PERFORMANCE VERIFICATION OF SOLAR-FLARE PREDICTION MODELS

from Climatology to Skill and from Forecast Probabilities to Certainty

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RCAAM of the Academy of Athens

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* A-EFFort (ESA/SSA): a-effort.academyofathens.gr
* FLARECAST (EC/H2020): flarecast.eu

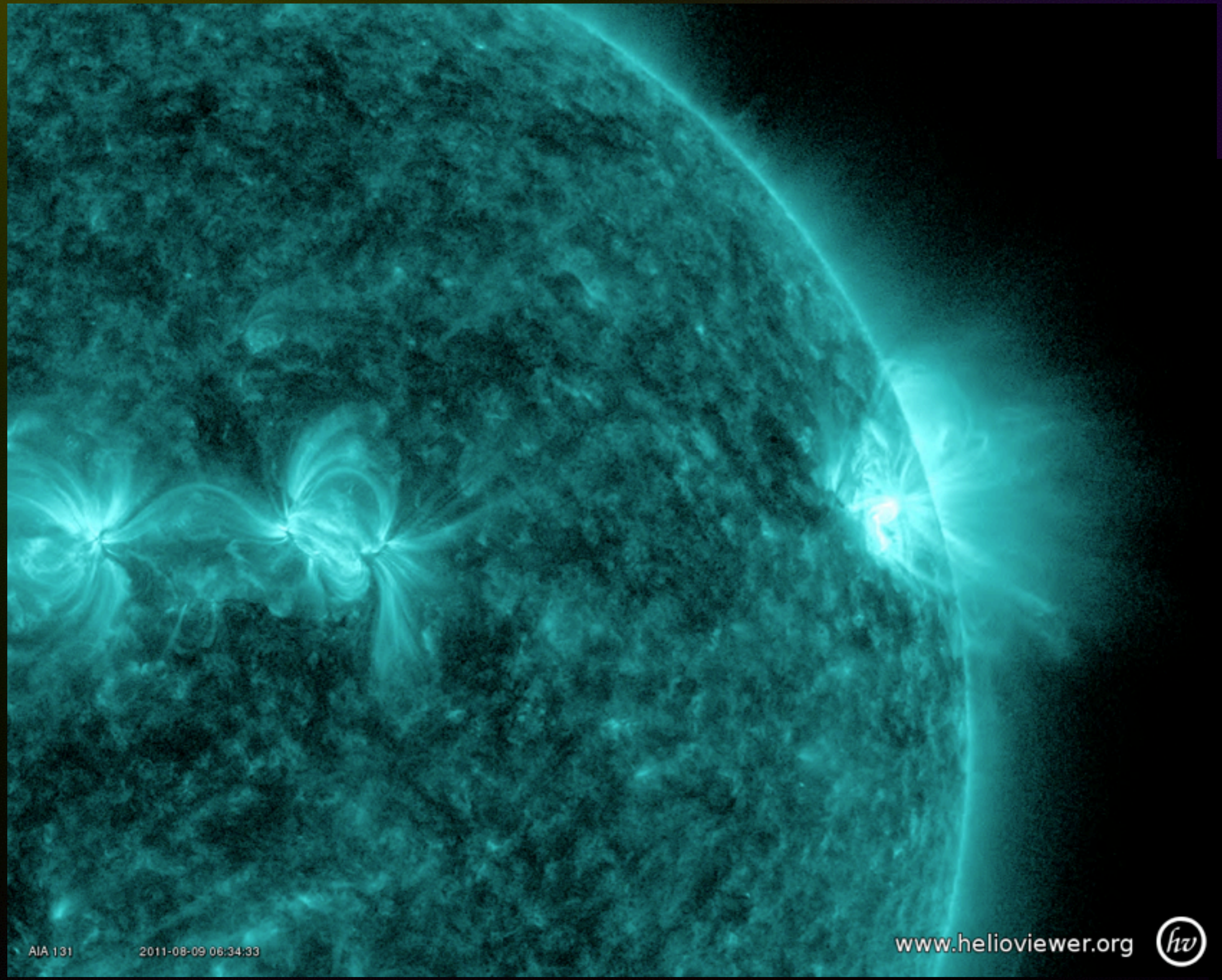
SCIENCE FOR SPACE WEATHER

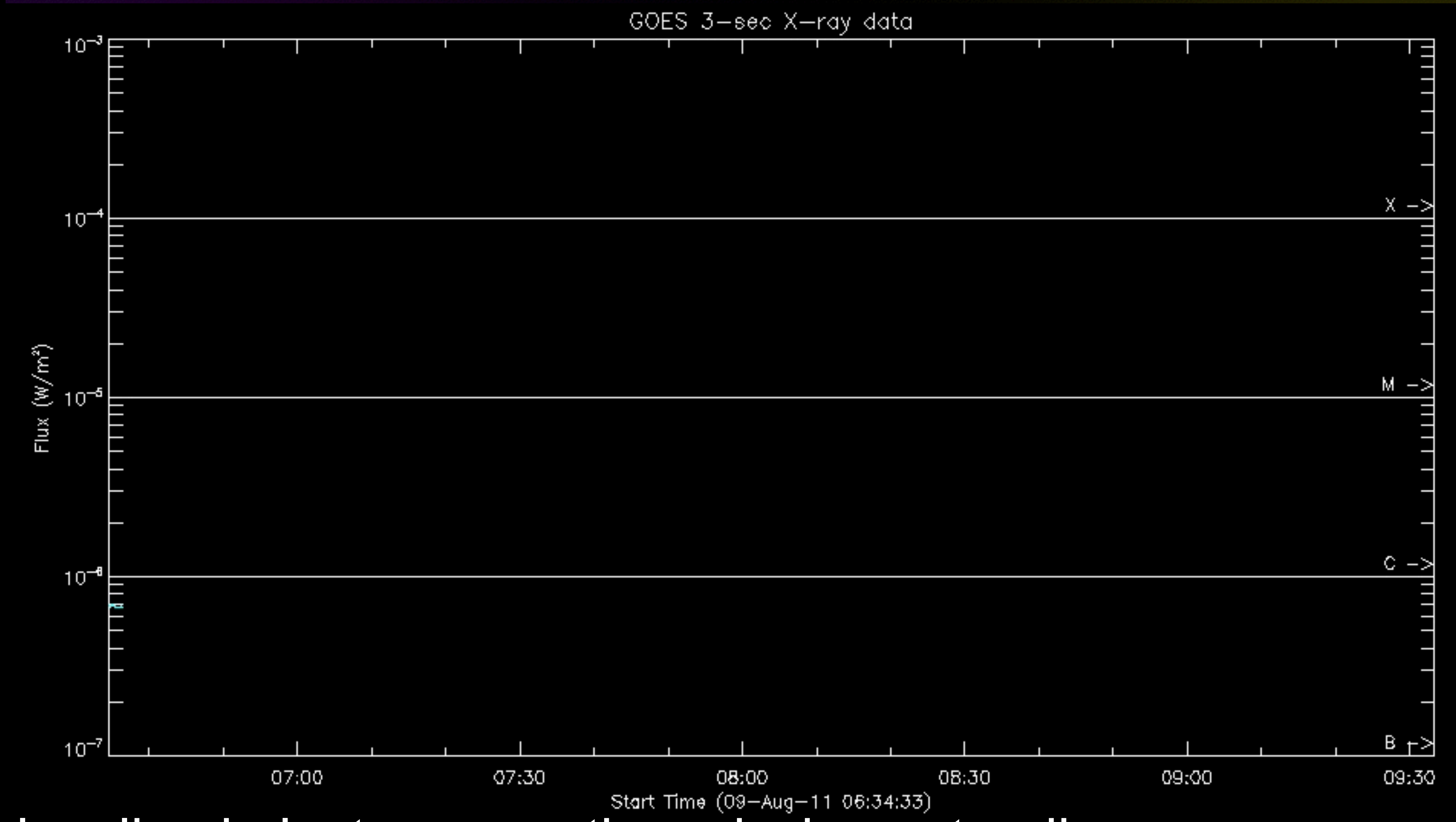
Goa, India, Jan 24 - 29, 2016

OUTLINE

- Solar flares and the prediction challenge
- Validation of flare prediction methods
  - *Dichotomous validation*
  - *Probabilistic validation*
- Tailoring prediction methods to the customers' needs
  - *Multi-variable forecasting*
  - *Ensemble forecasting*
- Conclusion

SOLAR FLARES: THE SINGLE …





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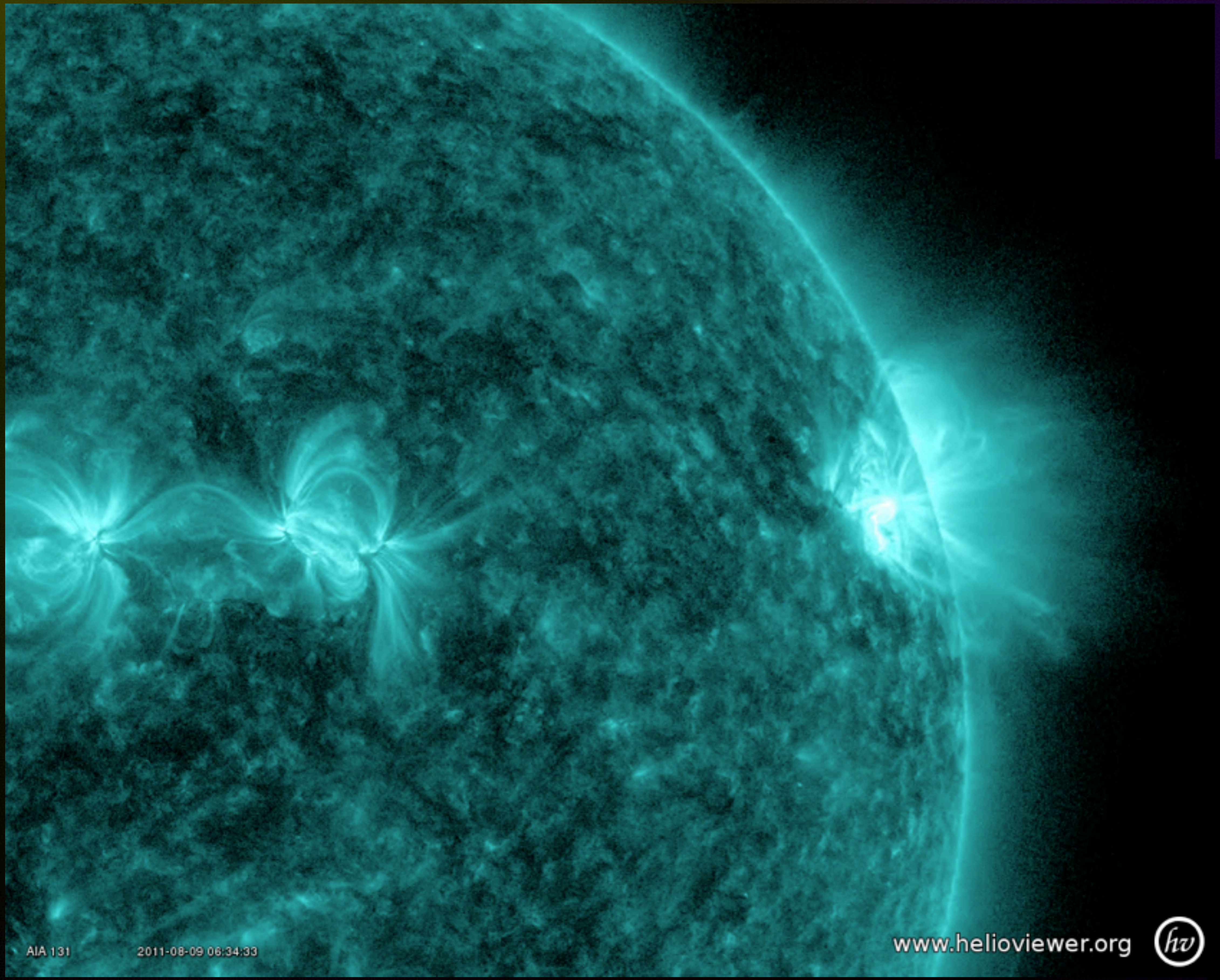

