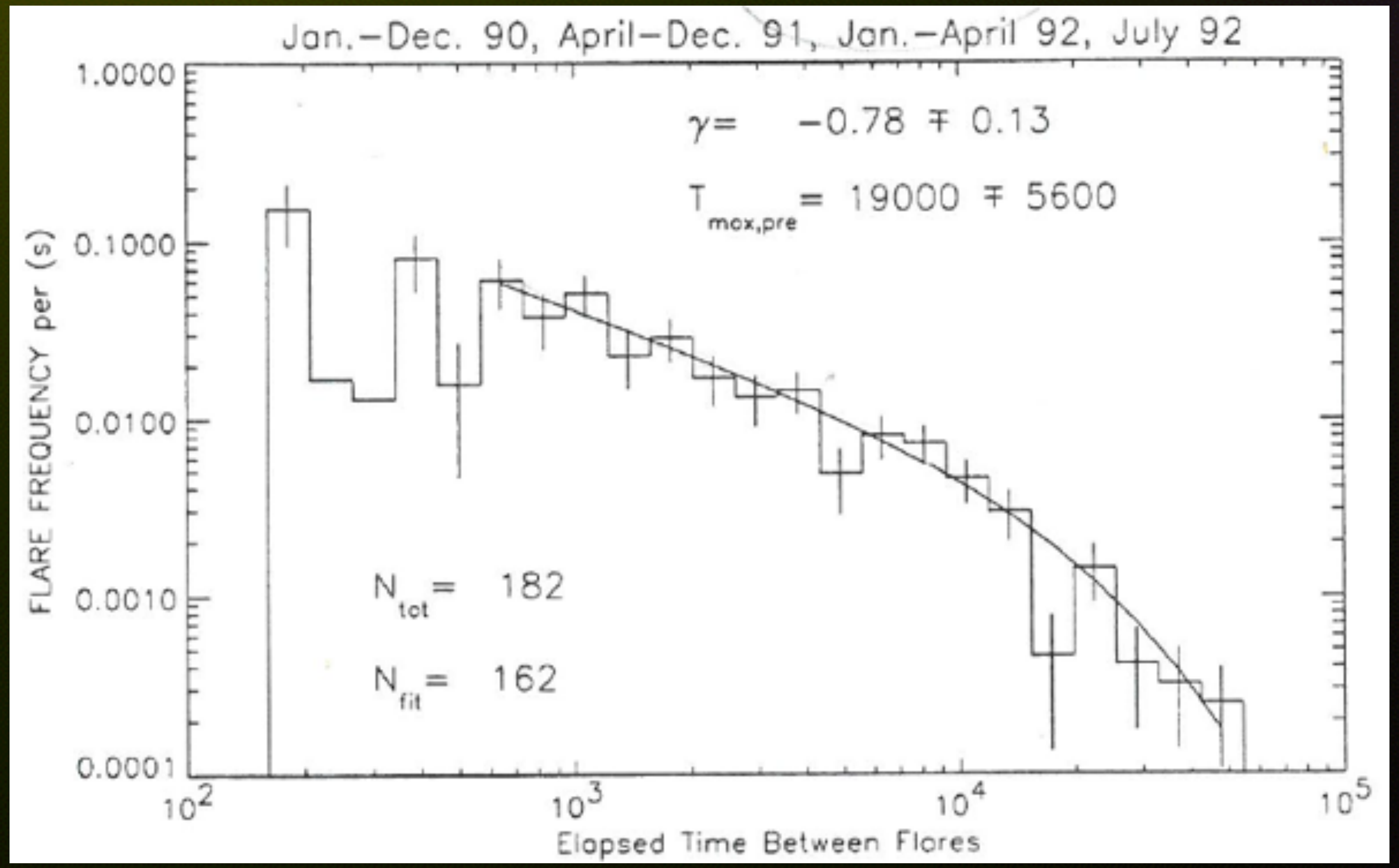

Crosby, PhD Thesis (1996)

Exponential law of waiting times: a totally random, memoryless flare occurrence along the classical self-organized criticality concept

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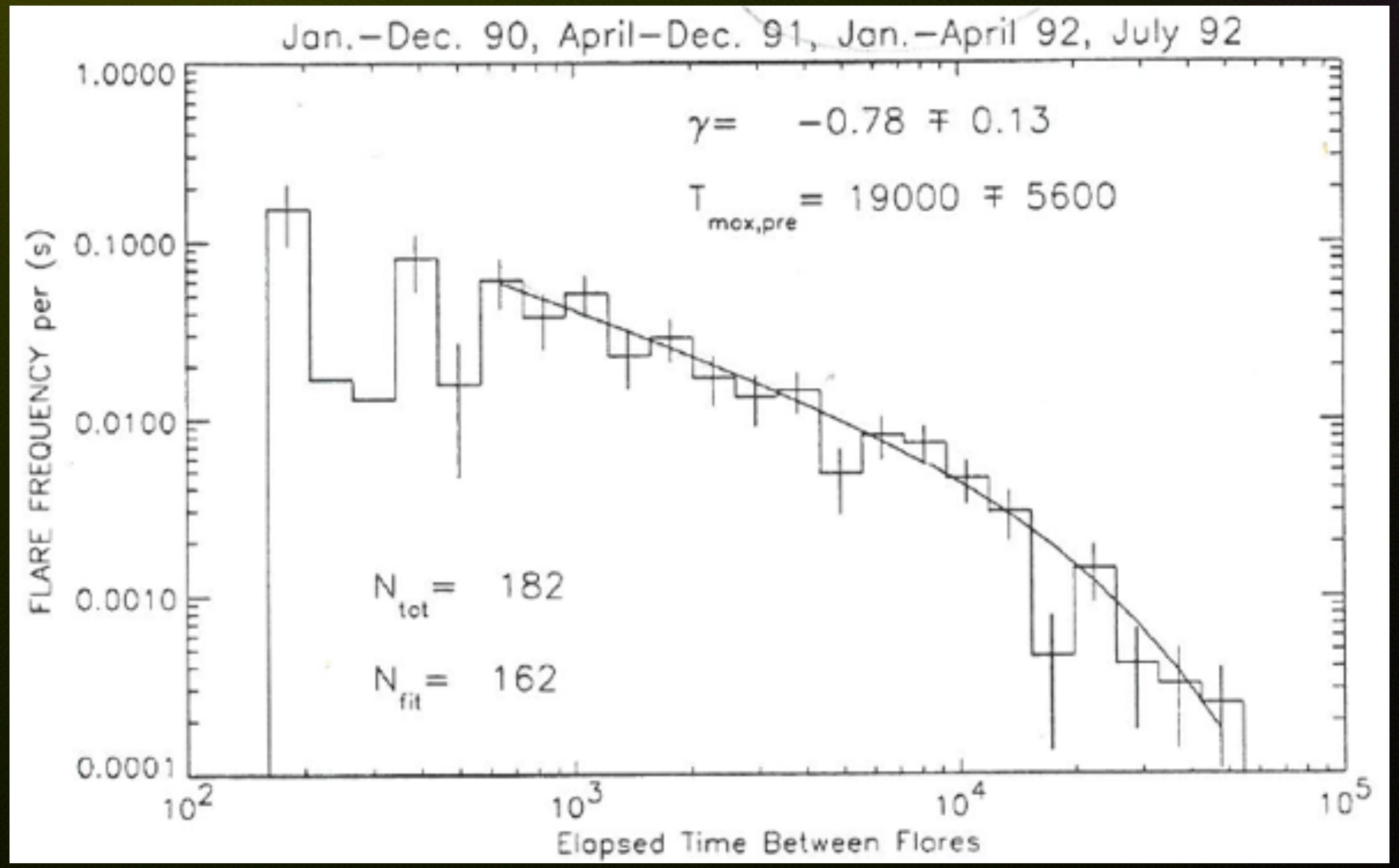

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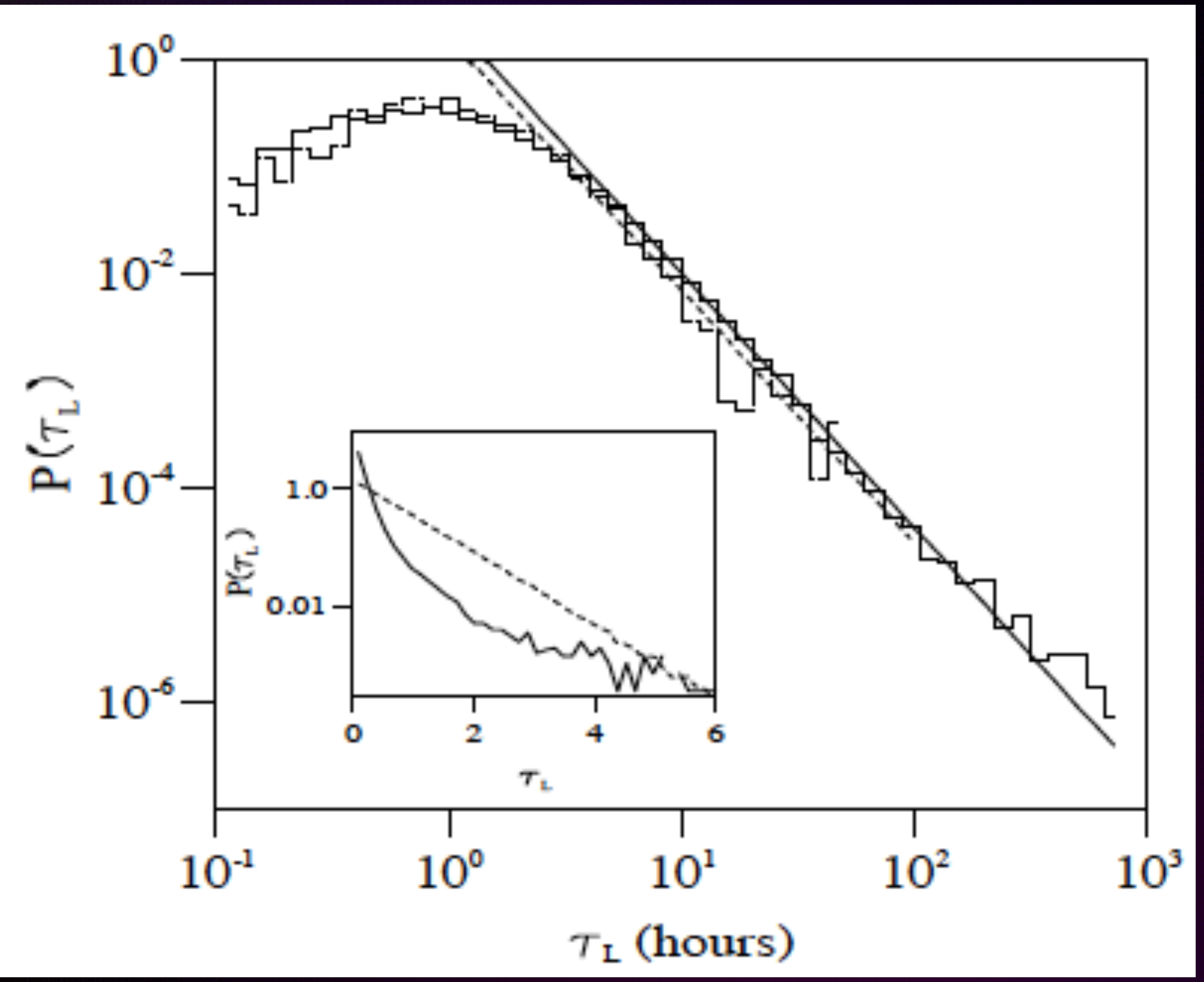

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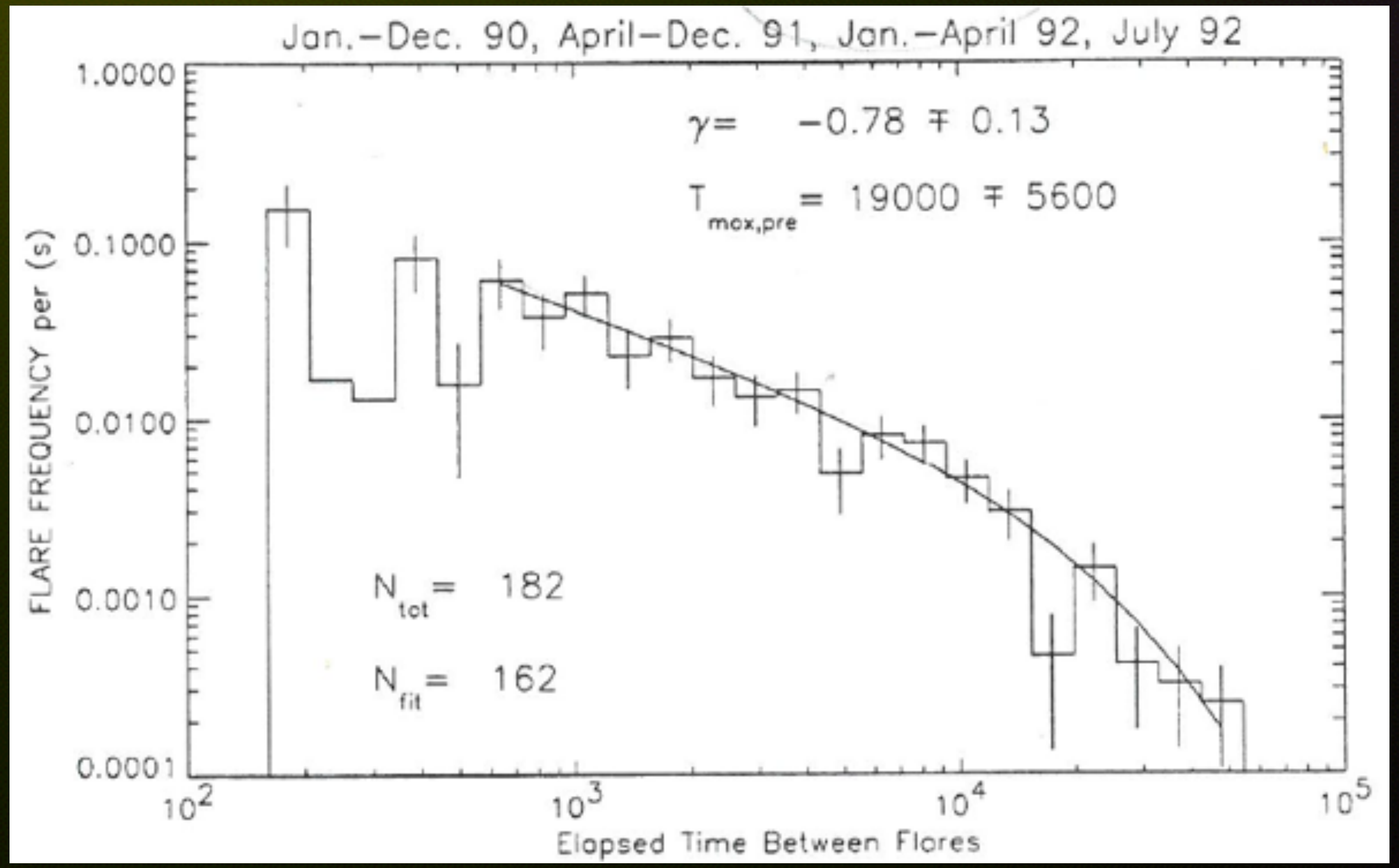

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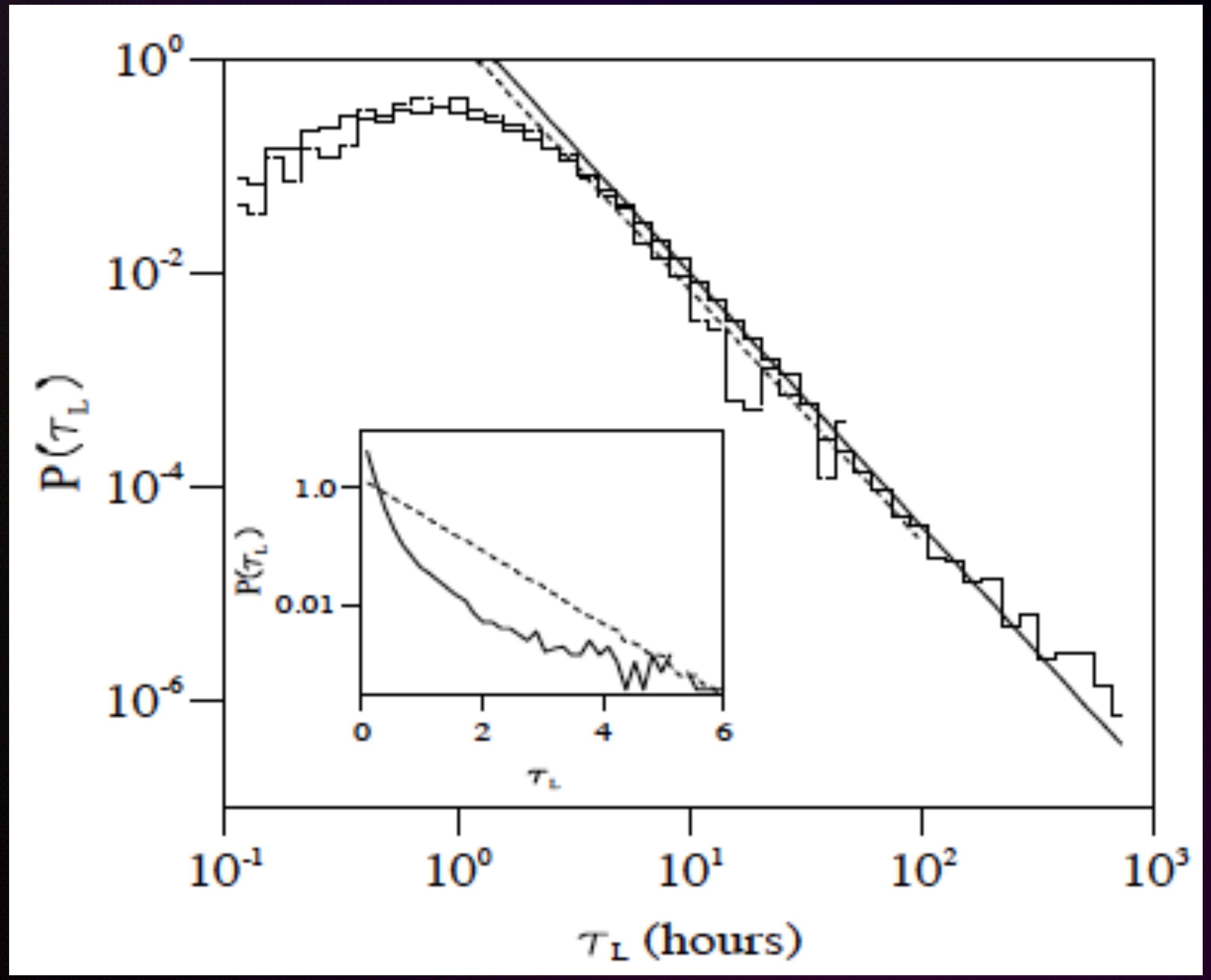

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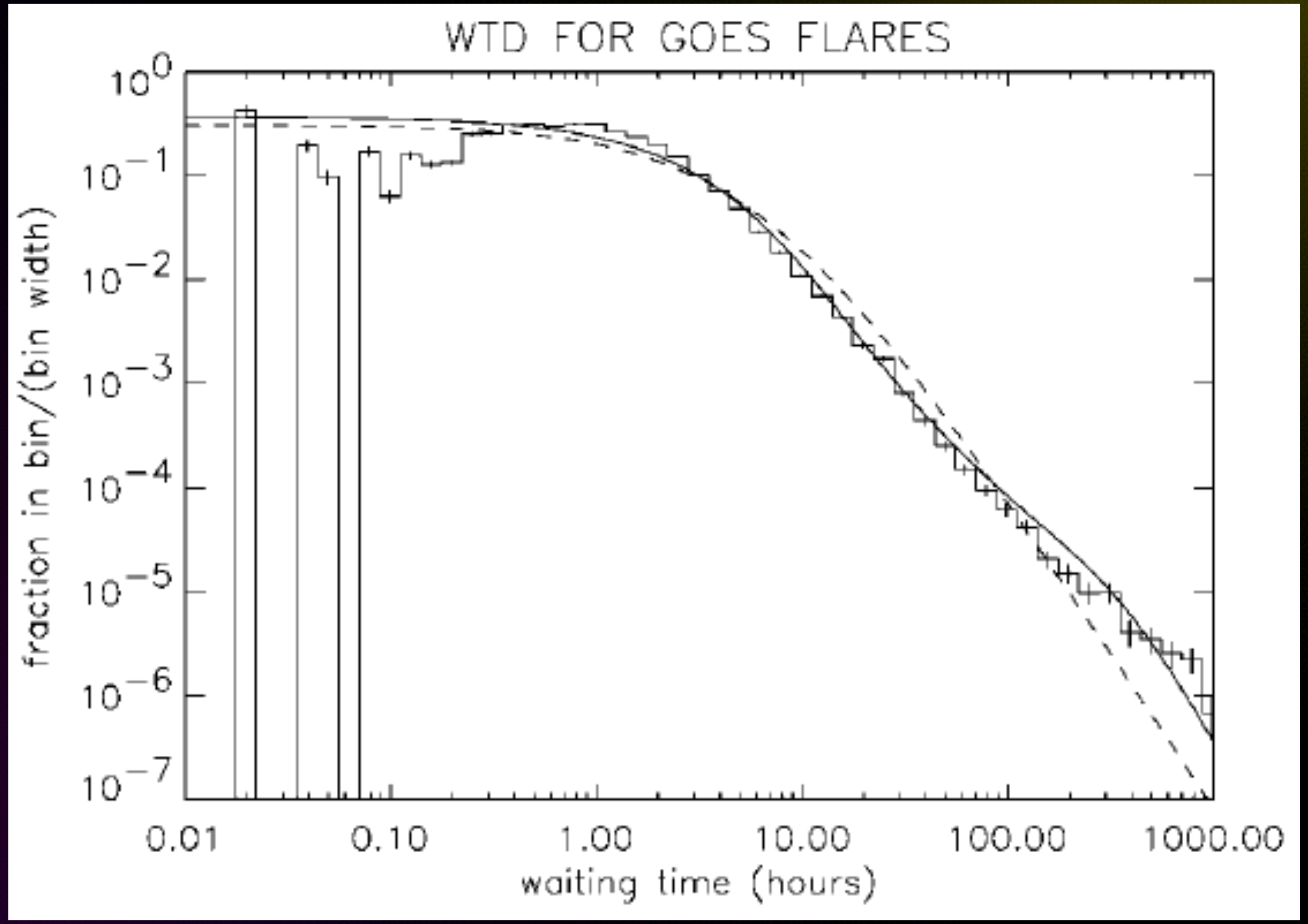


