ΑΚΑΔΗΜΙΑ ΑΘΗΝΩΝ

The Whys and Hows of Solar Eruption Prediction

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SolFER Colloquium

Solar Physics Seminars of Global Reach

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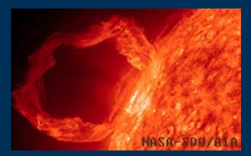
Outline

- **Solar Eruption Occurrence: the Whys**
  - The seeds for understanding
  - Flares, CMEs, SEP events and their tantalizing triggering
  - The ‘point of no return’ in eruptive solar active regions
  - Repercussions of solar eruptions and the need for forecasting
- **Solar Eruption Prediction: the Hows**
  - Forecast utilizing a theory analog
  - Data, model and performance verification
  - Keeping it modular and self-consistent: ‘horizontal’ and ‘vertical’ expansion
  - The need for an osmosis of expertise
- Conclusion

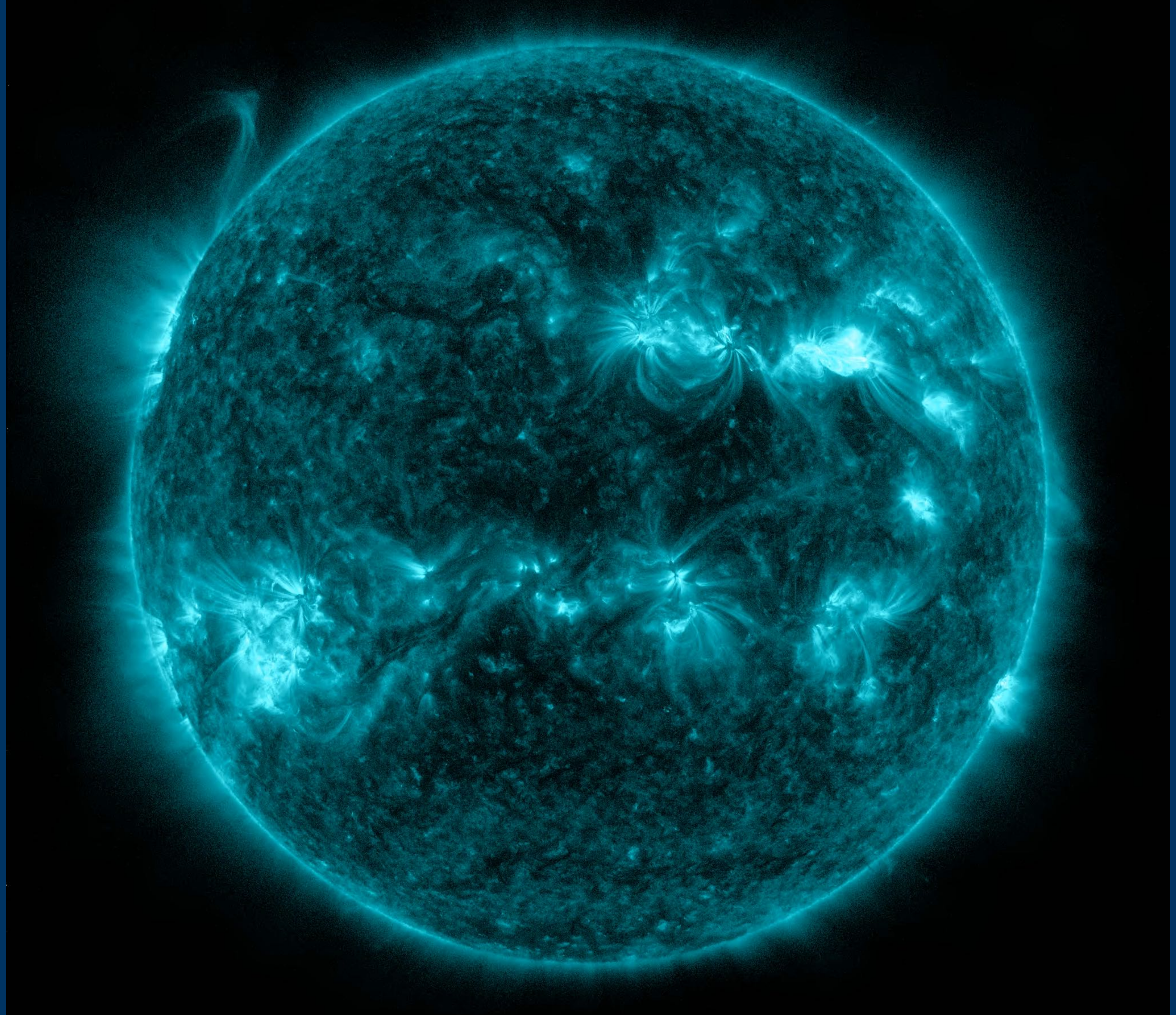


The Whys

Solar flares: magnetically driven instabilities

Solar flare (American Heritage Dictionary): a sudden eruption of magnetic energy released on or near the surface of the Sun, usually associated with sunspots and accompanied by bursts of electromagnetic radiation and particles

GOES X1.3 flare on March 30, 2022 @ 17:21 — 17:46 UT



Credit: NASA Scientific Visualization Studio

- A reservoir of magnetic energy: slow build-up; fast release

$$\frac{1}{8\pi}\int_{V_{flare}} \mathbf{B}_{pre}\cdot\mathbf{B}_{pre}\,dV = \frac{1}{8\pi}\int_{V_{flare}} \mathbf{B}_{post}\cdot\mathbf{B}_{post}\,dV + \mathscr{E}$$

$$V_{flare} << V_{corona} \qquad \mathscr{E} \equiv \{heat; emission; acceleration\}$$

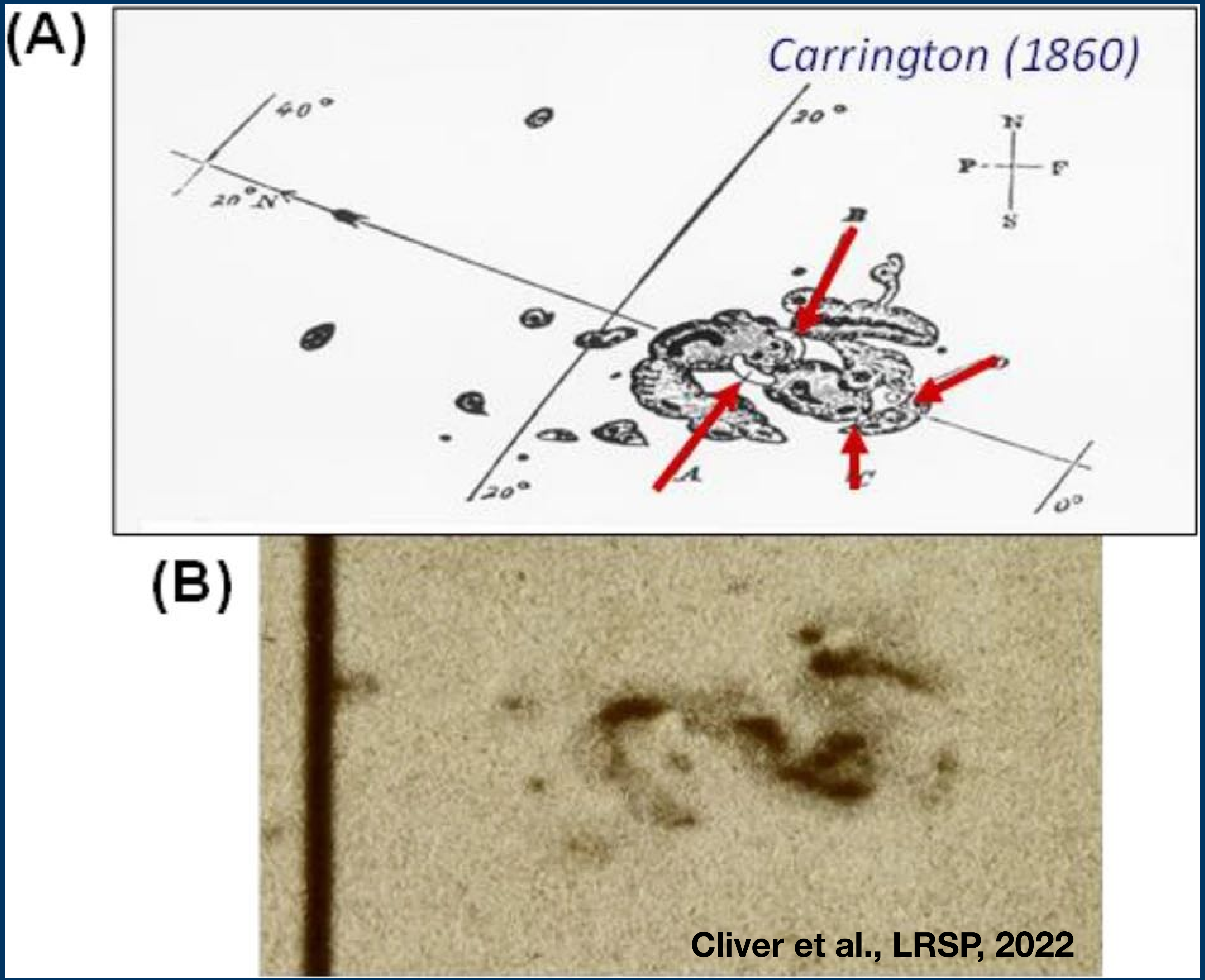
$$\mathscr{E}_{total} = \frac{1}{8\pi}\int_V \mathbf{B}_{vacuum}\cdot\mathbf{B}_{vacuum}\,dV + \underbrace{\frac{1}{2c}\int_V \mathbf{A}_{cur}\cdot\mathbf{J}\,dV}_{\mathscr{E}_{free}}$$

$$\boxed{\begin{gathered}\mathbf{B}_{total} = \mathbf{B}_{vacuum} + \mathbf{B}_{cur}\\ \nabla\times\mathbf{A}_{cur} = \mathbf{B}_{cur} \qquad \nabla\times\mathbf{B}_{cur} = \frac{4\pi}{c}\mathbf{J}\end{gathered}}$$