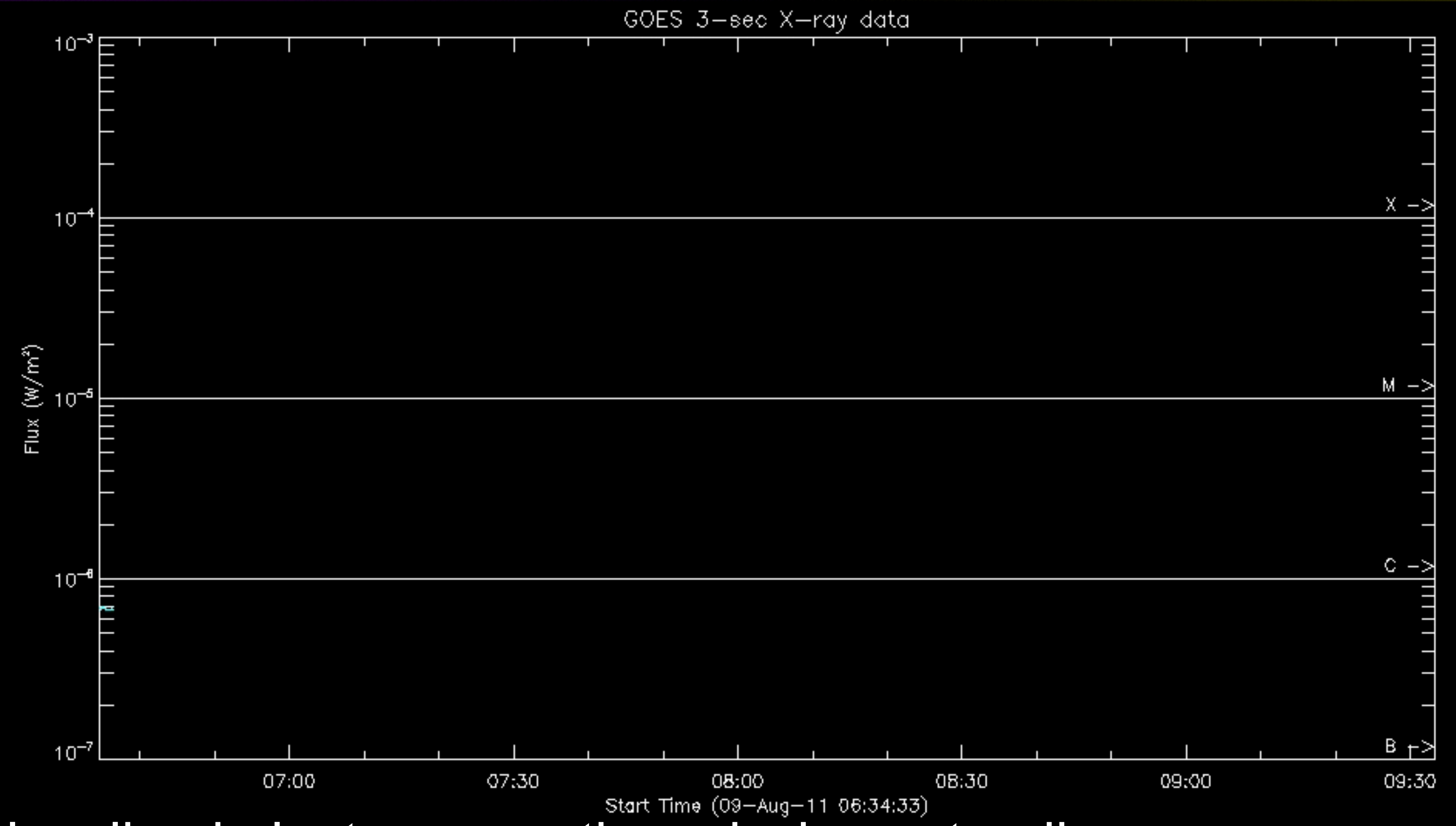

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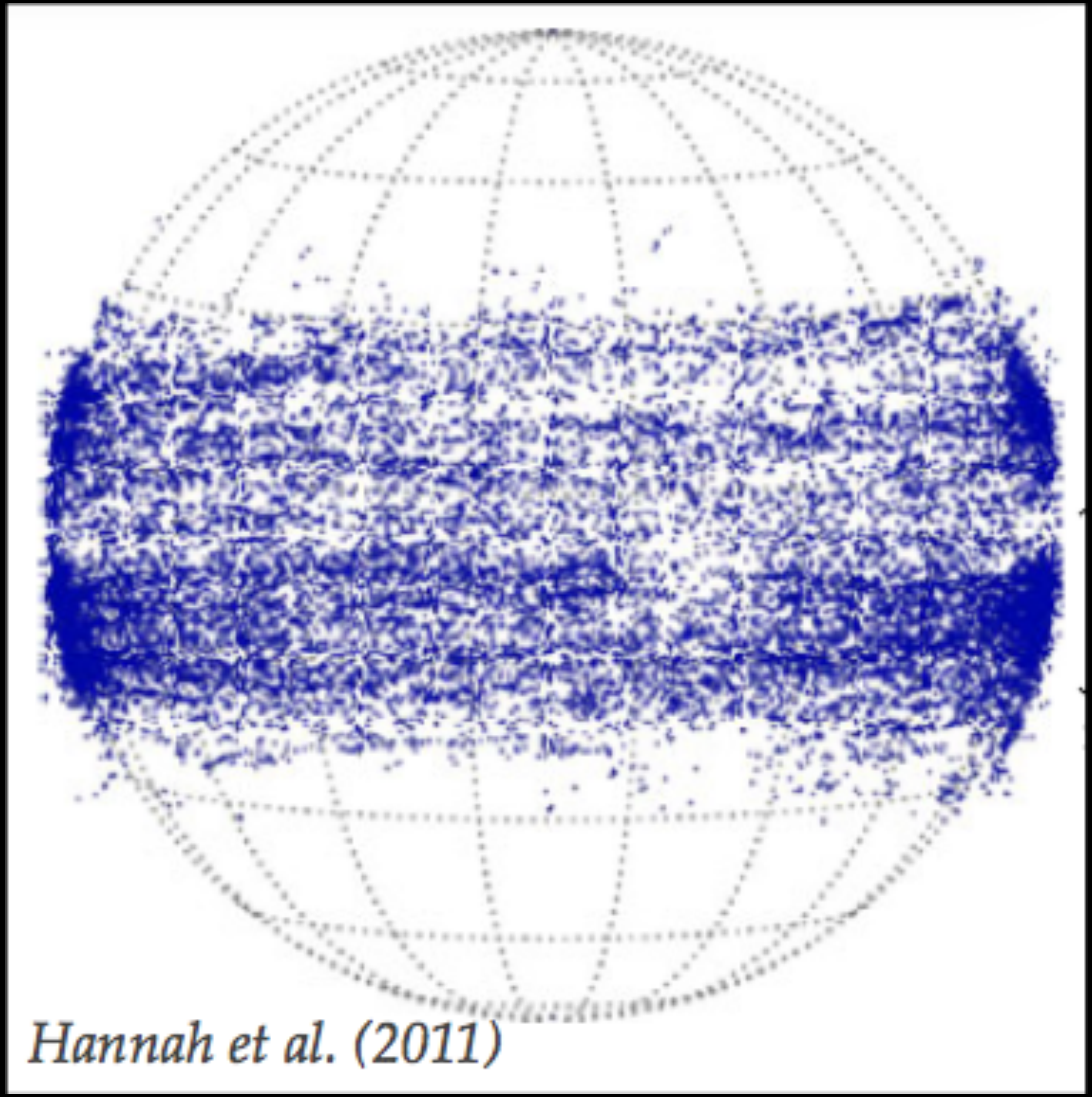
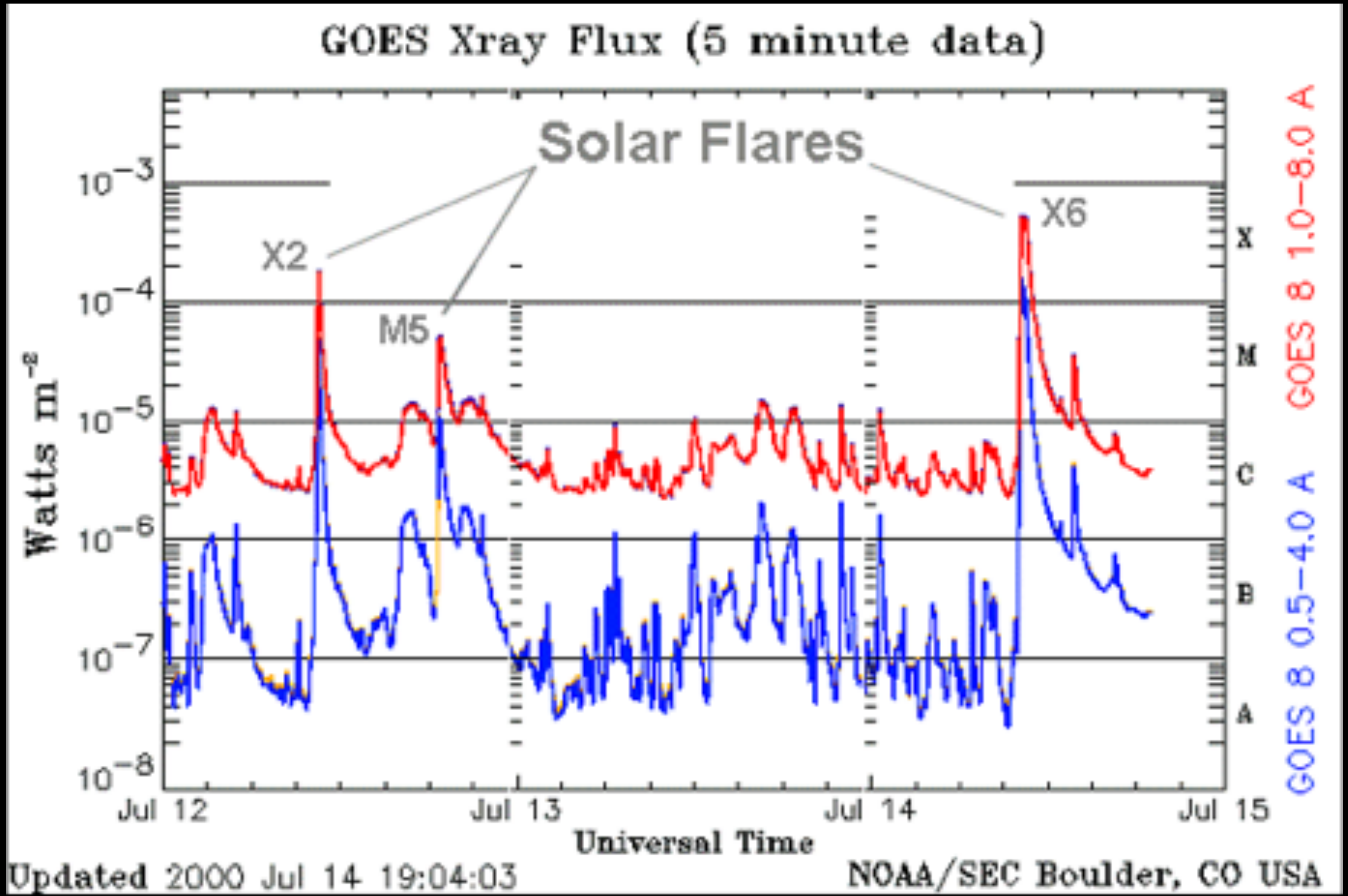
SOLAR FLARES: … AND THE PLENTY

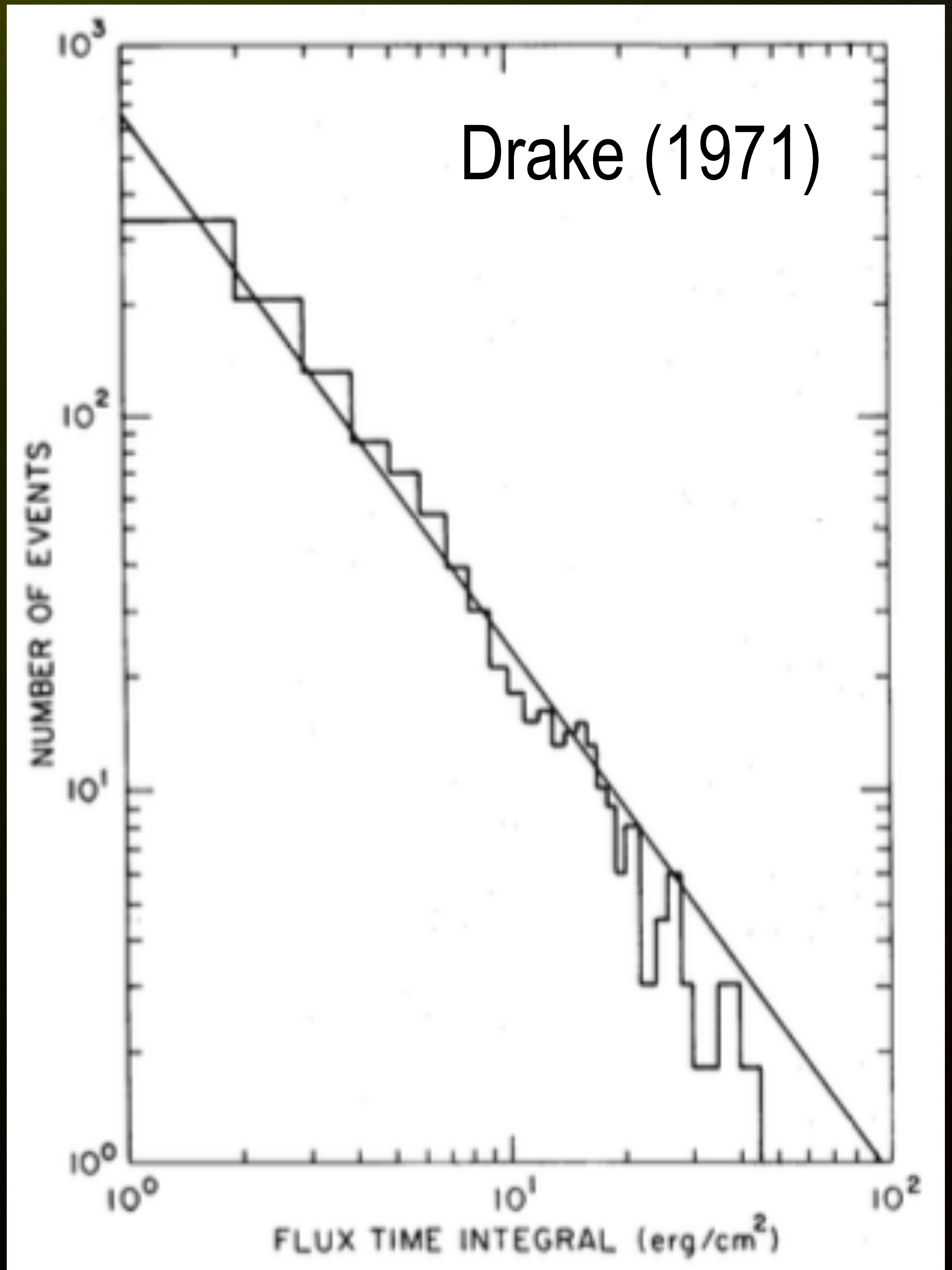


Location of some 27,000 flares from the RHESSI database



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

WHAT ARE SOLAR FLARES, PHYSICALLY AND STATISTICALLY?



Flare occurrence number vs. integrated photon flux

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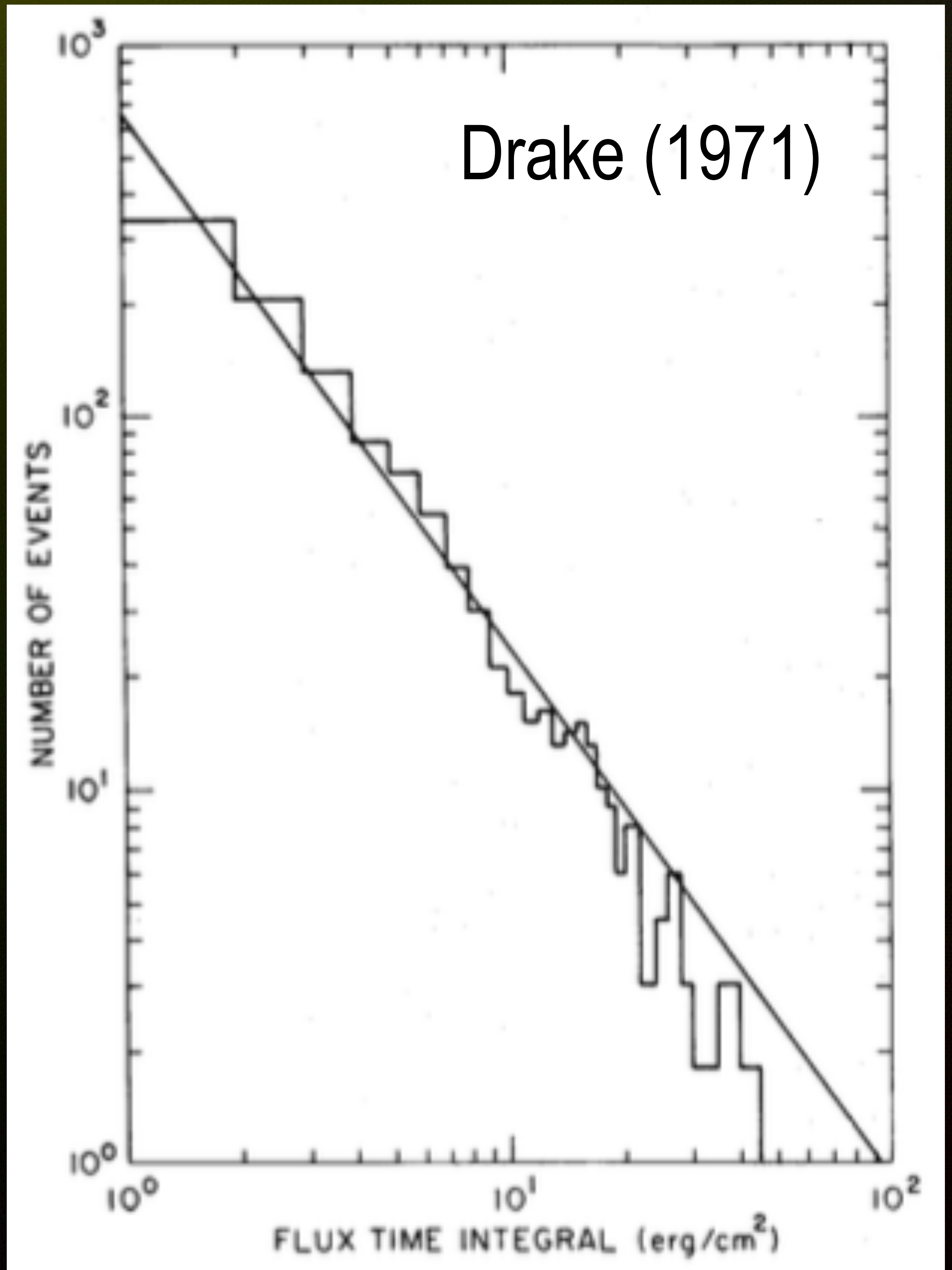

Flare occurrence number vs. integrated photon flux

Flares are (**Rosner & Vaiana 1978**):

- Stochastic relaxation (storage and release) processes
- Physically uncoupled / independent
- Brief, comparing to intermediate times between flares

$$P(t) = \bar{\nu} e^{-\bar{\nu} t}$$

- Leading to a power-law occurrence frequency for flare enegies

$$P(E) \sim \left(1 + E/E_0\right)^{-\gamma}$$

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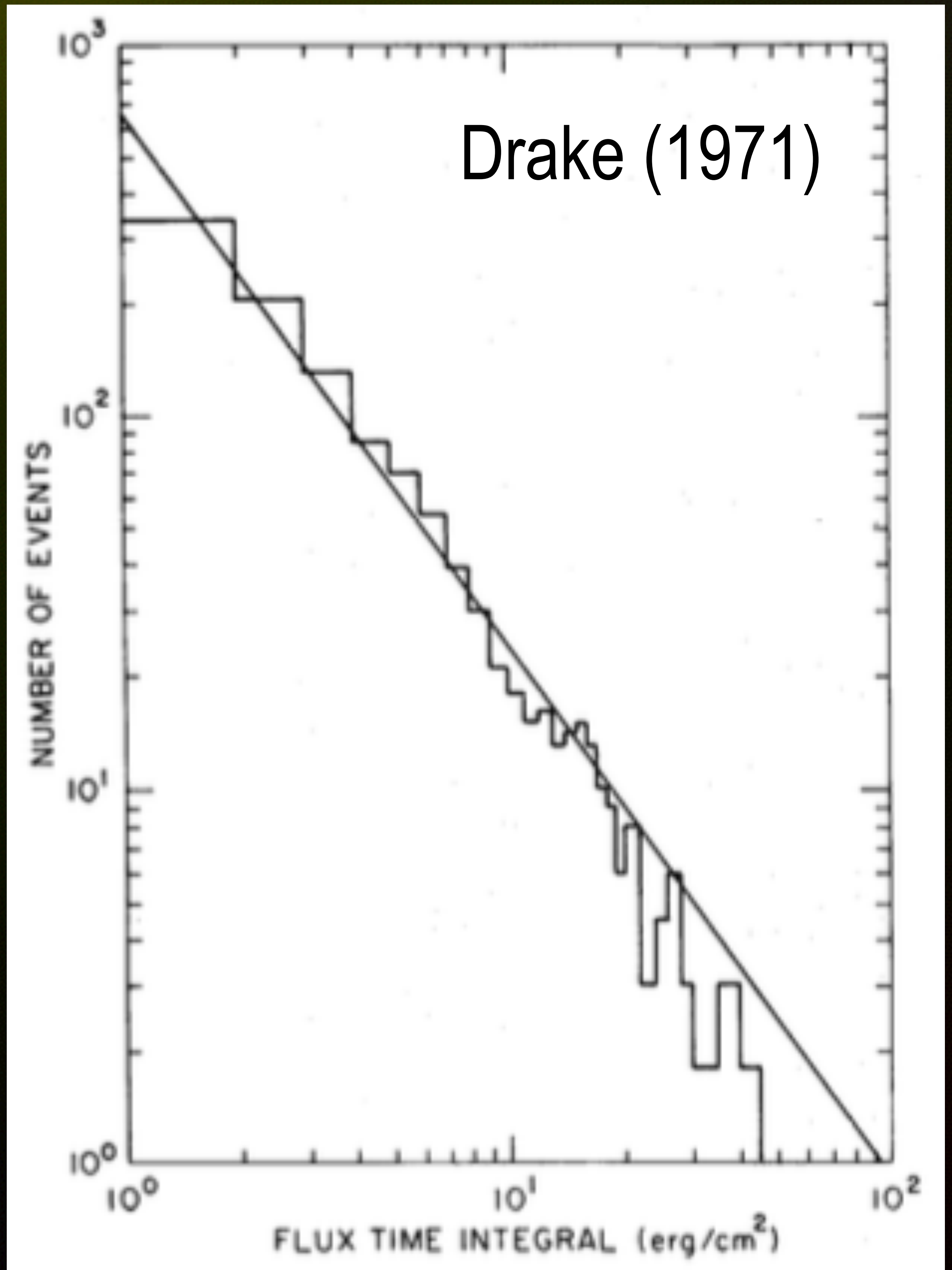