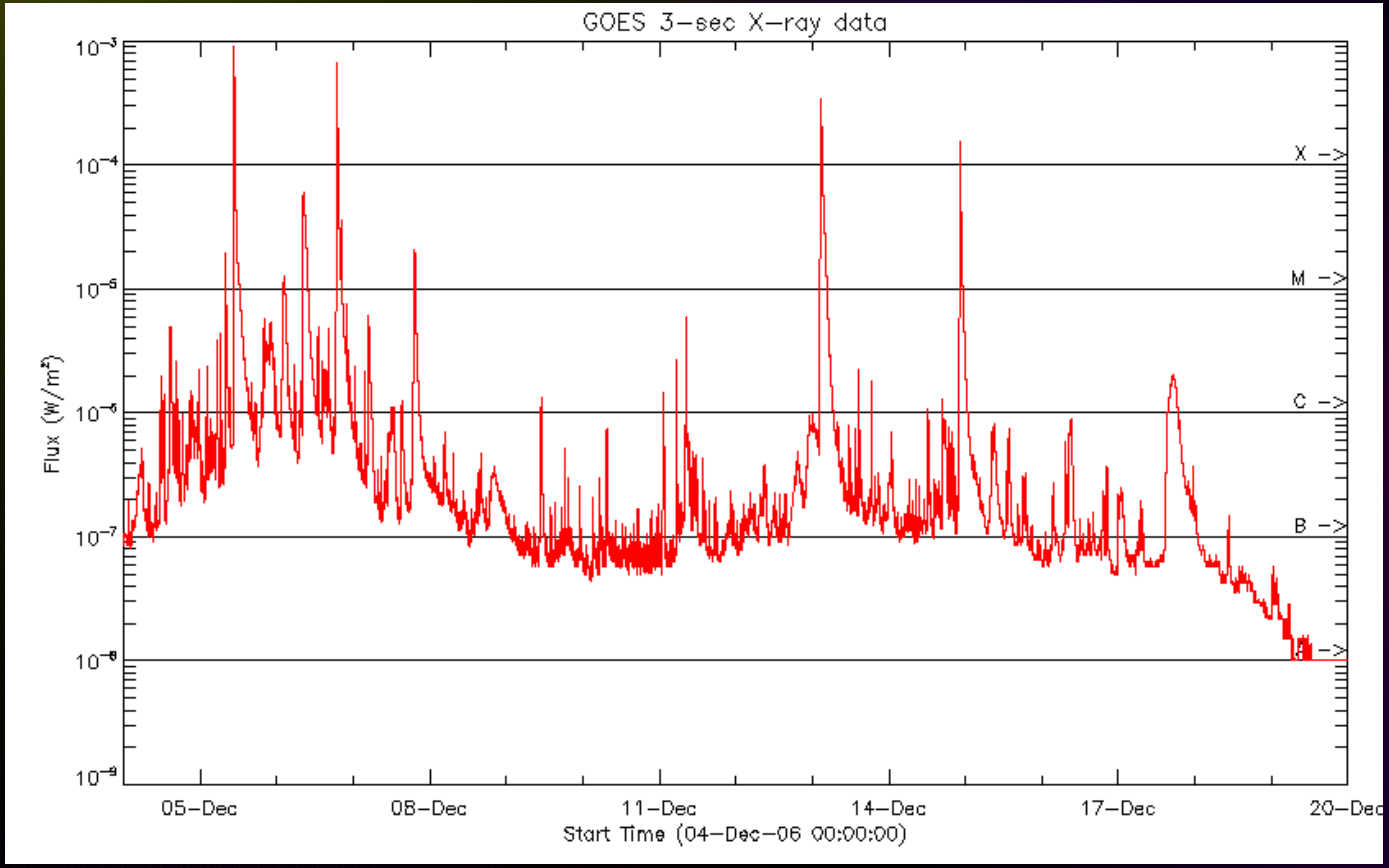
Wheatland (2000)

Exponential law of waiting times: a totally random, memoryless flare occurrence along the classical self-organized criticality concept

Robust power-law of waiting times: a system perfectly keeping a memory in giving flares

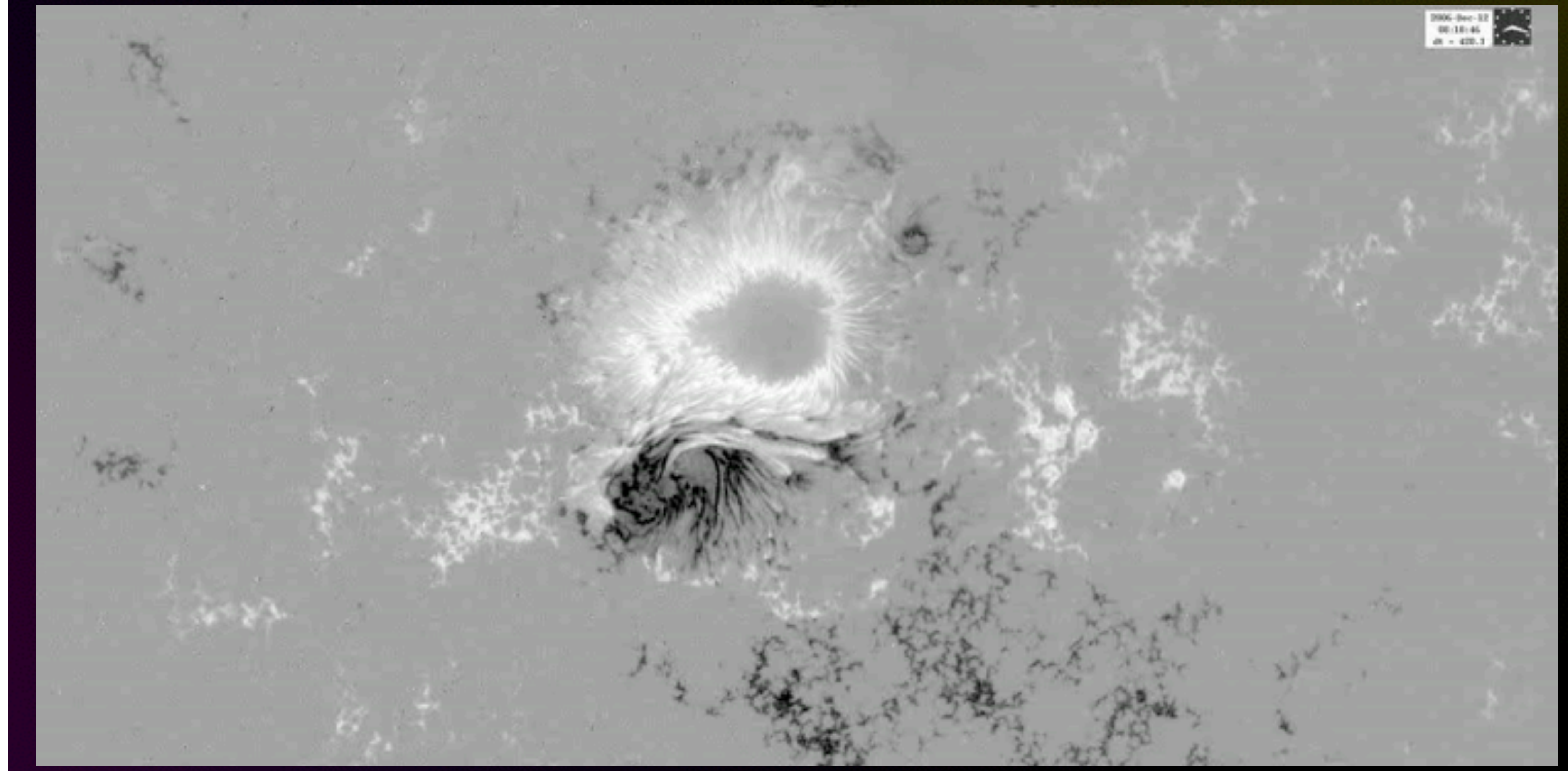
Time-dependent Poisson scaling in waiting times: some memory kept, with stochasticity demonstrated in an exponential distribution of different flaring rates

A MIX OF STOCHASTICITY AND MEMORY



Response of NOAA AR 10930 over a two-week period in Dec 2006

- NOAA AR 10930
- Period observed: ~16 days



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- Flaring features of active regions, i.e., complex magnetic PILs, continuously and consistently driven
- Typical situation of a pink-noise dynamical response timeseries

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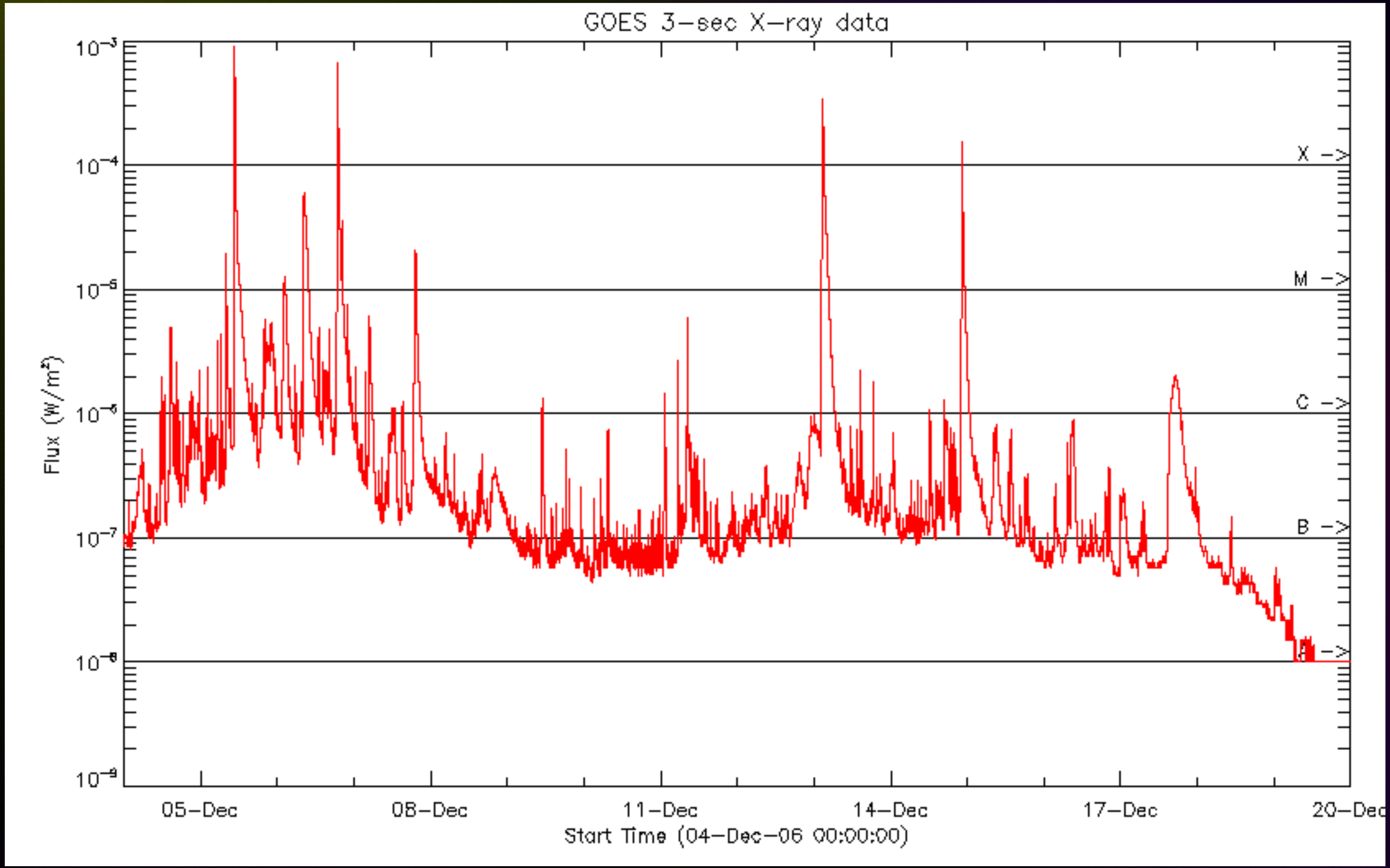

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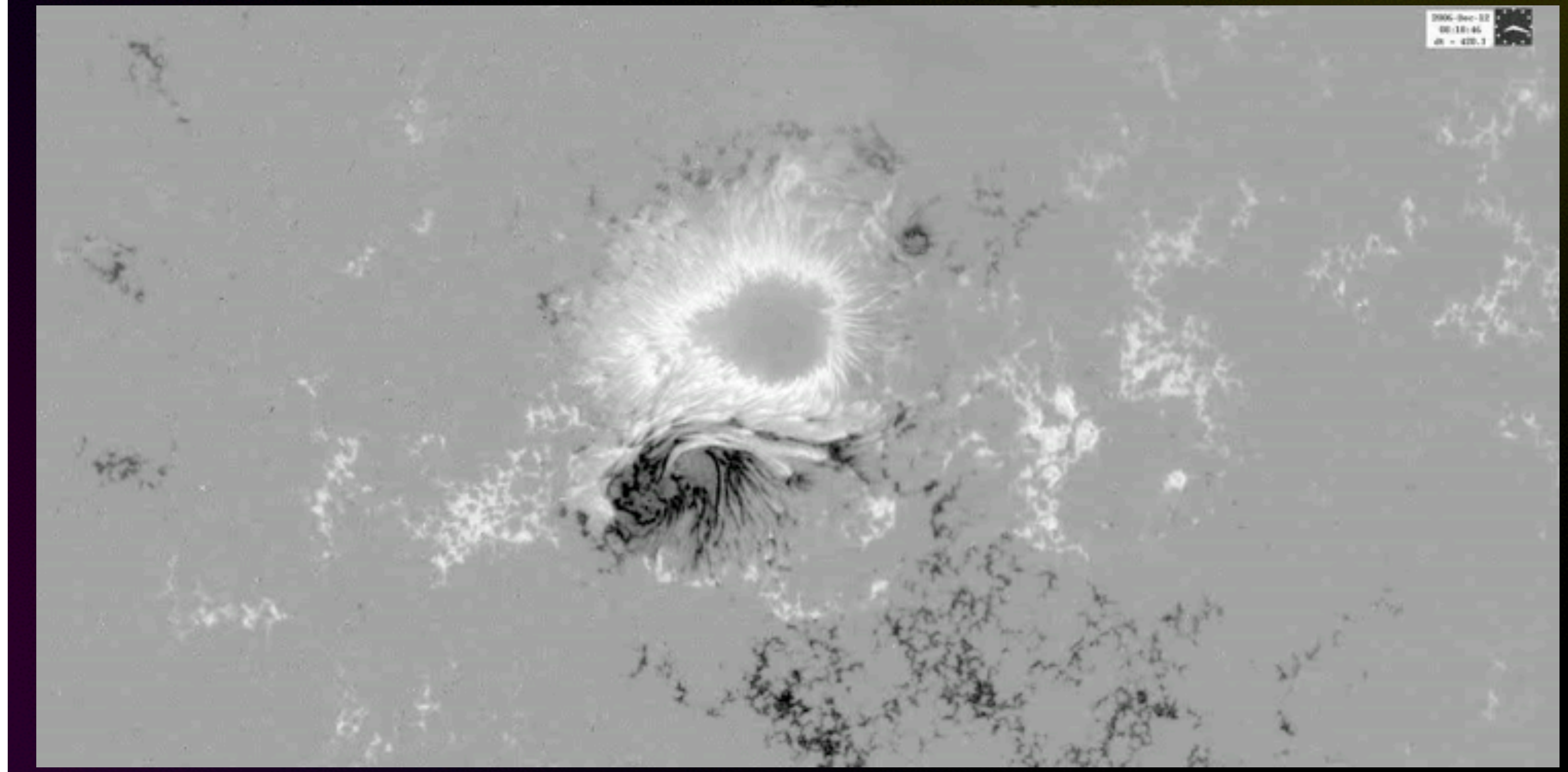

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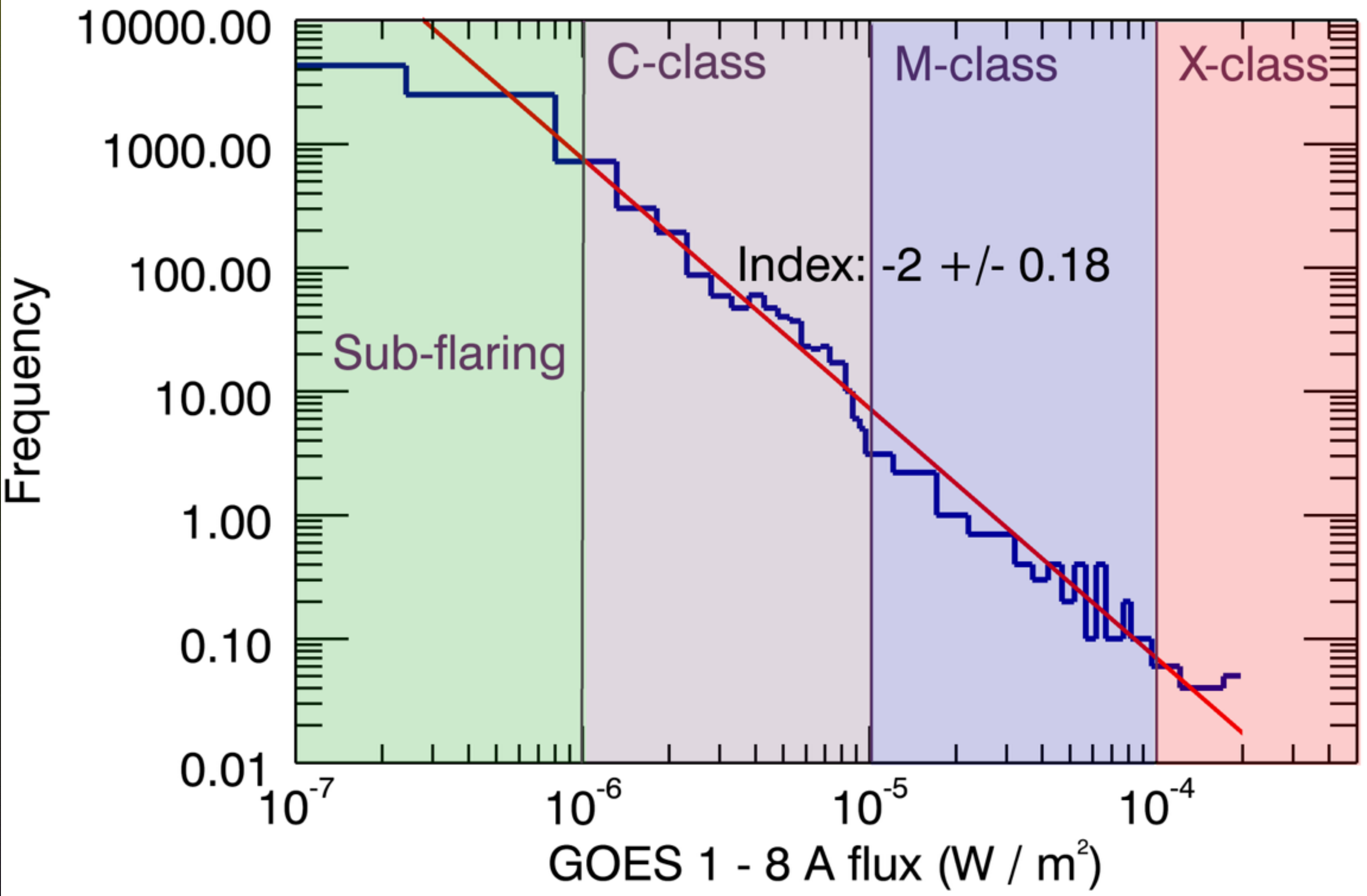

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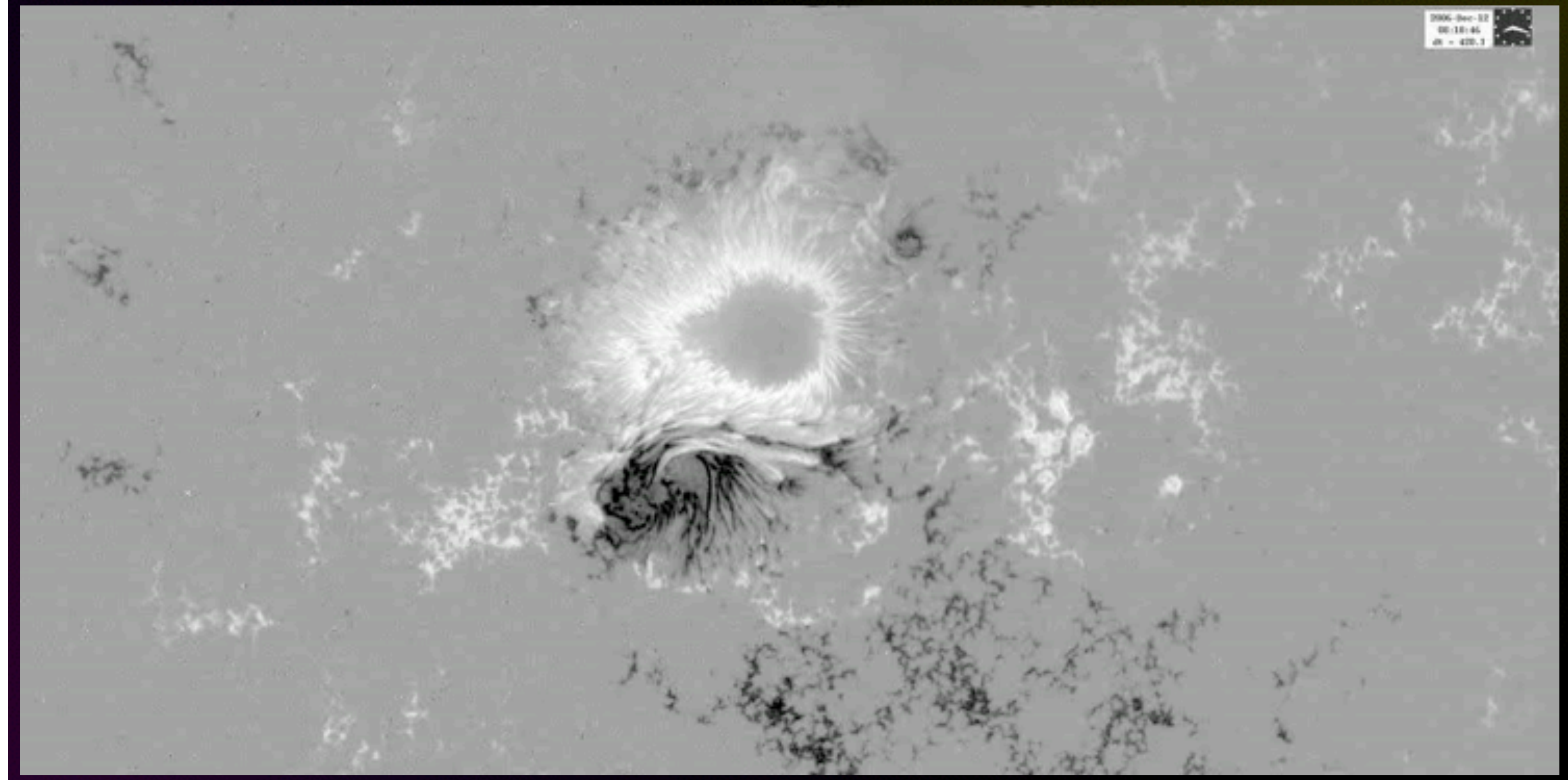