Sakurai, SoPh, 1981

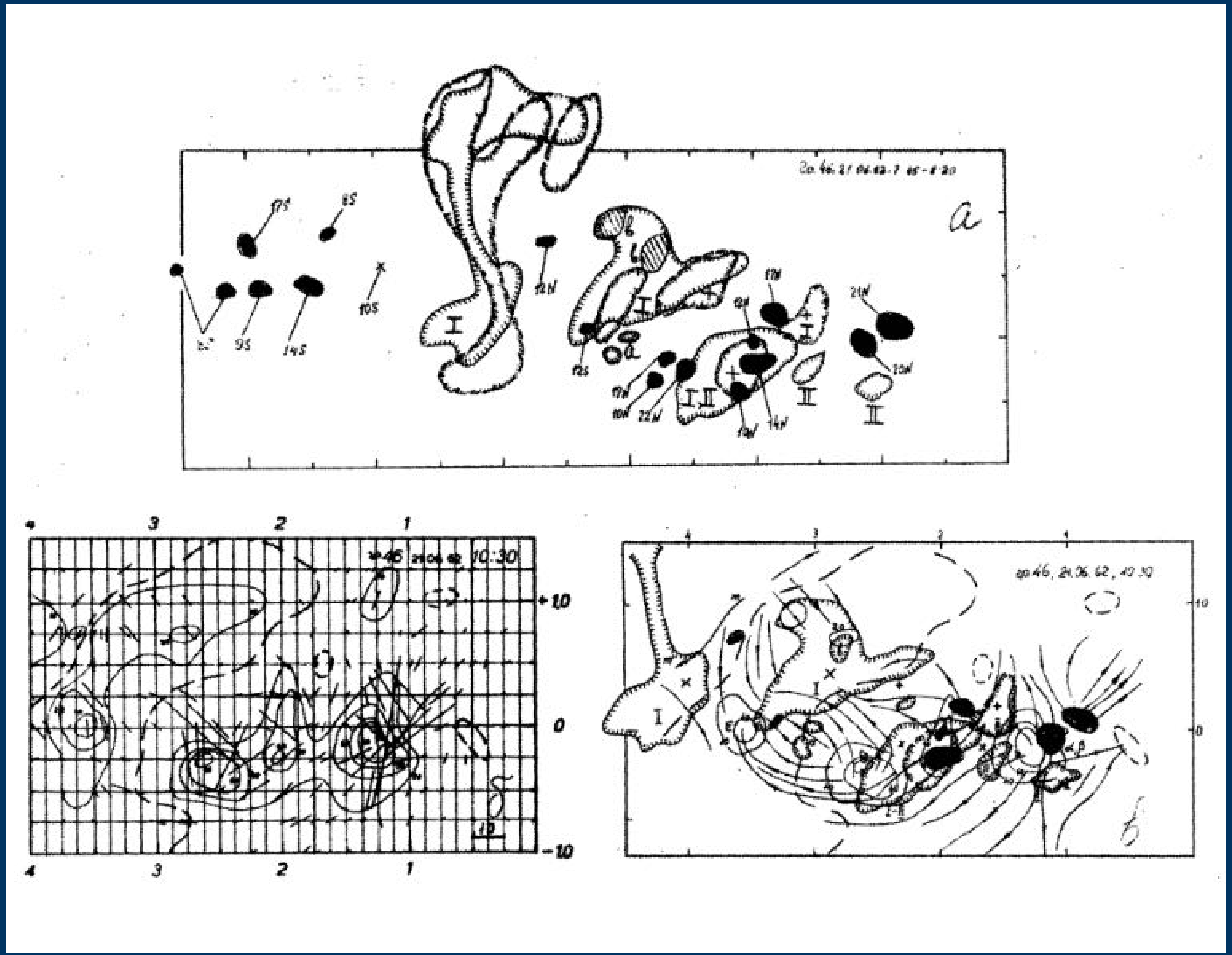
$$\mathscr{E} < \mathscr{E}_{free}$$

History of observations



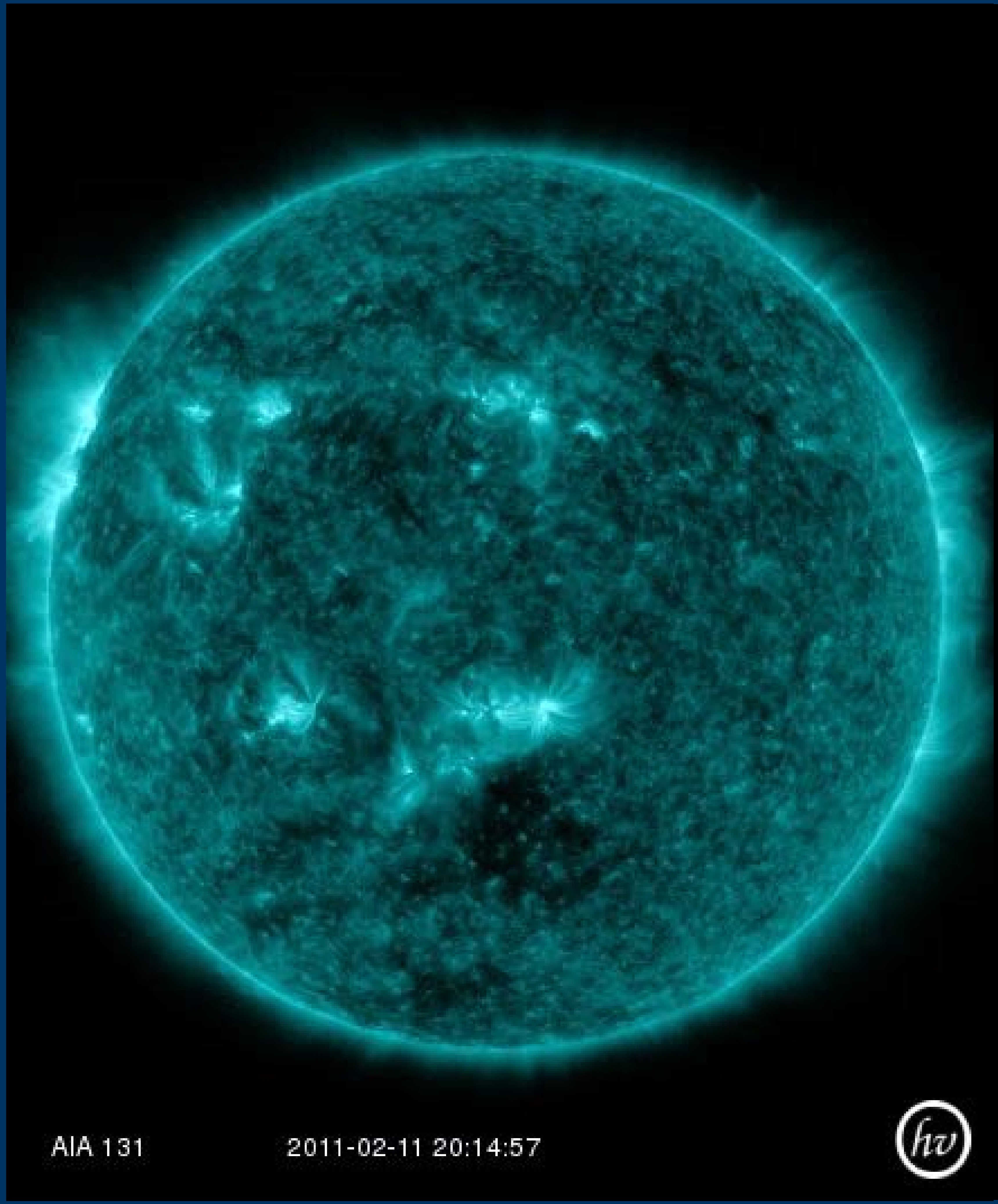
Cliver et al., LRSP, 2022

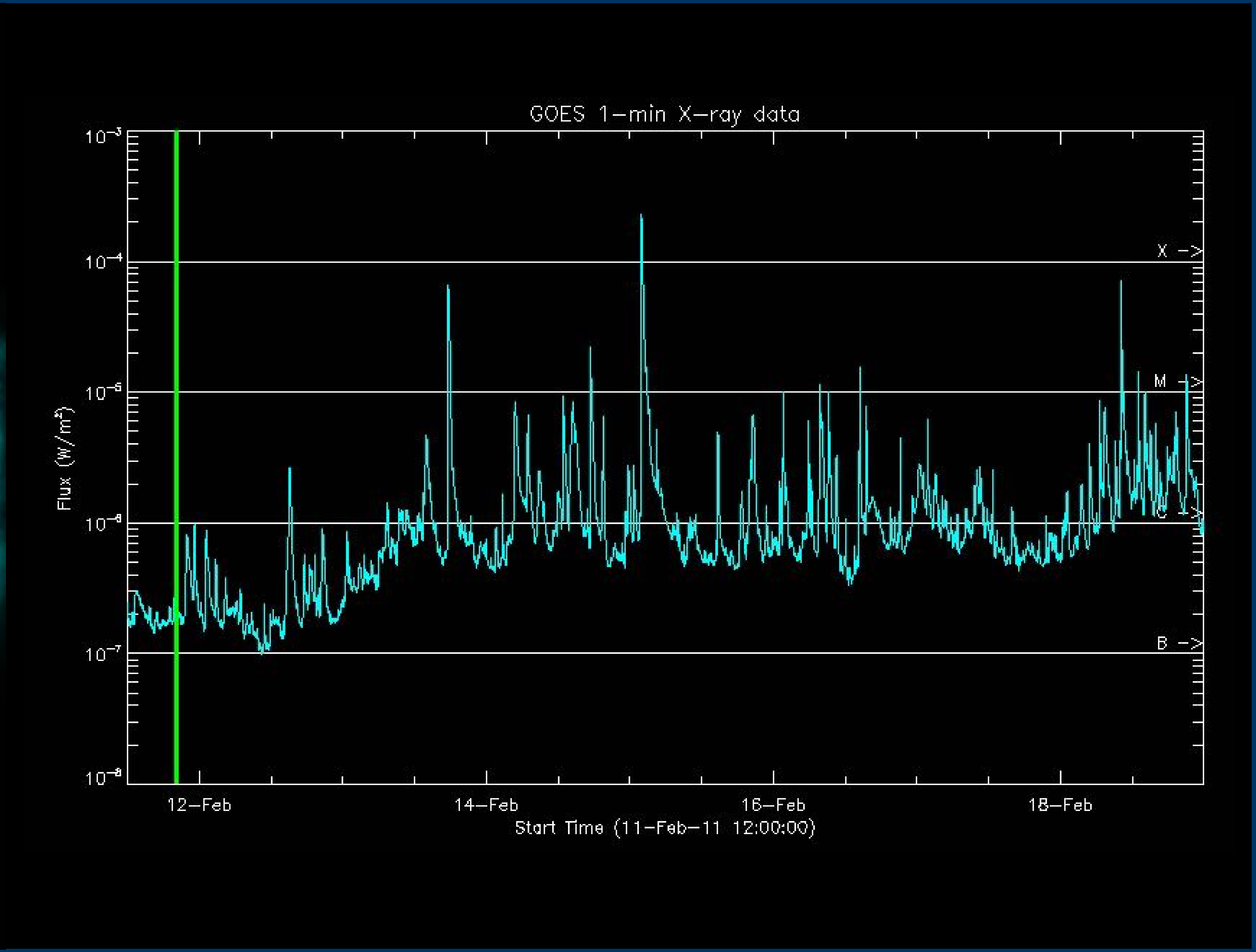
Major flares are endemic in some coronal neighborhoods with high free energy accumulation — i.e., above sunspot complexes, known as solar active regions