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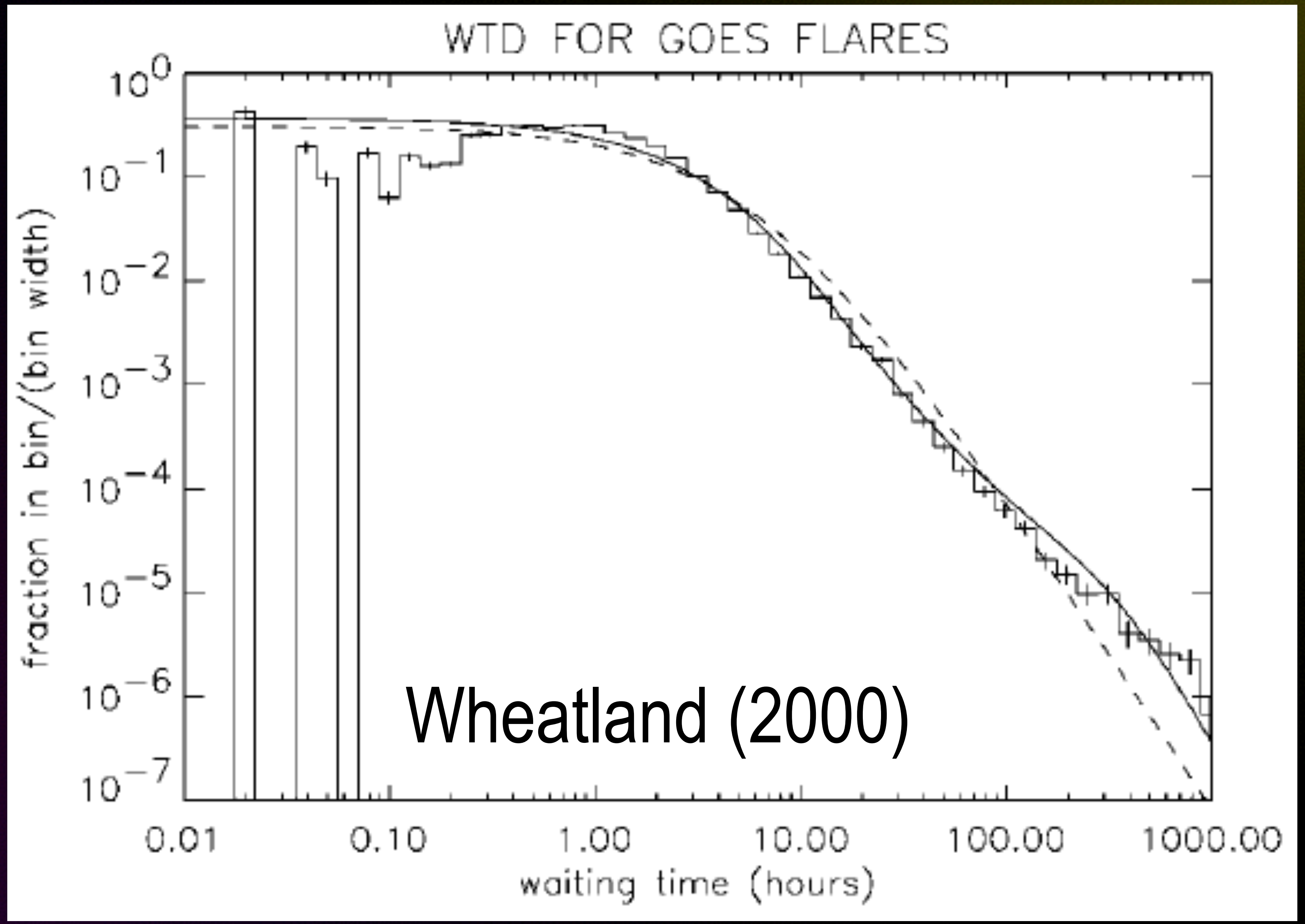
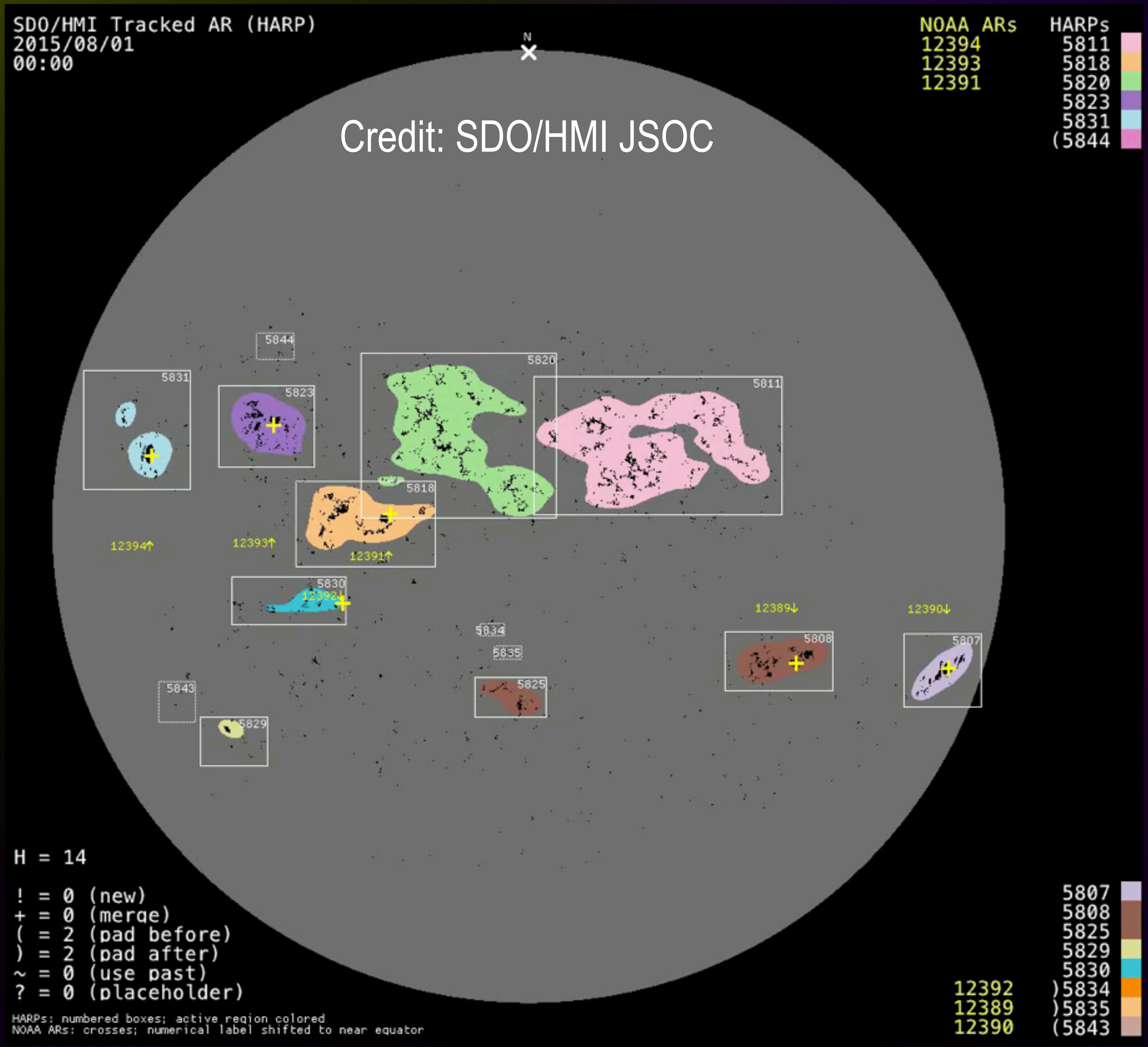


Flare occurrence is a time-dependent Poisson process (also Wheatland & Litvinenko 2002). This can explain power laws in the flare distribution functions.

$$P(k) = \frac{\bar{\nu}^k}{k!} e^{-\bar{\nu}}$$

Gallagher et al. (2002)

THE FLARE-PREDICTION CHALLENGE …



Objective: predict solar flares from near real-time (NRT) observations of solar evolution

- Prediction typically incolves solar photospheric (LOS or vector) magnetic field measurements. SDO/HMI is the most prominent source of these data
- Predictive parameters are inferred locally
- Observational cadence:
  - — 45 s, for full-disk LOS data
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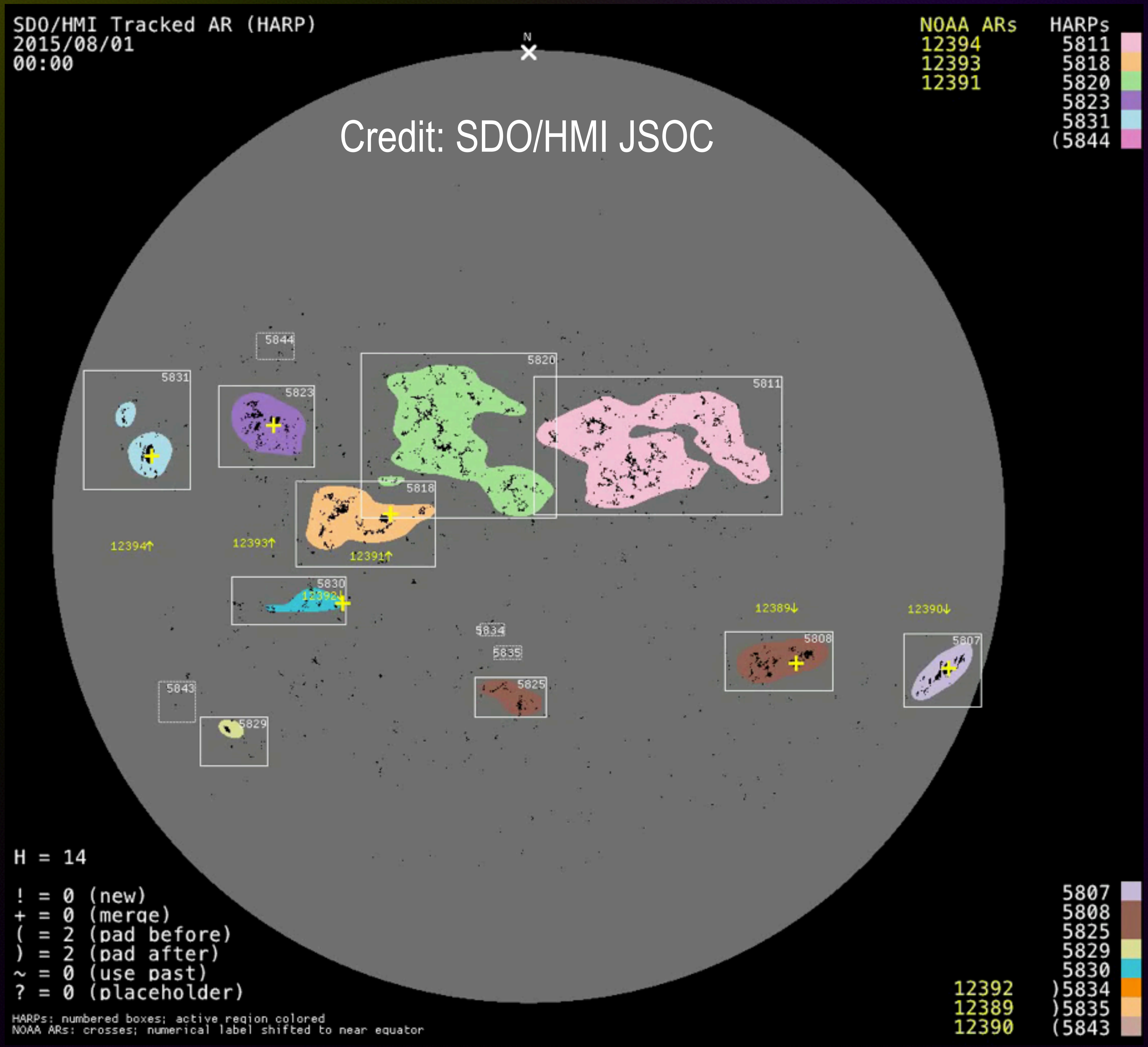

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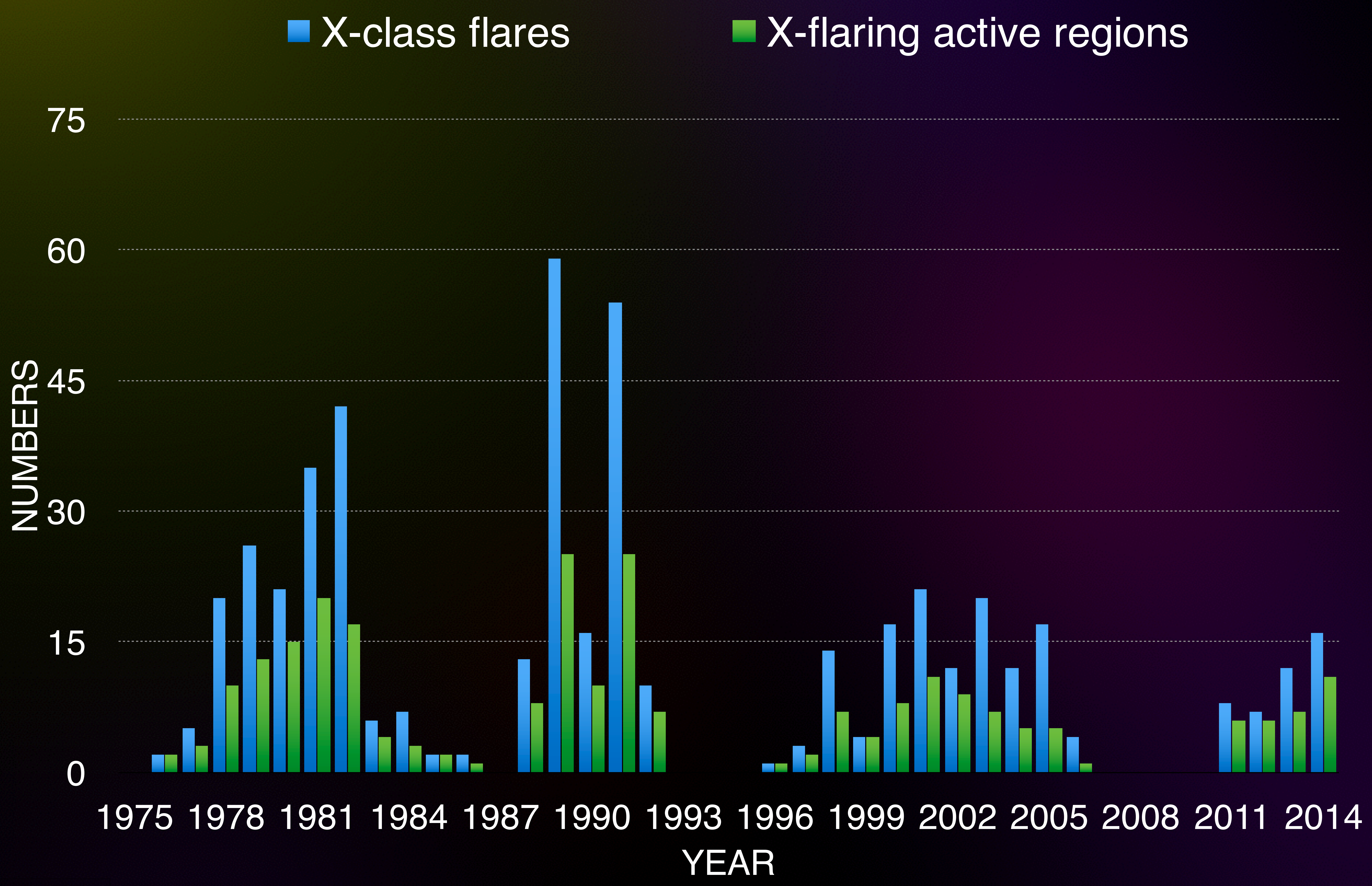