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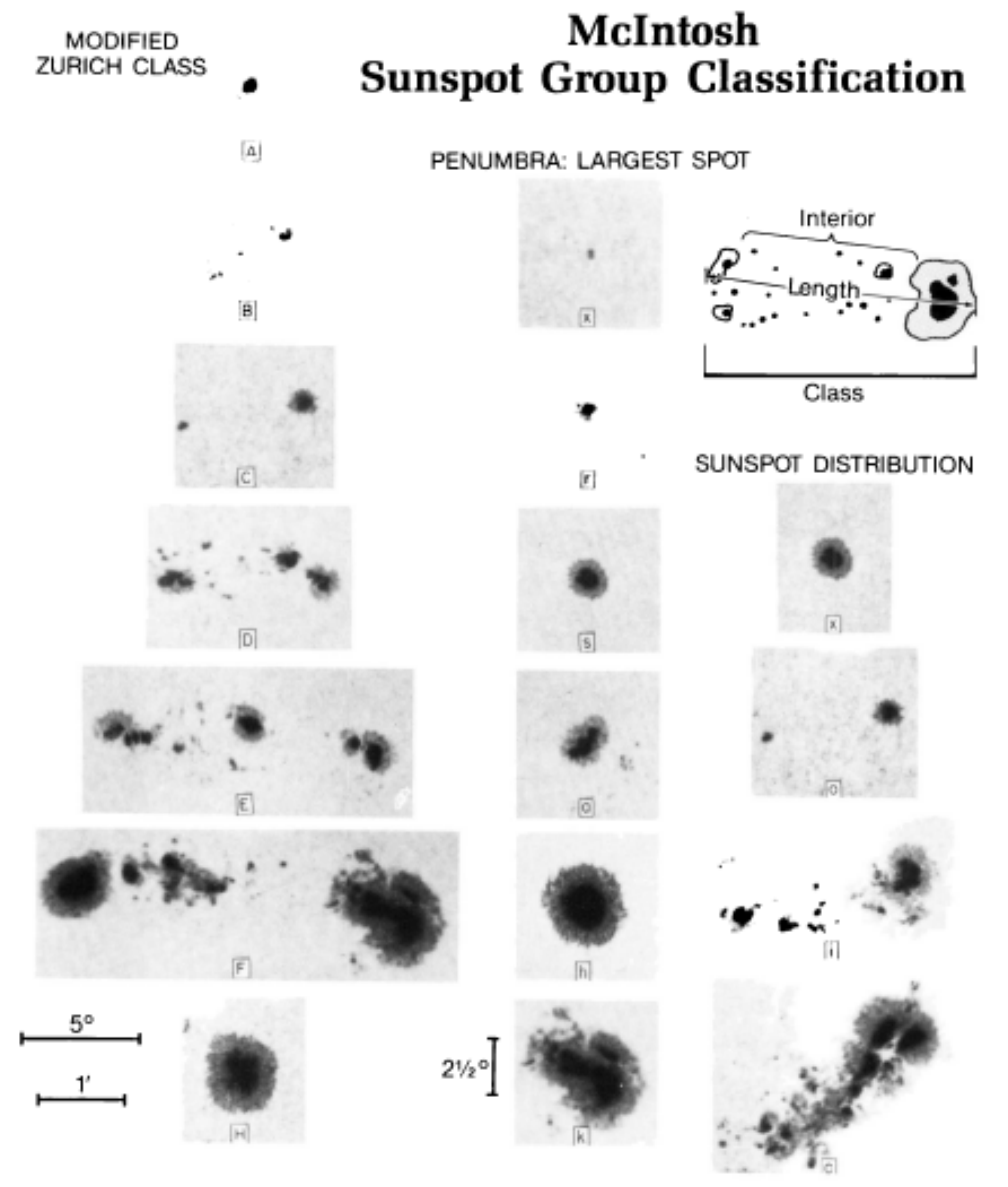

Fig. 1. The 3-component McIntosh classification, with examples of each category.

McIntosh (1990)

Mount Wilson classification

alpha: A unipolar sunspot group.

beta: A sunspot group having both positive and negative magnetic polarities (bipolar), with a simple and distinct division between the polarities.

gamma: A complex active region in which the positive and negative polarities are so irregularly distributed as to prevent classification as a bipolar group.

beta-gamma: A sunspot group that is bipolar but which is sufficiently complex that no single, continuous line can be drawn between spots of opposite polarities.

delta: A qualifier to magnetic classes(see below) indicating that umbrae separated by less than 2 degrees within one penumbra have opposite polarity.

beta-delta: A sunspot group of general beta magnetic classification but containing one (or more) delta spot(s).

beta-gamma-delta: A sunspot group of beta-gamma magnetic classification but containing one (or more) delta spot(s).

gamma-delta: A sunspot group of gamma magnetic classification but containing one (or more) delta spot(s).

Source: spaceweather.com

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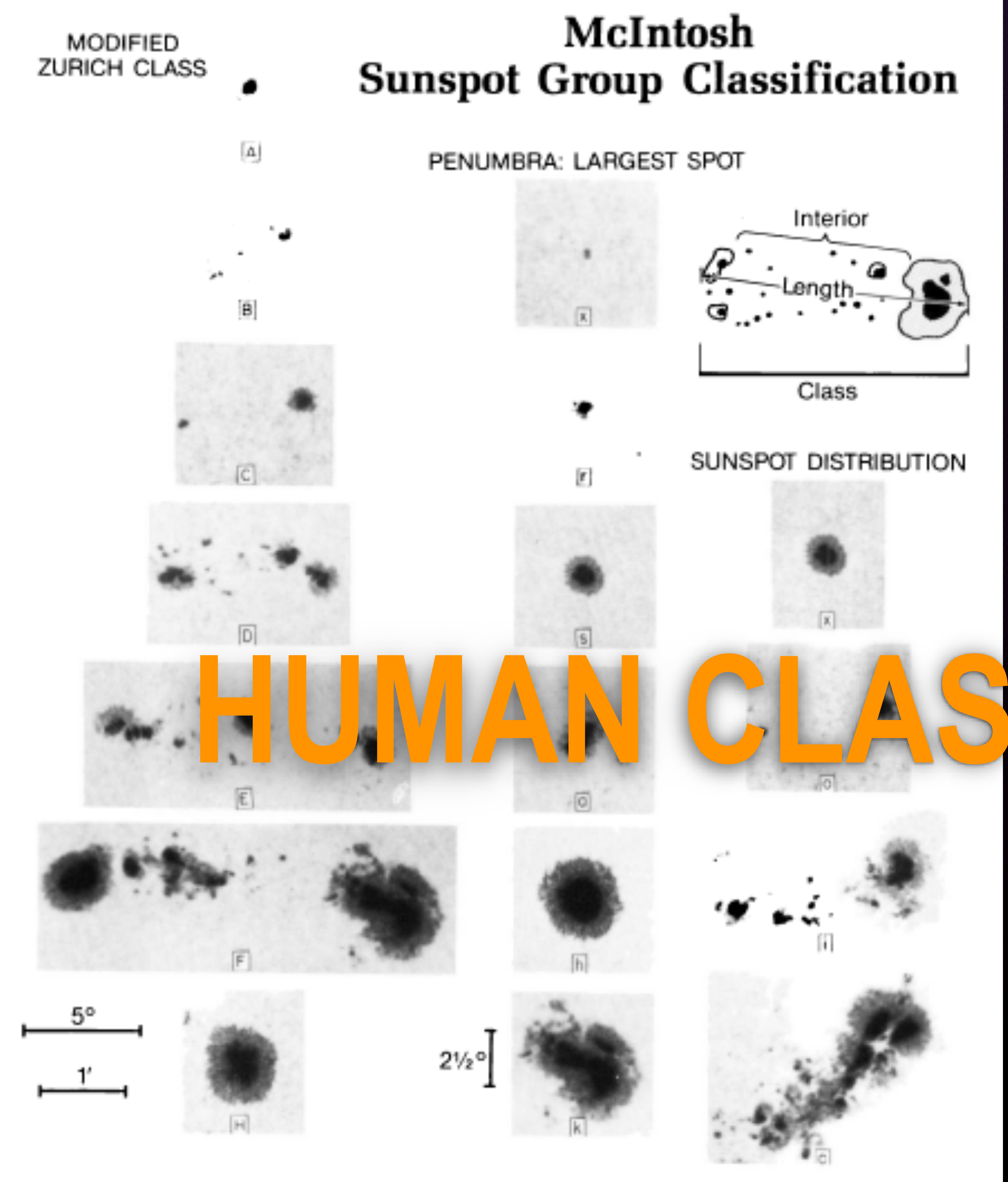

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HUMAN CLASSIFICATION, SUBJECTIVE

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- Analytical methods
- Local helioseismology methods
- Other (slightly exotic) methods

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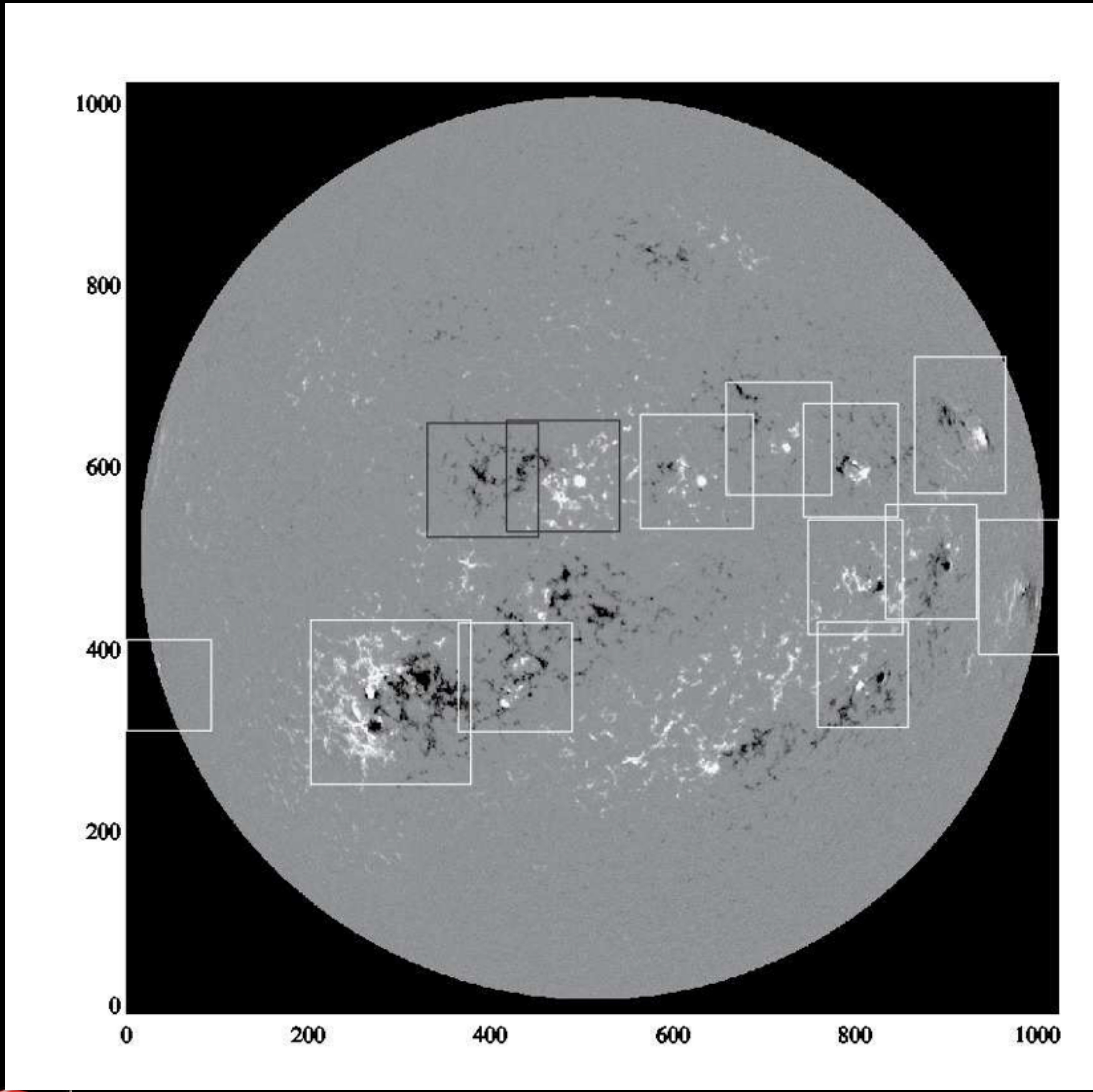
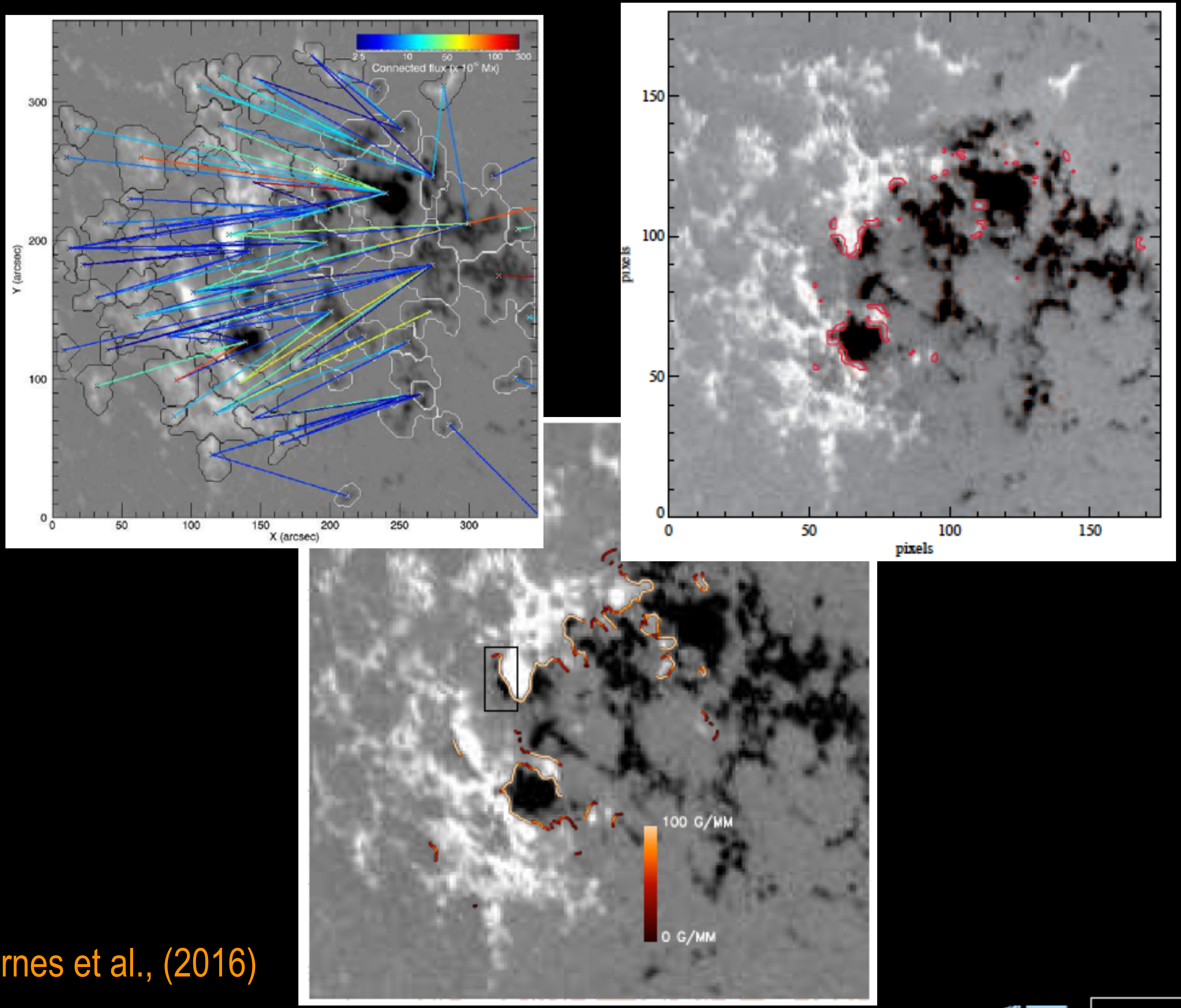
- Morphological methods — Falconer et al. (2001, 2002, 2003, 2008, 2009, 2011); Georrgoulis & Rust (2007); Schrijver (2007); Mason & Hoeksema (2010); Leka & Barnes (2003a; b); Cabnfield et al. (1999); Barnes & Leka (2008), Korsos et al. (2015)
- Statistical methods (on historical & archived data) — Wheatland (2001); Moon et al. (2001); Gallagher et al. (2002); Wheatland (2004, 2005a, b)
- Machine-learning, combinatorial, & assimilation methods — Belanger et al. (2007); Qahwaji & Colak (2007); Colak & Qahwaji (2008, 2009); Qahwaji et al. (2008); Al-Omari et al. (2010); Yu et al. (2009; 2010a, b); Huang et al. (2010) ; Bobra & Couvidat (2014); Bobra & Ilonidis (2015); Boucheron et al., (2015); Nishizuka et al., (2016)
- Analytical methods — Wheatland & Glukhov (1998); Wheatland (2008)
- Local helioseismology methods — Reinard et al. (2010); Komm et al. (2011), etc.
- Other (slightly exotic) methods — Jenkins & Fischbach (2009); Javorsek et al. (2012); Strugarek & Charbonneau (2014)

ANALYSIS OF PHOTOSPHERIC ACTIVE-REGION MAGNETOGRAMS



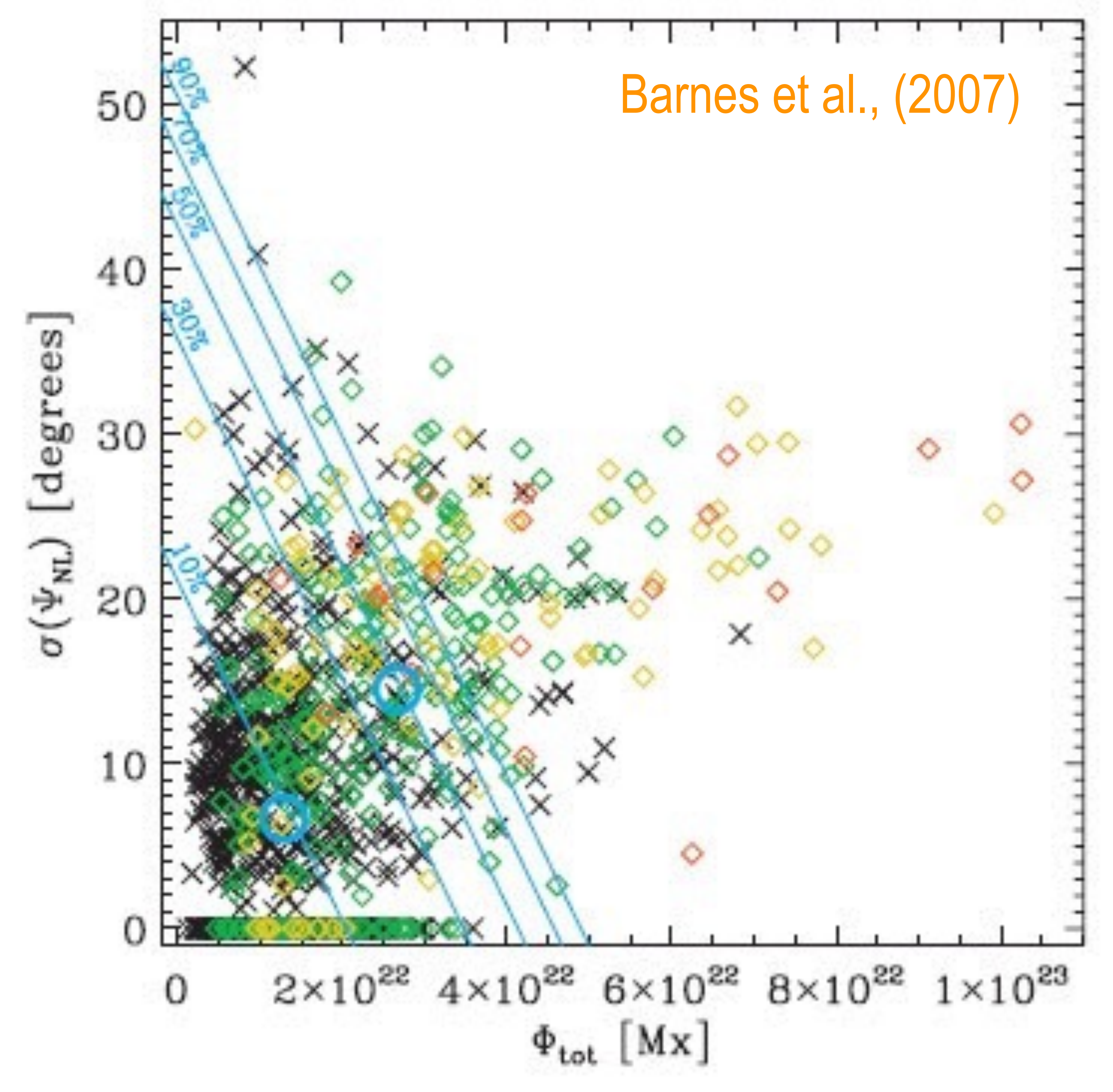


Barnes et al., (2016)