Severny, ARA&A, 1964

Flares occurring from magnetically complex solar regions with enhanced linear polarization signal, meaning strong <u>transverse</u> fields

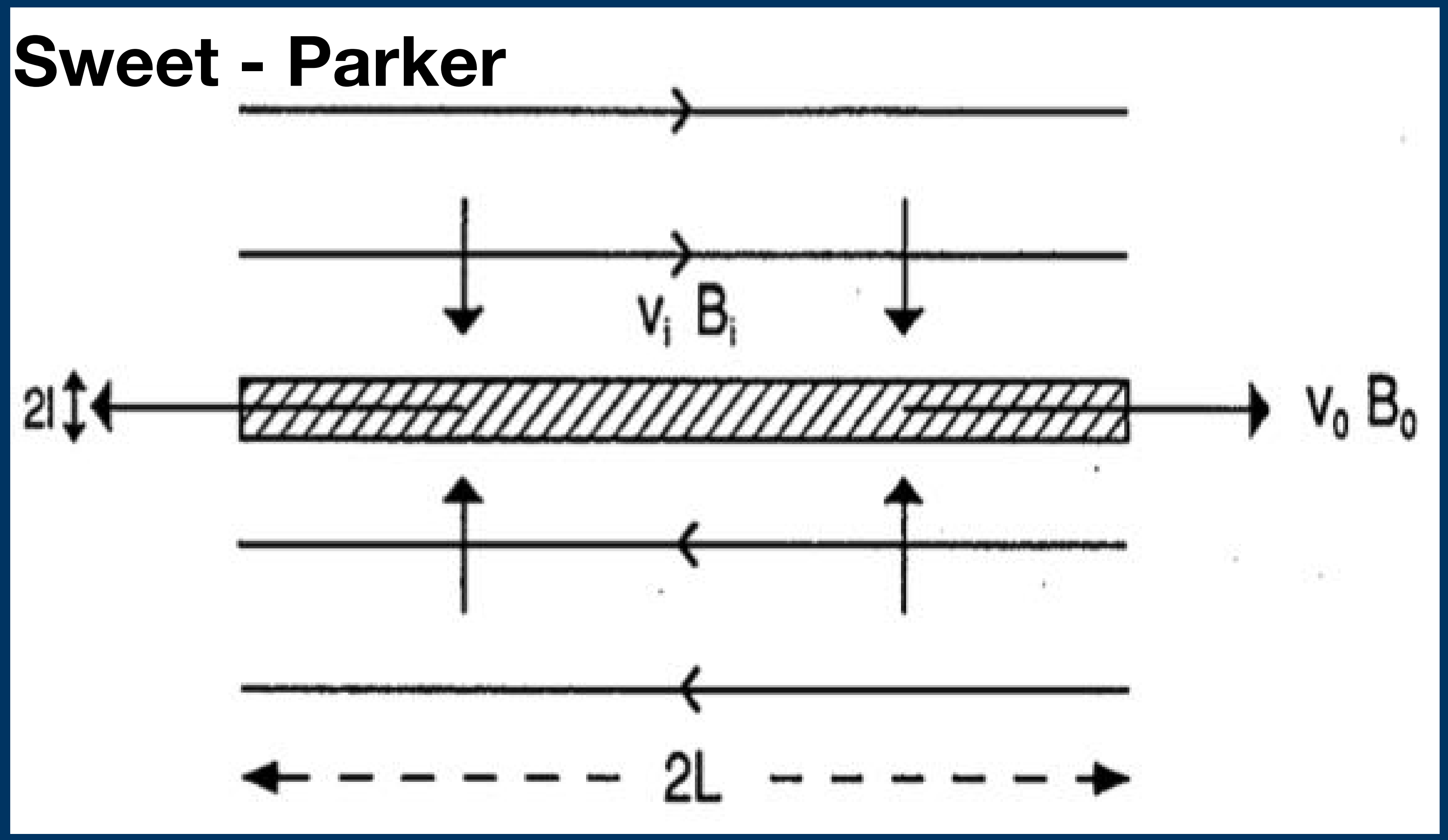
Solar Flares: swarms of them during high solar activity intervals