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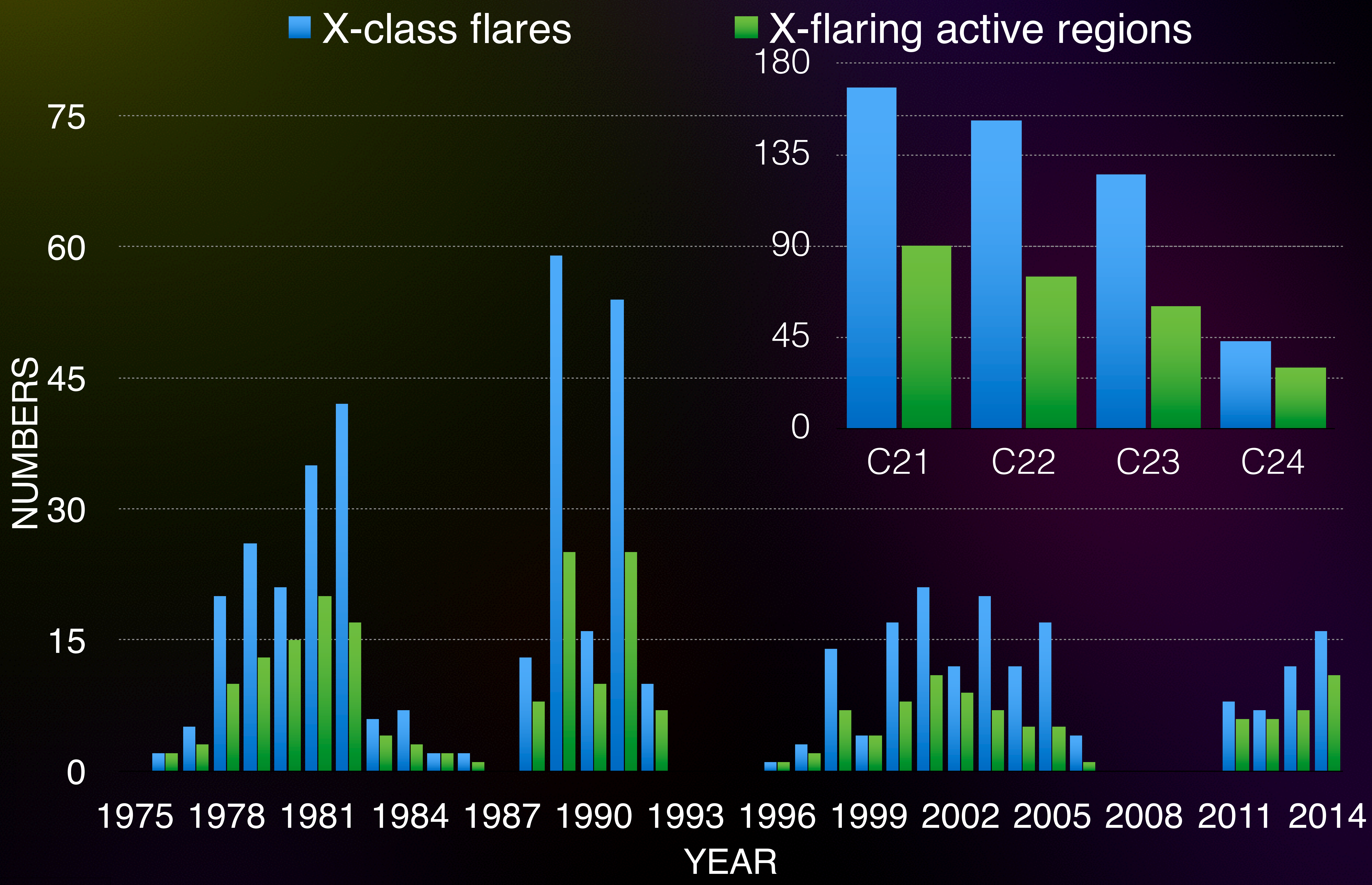

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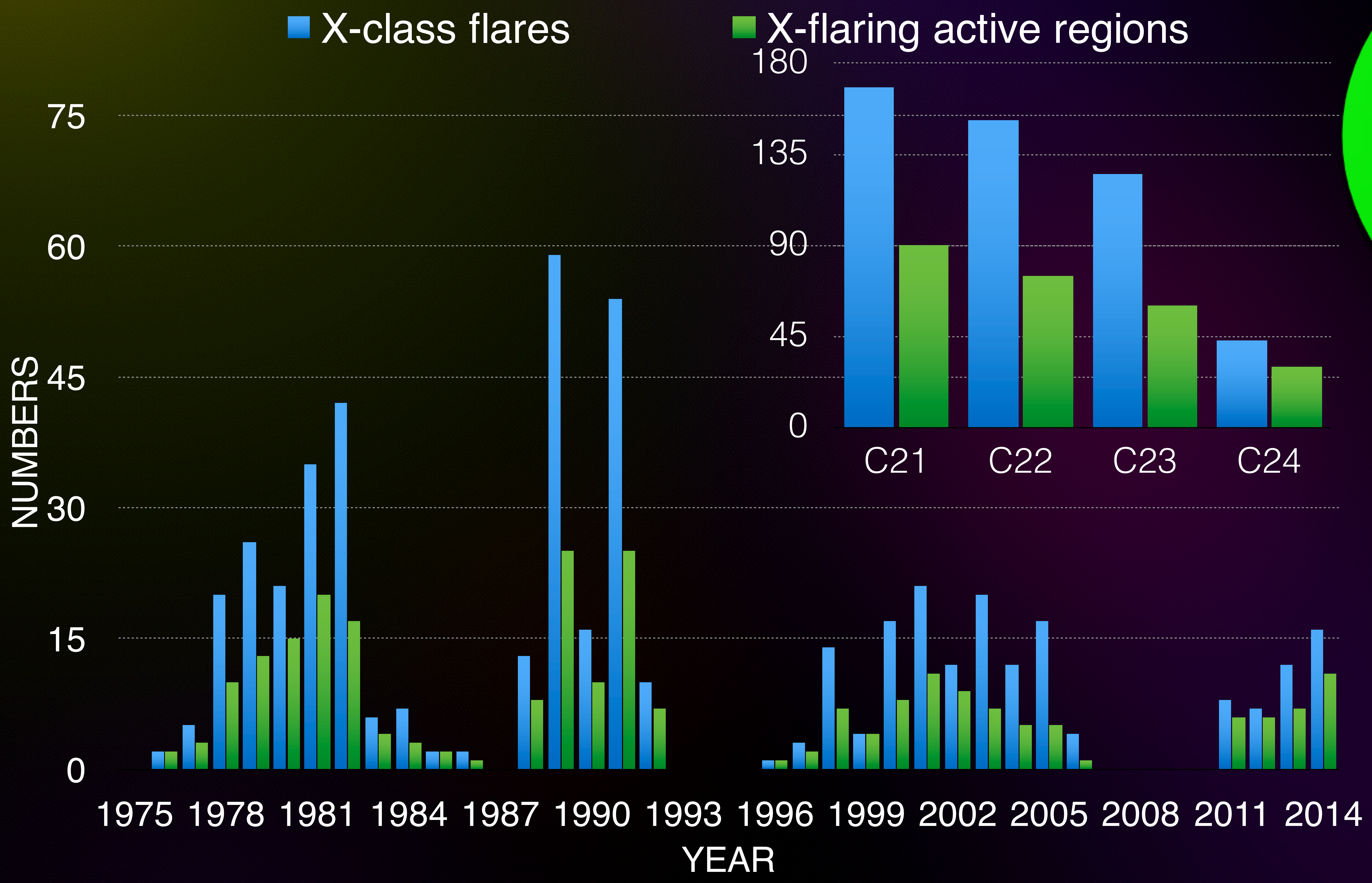
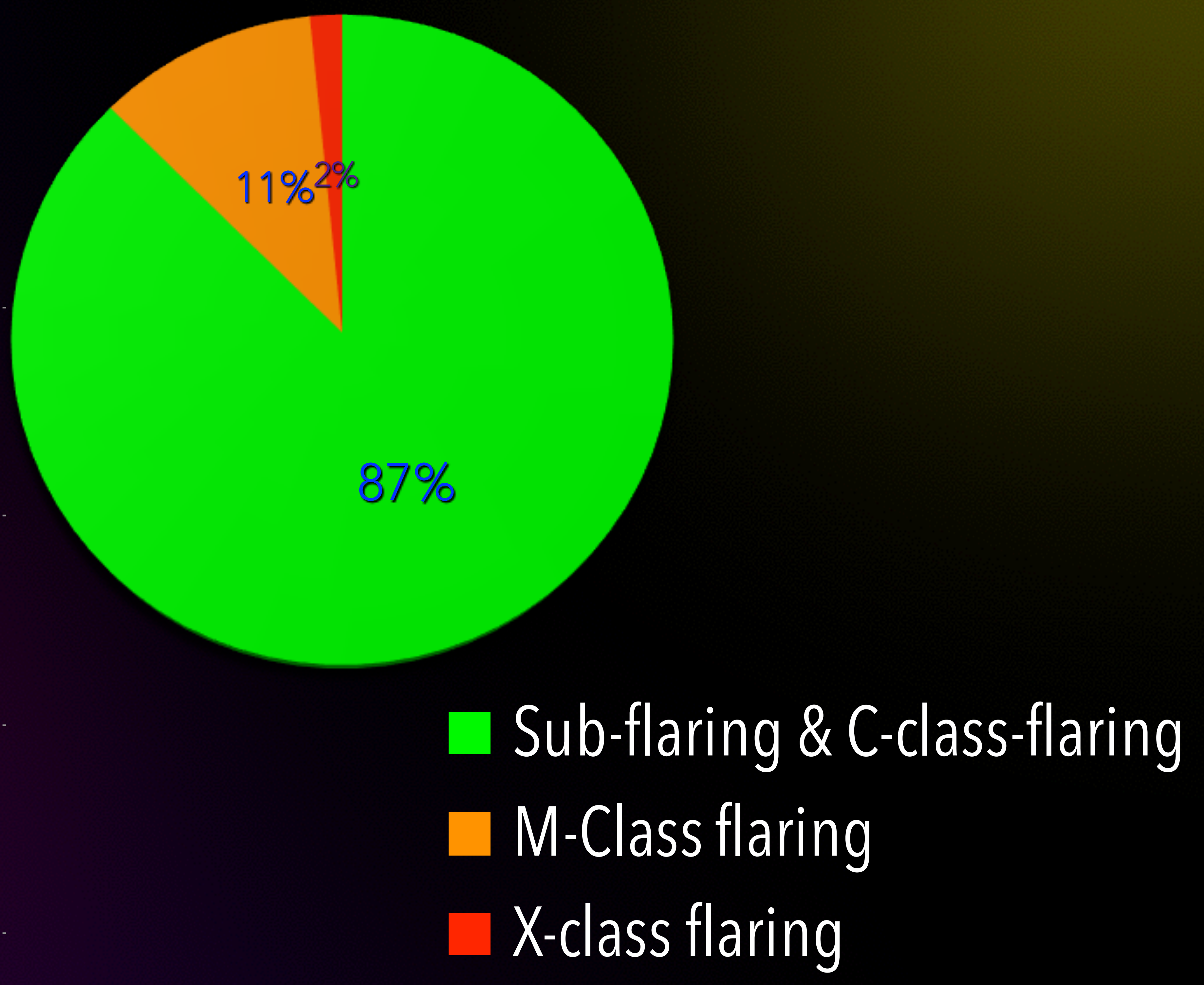
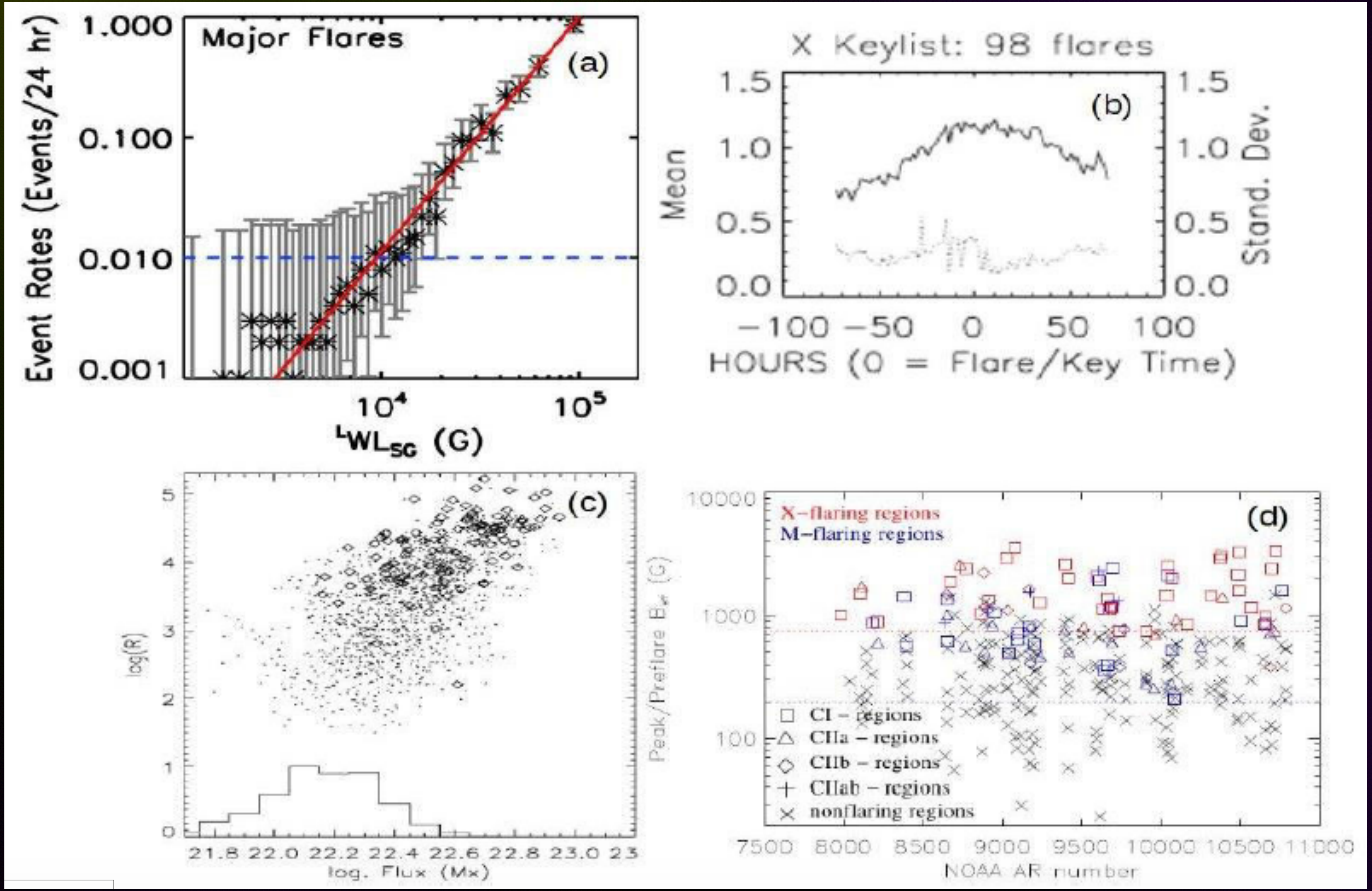




Only ~2% of active regions gave at least one X-class flare in C23!

DIFFERENT METHODS IN OPERATION WORLDWIDE

Mainly aiming to quantify the magnetic complexity of the host active regions



Upper left: WL_{SG} - Falconer et al. (2011)

Upper right: GWILL 0- Mason & Hoeksema (2010)

Lower left: R - Schrijver (2007)

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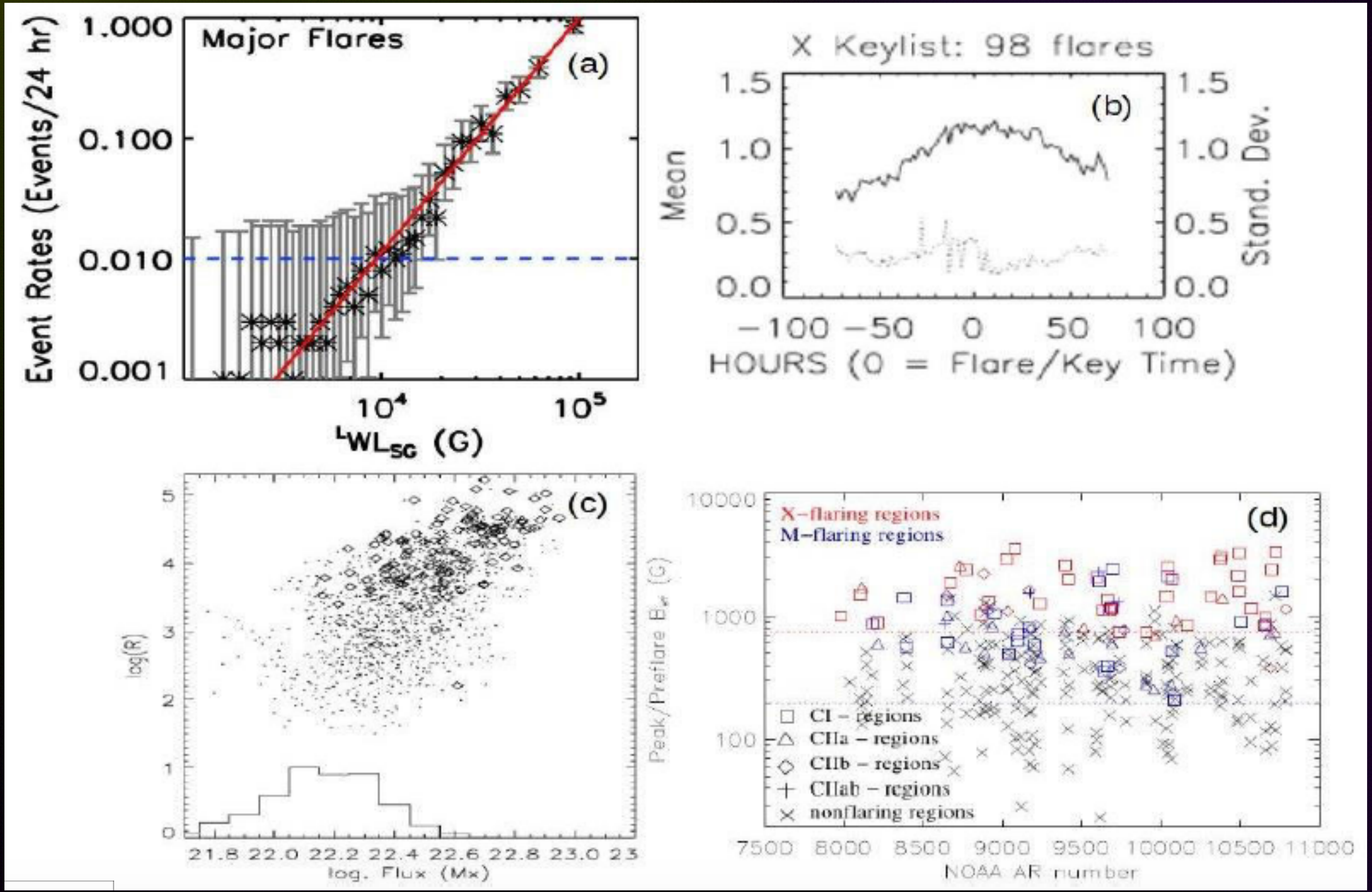