PROPERTIES TRANSLATED TO PREDICTIVE PROBABILITIES

Keyword	Description	Formula	F-Score	Selection
TOTUSJH	Total unsigned current helicity	$H_{c_{\text{total}}} \propto \sum \lvert B_z \cdot J_z \rvert$	3560	Included
TOTBSQ	Total magnitude of Lorentz force	$F \propto \sum B^2$	3051	Included
TOTPOT	Total photospheric magnetic free energy density	$\rho_{\text{tot}} \propto \sum \left(\boldsymbol{B}^{\text{Obs}} - \boldsymbol{B}^{\text{Pot}}\right)^2 dA$	2996	Included
TOTUSJZ	Total unsigned vertical current	$J_{z_{\text{total}}} = \sum \lvert J_z \rvert dA$	2733	Included
ABSNJZH	Absolute value of the net current helicity	$H_{c_{\text{abs}}} \propto \left\lvert \sum B_z \cdot J_z \right\rvert$	2618	Included
SAVNCPP	Sum of the modulus of the net current per polarity	$J_{z_{\text{sum}}} \propto \left\lvert \sum^{B_z^+} J_z dA \right\rvert + \left\lvert \sum^{B_z^-} J_z dA \right\rvert$	2448	Included
USFLUX	Total unsigned flux	$\Phi = \sum \lvert B_z \rvert dA$	2437	Included
AREA_ACR	Area of strong field pixels in the active region	Area $= \sum$ Pixels	2047	Included
TOTFZ	Sum of z-component of Lorentz force	$F_z \propto \sum (B_x^2 + B_y^2 - B_z^2) dA$	1371	Included
MEANPOT	Mean photospheric magnetic free energy	$\overline{\rho} \propto \frac{1}{N} \sum \left(\boldsymbol{B}^{\text{Obs}} - \boldsymbol{B}^{\text{Pot}}\right)^2$	1064	Included
R_VALUE	Sum of flux near polarity inversion line	$\Phi = \sum \lvert B_{LoS} \rvert dA$ within R mask	1057	Included
EPSZ	Sum of z-component of normalized Lorentz force	$\delta F_z \propto \frac{\sum (B_x^2 + B_y^2 - B_z^2)}{\sum B^2}$	864.1	Included
SHRGT45	Fraction of Area with shear $> 45°$	Area with shear $> 45°$ / total area	740.8	Included
MEANSHR	Mean shear angle	$\overline{\Gamma} = \frac{1}{N} \sum \arccos\left(\frac{\boldsymbol{B}^{\text{Obs}} \cdot \boldsymbol{B}^{\text{Pot}}}{\lvert \boldsymbol{B}^{\text{Obs}} \rvert \lvert \boldsymbol{B}^{\text{Pot}} \rvert}\right)$	727.9	Discarded
MEANGAM	Mean angle of field from radial	$\overline{\gamma} = \frac{1}{N} \sum \arctan\left(\frac{B_h}{B_z}\right)$	573.3	Discarded
MEANGBT	Mean gradient of total field	$\overline{\lvert \nabla B_{\text{tot}} \rvert} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B}{\partial x}\right)^2 + \left(\frac{\partial B}{\partial y}\right)^2}$	192.3	Discarded
MEANGBZ	Mean gradient of vertical field	$\overline{\lvert \nabla B_z \rvert} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B_z}{\partial x}\right)^2 + \left(\frac{\partial B_z}{\partial y}\right)^2}$	88.40	Discarded
MEANGBH	Mean gradient of horizontal field	$\overline{\lvert \nabla B_h \rvert} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B_h}{\partial x}\right)^2 + \left(\frac{\partial B_h}{\partial y}\right)^2}$	79.40	Discarded
MEANJZH	Mean current helicity (B_z contribution)	$\overline{H_c} \propto \frac{1}{N} \sum B_z \cdot J_z$	46.73	Discarded
TOTFY	Sum of y-component of Lorentz force	$F_y \propto \sum B_y B_z dA$	28.92	Discarded
MEANJZD	Mean vertical current density	$\overline{J_z} \propto \frac{1}{N} \sum \left(\frac{\partial B_y}{\partial x} - \frac{\partial B_x}{\partial y}\right)$	17.44	Discarded
MEANALP	Mean characteristic twist parameter, α	$\alpha_{\text{total}} \propto \frac{\sum J_z \cdot B_z}{\sum B_z^2}$	10.41	Discarded
TOTFX	Sum of x-component of Lorentz force	$F_x \propto -\sum B_x B_z dA$	6.147	Discarded
EPSY	Sum of y-component of normalized Lorentz force	$\delta F_y \propto \frac{-\sum B_y B_z}{\sum B^2}$	0.647	Discarded
EPSX	Sum of x-component of normalized Lorentz force	$\delta F_x \propto \frac{\sum B_x B_z}{\sum B^2}$	0.366	Discarded

Bobra & Couvidat (2014)



Discriminant analysis: Two-function, linear DA for four-class prediction (non-flaring, C, M, and X-class)

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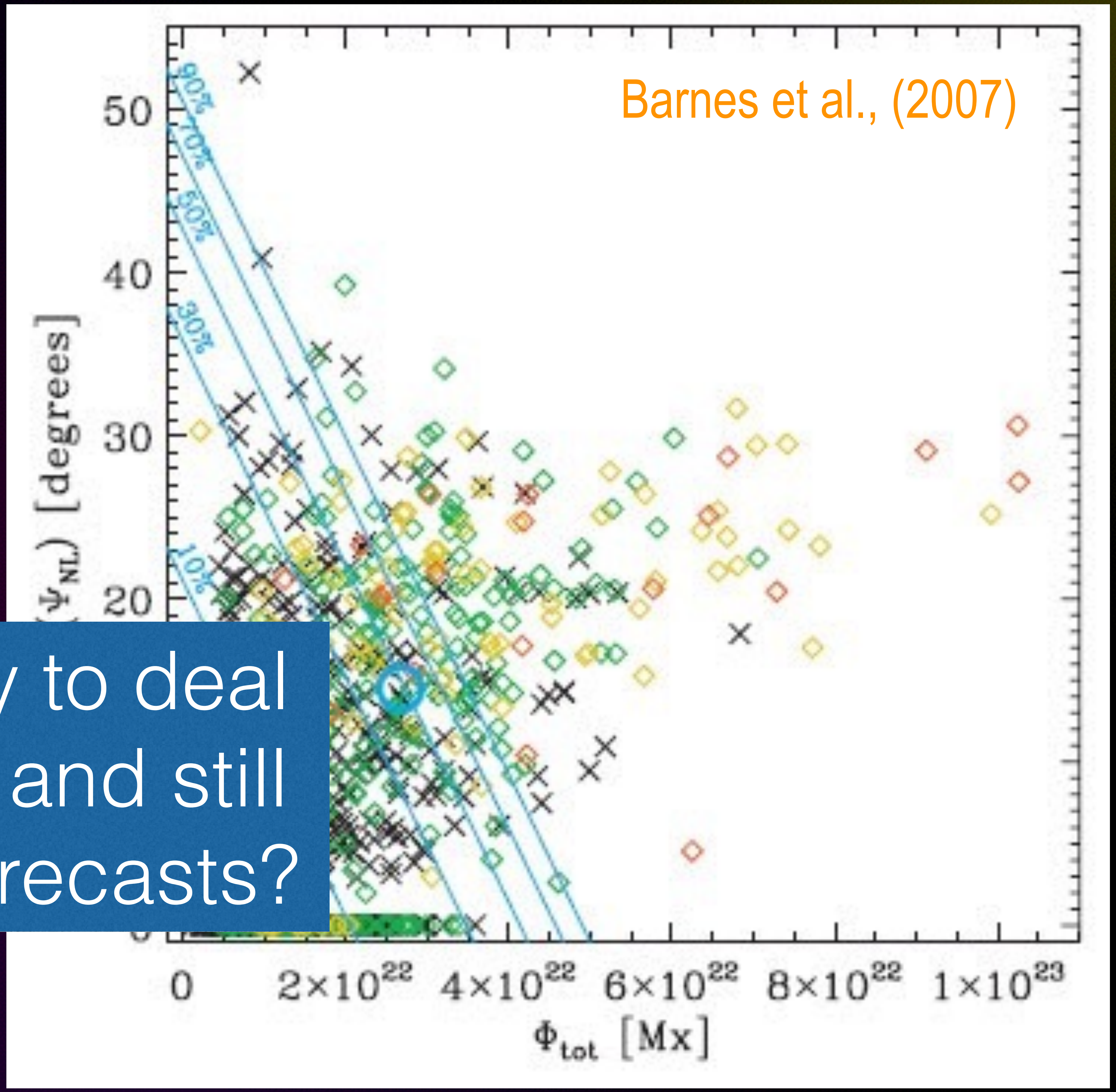
MEANPOT	Mean photospheric magnetic free energy	$\overline{\rho} \propto \frac{1}{N} \sum \left(\boldsymbol{B}^{\rm Obs} - \boldsymbol{B}^{\rm Pot}\right)^2$	1064	Included
R_VALUE	Sum of flux near polarity inversion line	$\Phi = \sum \lvert B_{LoS} \rvert dA$ within R mask	1057	Included
EPSZ	Sum of z-component of normalized Lorentz force	$\delta F_z \propto \frac{\sum (B_x^2 + B_y^2 - B_z^2)}{\sum B^2}$	864.1	Included
SHRGT45	Fraction of Area with shear $> 45°$	Area w[illegible]	[illegible]	[illegible]
MEANSHR	Mean shear angle	$\overline{\Gamma} =$ [illegible]	[illegible]	[illegible]
MEANGAM	Mean angle of field from radial	$\overline{\gamma}$ [illegible]	[illegible]	[illegible]
MEANGBT	Mean gradient of total field	$\overline{\lvert \nabla B_{\rm tot} \rvert}$ [illegible]	[illegible]	[illegible]
MEANGBZ	Mean gradient of vertical field	$\overline{\lvert \nabla B_z \rvert} =$ [illegible]	[illegible]	[illegible]
MEANGBH	Mean gradient of horizontal field	$\overline{\lvert \nabla B_h \rvert} =$ [illegible]	[illegible]	[illegible]
MEANJZH	Mean current helicity (B_z contribution)	$\overline{H_c} \propto \frac{1}{N} \sum B_z \cdot J_z$	46.73	Discarded
TOTFY	Sum of y-component of Lorentz force	$F_y \propto \sum B_y B_z dA$	28.92	Discarded
MEANJZD	Mean vertical current density	$\overline{J_z} \propto \frac{1}{N} \sum \left(\frac{\partial B_y}{\partial x} - \frac{\partial B_x}{\partial y}\right)$	17.44	Discarded
MEANALP	Mean characteristic twist parameter, α	$\alpha_{\rm total} \propto \frac{\sum J_z \cdot B_z}{\sum B_z^2}$	10.41	Discarded
TOTFX	Sum of x-component of Lorentz force	$F_x \propto -\sum B_x B_z dA$	6.147	Discarded
EPSY	Sum of y-component of normalized Lorentz force	$\delta F_y \propto \frac{-\sum B_y B_z}{\sum B^2}$	0.647	Discarded
EPSX	Sum of x-component of normalized Lorentz force	$\delta F_x \propto \frac{\sum B_x B_z}{\sum B^2}$	0.366	Discarded

What is the optimal way to deal with all this information and still achieve reliable NRT forecasts?

Bobra & Couvidat (2014)



Discriminant analysis: Two-function, linear DA for four-class prediction (non-flaring, C, M, and X-class)

RECENT TREDS IN FLARE PREDICTION

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$$predictor = \omega_1\ predictor_1 + \omega_2\ predictor_2 + \ldots + \ \omega_n\ predictor_n$$

$$\omega_1, \ \omega_2 \ ,\ldots, \ \omega_n \quad \text{unrestricted}$$

  - — Ensemble forecasting:

$$P(flare) = \omega_1\ P_1(flare) + \omega_2\ P_2(flare) + \ldots + \ \omega_n\ P_n(flare)$$

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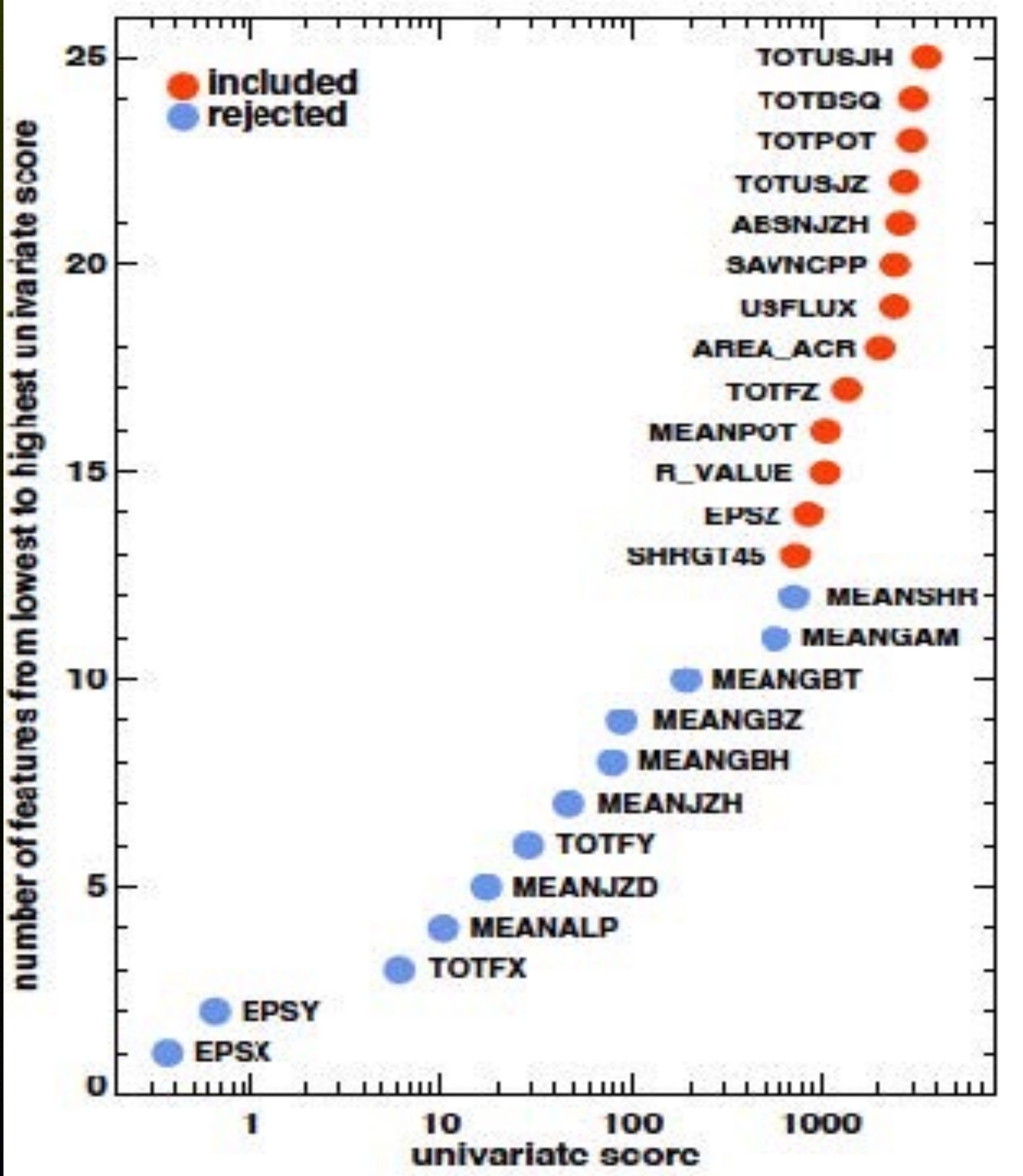
However: optimization means different things to different communities!

INDICATIVE RESULTS

- Multivariate forecasting



Bobra & Couvidat (2014)

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- Machine-learning classifiers adopted

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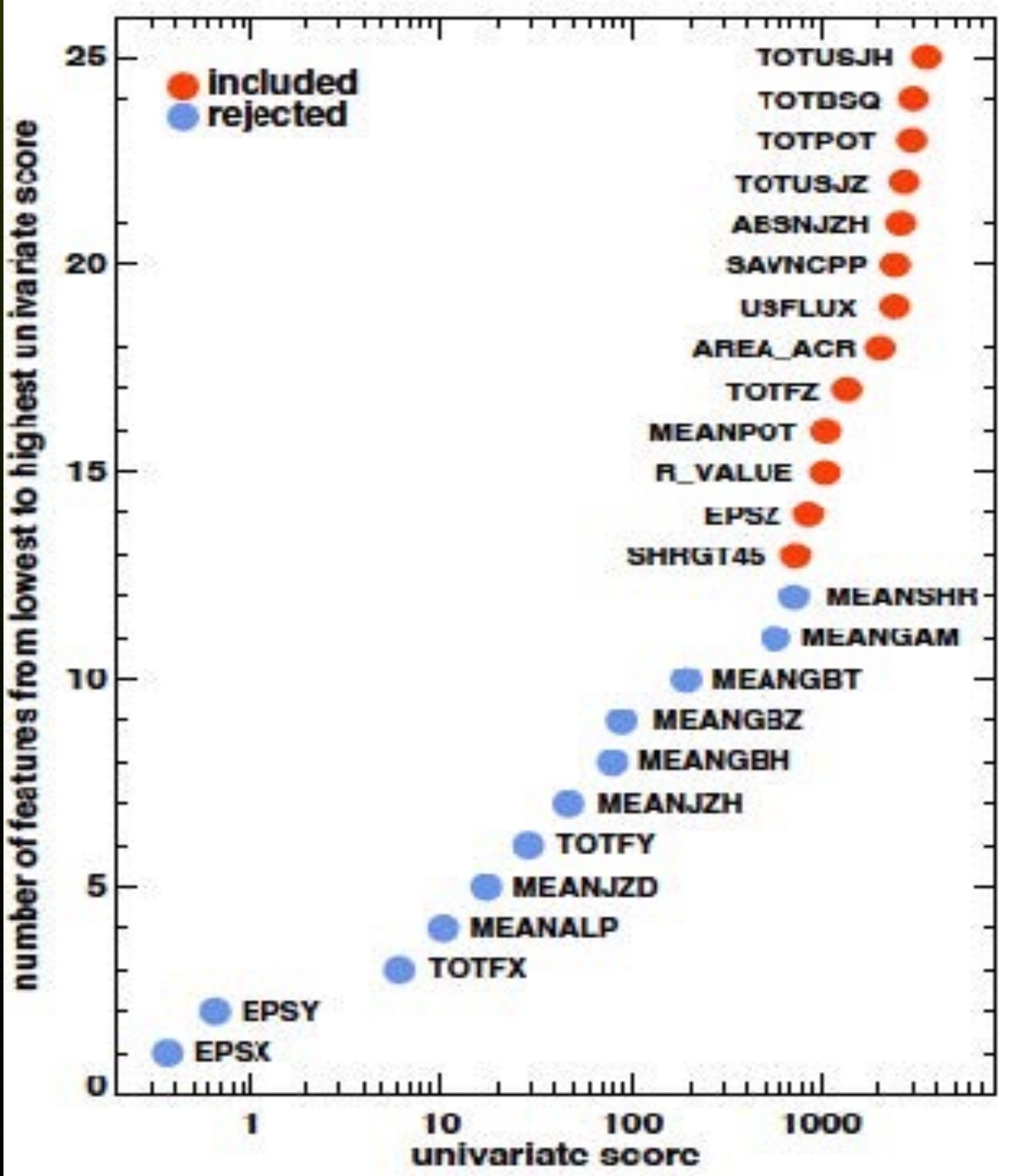

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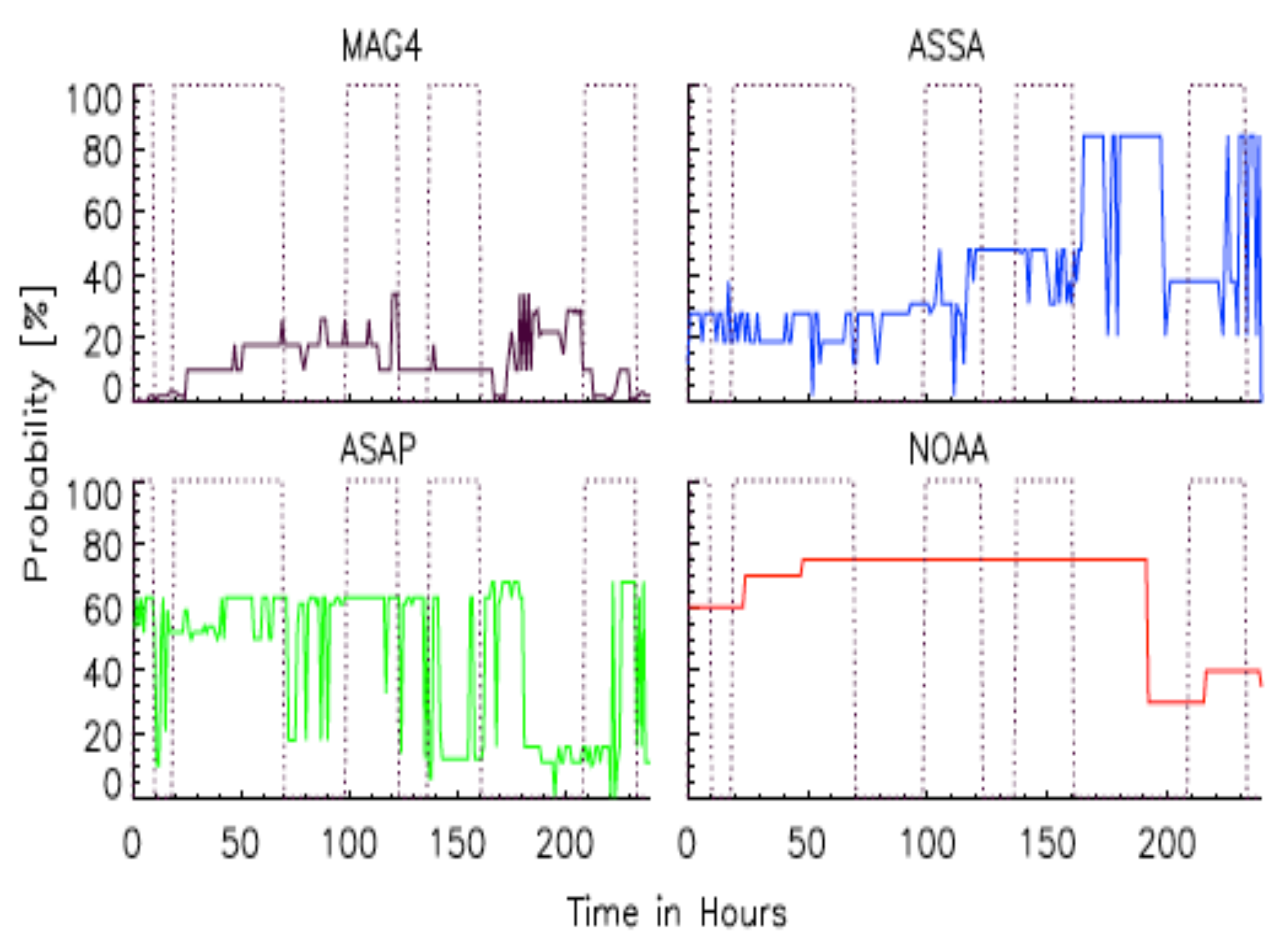