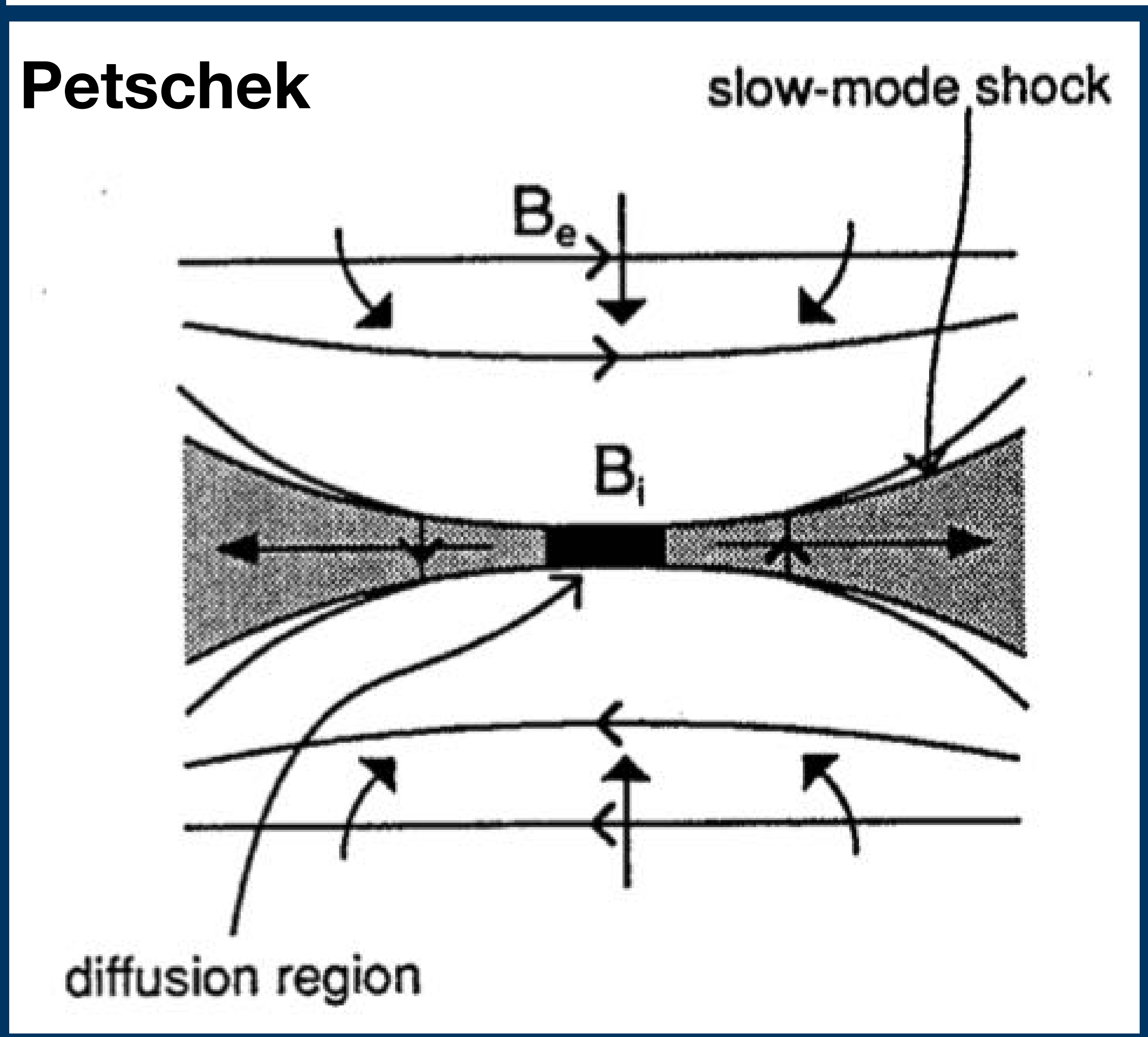




History and contemporary realization

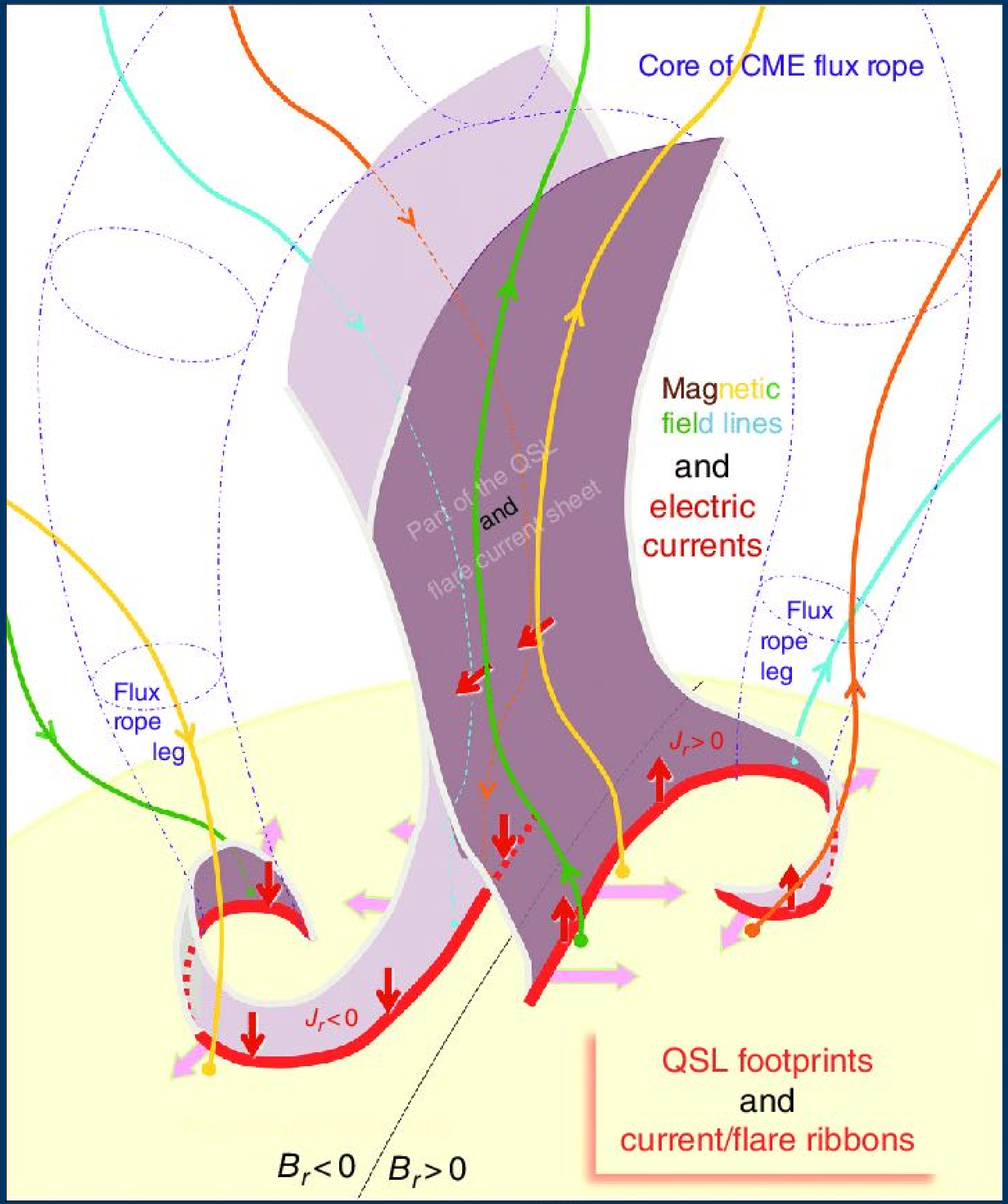
Janvier et al., ApJ, 2014





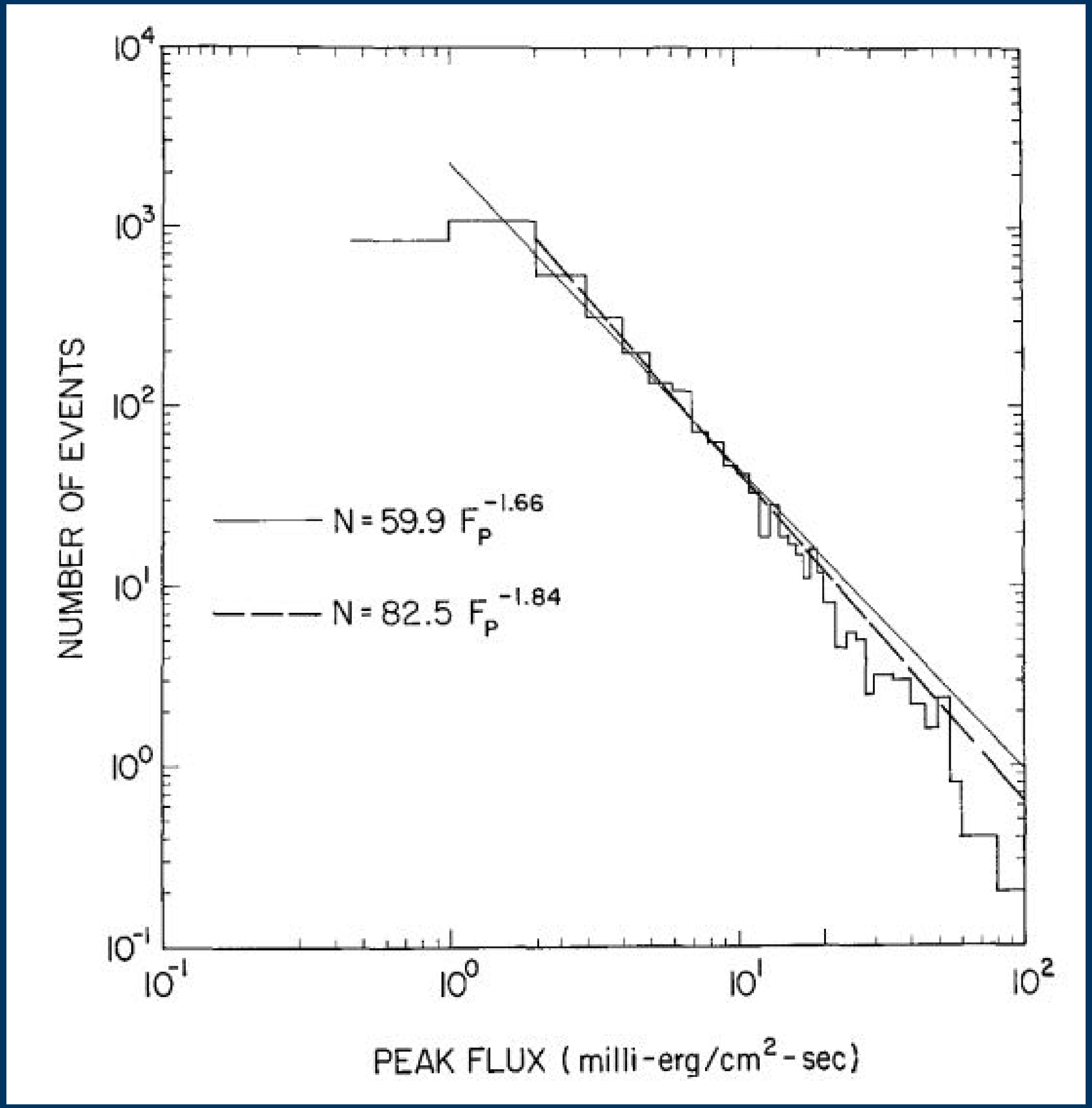
from Priest, 1994, in Plasma Astrophysics

Magnetic reconnection:
the key to tap into coronal free energy



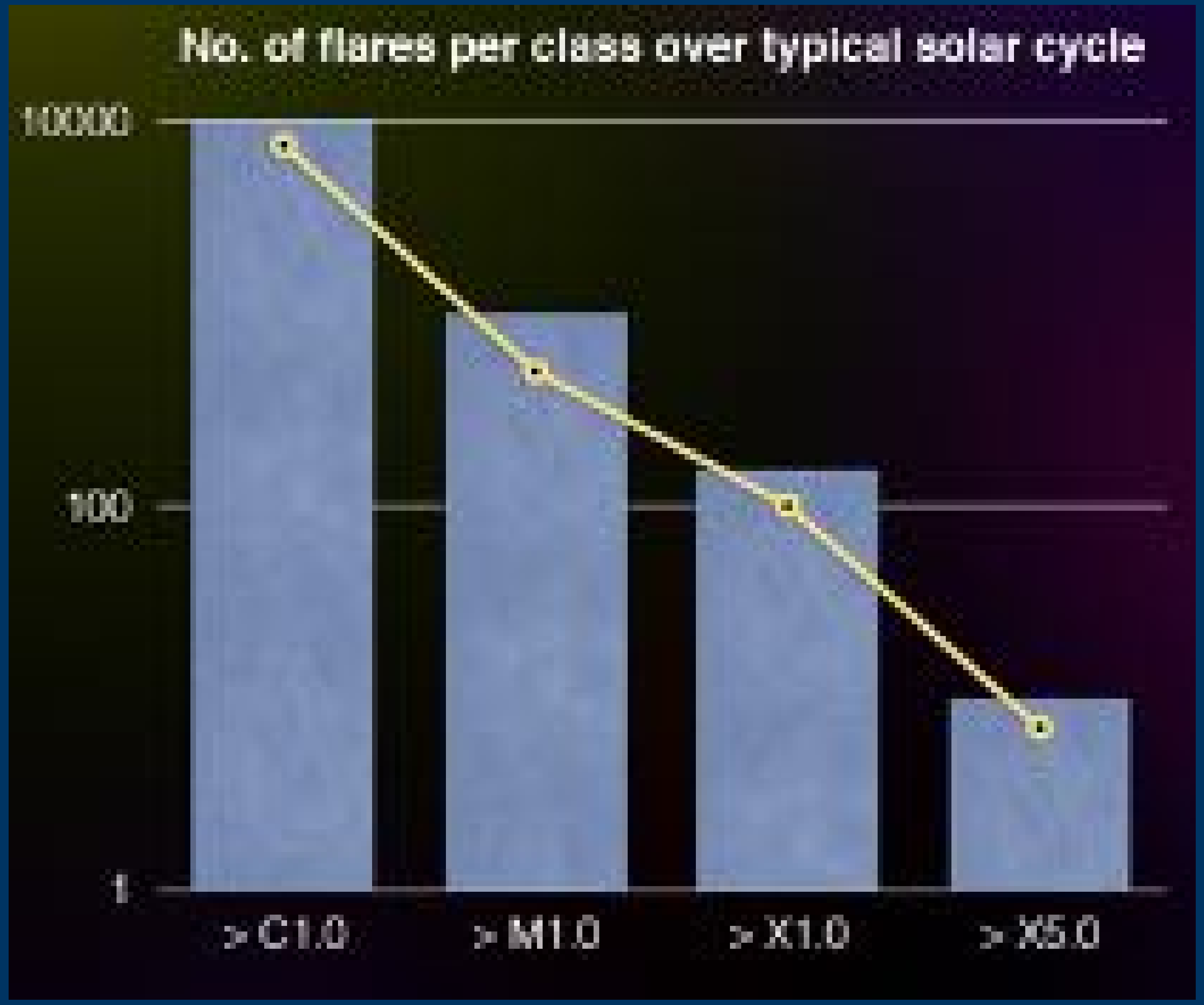
The standard flare model in three dimensions