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Operational flare-prediction services:

- NOAA / SWPC
- Max Millennium / Solar Monitor
- UK Met Office
- U. Bradford / ASAP
- NASA / SRAG / MAG4
- ASSA / KSPC
- ESA / A-EFFort

ESA's SSA / SWE A-EFFort METHOD

A-EFFort
Athens Effective
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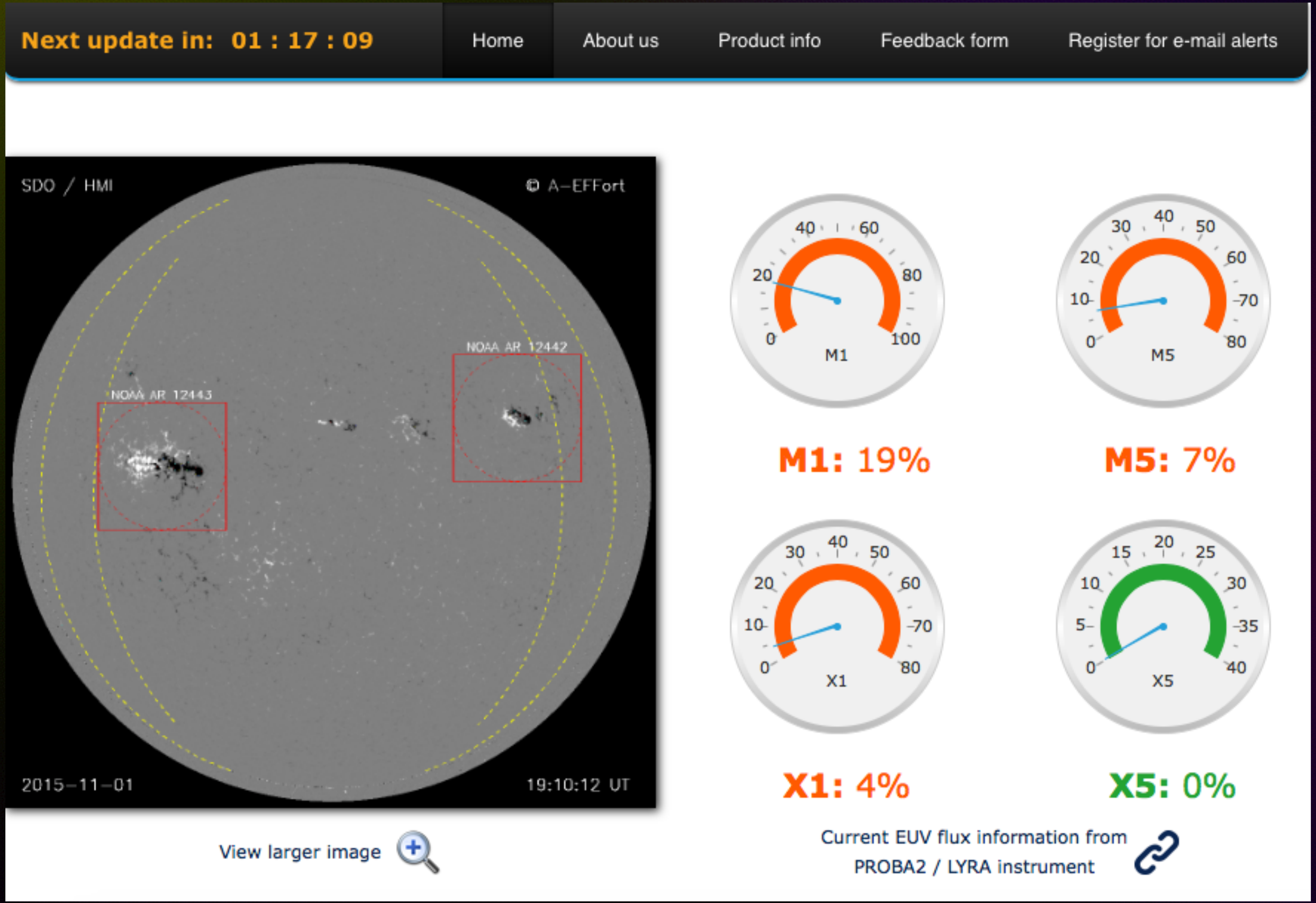
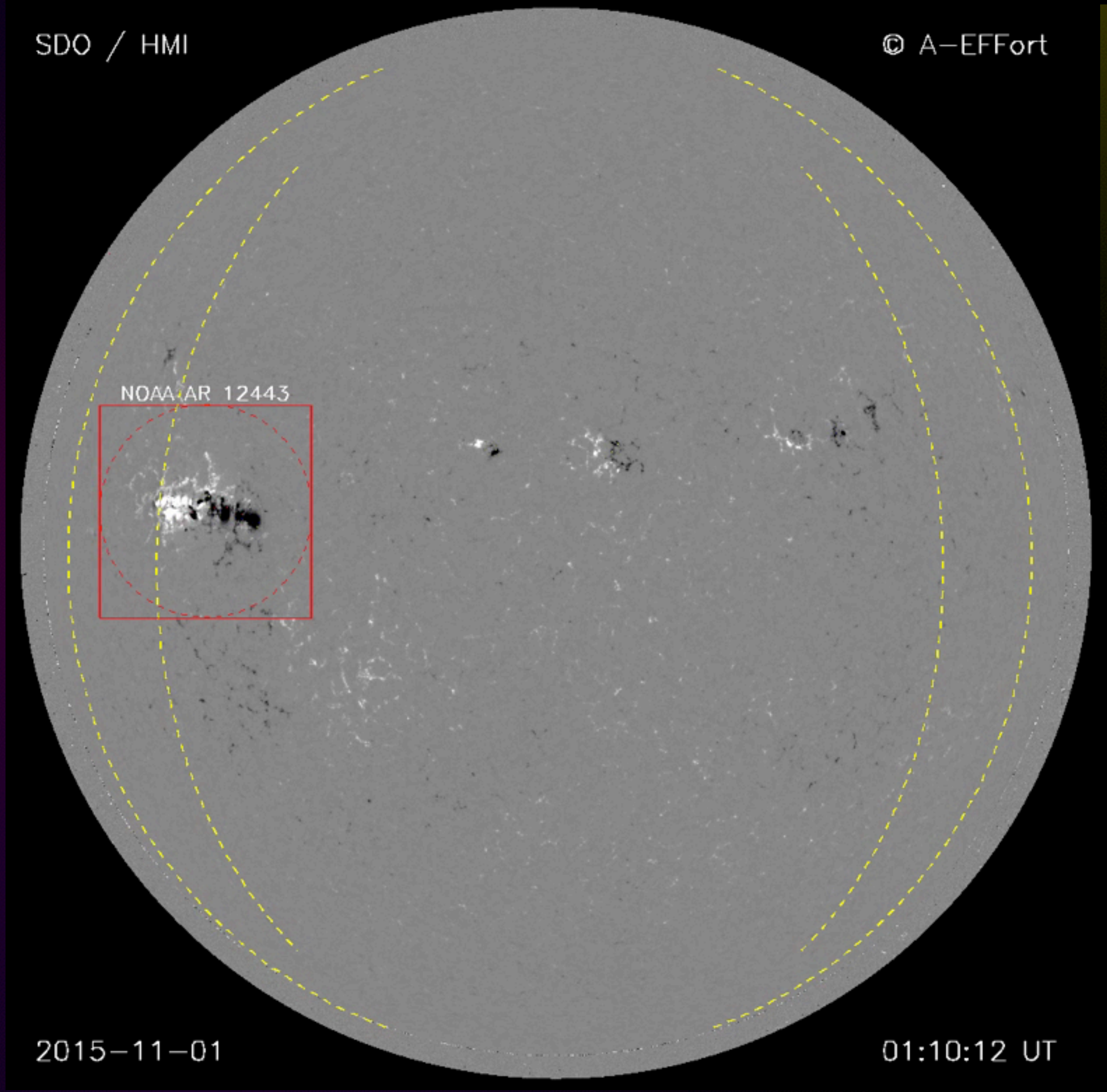


ESA's SSA/SWE A-EFFort interface a-effort.academyofathens.gr



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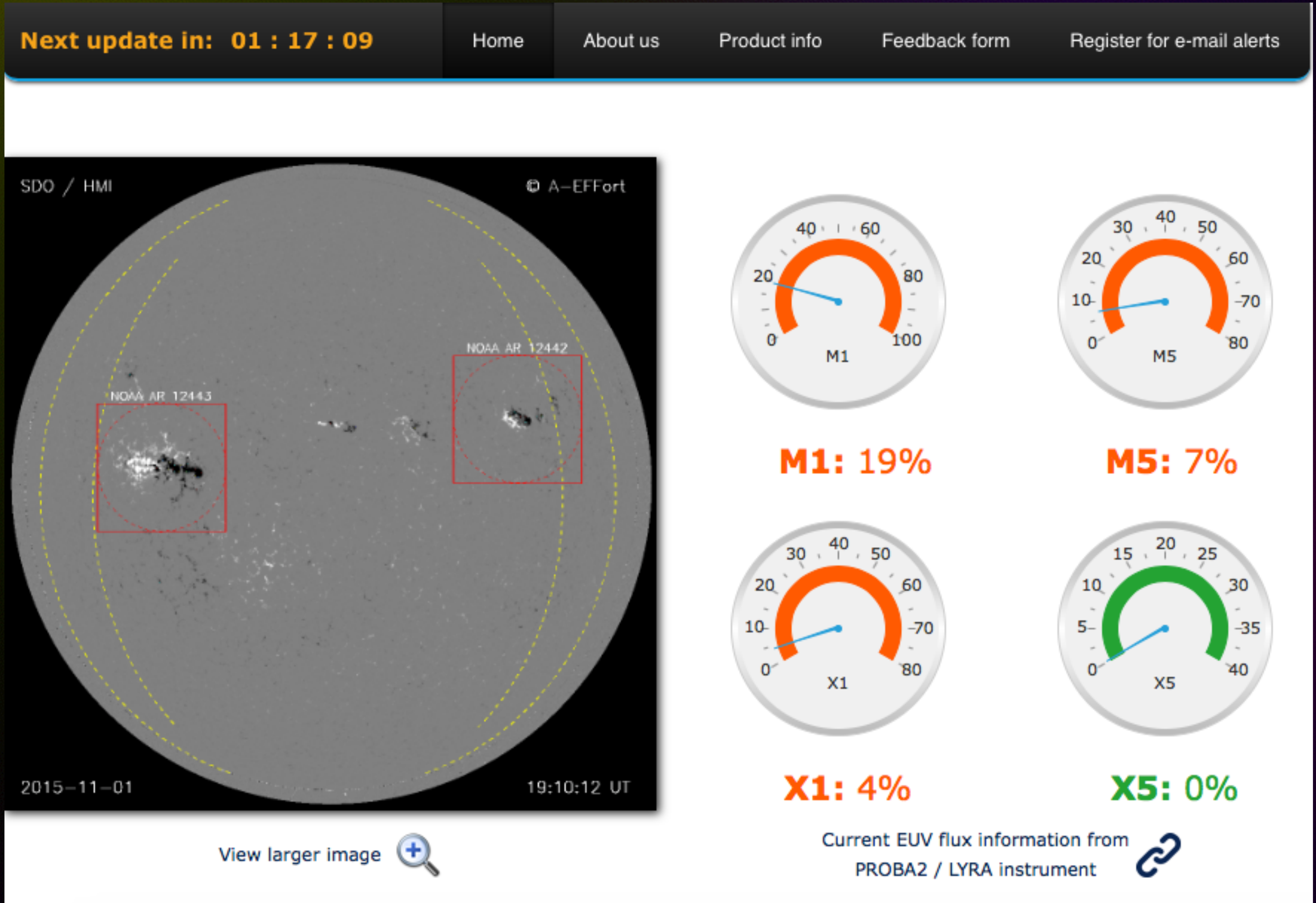

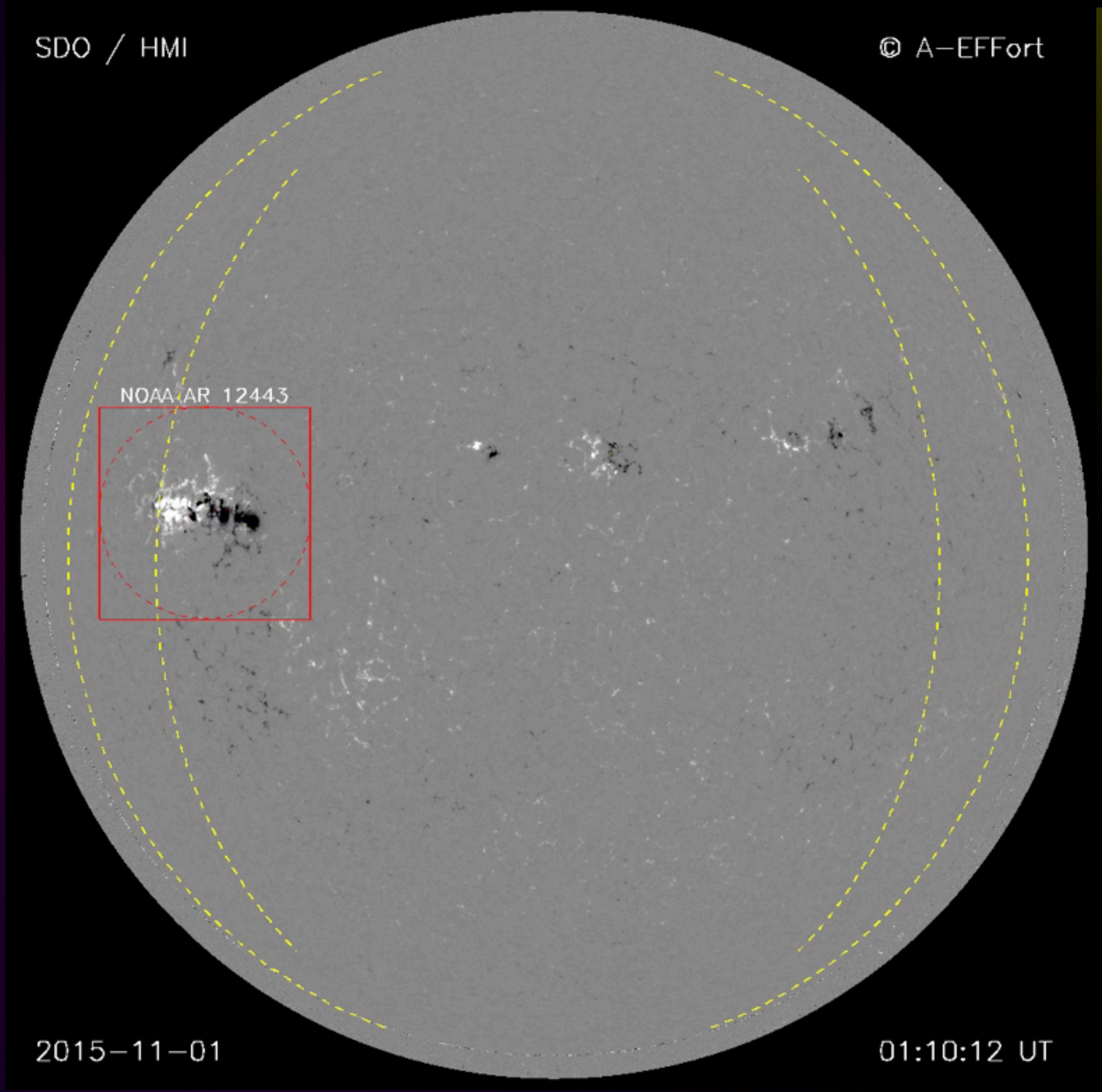

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IN FACT, MANY DIFFERENT METHODS…

Keyword	Description	Formula	F-Score	Selection
TOTUSJH	Total unsigned current helicity	$H_{c_{\rm total}} \propto \sum \lvert B_z \cdot J_z \rvert$	3560	Included
TOTBSQ	Total magnitude of Lorentz force	$F \propto \sum B^2$	3051	Included
TOTPOT	Total photospheric magnetic free energy density	$\rho_{\rm tot} \propto \sum \left(\boldsymbol{B}^{\rm Obs} - \boldsymbol{B}^{\rm Pot}\right)^2 dA$	2996	Included
TOTUSJZ	Total unsigned vertical current	$J_{z_{\rm total}} = \sum \lvert J_z \rvert dA$	2733	Included
ABSNJZH	Absolute value of the net current helicity	$H_{c_{\rm abs}} \propto \left\lvert \sum B_z \cdot J_z \right\rvert$	2618	Included
SAVNCPP	Sum of the modulus of the net current per polarity	$J_{z_{\rm sum}} \propto \left\lvert \sum^{B_z^+} J_z dA \right\rvert + \left\lvert \sum^{B_z^-} J_z dA \right\rvert$	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	$\text{Area} = \sum \text{Pixels}$	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	$\overline{\rho} \propto \frac{1}{N} \sum \left(\boldsymbol{B}^{\rm Obs} - \boldsymbol{B}^{\rm Pot}\right)^2$	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 with shear > 45° / total area	740.8	Included
MEANSHR	Mean shear angle	$\overline{\Gamma} = \frac{1}{N} \sum \arccos\left(\frac{\boldsymbol{B}^{\rm Obs} \cdot \boldsymbol{B}^{\rm Pot}}{\lvert B^{\rm Obs} \rvert \lvert B^{\rm Pot} \rvert}\right)$	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
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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
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Bobra & Couvidat, ApJ, 2015

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What is the optimal way to deal with all this information and still achieve reliable NRT forecasts within a preset forecast window?