Guerra et al., (2015)

- Homogenizing the results of multiple flare prediction methods, using them with equal or non-equal weights for an ensemble forecasting

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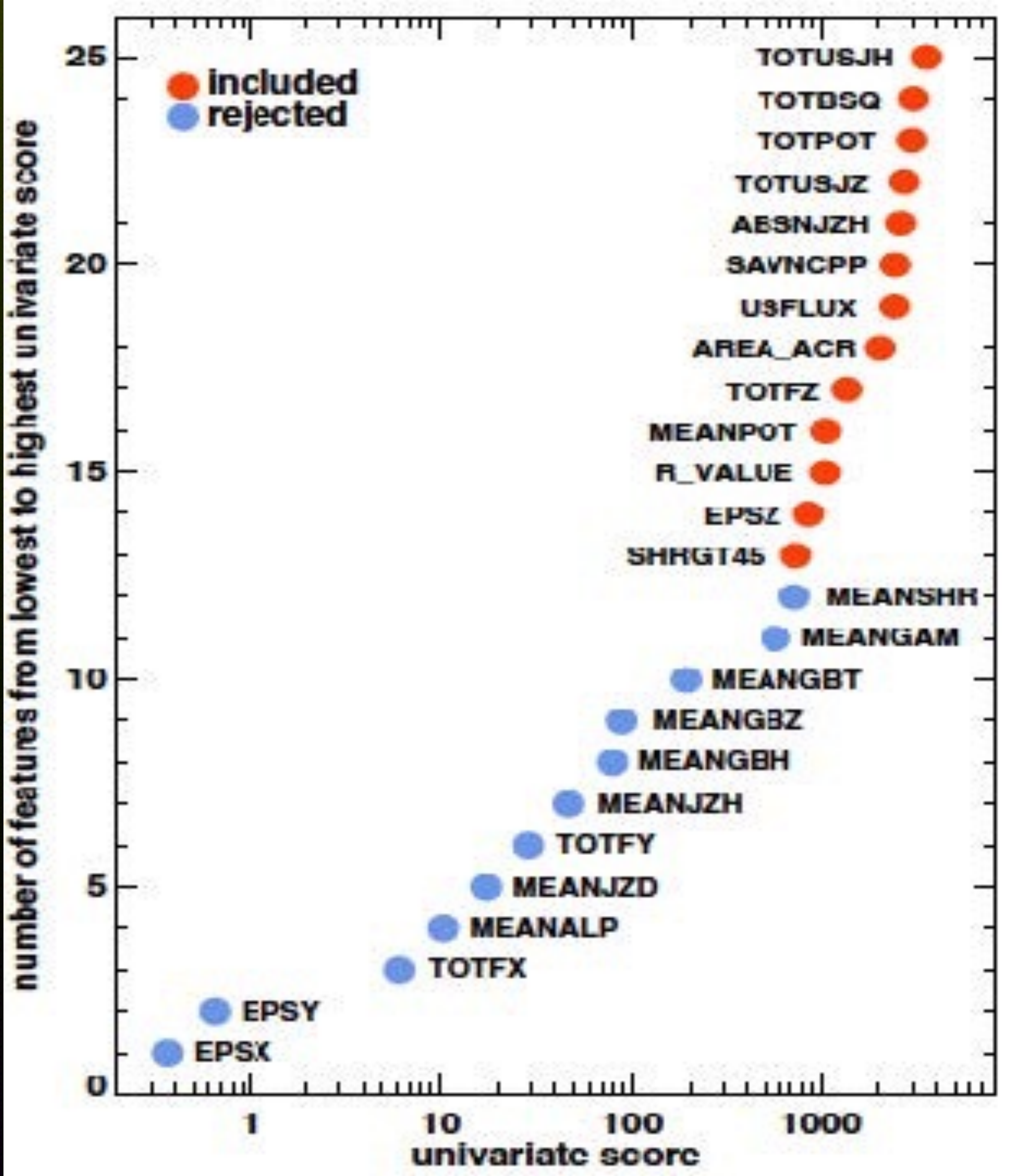

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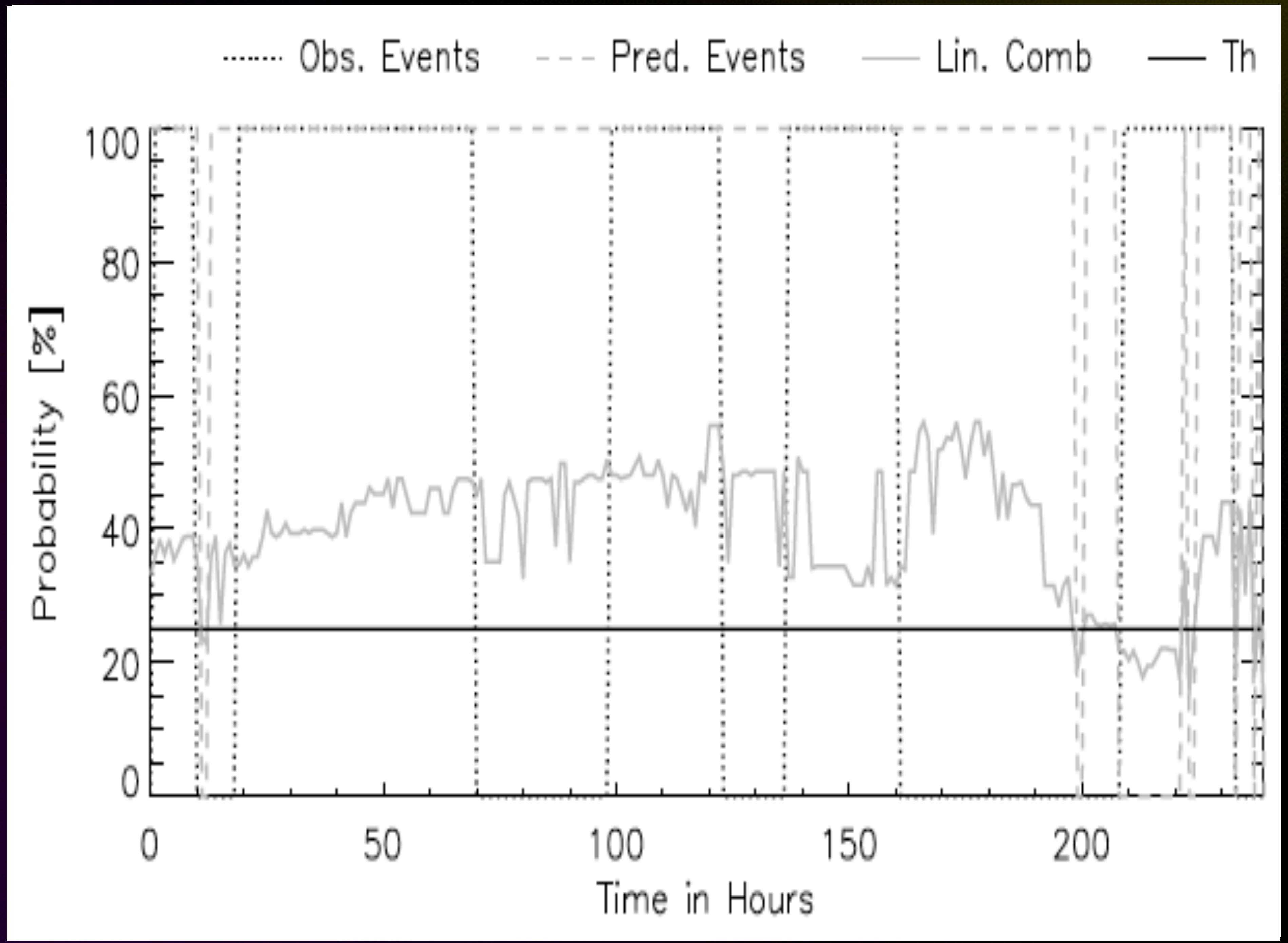

Guerra et al., (2015)

JUDGING WHICH METHODS WORK: VALIDATION

- Existing methods are borrowed from terrestrial weather forecasting
- Two types of validation
  - On binary (YES / NO) prediction output
  - On probabilistic $(0 < p < 1)$ prediction output
- **Both are used in flare prediction**

VALIDATION: BORROWED BY TERRESTRIAL WEATHER FORECASTING

Binary validation: Flare (YES) or No Flare (NO)

Tailoring according to different end user needs

	Forecast Flare	Forecast No-flare
Observed Flare	TP	FN
Observed No-flare	FP	TN

Table courtesy: Shaun Bloomfield

2 x 2 contingency table

- TP : true positives
- FN : false negatives
- FP : false positives
- TN : true negatives

- Generalized skill score:

$$SS = \frac{score - score_{reference}}{score_{perfect} - score_{reference}}$$

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Tailoring according to different end user needs

- Heidke skill score (ref: random prediction):

$$HSS = \frac{2(TP + TN) - N}{N}$$

- Appleman skill score (ref: climatology [v]):

$$ApSS = \frac{TP - FP}{N}$$

- True skill statistic (ref: weighting POD w. POFD):

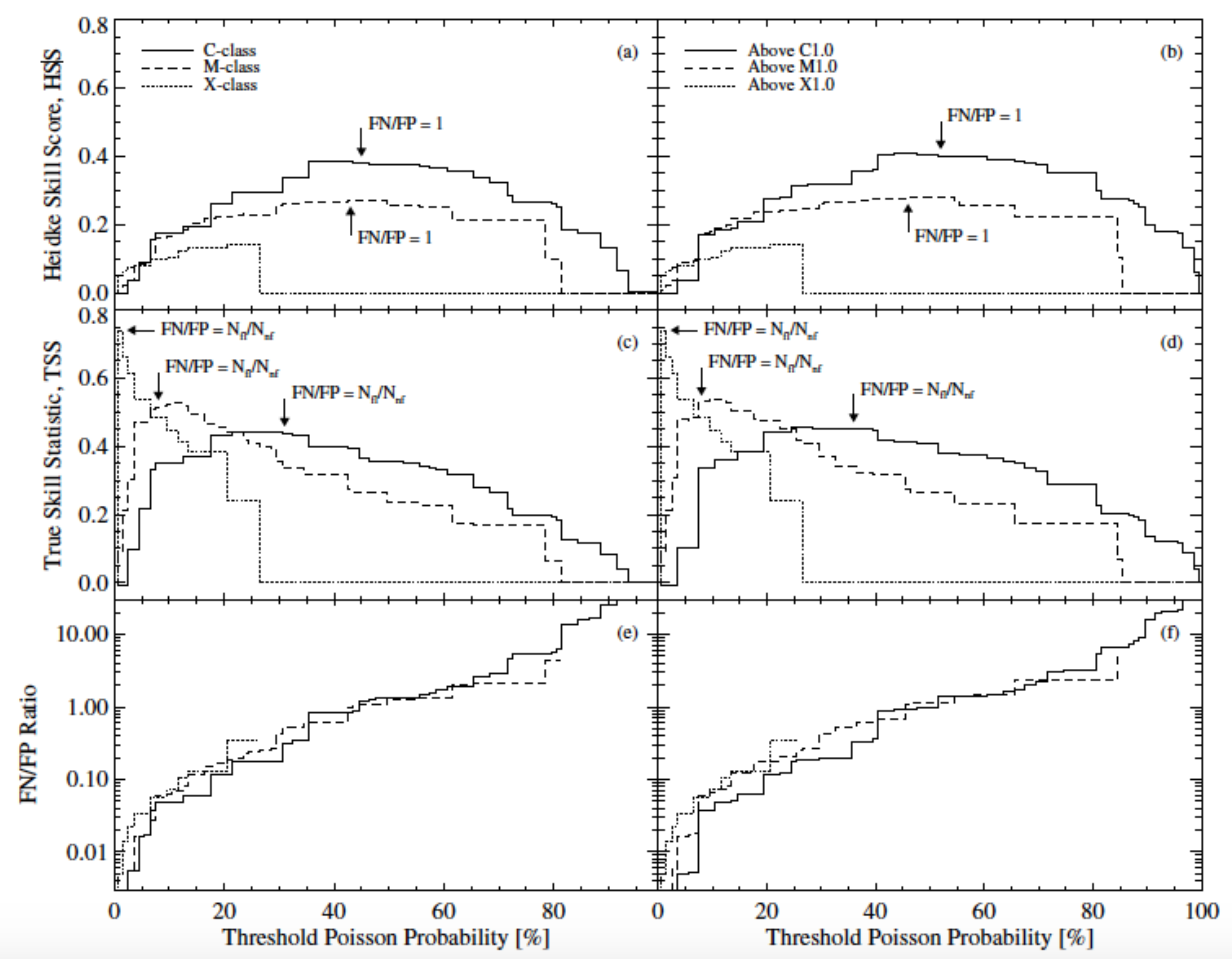
$$TSS = POD - POFD$$

(SOME) BINARY FORECAST VERIFICATION METRICS

Metric Name	Short Name	Format	Worst Score	"No skill" Score	Perfect Score
Accuracy	ACC	(TP + TN) / N	0	...	1
Probability of detection	POD	TP / (TP + FN)	0	...	1
Probability of false detection (false alarm rate)	POFD	FP / (FP + TN)	1	...	0
False alarm ratio	FAR	FP / (TP + FP)	1	...	0
True skill statistic	TSS	POD - POFD	-1	0	1
Heidke skill score	HSS	$(TP + TN - E_{random}) / (N - E_{random})$	-1	0	1

Slide courtesy: Shaun Bloomfield

SOME INDICATIVE RESULTS



Bloomfield et el., (2012)

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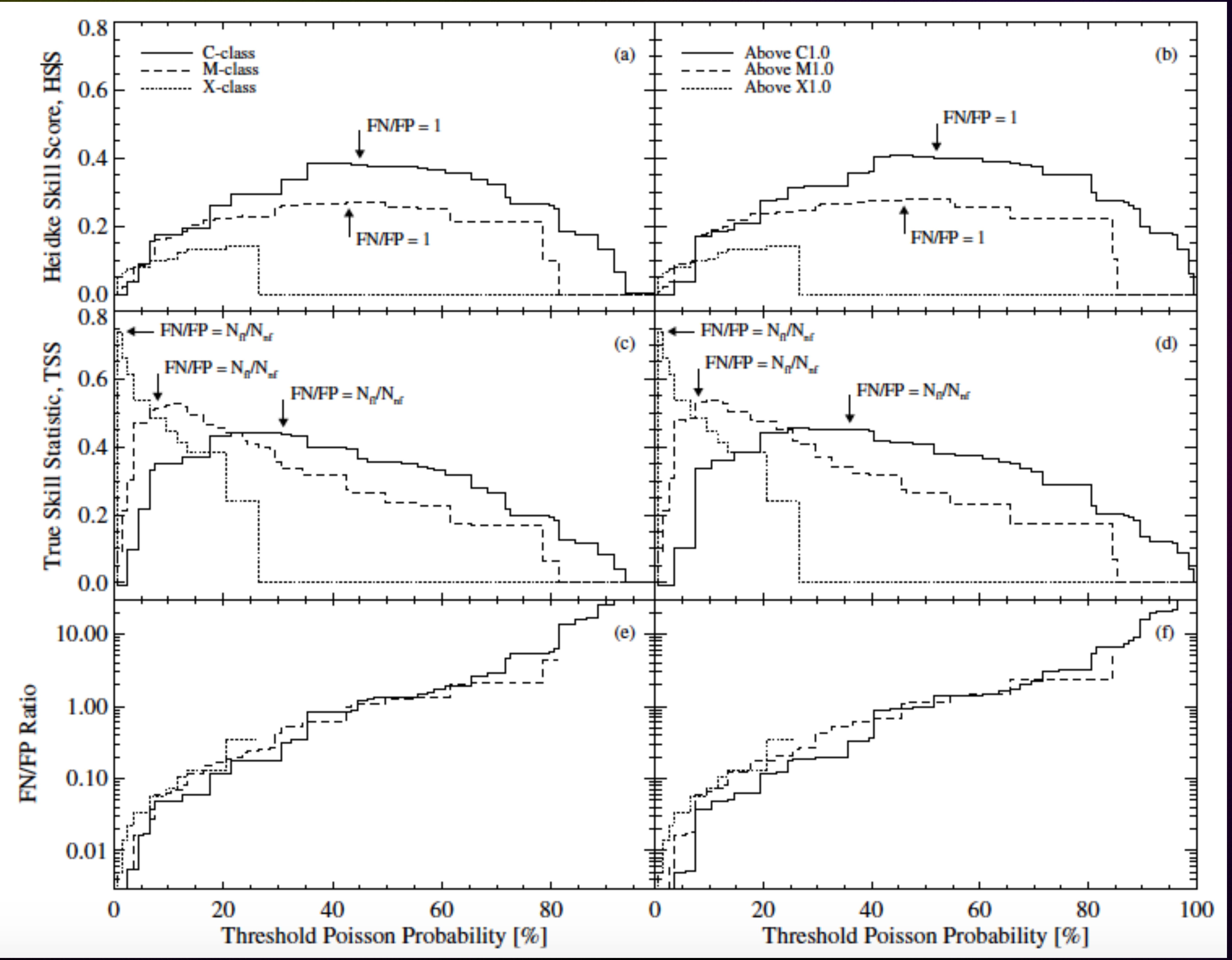

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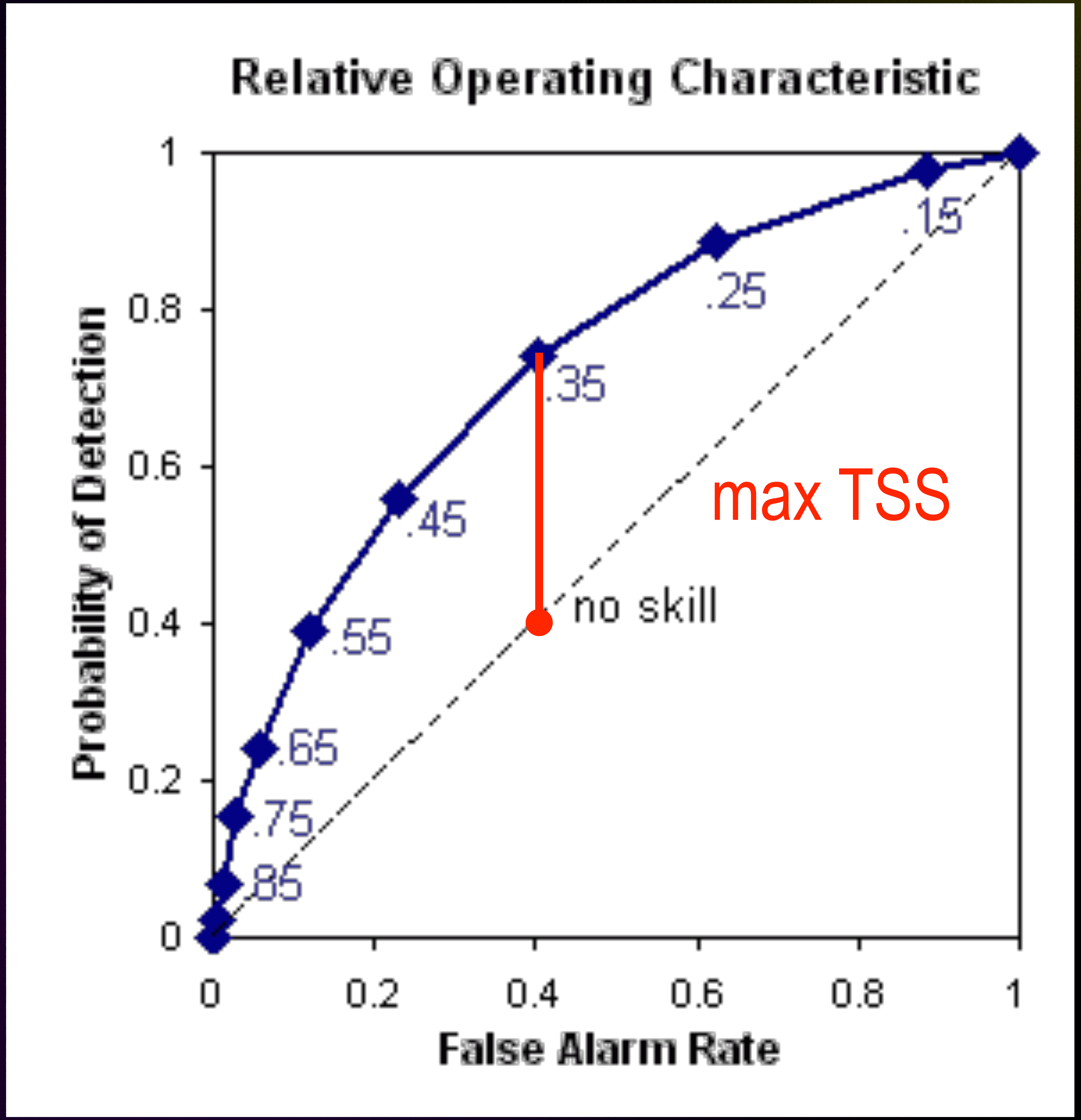
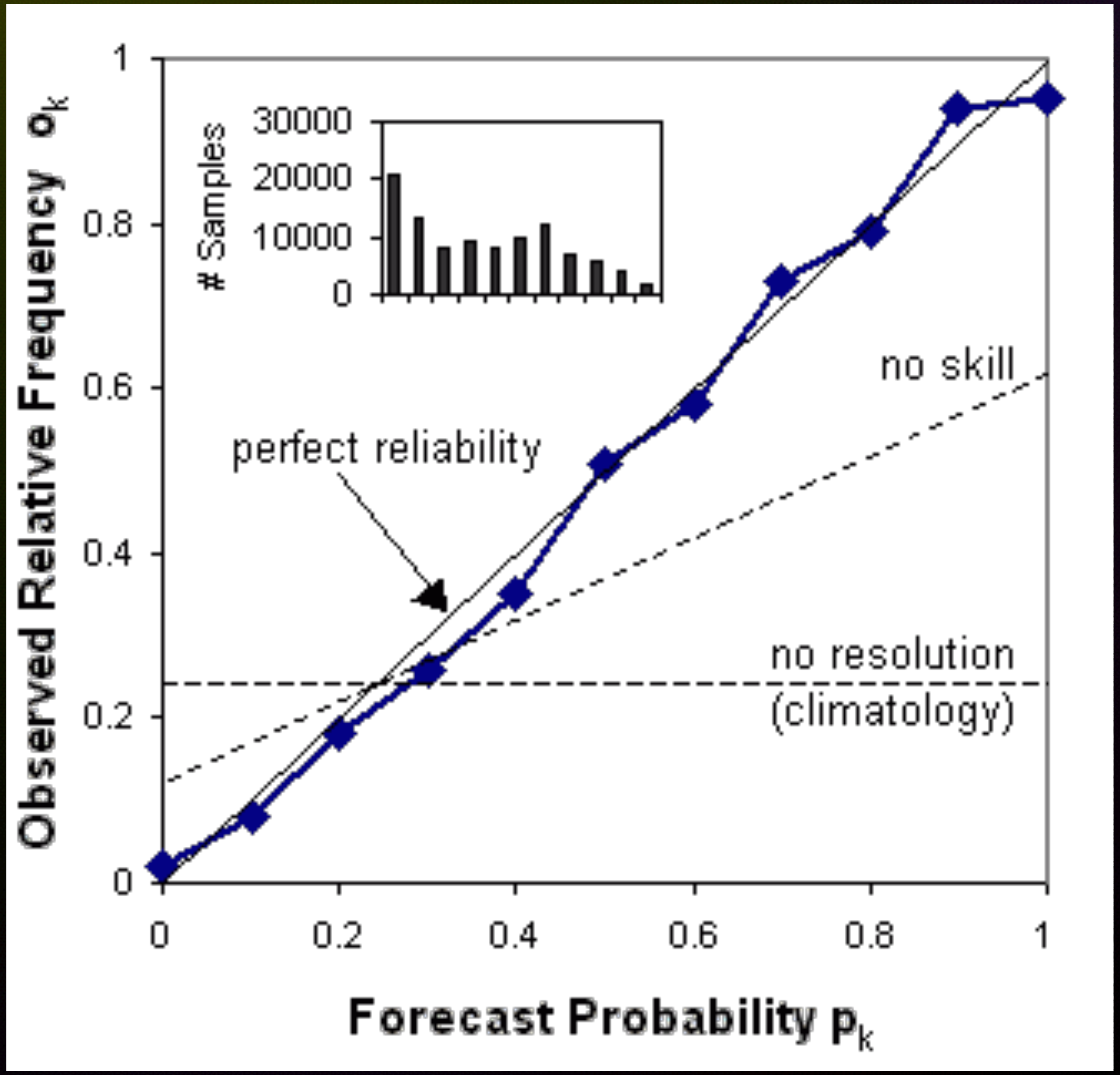