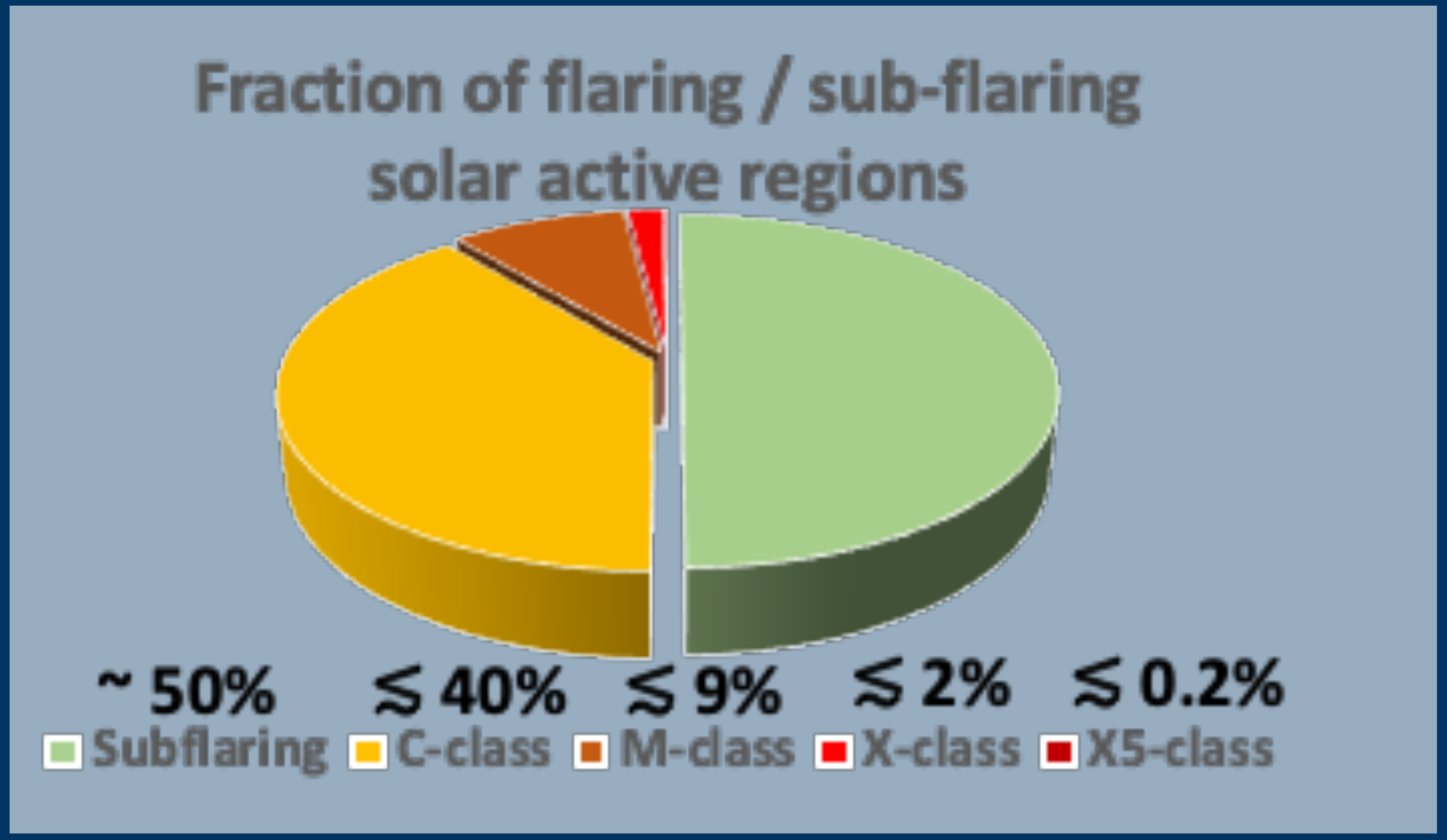
And then, the stunning statistics



Drake, SoPh, 1971 - 4028 bursts

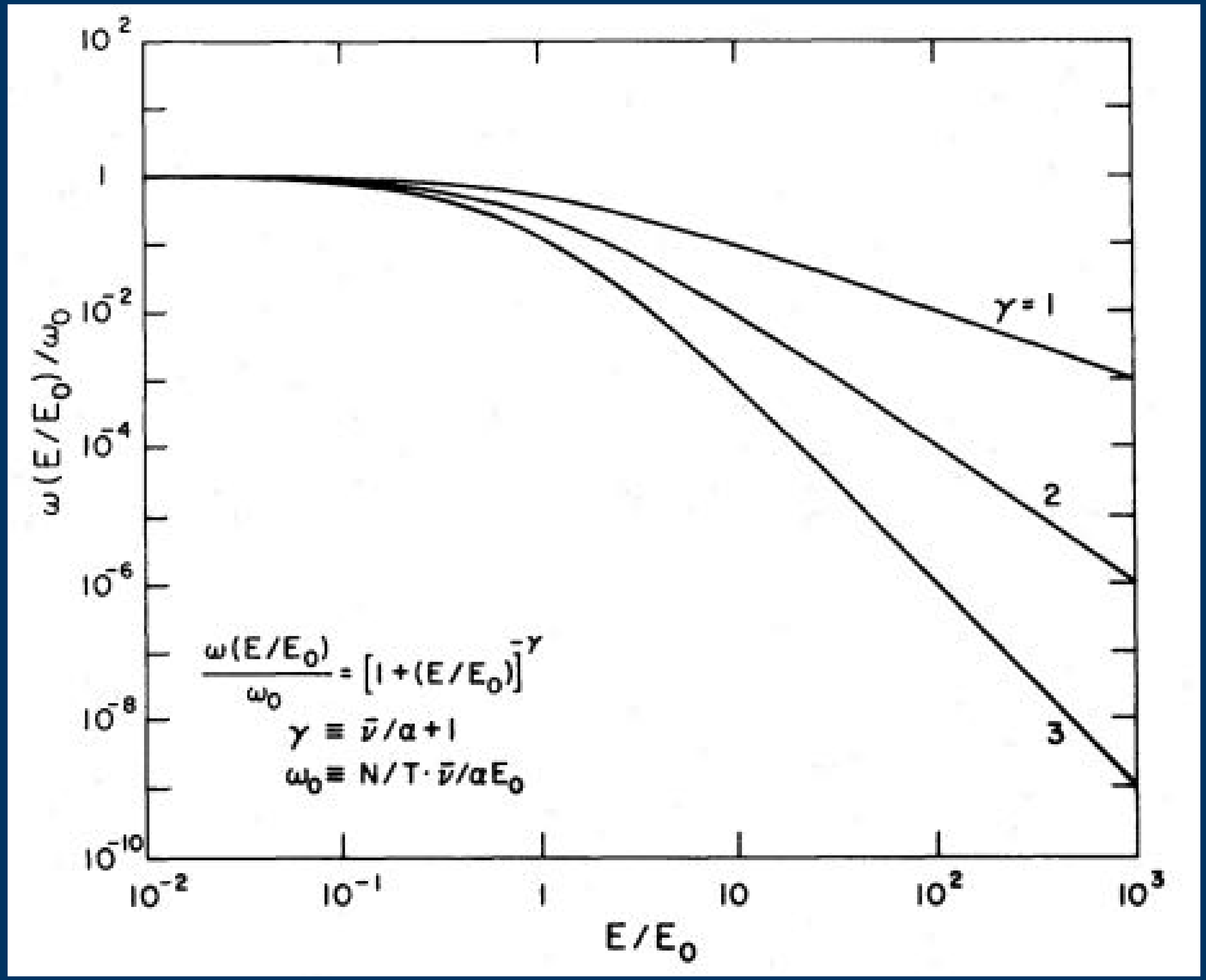
A compilation of solar cycle 23 — without loss of generality





Flare events follow well-defined power law statistics in terms of occurrence frequency vs. size

A first attempt to a statistical interpretation



Rosner & Vaiana, ApJ, 1978

Flares are:

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

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

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

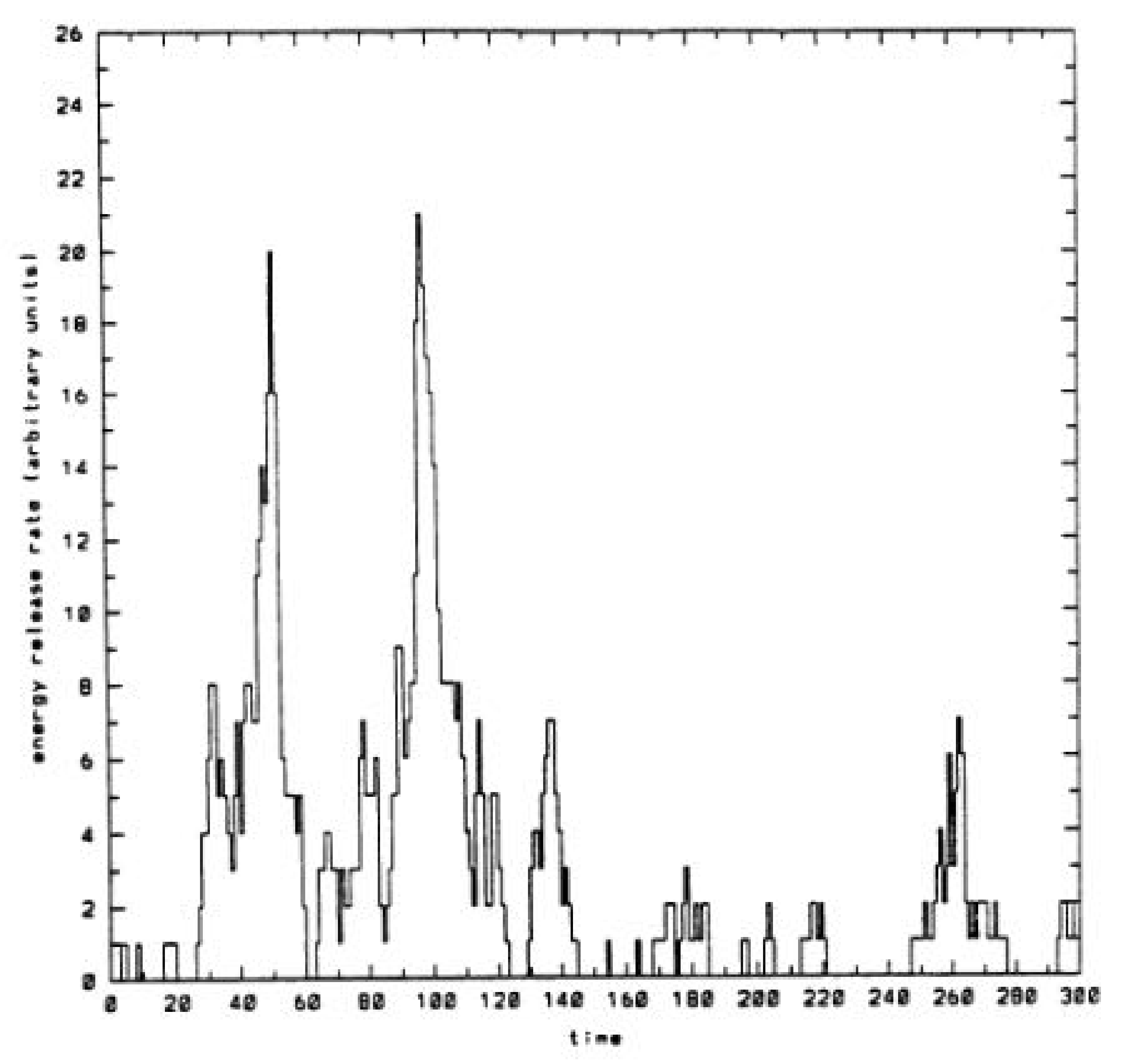
$$P(E) \sim (1 + \frac{E}{E_0})^{-\gamma}$$