Bobra & Couvidat, ApJ, 2015

VALIDATION : BORROWED BY TERRESTRIAL WEATHER FORECASTING

Categorical (dichotomous) validation: Flare (YES) or No Flare (NO)

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

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- 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):

$$TSS = POD - POFD$$

CATEGORICAL 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

CATEGORICAL VALIDATION IN A PROBABILISTIC FORECASTING?

One needs a threshold probability p_{thres} ($p \geq p_{thres}$ —> YES ; $p < p_{thres}$ —> NO)

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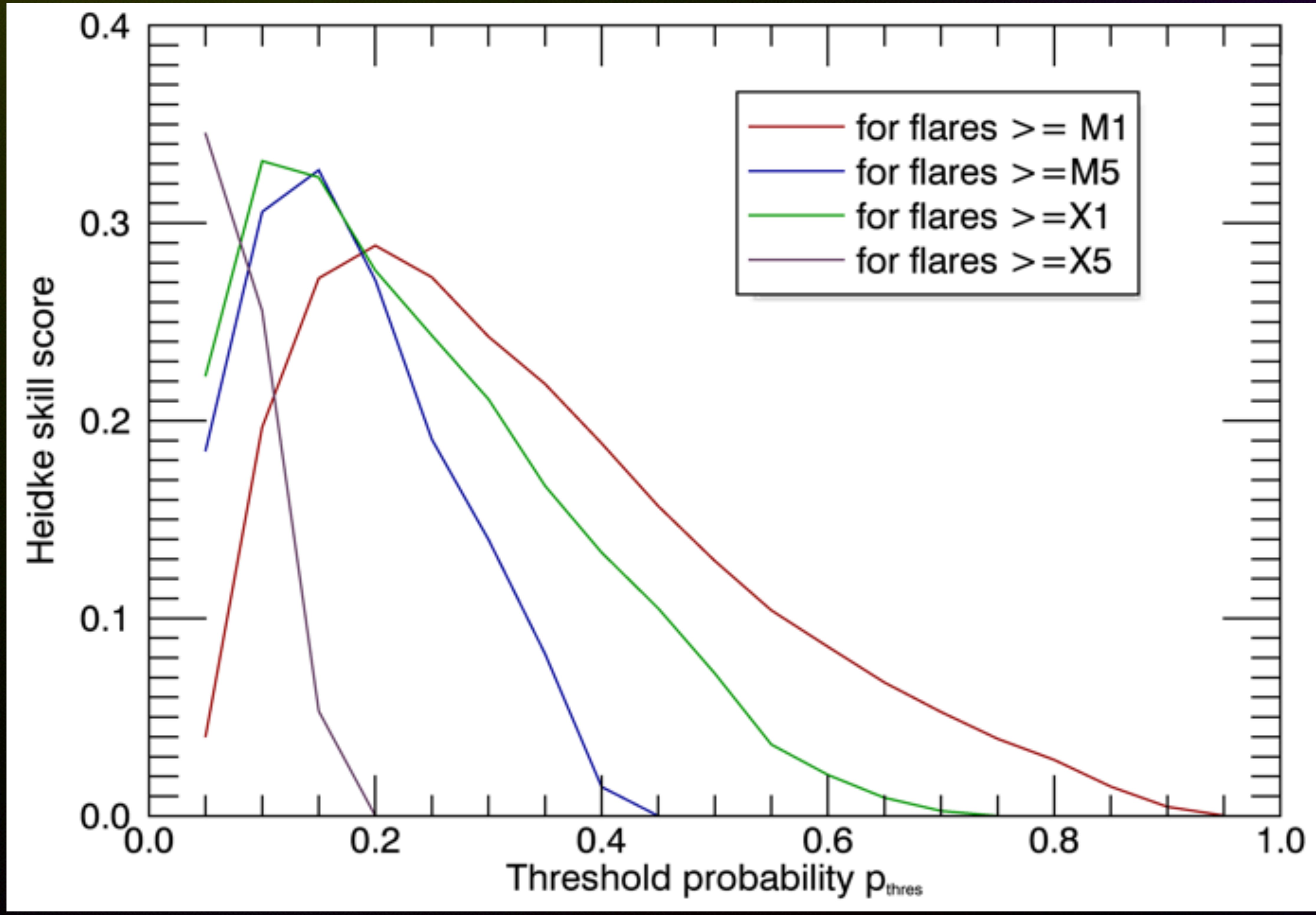

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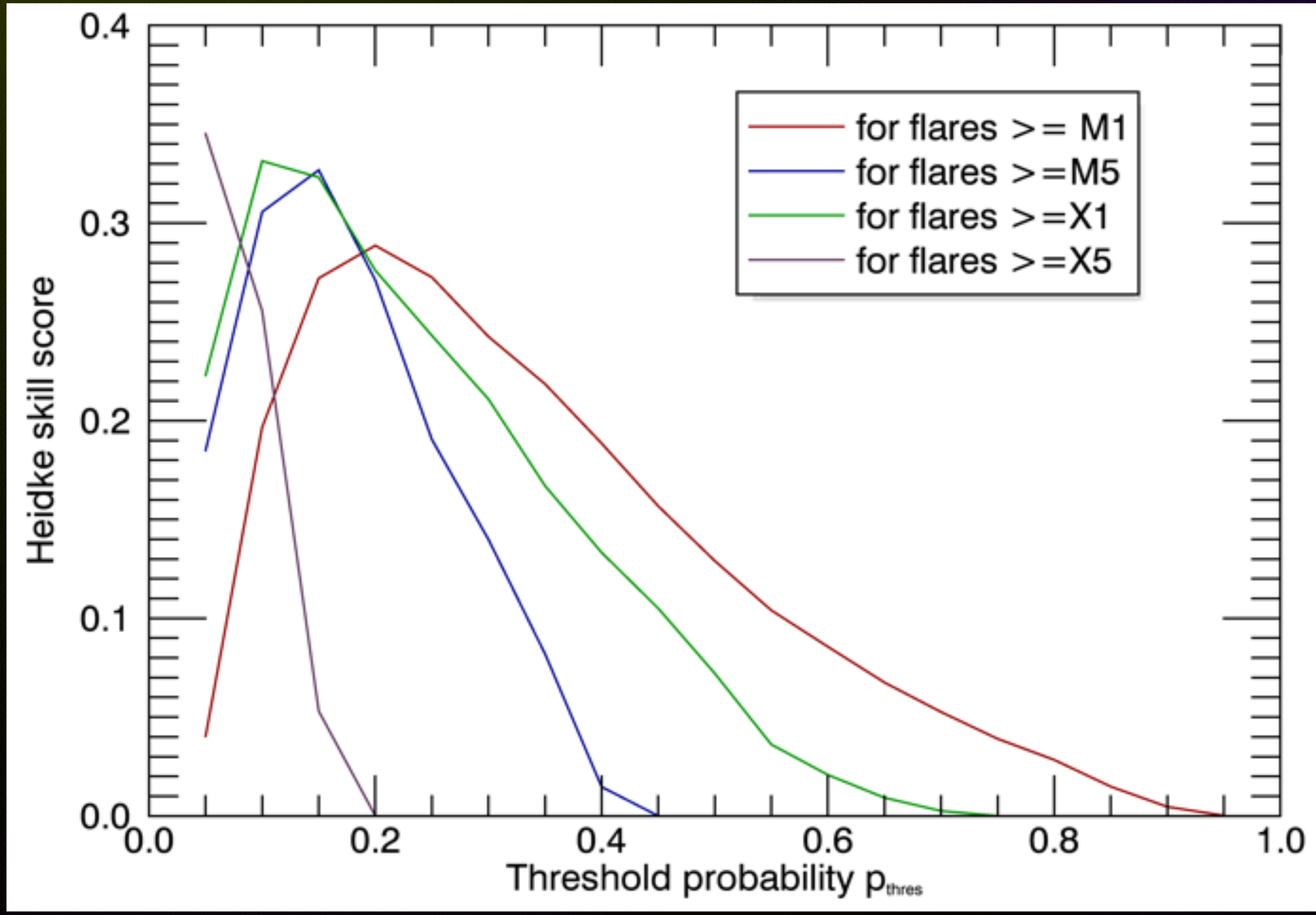

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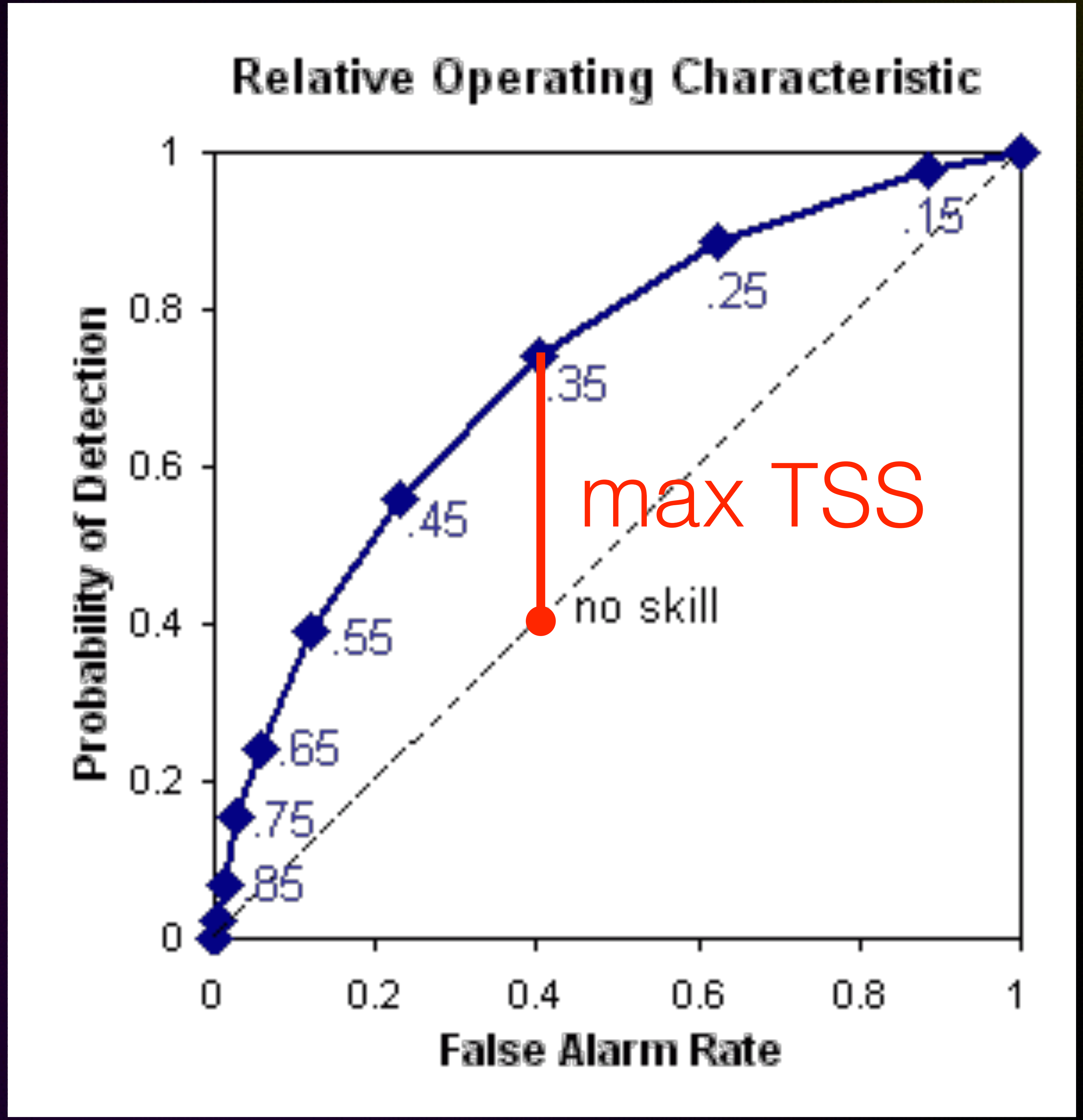
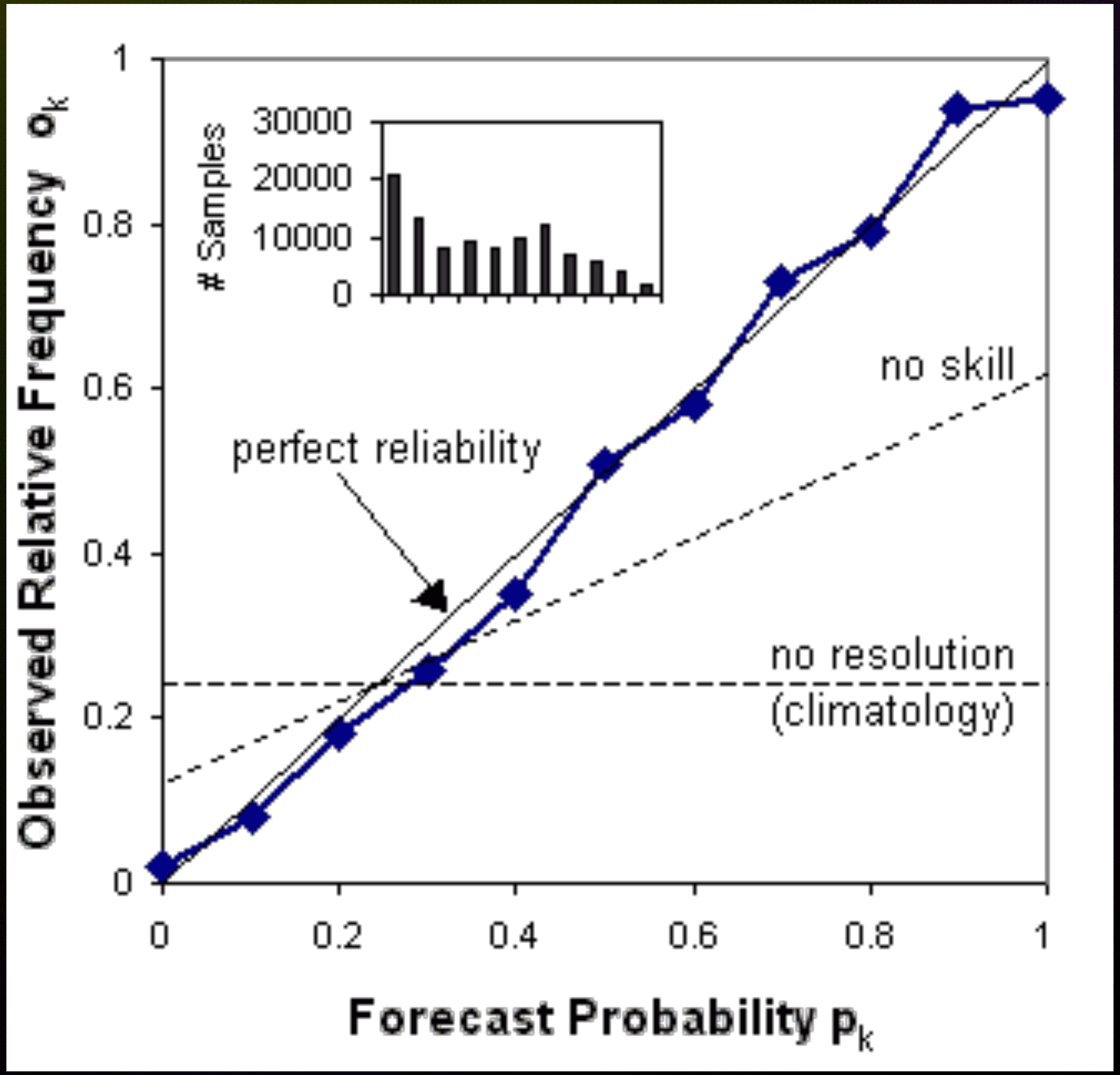


Example ROC curve (TSS vs. p_{thres})