Example ROC curve (TSS vs. p_{thres})

PROBABILISTIC VALIDATION

Accept that a probability 0 < p < 1 is assigned to each prediction



Reliabillity diagram

$$SS = 1 - \frac{MSE_{forecast}}{MSE_{reference}}$$

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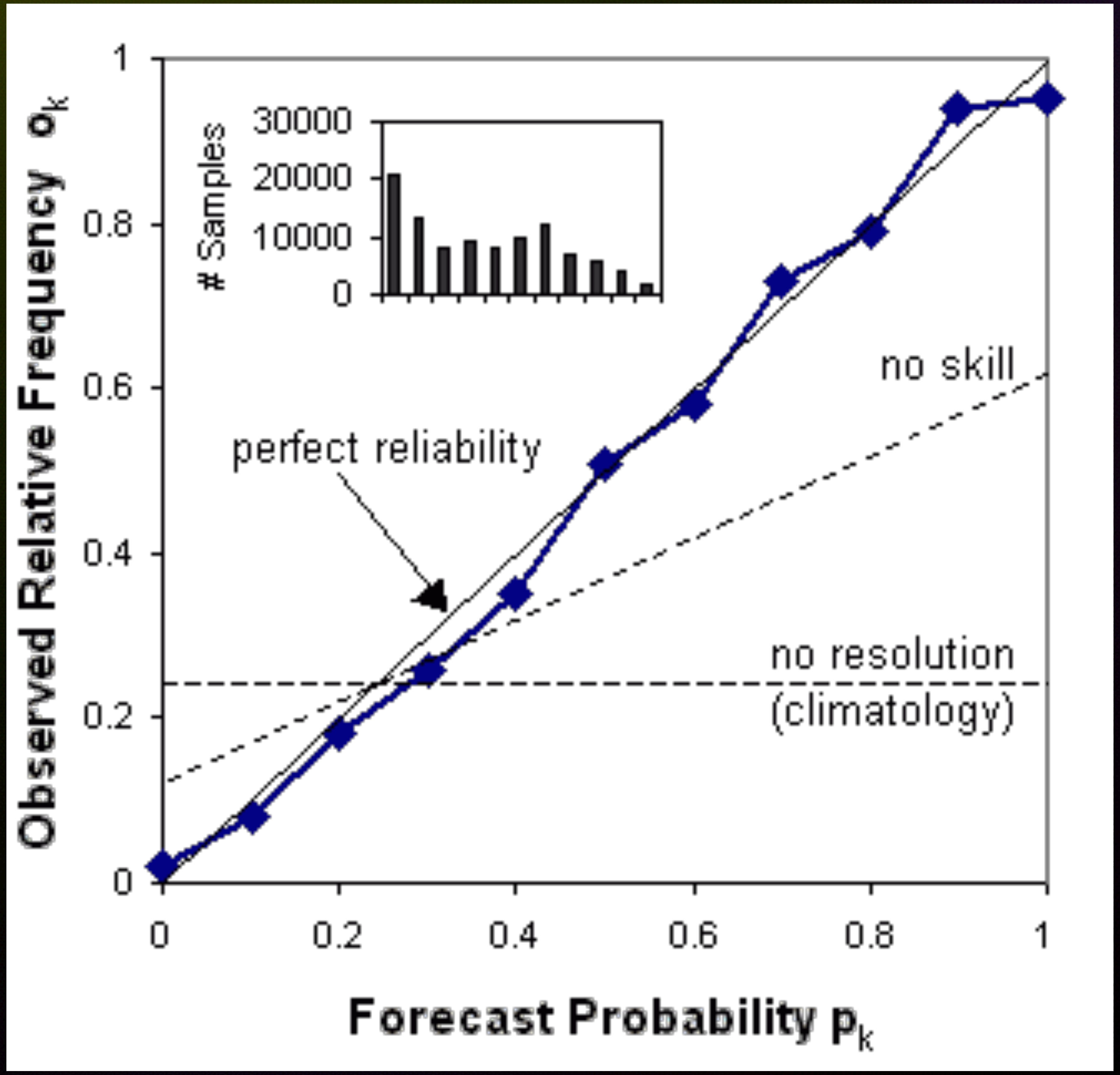

Reliabillity diagram

- Correlate forecast probability with observed frequency
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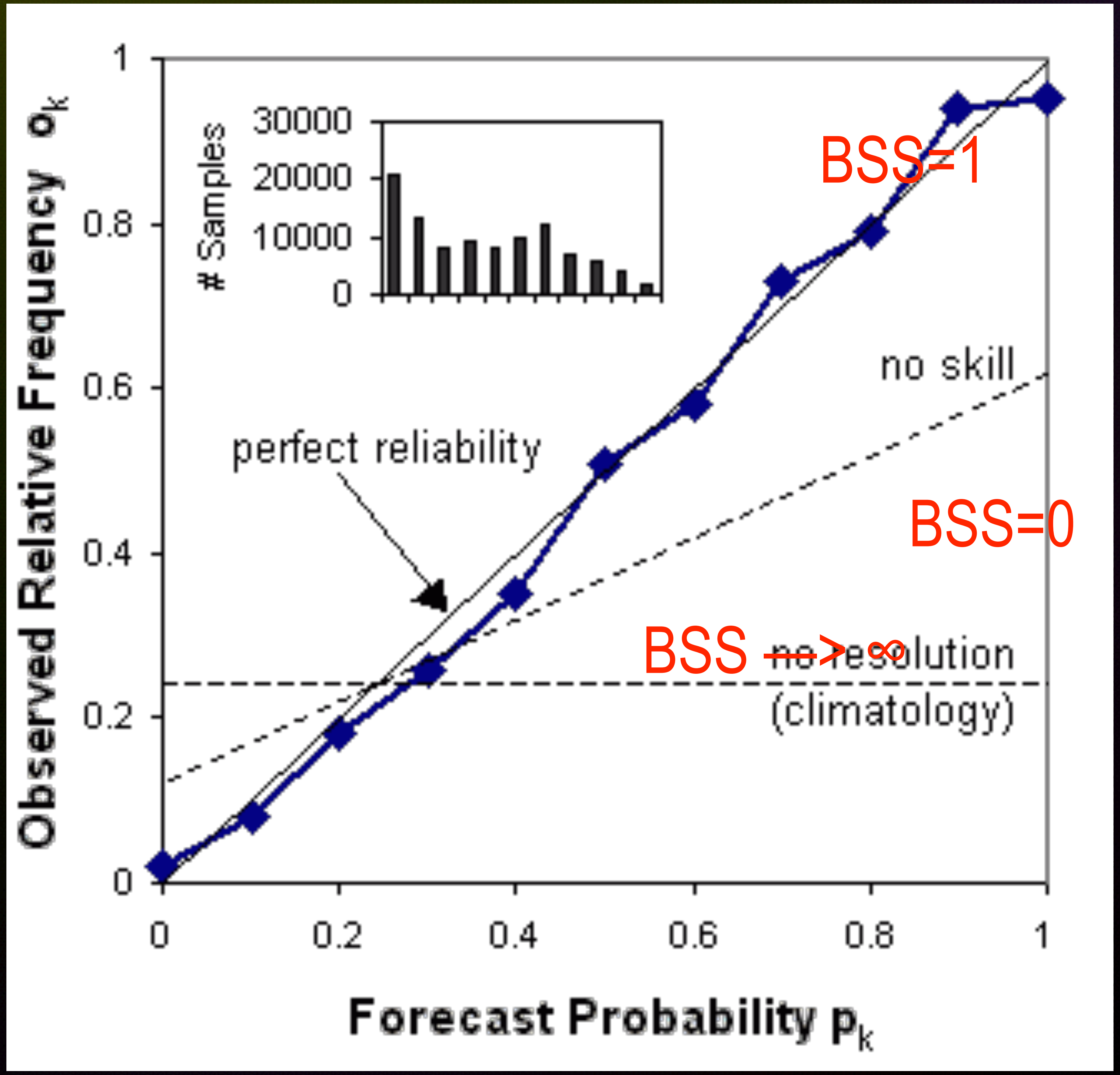

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- Brier skill score (reference: climatology):

$$BSS = 1 - \frac{\langle (o-p)^2 \rangle}{\langle (o-\bar{o})^2 \rangle}$$

$$BSS \in (-\infty, 1)$$

FIRST EFFORT TO COMPARE METHOD PERFORMANCES ON COMMON DATA SETS

Recently published (Barnes et al., 2016)

Parameter/ Method	Statistical Method	C1.0+, 24 hr ApSS	C1.0+, 24 hr BSS	M1.0+, 12 hr ApSS	M1.0+, 12 hr BSS	M5.0+, 12 hr ApSS	M5.0+, 12 hr BSS
B_{eff}	Bayesian	0.12	0.06	0.00	0.03	0.00	0.02
ASAP	Machine	0.25	0.30	0.01	-0.01	0.00	-0.84
BBSO	Machine	0.08	0.10	0.03	0.06	0.00	-0.01
WL_{SG2}	Curve fitting	N/A	N/A	0.04	0.06	0.00	0.02
NWRA MAG 2-VAR	NPDA	0.24	0.32	0.04	0.13	0.00	0.06
$\log(\mathcal{R})$	NPDA	0.17	0.22	0.01	0.10	0.02	0.04
GCD	NPDA	0.02	0.07	0.00	0.03	0.00	0.02
NWRA MCT 2-VAR	NPDA	0.23	0.28	0.05	0.14	0.00	0.06
SMART2	CCNN	0.24	-0.12	0.01	-4.31	0.00	-11.2
Event Statistics, 10 prior	Bayesian	0.13	0.04	0.01	0.10	0.01	0.00
McIntosh	Poisson	0.15	0.07	0.00	-0.06	N/A	N/A

Event List	Event	No Event	Event Rate	Event	No Event	Event Rate	Event	No Event	Event Rate
	AD			MCD#1			MCD#2		
C1.0+, 24 hr	2609	10356	0.201	789	3751	0.174	249	128	0.660
M1.0+, 12 hr	400	12565	0.031	102	3162	0.031	70	220	0.241
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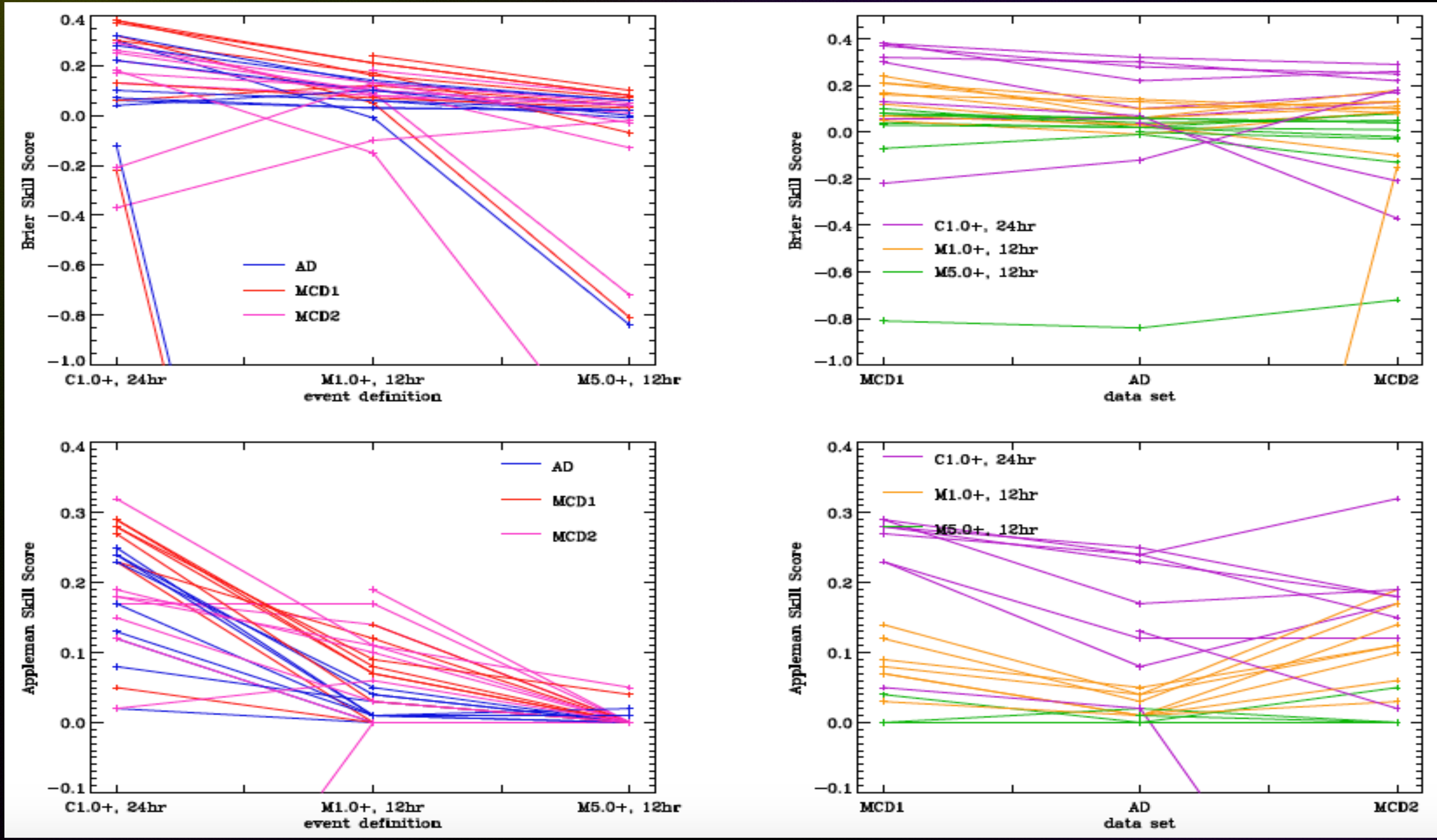
Apparently worse BSS for scarcer (i.e., increasing flare class) events

Typically a bit - but not much - better than climatology (> 0) / quite often worse than climatology (< 0)

FIRST EFFORT TO COMPARE METHOD PERFORMANCES ON COMMON DATA SETS



Generally, there is no method clearly outperforming the others

Barnes et al., (2016)

VALIDATION REQUIREMENTS

- Balanced dataset of flaring and non-flaring populations (correct flaring rates)

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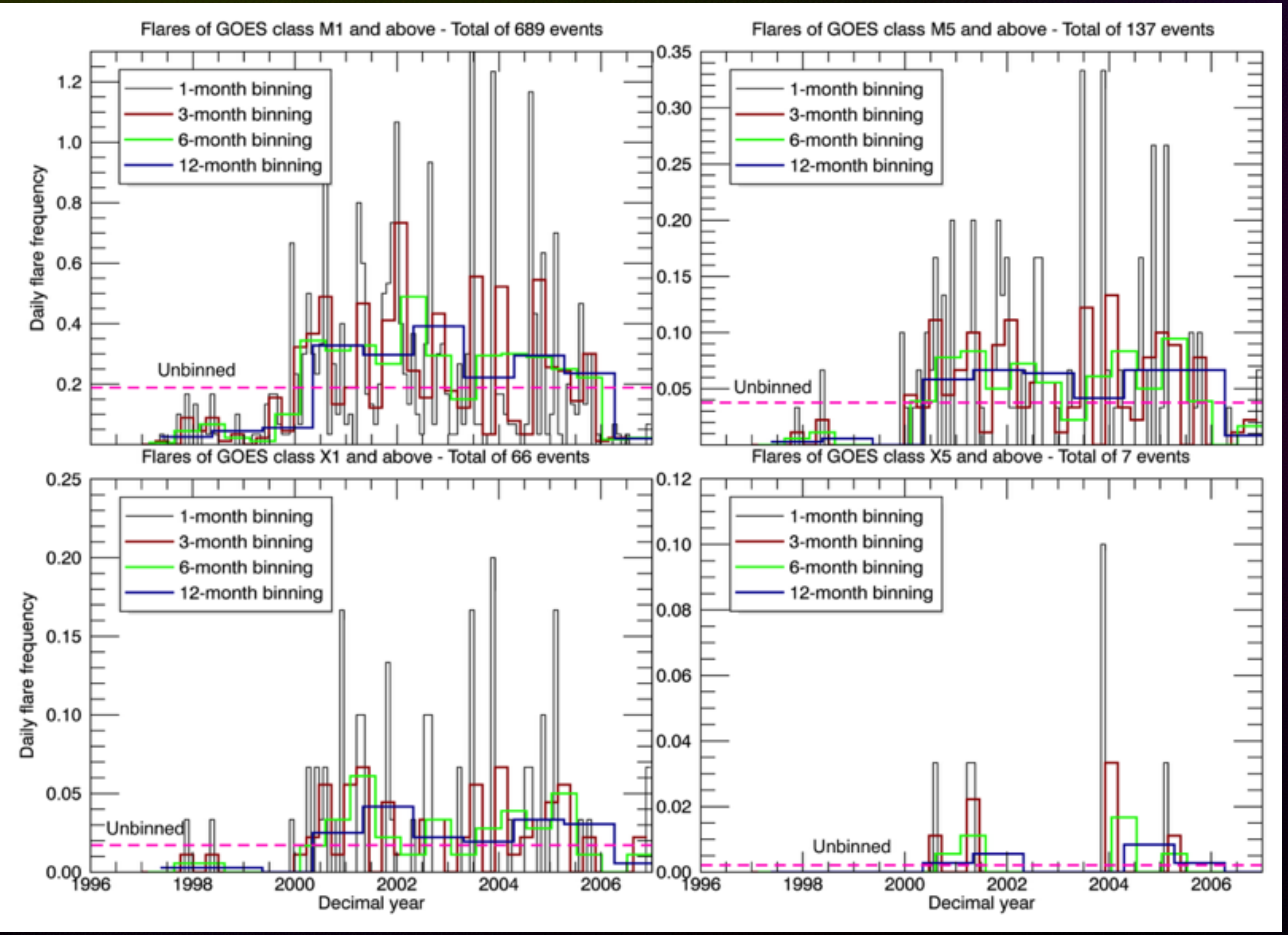
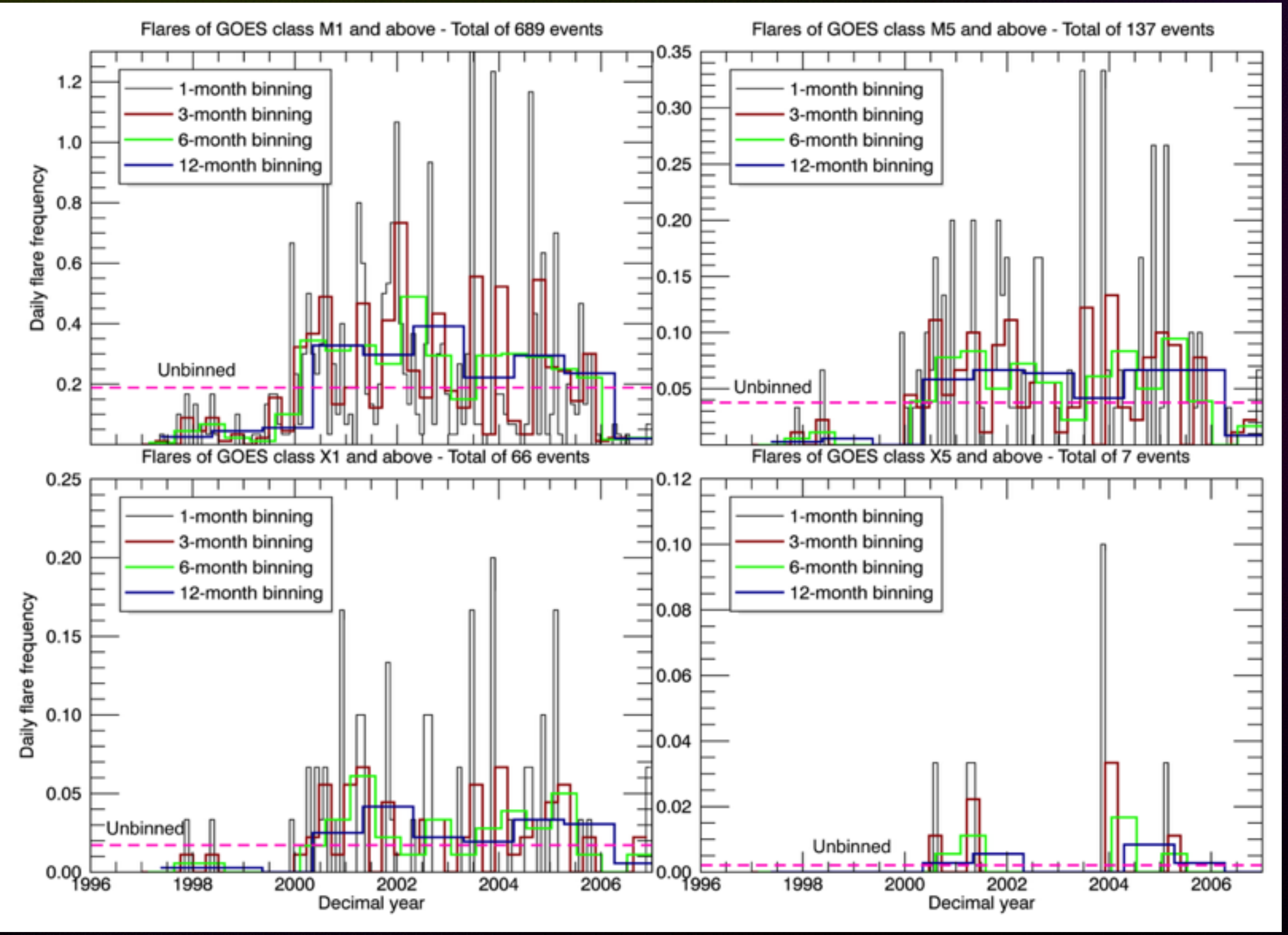