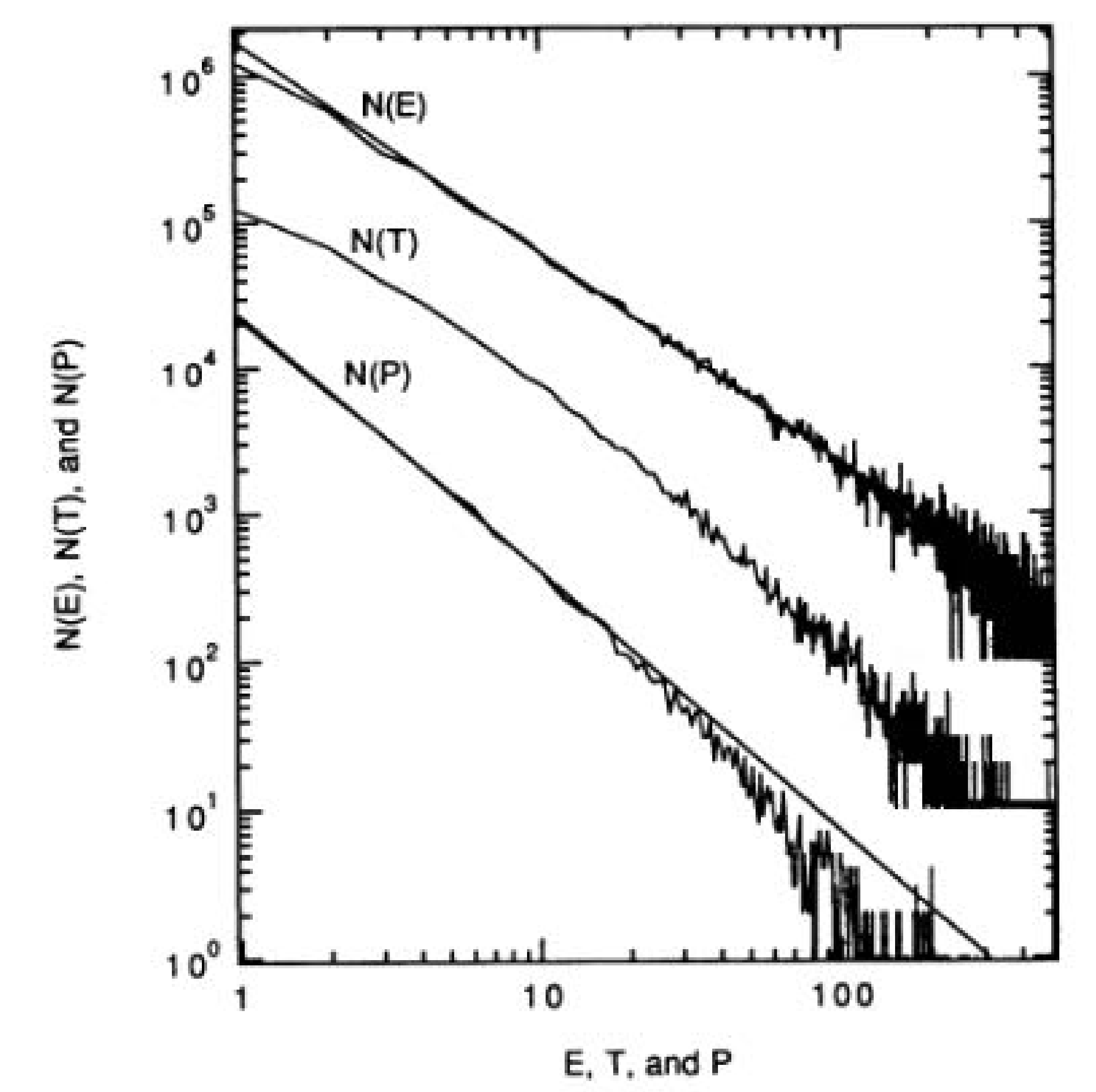
Power-law distribution of flare size later attributed to the concept of self-organized criticality (1980s - 1990s) & the concept of marginal stability - Bak et al.

Credit: Christensen & Moloney (2005)

Oh, the irony: instabilities in a self-organized or SOC system are stochastically triggered, hence hardly predictable

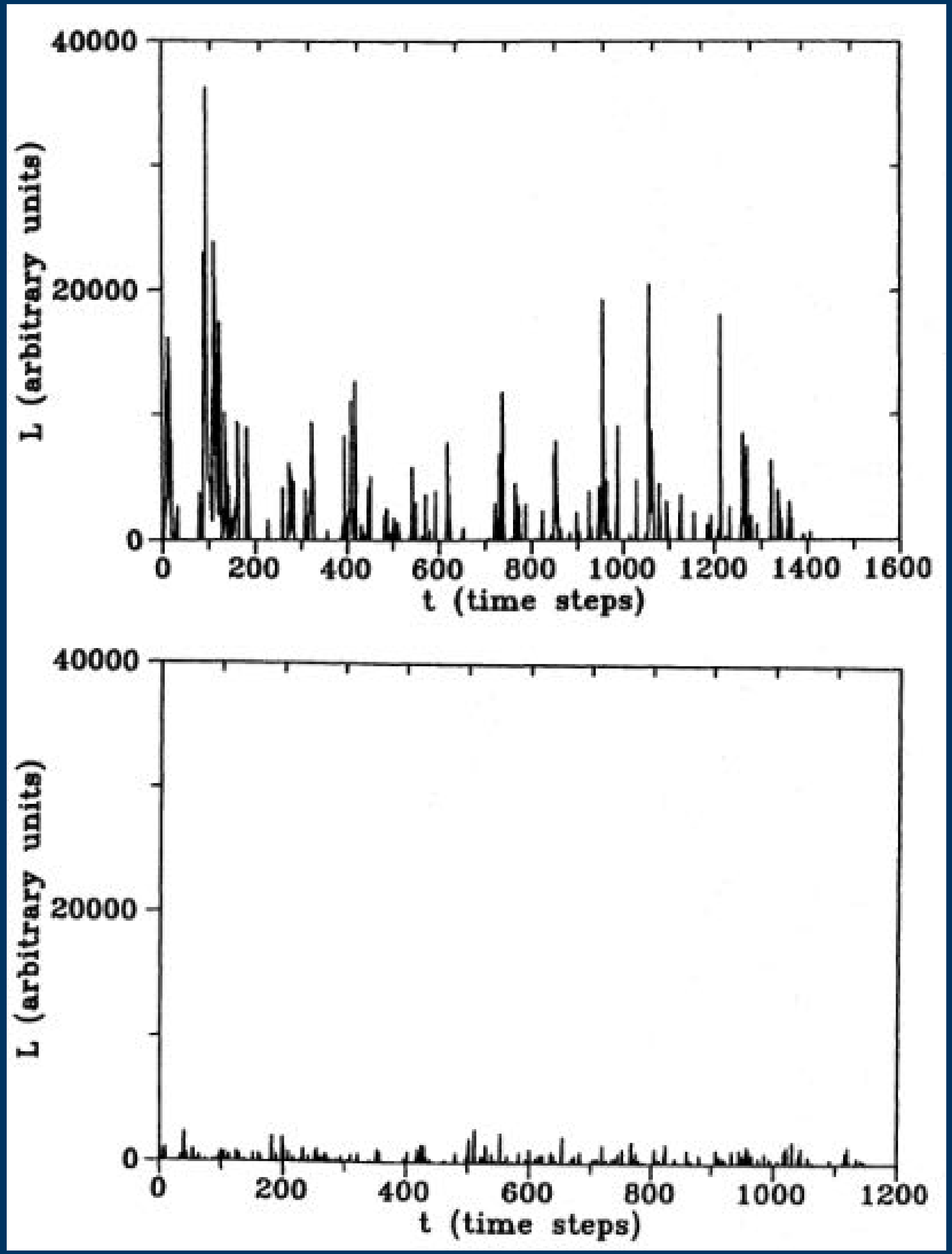
Energy avalanches and the statistical flare