Source: WMO Forecast Verification Research

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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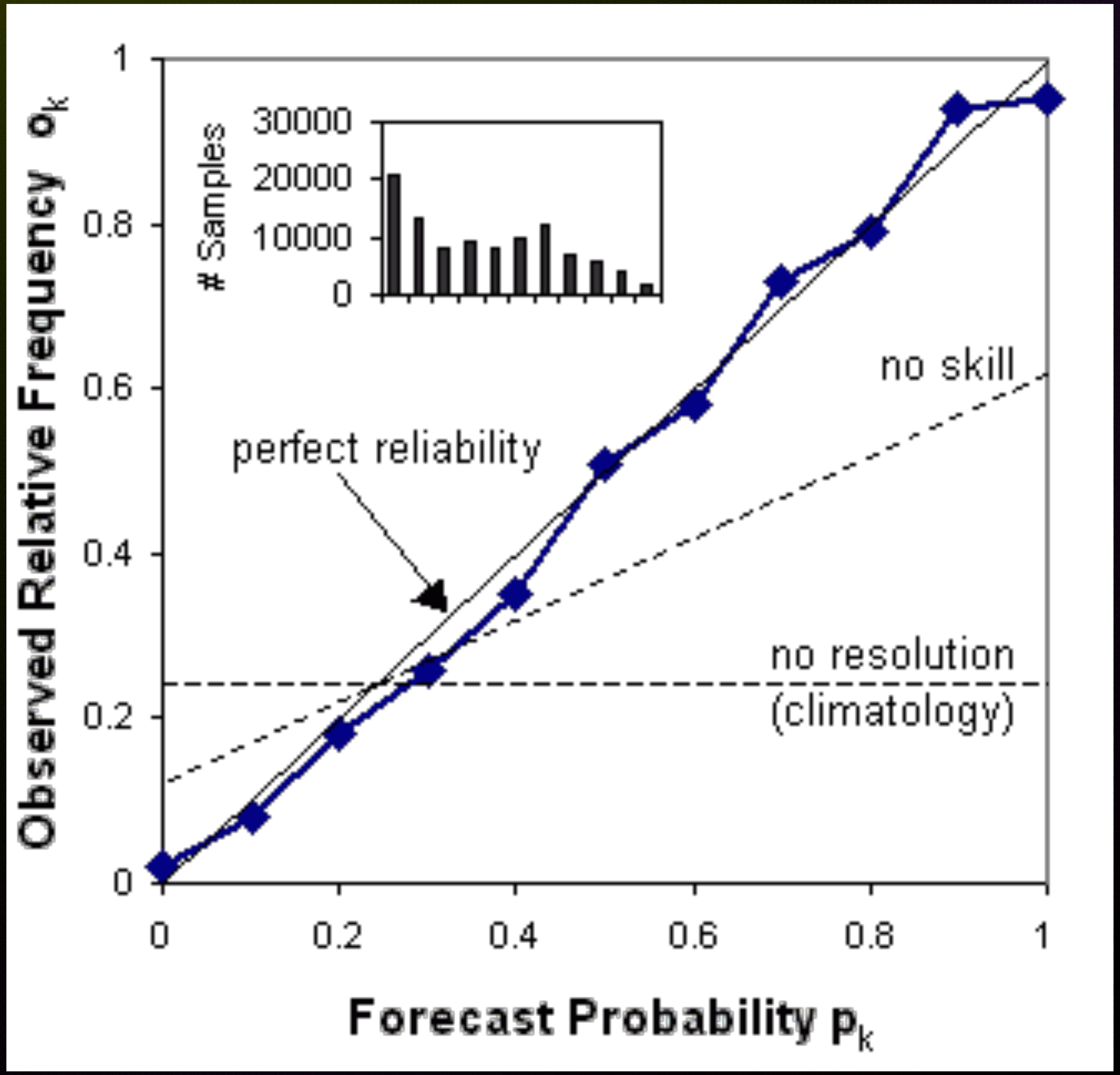


Reliabillity diagram

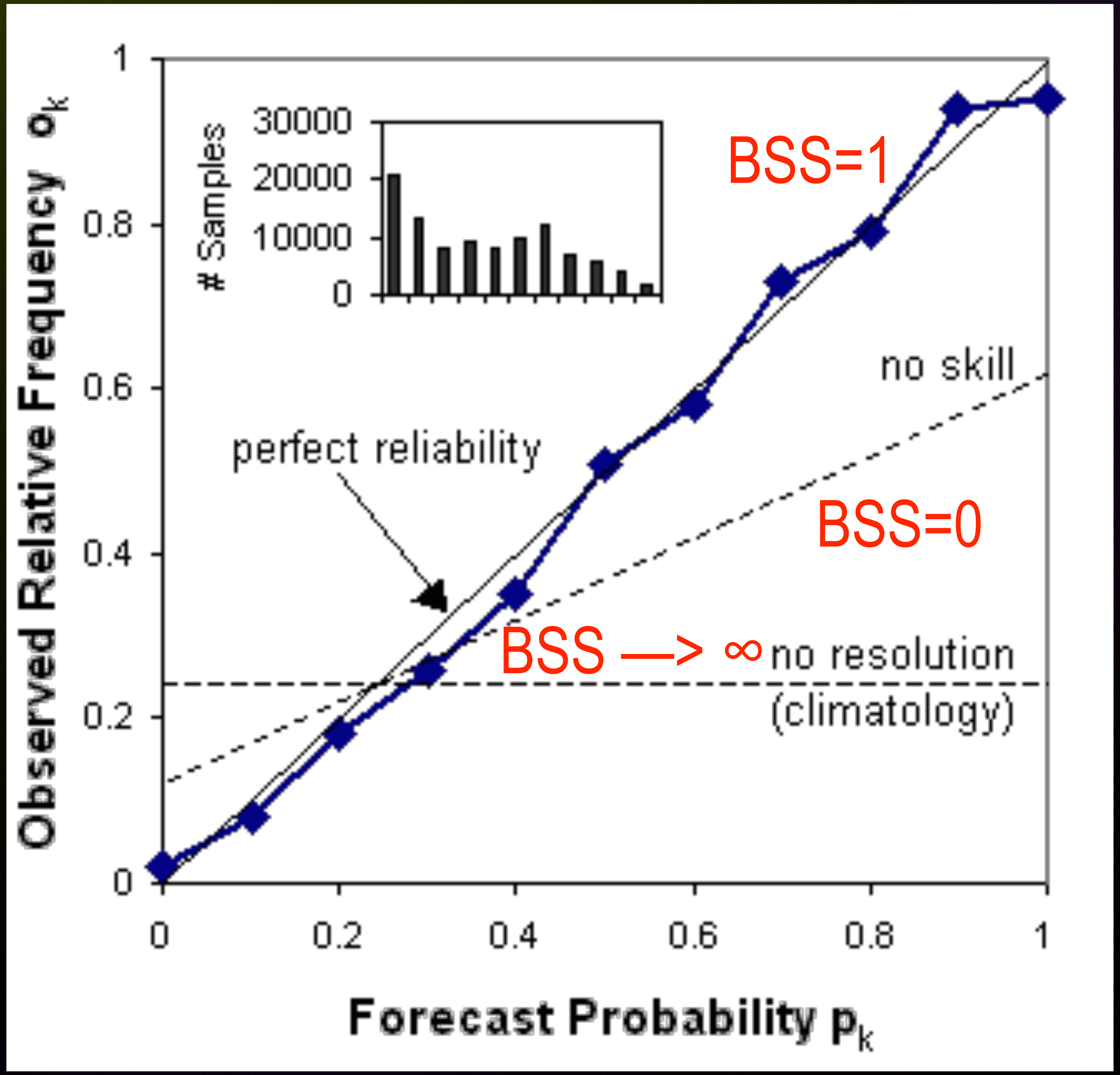
- Correlate forecast probability with observed frequency
- Compare your skill against climatology (mean flaring rate within forecast window)
- Generalized skill score:

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

$$MSE = \; < (o - p)^2 >$$

PROBABILISTIC VALIDATION

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



Reliabillity diagram

- Correlate forecast probability with observed frequency
- Compare your skill against climatology (mean flaring rate within forecast window)
- Generalized skill score:

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

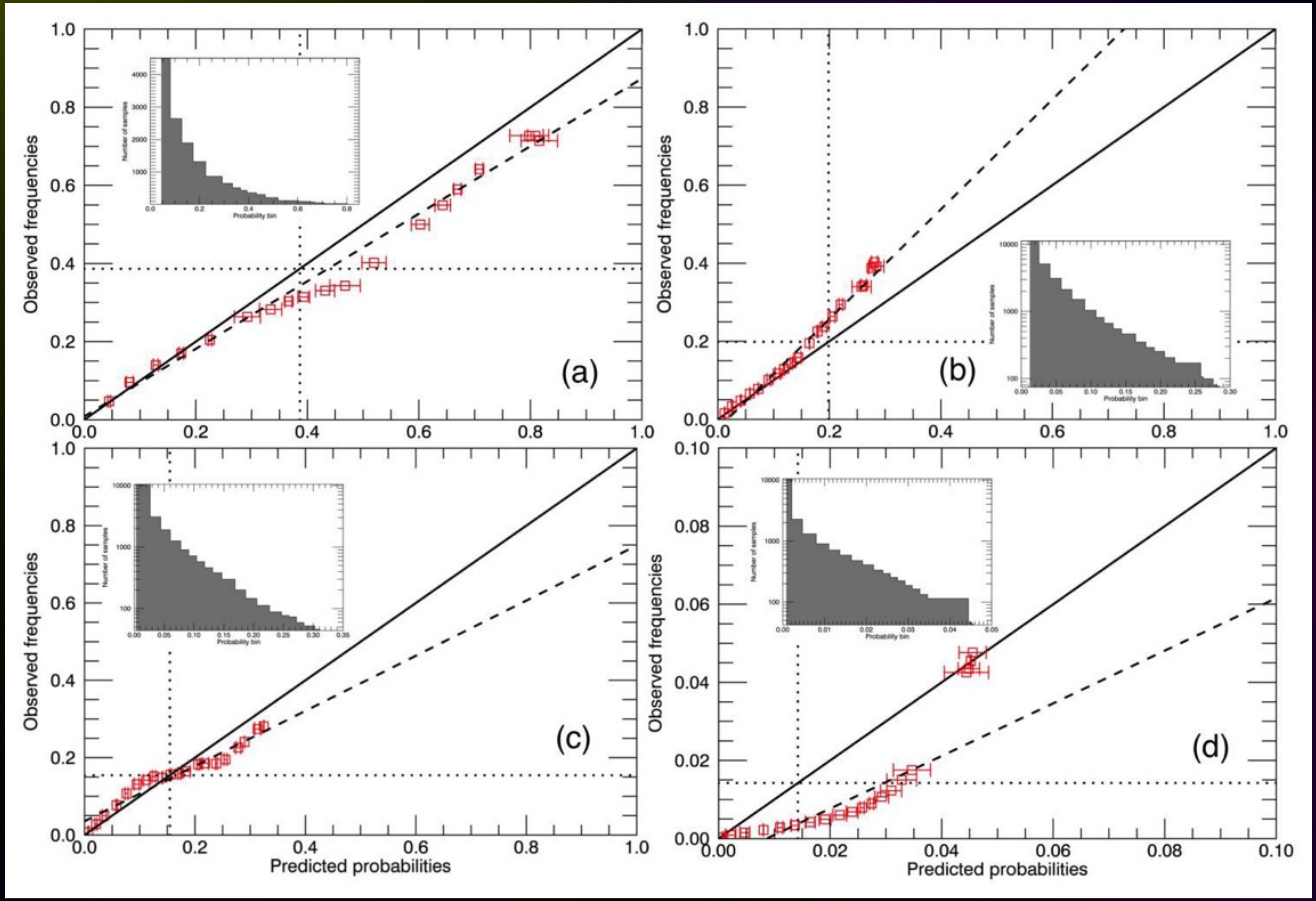
$$MSE = \; <(o-p)^2>$$

- Brier skill score (reference: climatology):

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

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

PROBABILISTIC VALIDATION



Example probabilistic validation (A-EFFort):

(a) M1 and above: BSS = 0.88

(b) M5 and above: BSS = 0.78

(c) X1 and above: BSS = 0.80

(d) X5 and above: BSS = 0.38

TAILORING FLARE PREDICTION METHODS TO THE CUSTOMER NEEDS

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$$predictor = \omega_1 \; predictor_1 + \omega_2 \; predictor_2 + ... + \; \omega_n \; predictor_n$$

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

  - — Ensemble forecasting:

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

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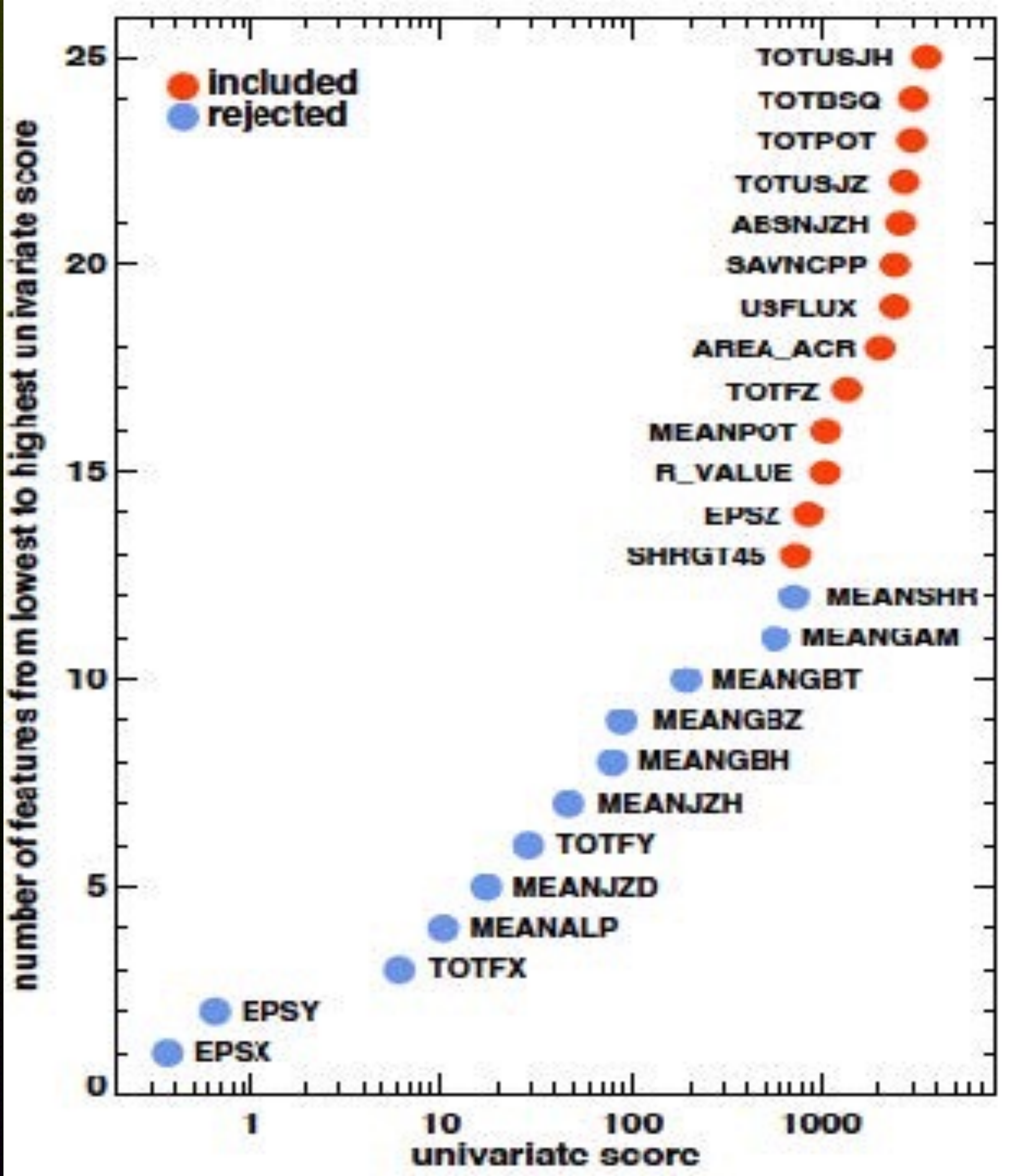
However: optimization means different things to different customers!

SOME RECENT, PRELIMINARY EXAMPLES

- Multivariate forecasting



Bobra & Couvidat (2015)

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- Machine-learning classifiers adopted

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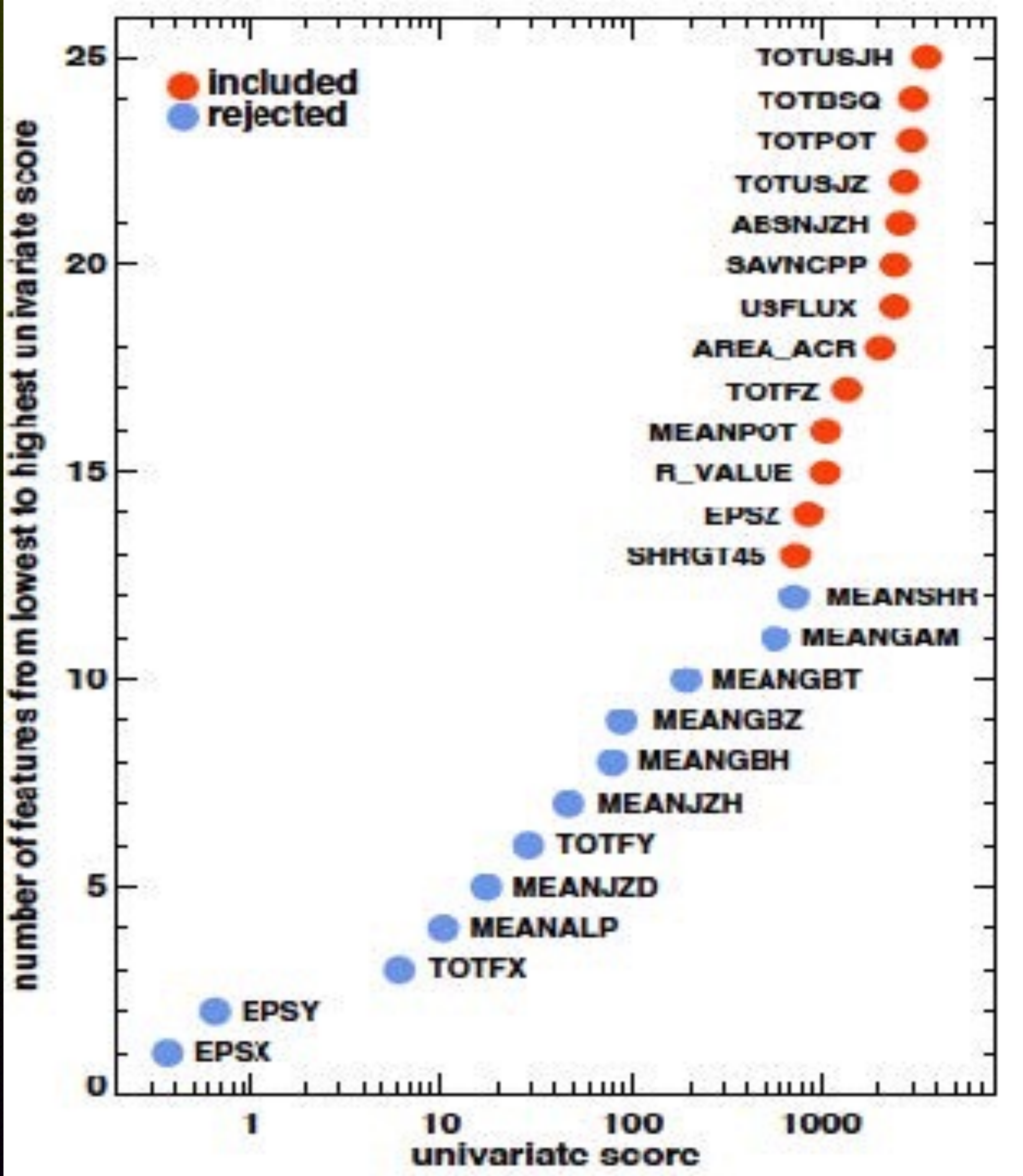