Flaring rates over solar cycle 23 (M1+, M5+, X1+, X5+)

VALIDATION REQUIREMENTS

- Balanced dataset of flaring and non-flaring populations (correct flaring rates)
- Large number of validation tests, using randomly chosen training and test sets



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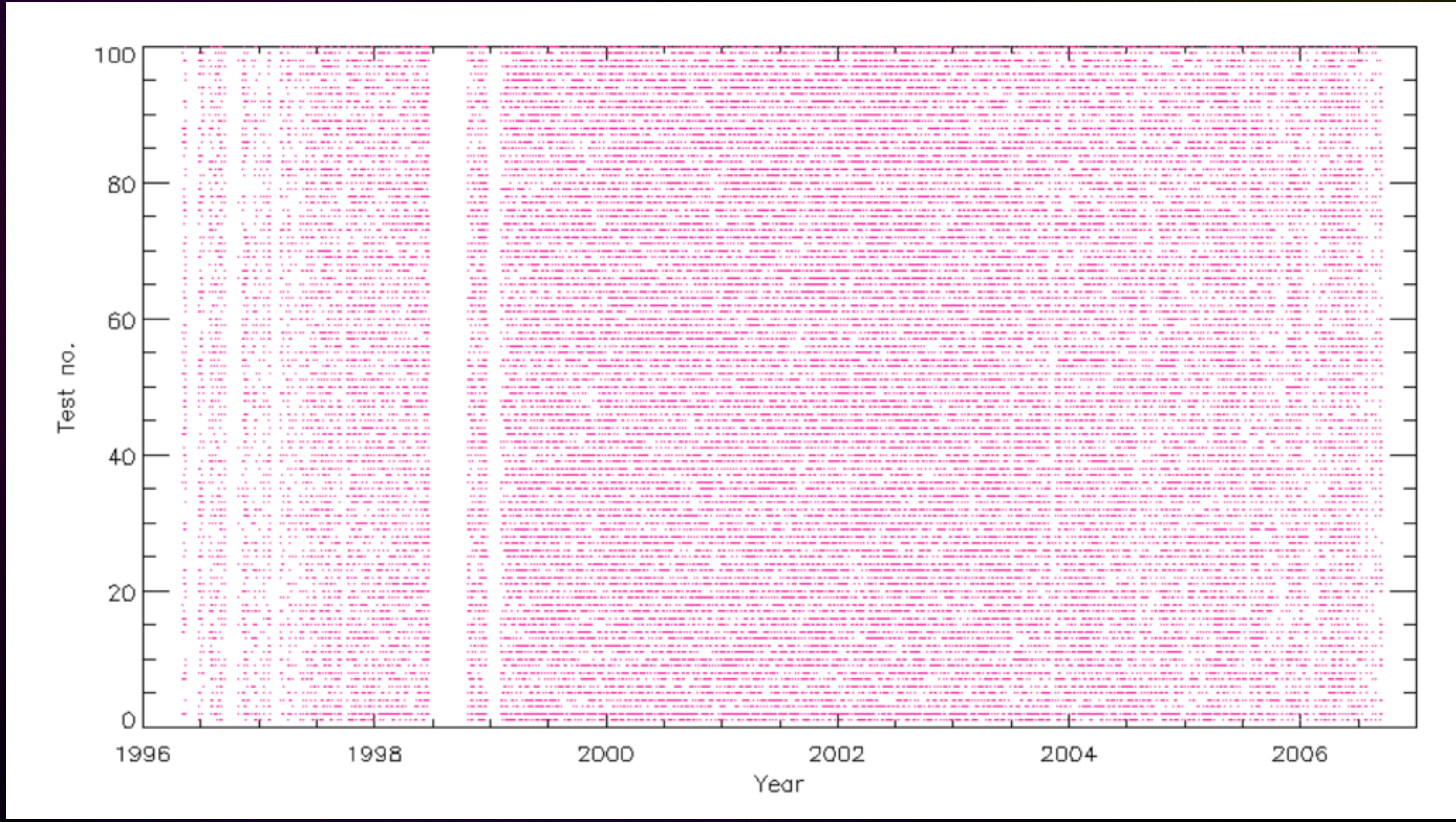
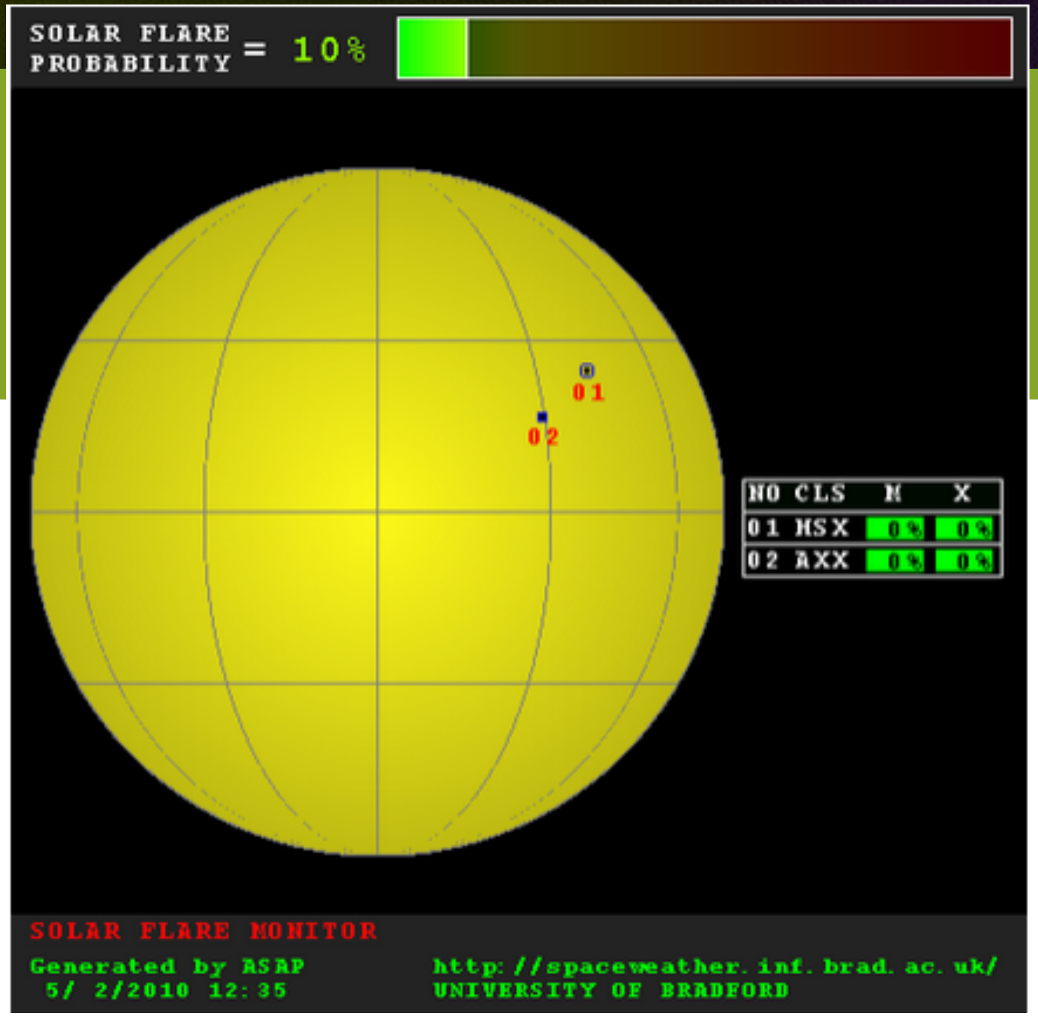


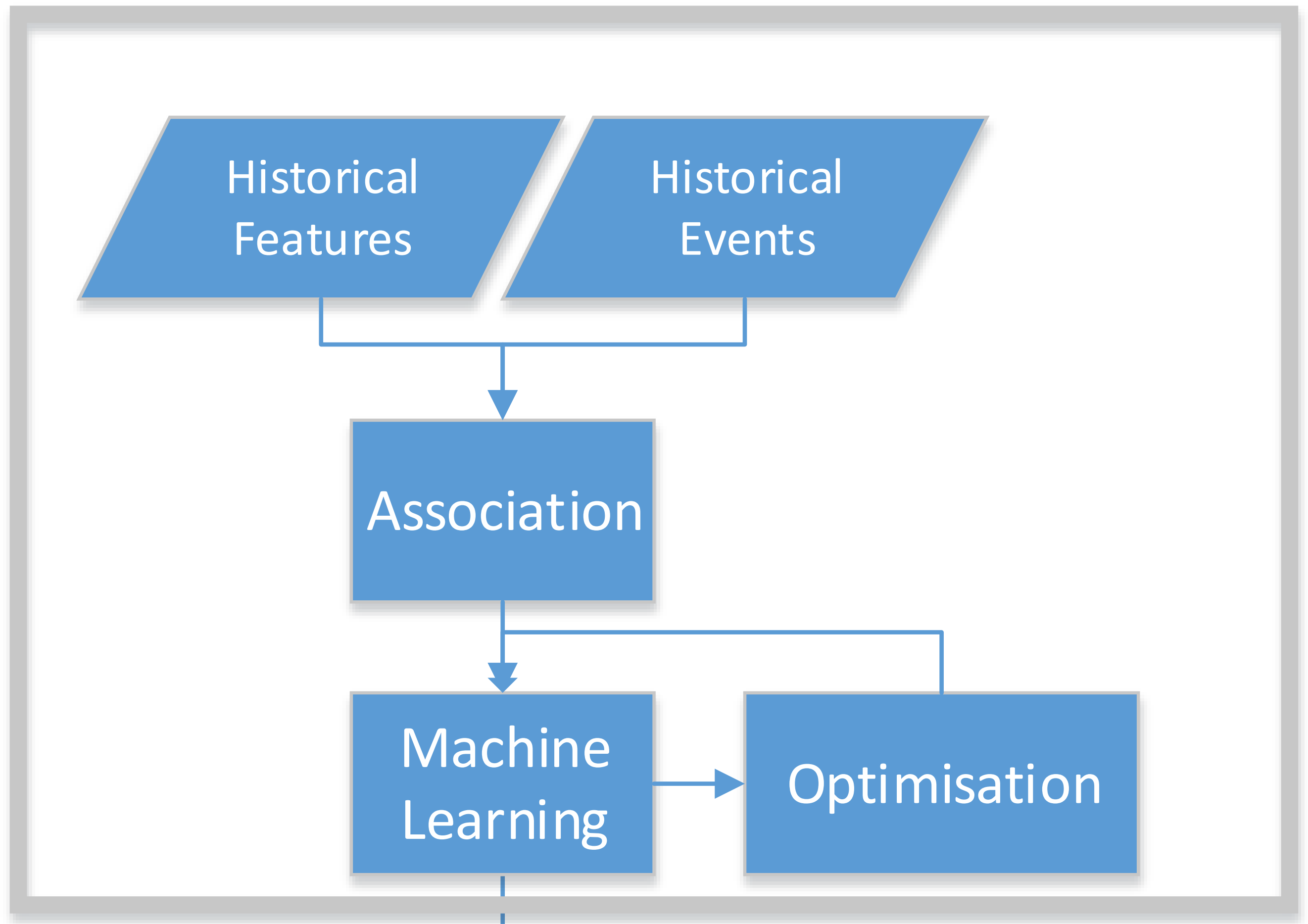
Random selection of training (white) and testing (red dots) subsets

FROM PREDICTION METHODS TO OPERATIONAL FLARE FORECASTING SERVICES

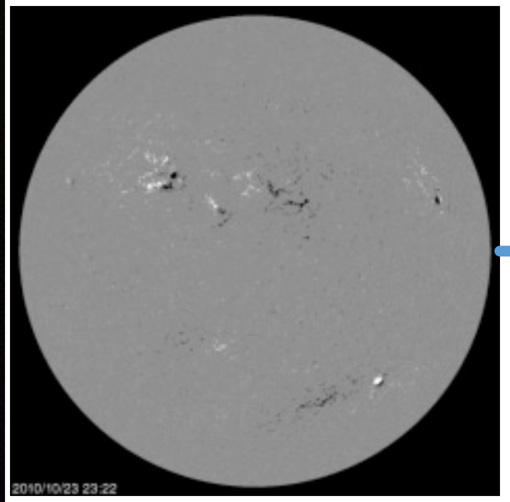
ASAP



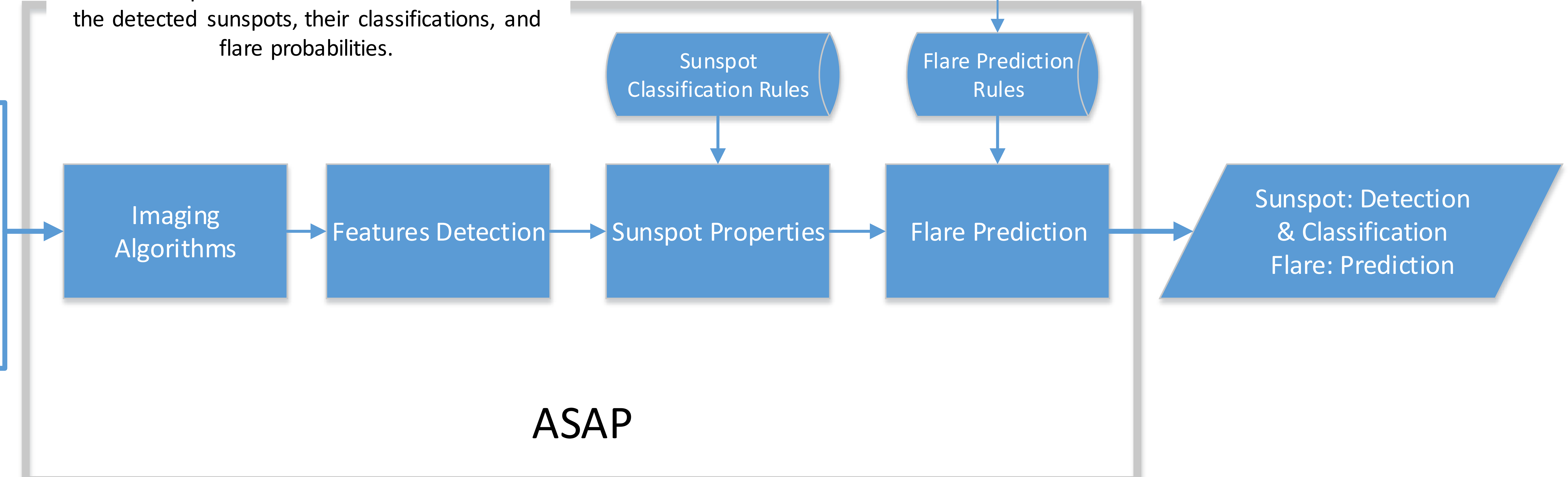
ASAP's Output: Flare Monitor. Visualisation of the detected sunspots, their classifications, and flare probabilities.



MDI Continuum



MDI Magnetogram



ASAP: The first flare prediction service utilizing machine learning methods

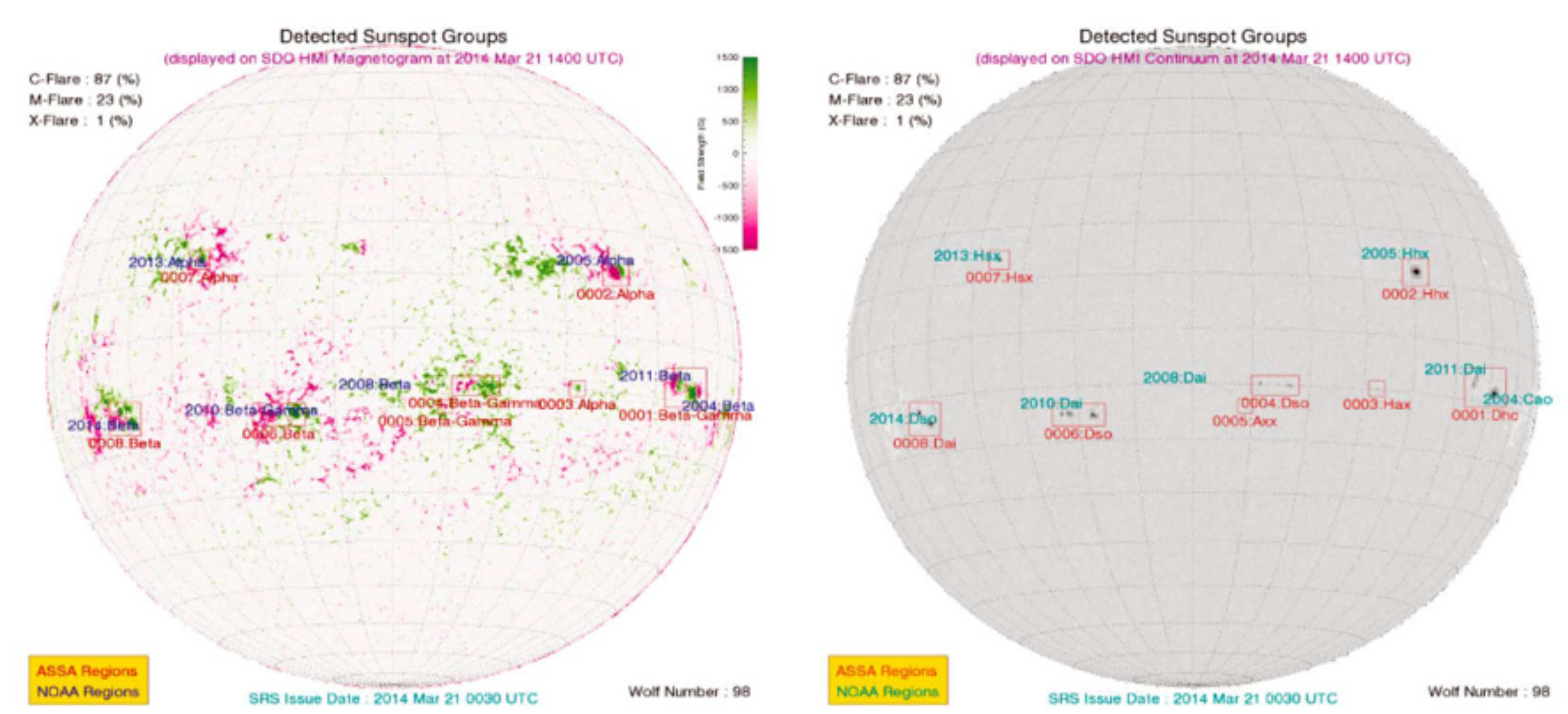
Besides the idea (prediction method), an infrastructure is also needed