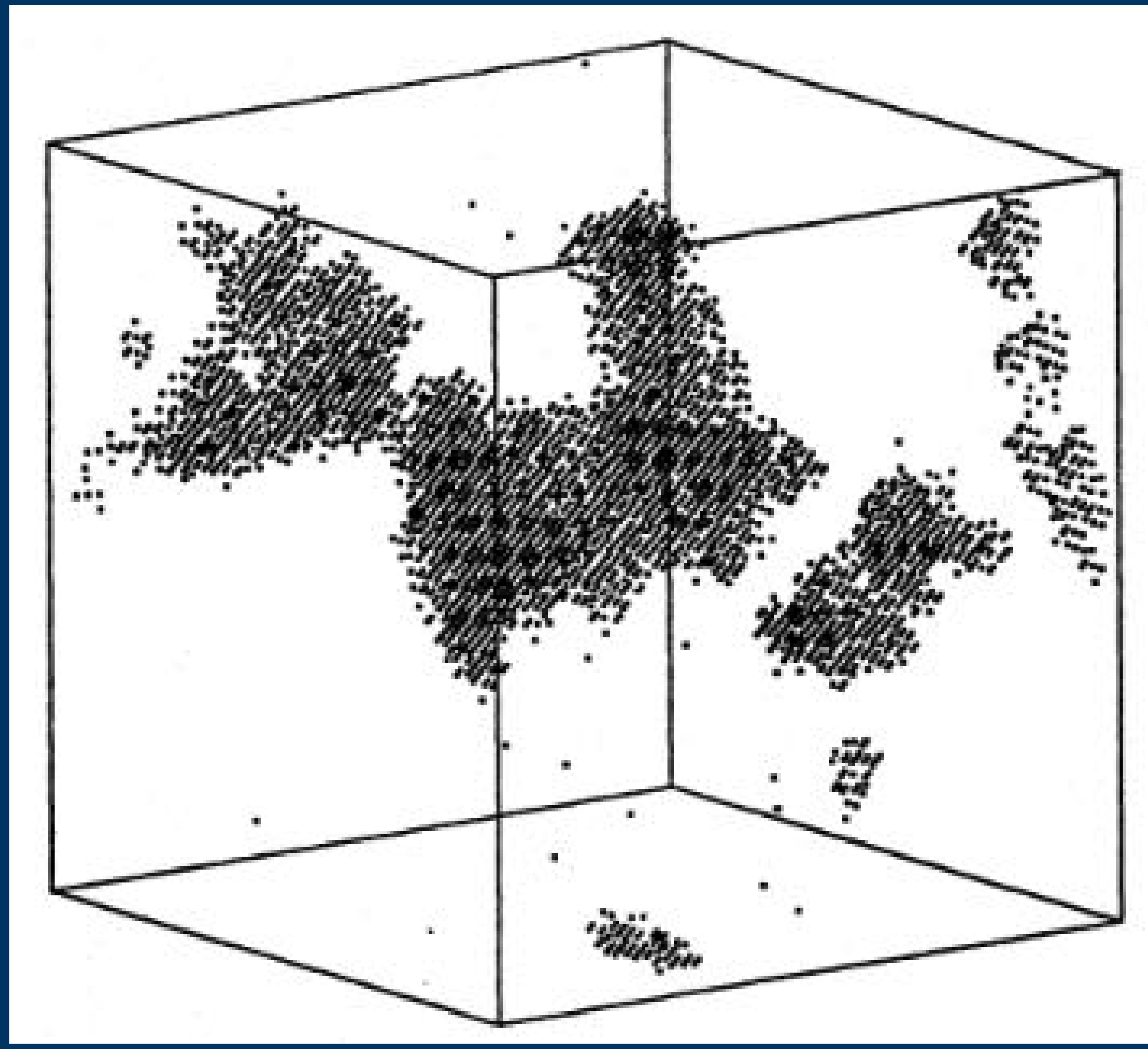


Lu & Hamilton, ApJL, 1991

Lu et al., ApJ, 1993



Vlahos et al., A&A, 1995



'This type of flare with spatiotemporal fragmentation and clustering in small and large structures will be called here the statistical flare'

Flares: *energy avalanches*

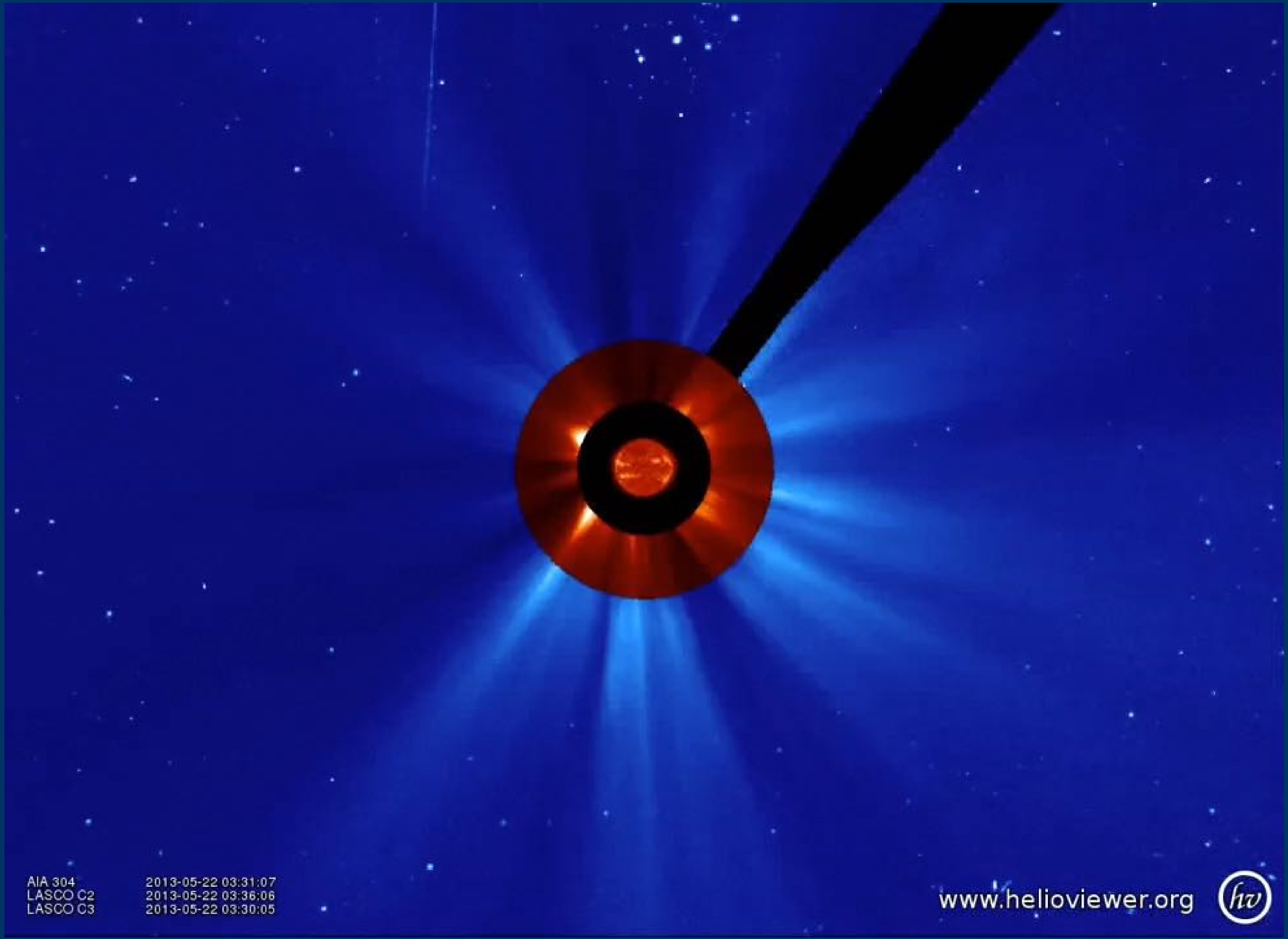
The “solar flare myth” in solar — terrestrial relations

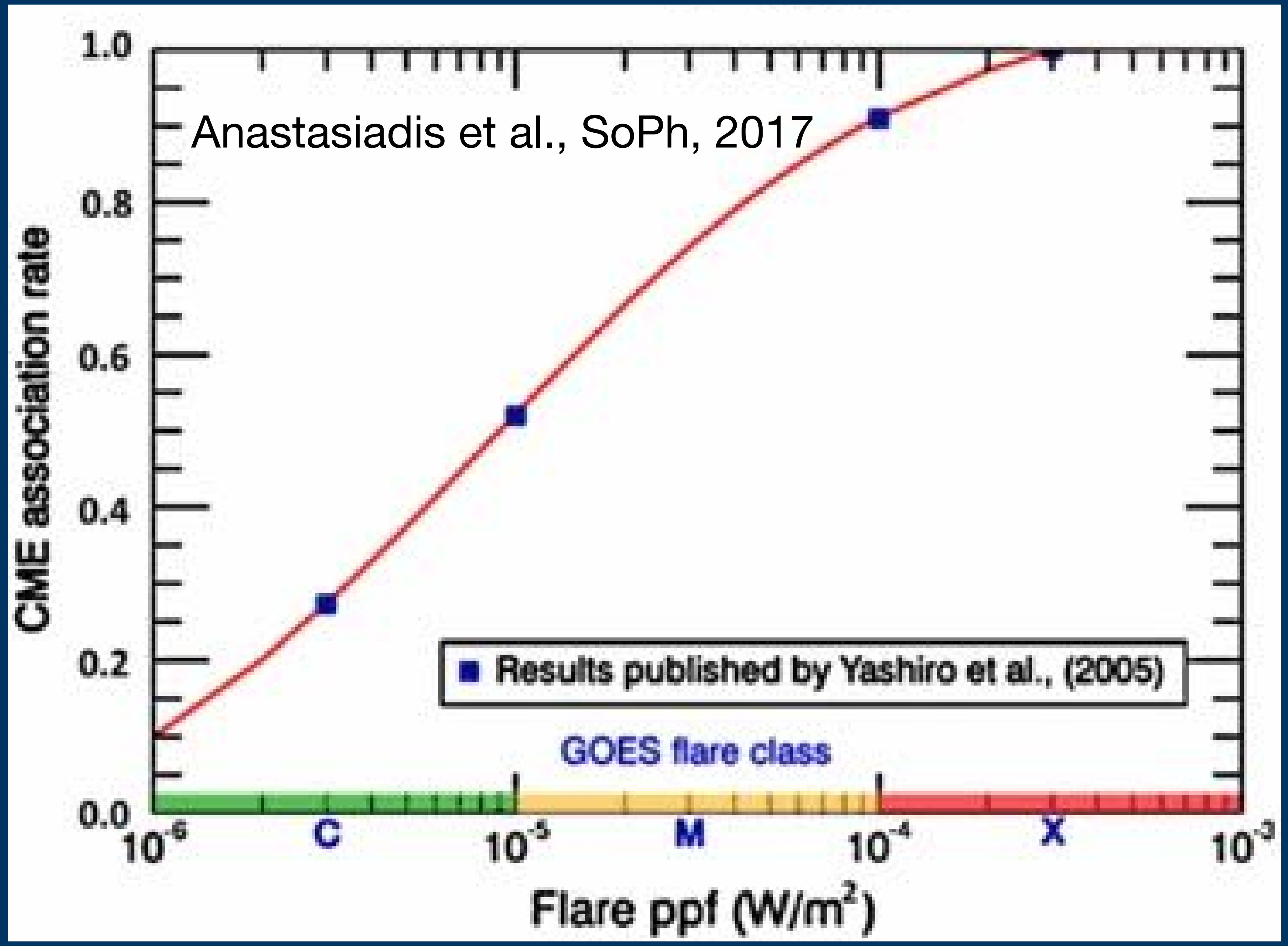
‘[flares dominate] … the popular perception of the relation between solar activity and interplanetary and geomagnetic events … Yet there is good evidence that this paradigm is wrong … this central role is given to events known as coronal mass ejections’, Gosling, JGR, 1993