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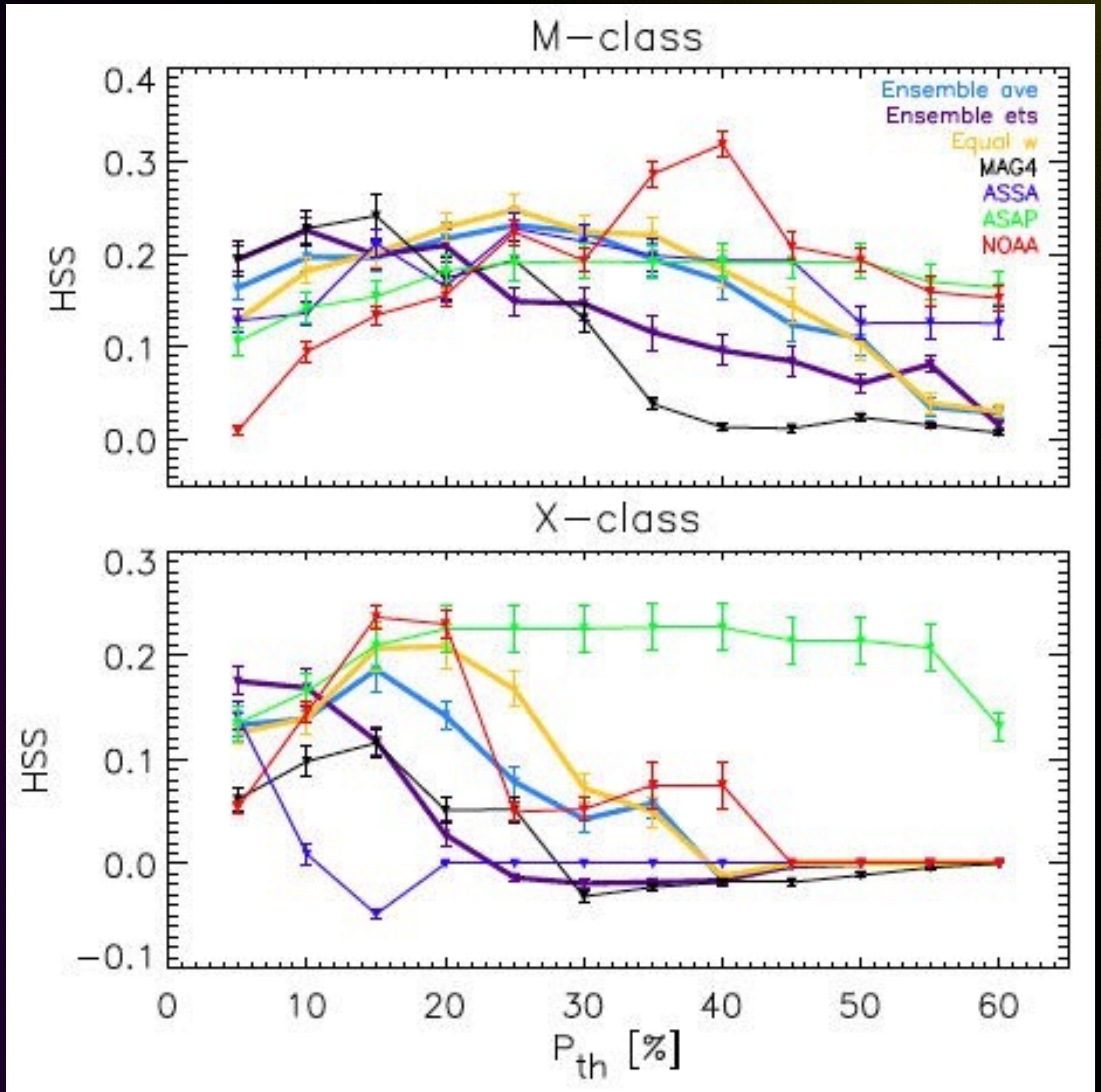
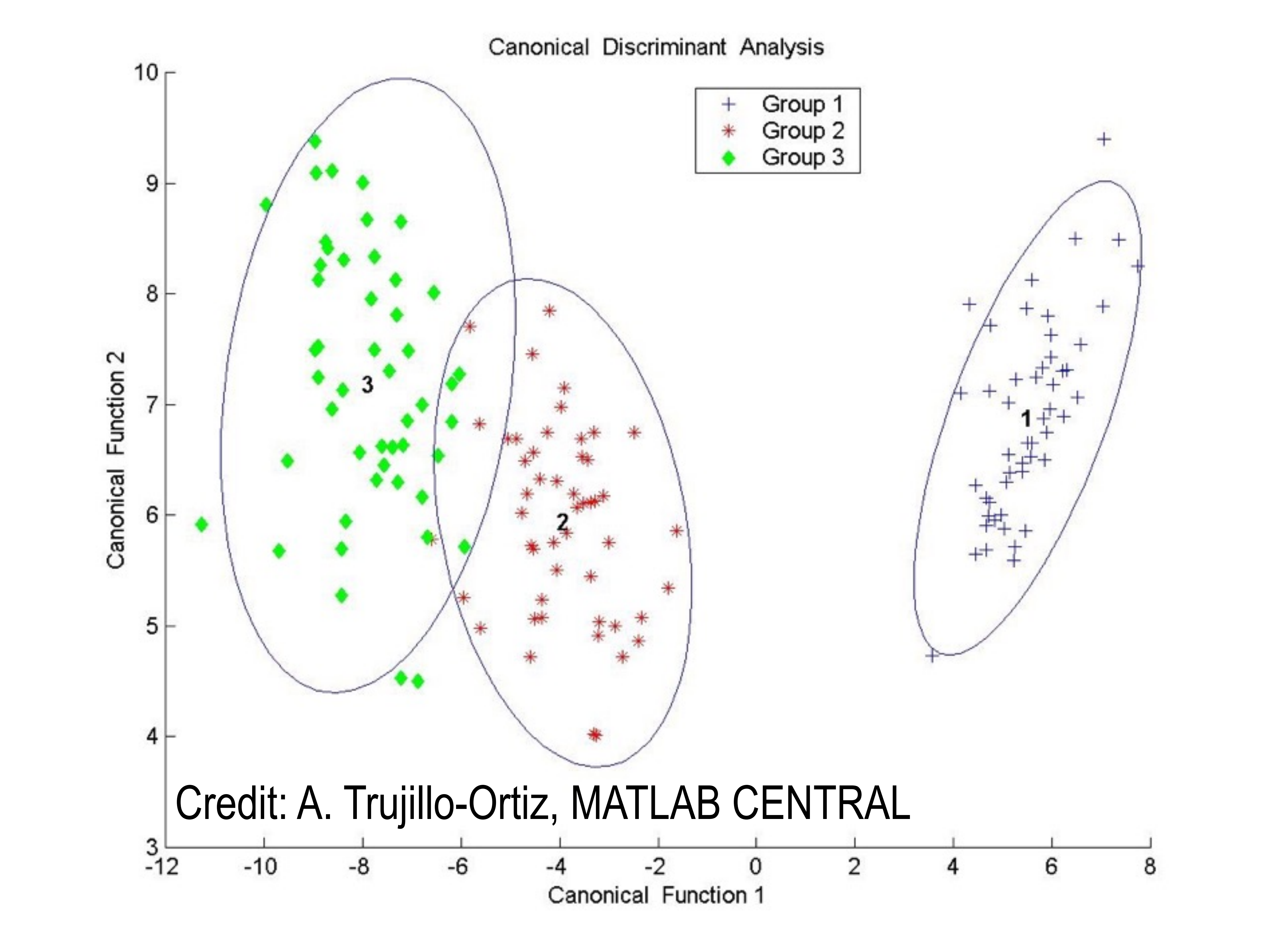
- Homogenizing the results of multiple flare prediction methods, using them with equal or non-equal weights for an ensemble forecasting

- Ensemble forecasting

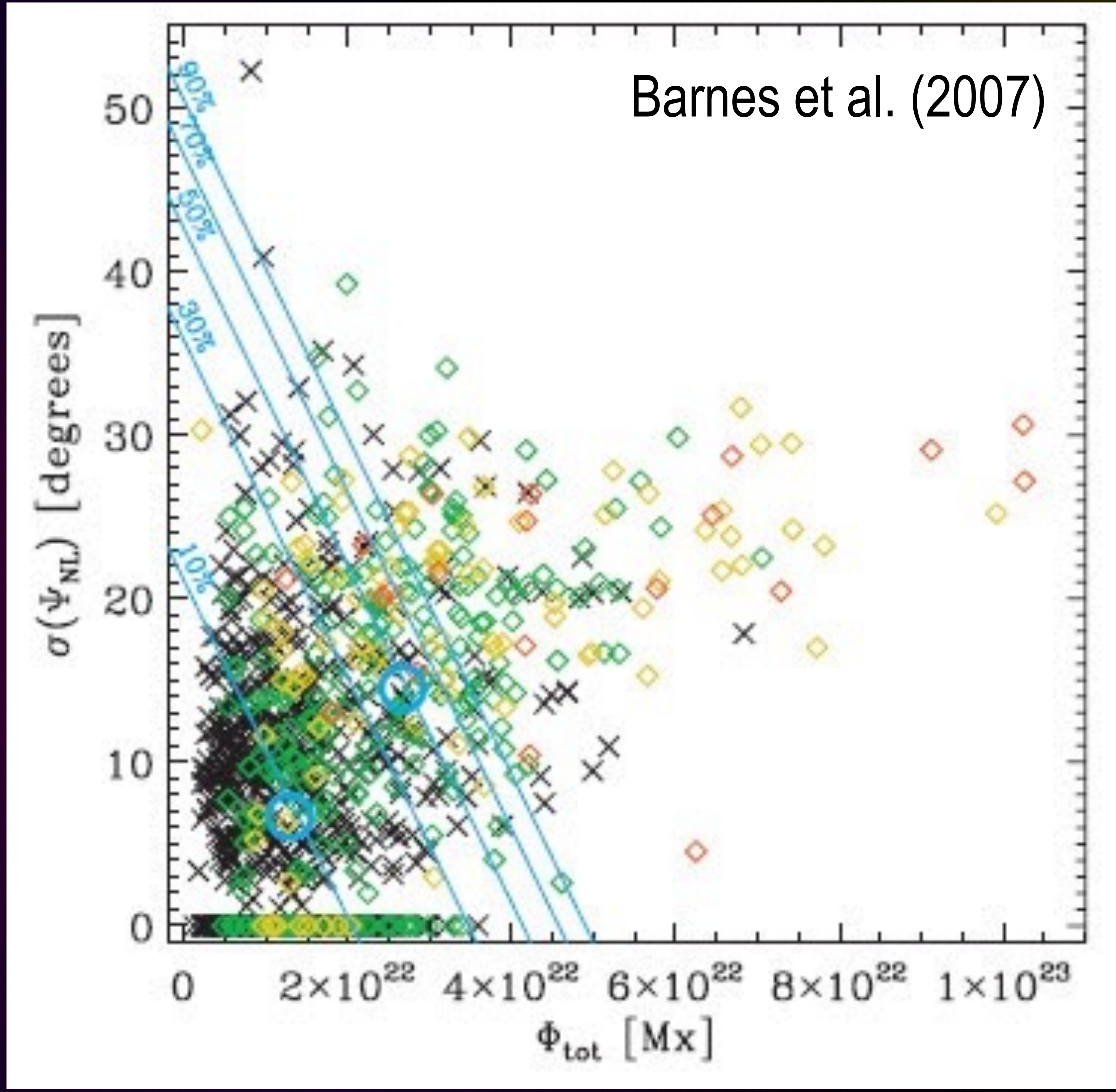


Guerra et al. (2015)

TAMING THE (LARGE) PARAMETER SPACE: DISCRIMINANT ANALYSIS and/or PCA



Example of two-function, three-group canonincal DA



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

FLARECAST: SYNTHESIS IN ACTION

FLARECAST is a European research project aiming to develop an automated solar-flare forecasting system with unmatched accuracy compared to existing facilities.

FLARECAST, using diverse European expertise, will:

- ★ use or reproduce already available predictors
- ★ classify predictors with respect to predictive ability
- ★ validate results in different ways

Project Partners:

- Academy of Athens, *Greece*
- Trinity College Dublin, *Ireland*
- Universita Degli Studi Di Genova, *Italy*
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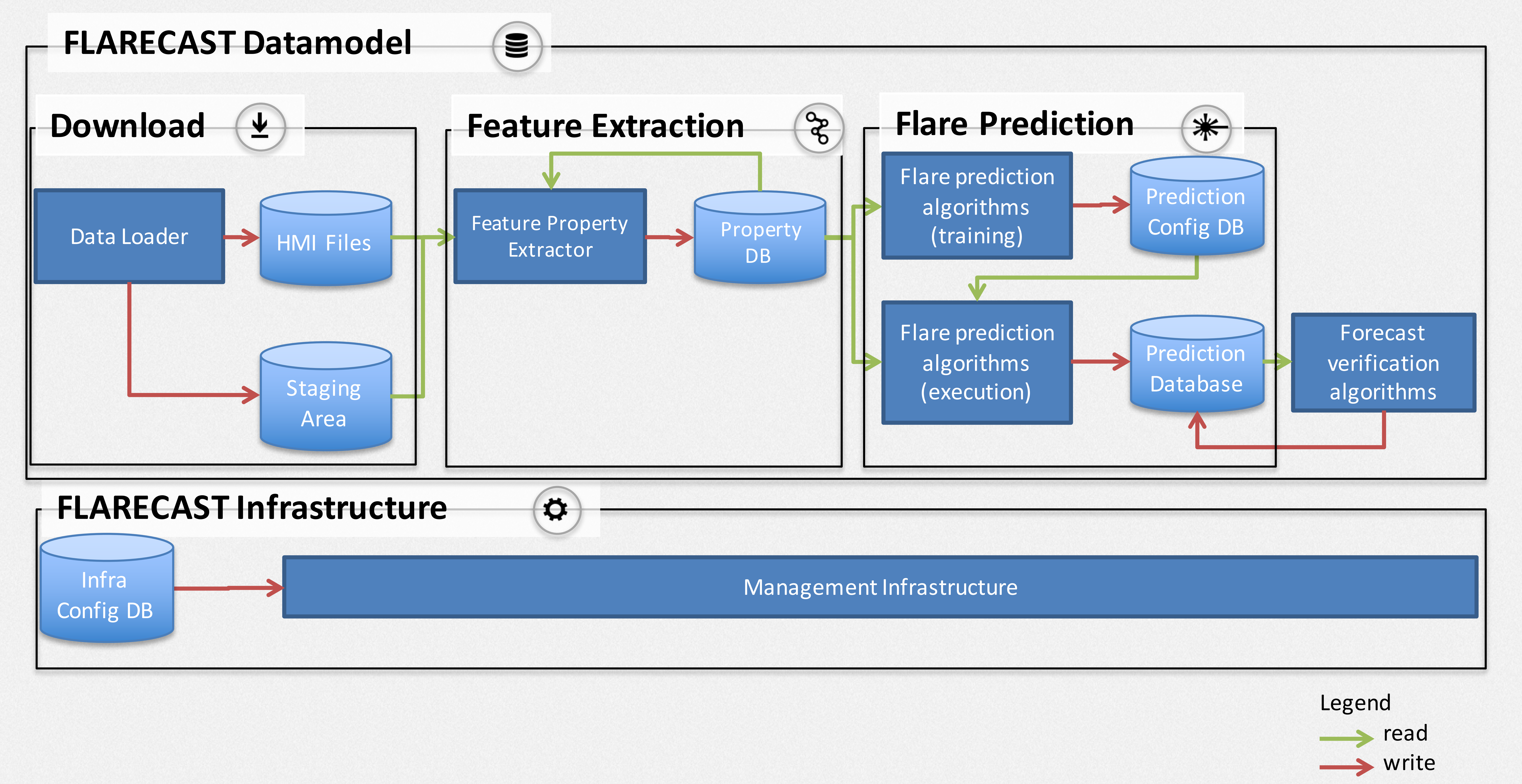
The FLARECAST forecasting system will be openly accessible, featuring open-source software that will allow end users to perform their own tests. In this way FLARECAST will aim to both revamp solar flare prediction and contribute to a better understanding of the drivers of flare activity.

FLARECAST DATAMODEL & INFRASTRUCTURE : COLLECTIVE EXPERTISE



CONCLUSIONS

- Solar flare prediction: consensus that it should be an asset of our space-weather forecasting toolbox
- Validation: a vital task, done in multiple ways as per the customer's needs
- We should understand how to enhance various validation metrics against others
- Our ultimate task should be to bring a purely probabilistic prediction (due to stochasticity of the process) as close as possible to a categorical (YES / NO) one
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All these tasks are being investigated by the FLARECAST Consortium

BACKUP SLIDES