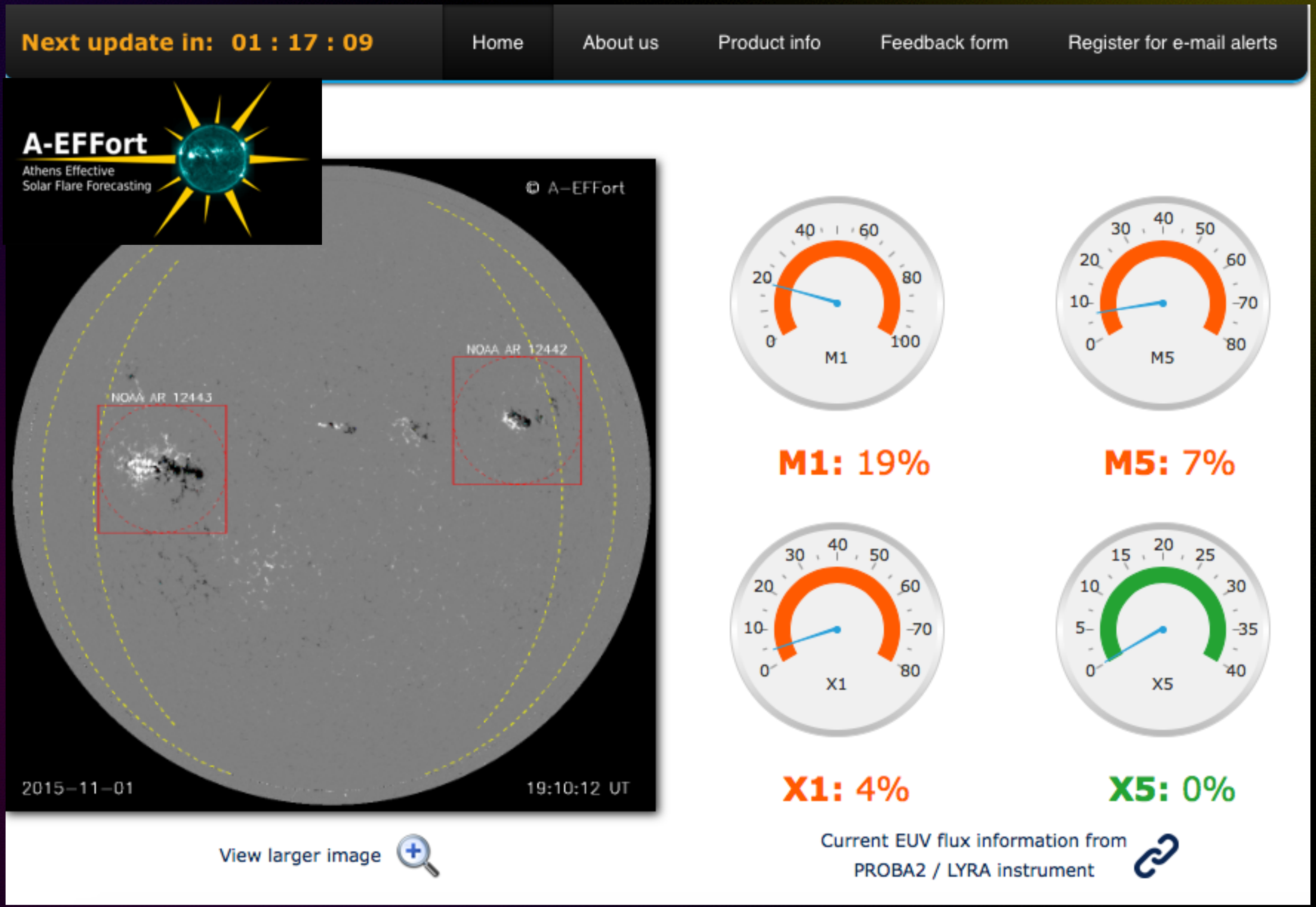
Complete automation means:

- Ease of calculations
- Ease of maintenance
- Resilience
- Modularity, for improvement

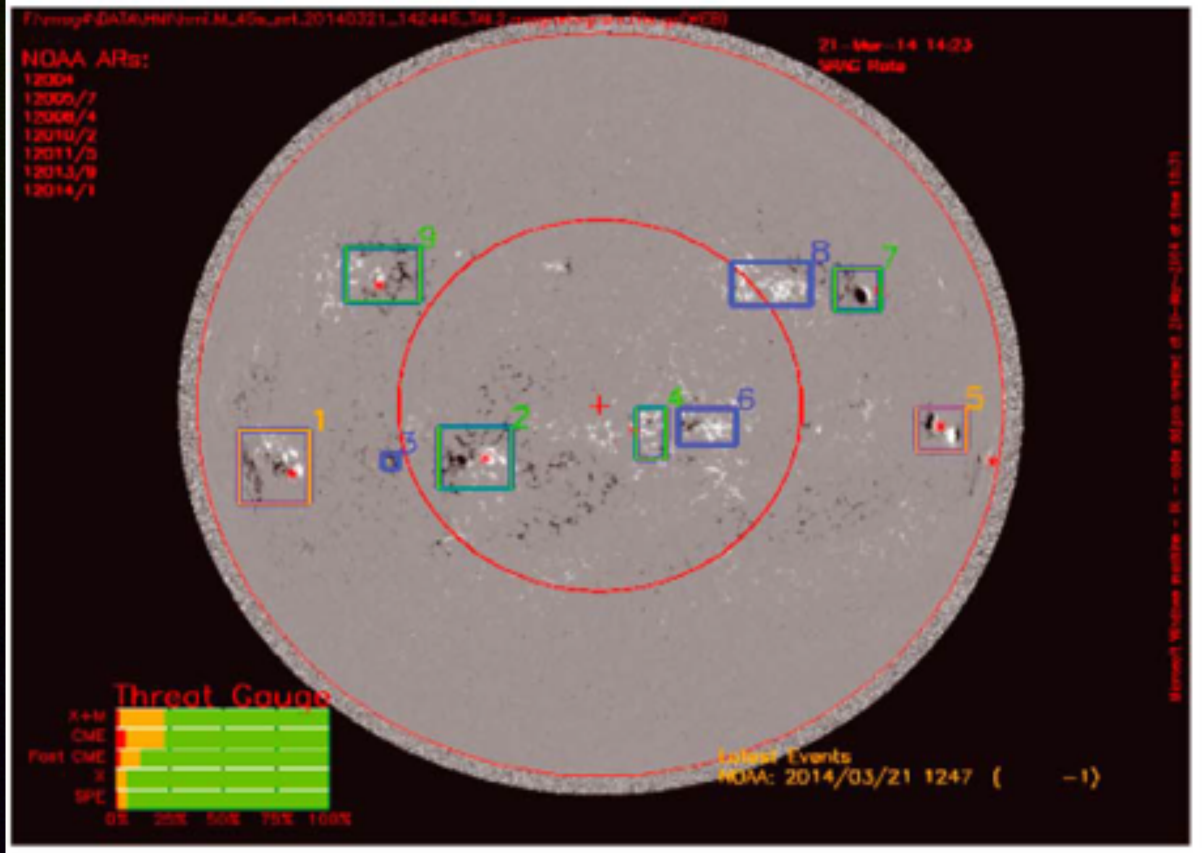
EXISTING FLARE PREDICTION SERVICES AROUND THE WORLD

ASSA

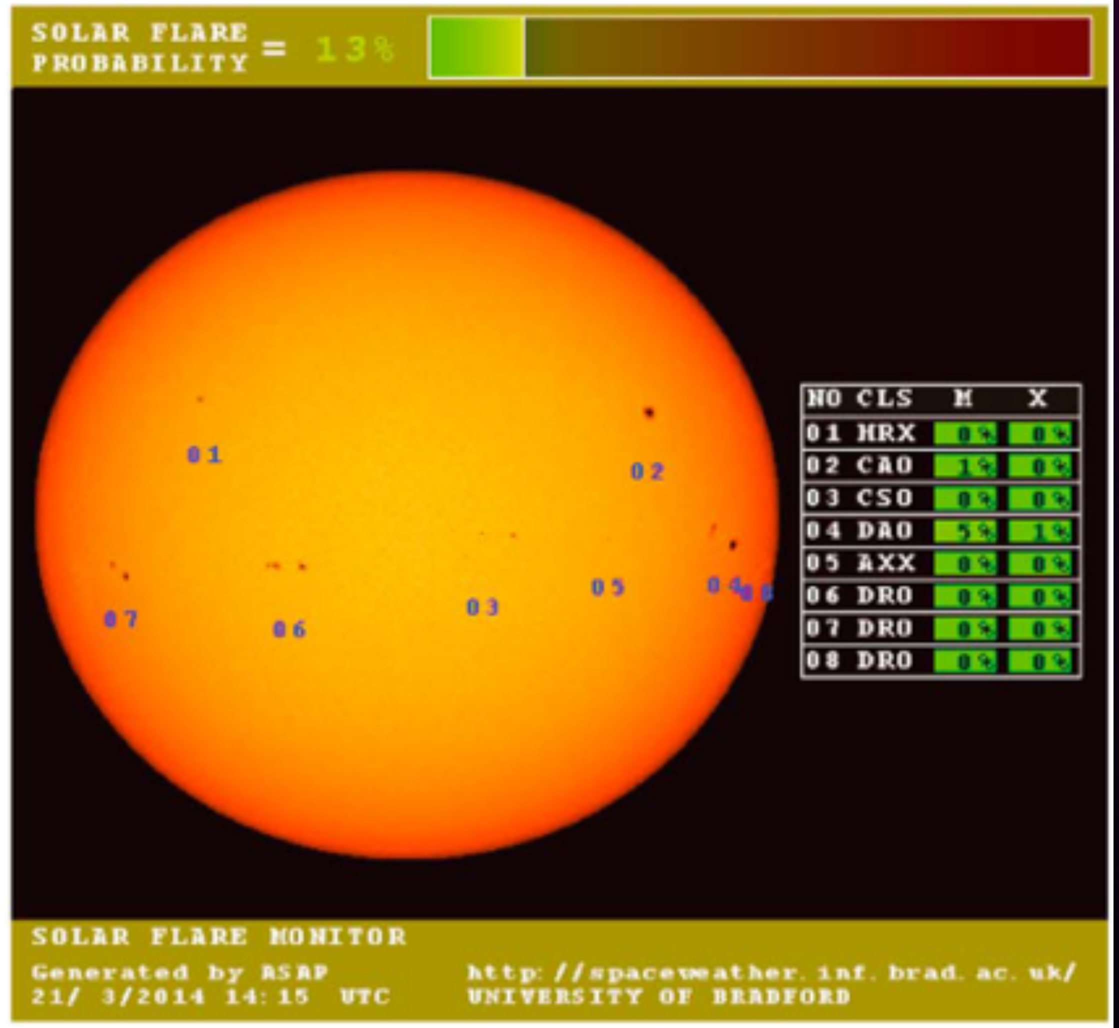




MAG4



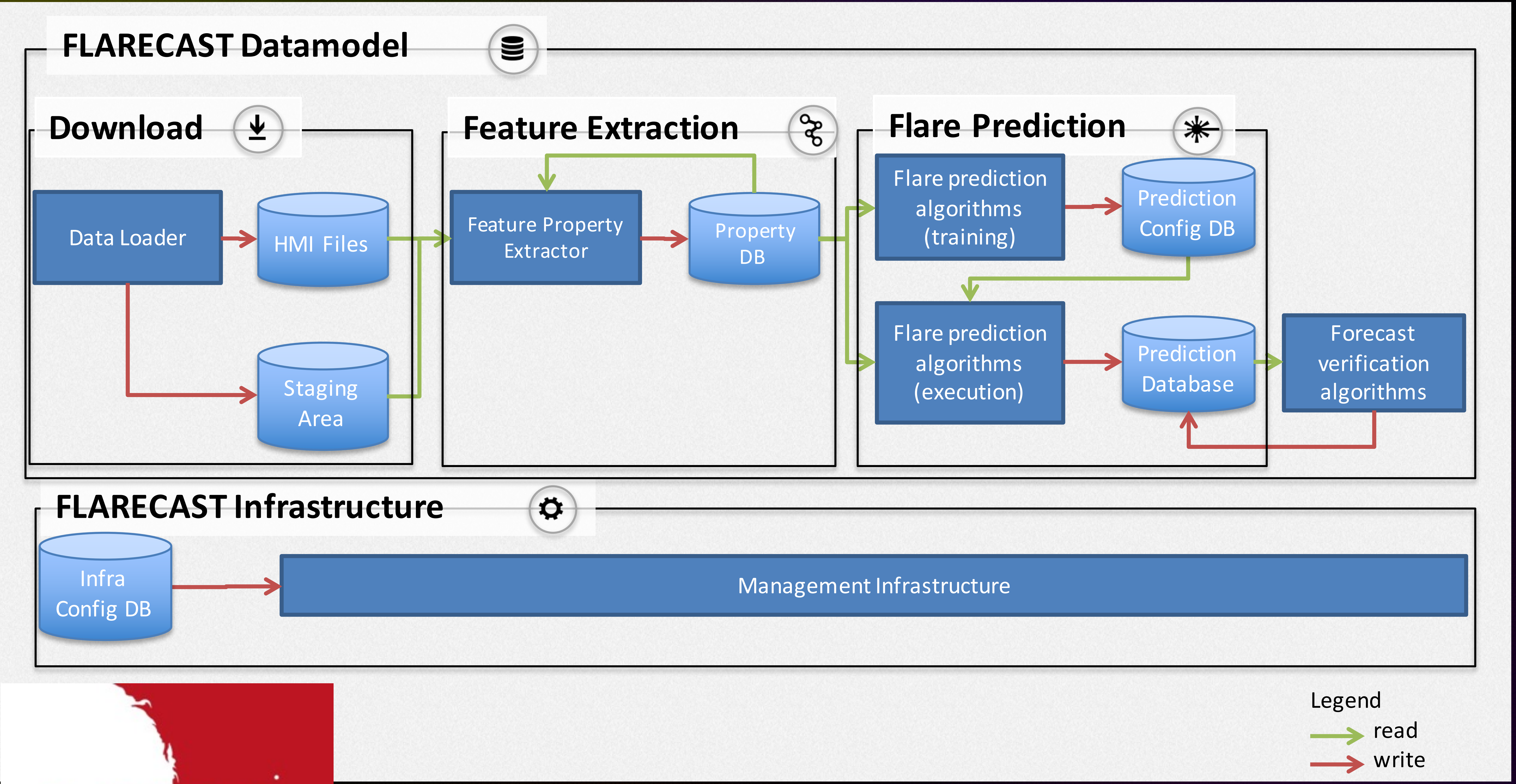
ASAP



www.SolarMonitor.org

Guerra et al., (2015)

A NUMBER OF FORTHCOMING SERVICES



DAFFS

Europe, USA, Japan

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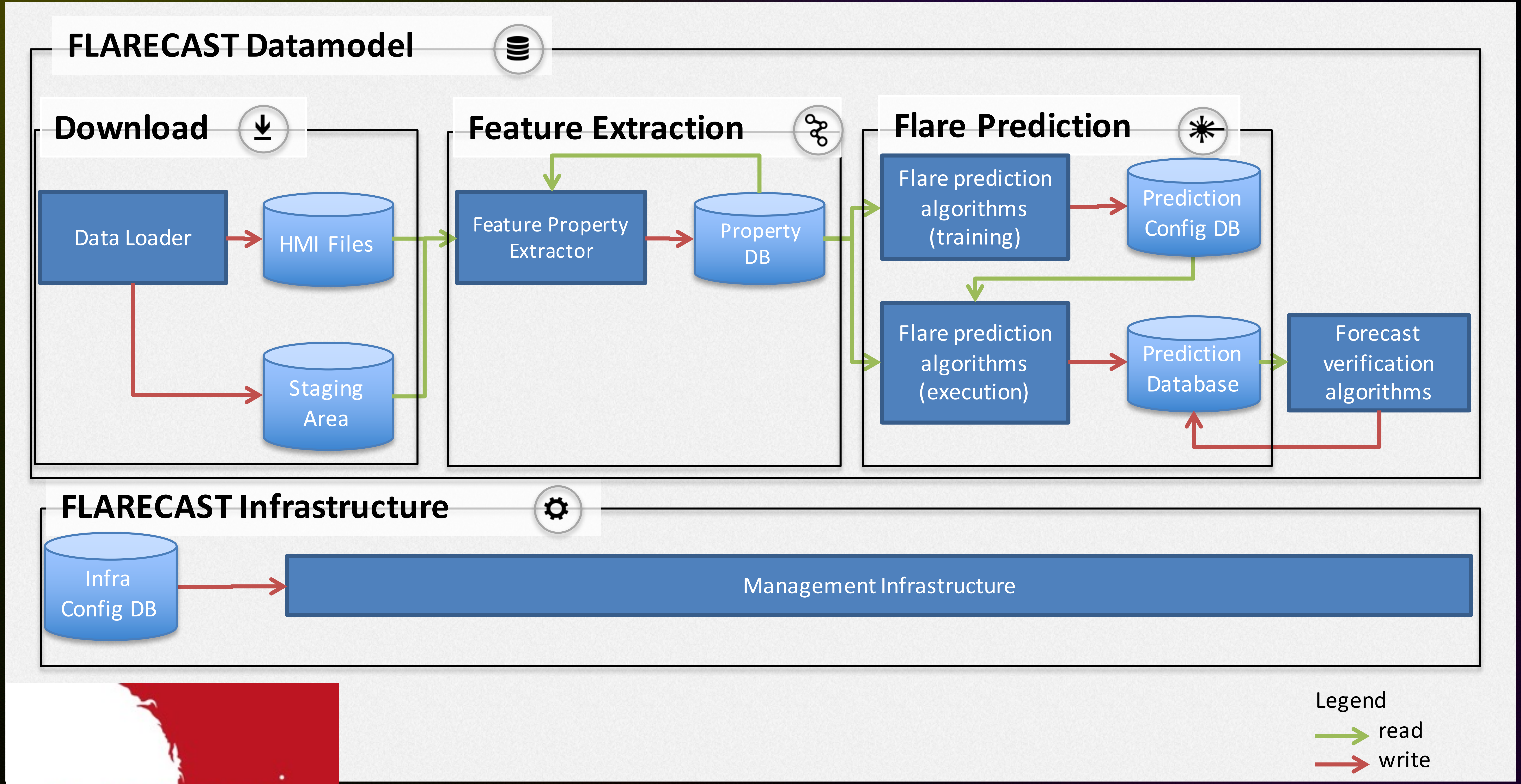

DAFFS

PSTEP

FLARECAST

Europe, USA, Japan

- **Fact:** Virtually all planned services rely essentially on multivariate predictors
- **Aphorism:** validation, validation, validation …

CONCLUSIONS

- ★ Consensus that reliable, automated solar flare prediction should be an asset of our SWE forecasting efforts
- ★ Can flares be predicted, however?
  - Quite likely, major flare prediction will remain probabilistic in the future
  - But is this due to the nature of the problem, or due to lack of crucial information or a flawed approach?
  - How far along we can go remains TBS — the goal of various flare forecasting efforts is to bring probabilistic flare prediction as close as possible to a binary (YES / NO one)
- ★ Customized, but always <u>unbiased</u>, validation : its importance cannot be stressed enough
- ★ Multivariate forecasting, enabled by machine-learning and other methods (i.e., PCA, DA) seems to be the norm for future services — we can do it nowadays, can't we?
- ★ <u>However, we need to raise Occam's razor</u> : how many / which parameters do we need for a sufficient forecasting? The answer will drive developments in our physical understanding of flare triggering

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Diverse expertise and ways of thinking are generally needed

All these issues and challenges referring to flare prediction …

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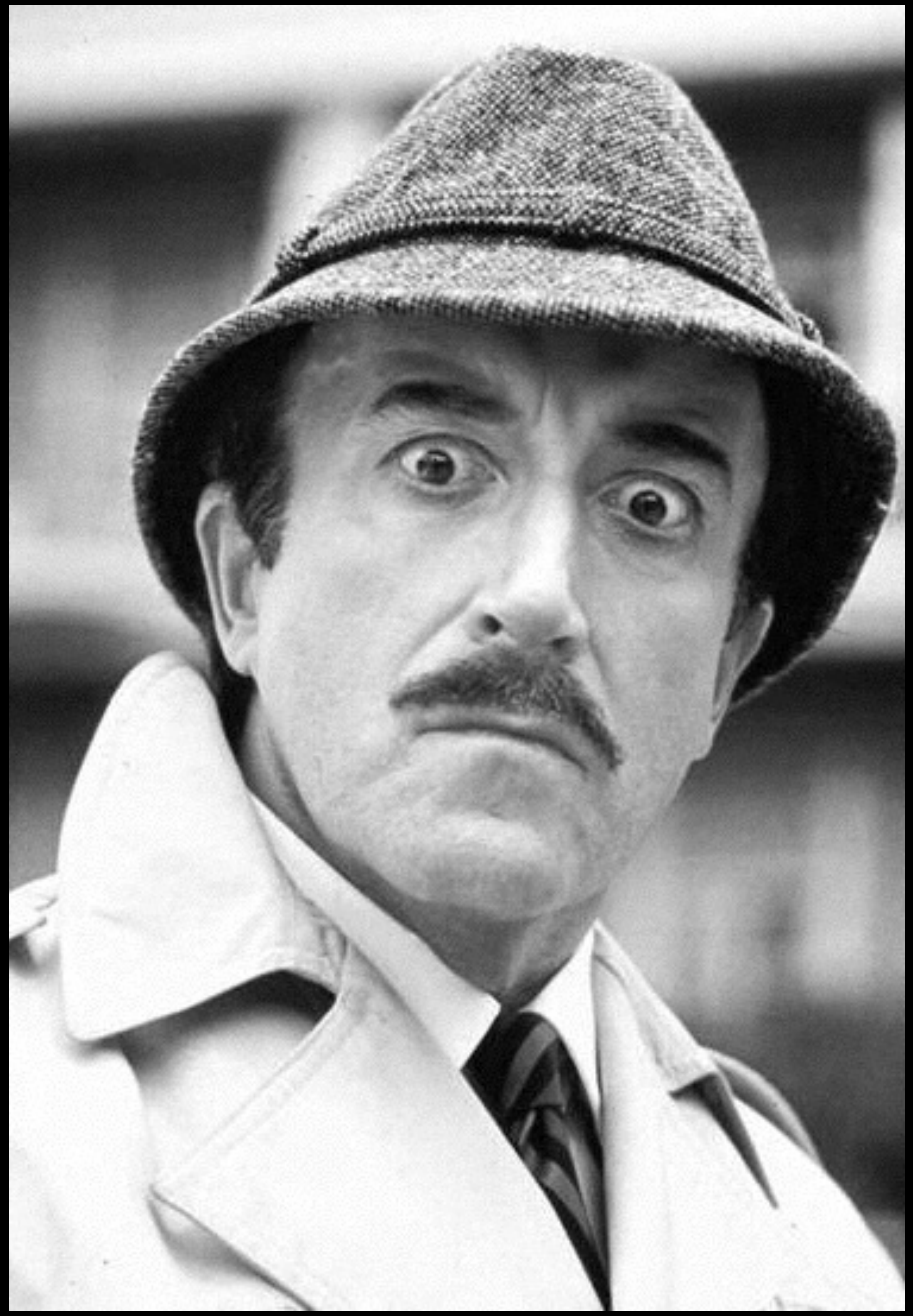

… we haven’t even touched CME and SEP prediction yet!

BACKUP SLIDES