‘The “Solar Flare Myth” … is a misunderstanding … just for this reason the term “eruptive flare” has been introduced for all solar active phenomena … resulting in a CME’, Svestka, SoPh, 1995

Coronal mass ejections (CMEs)

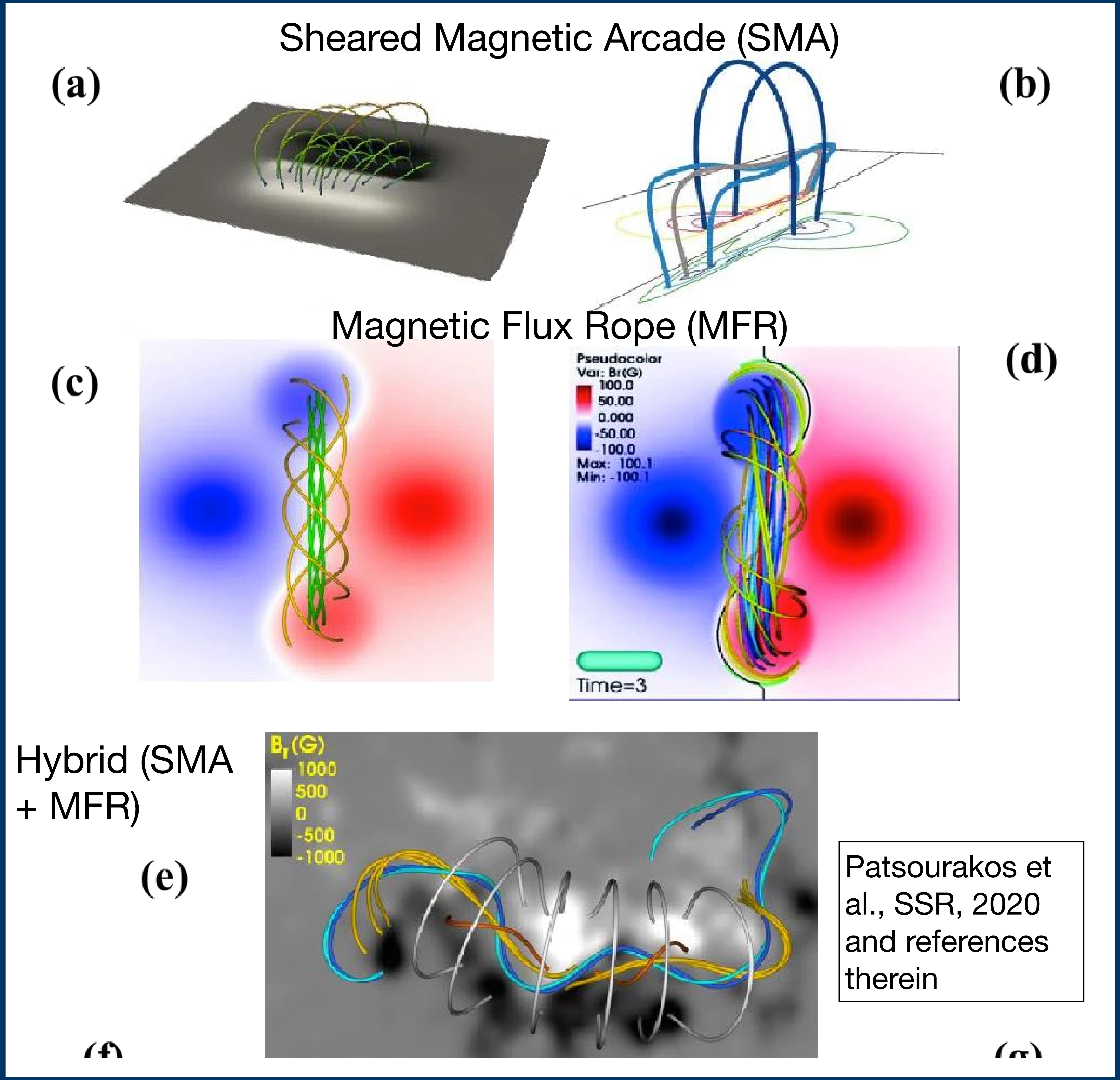
Coronal mass ejection (American Heritage Dictionary): a massive, bubble-shaped burst of plasma expanding outward from the Sun's corona, in which large amounts of superheated particles at emitted at nearly the speed of light





- All CMEs in active regions associate with flares
- Not all major flares associate to CMEs (i.e., 'eruptive' vs 'confined' flares)
- Stronger flares are likelier to be eruptive
- CMEs occur in the quiet Sun, too
- Quiet-Sun CMEs are slower than active region CMEs

What does it take for an ‘eruptive flare’?

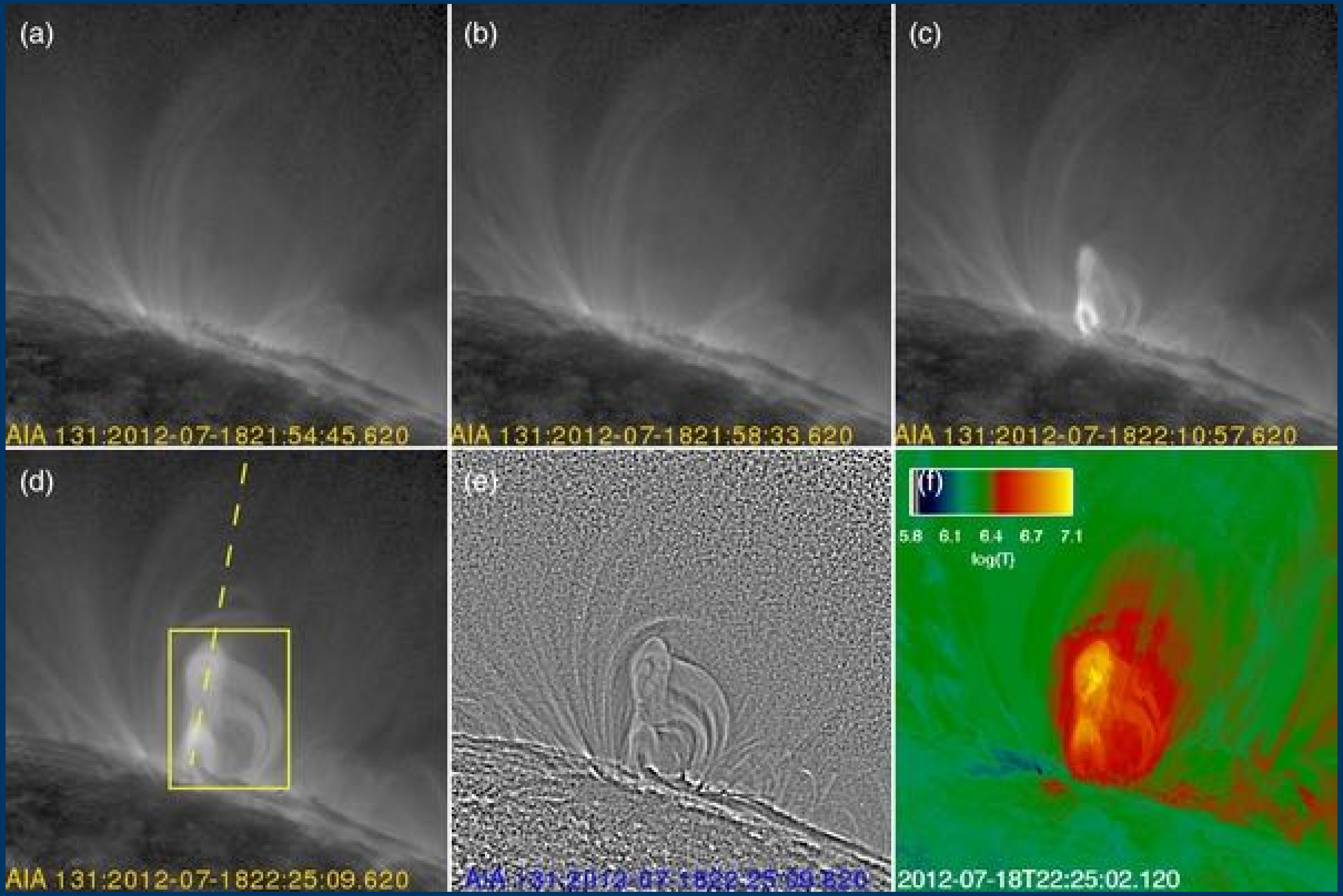


- Among a vast body of literature, one in principle has:
  - A strong, flux-massive magnetic polarity inversion line
  - A sheared magnetic arcade and/or a magnetic flux rope extending above the PIL
- Many different mechanisms:
  - Tether cutting
  - Catastrophe (uncontained instability)
  - Kink instability
  - Torus instability
  - Breakout
  - Lorentz ‘hoop’ force

for reviews, see Forbes 2000; Klimchuk 2001; Mikic & Lee 2006; Forbes et al. 2006; Chen 2011; Aulanier 2014; Schmieder et al., 2015; Cheng et al., 2017; Green et al., 2018; Toriumi & Wang, 2019; Patsourakos et al., 2020

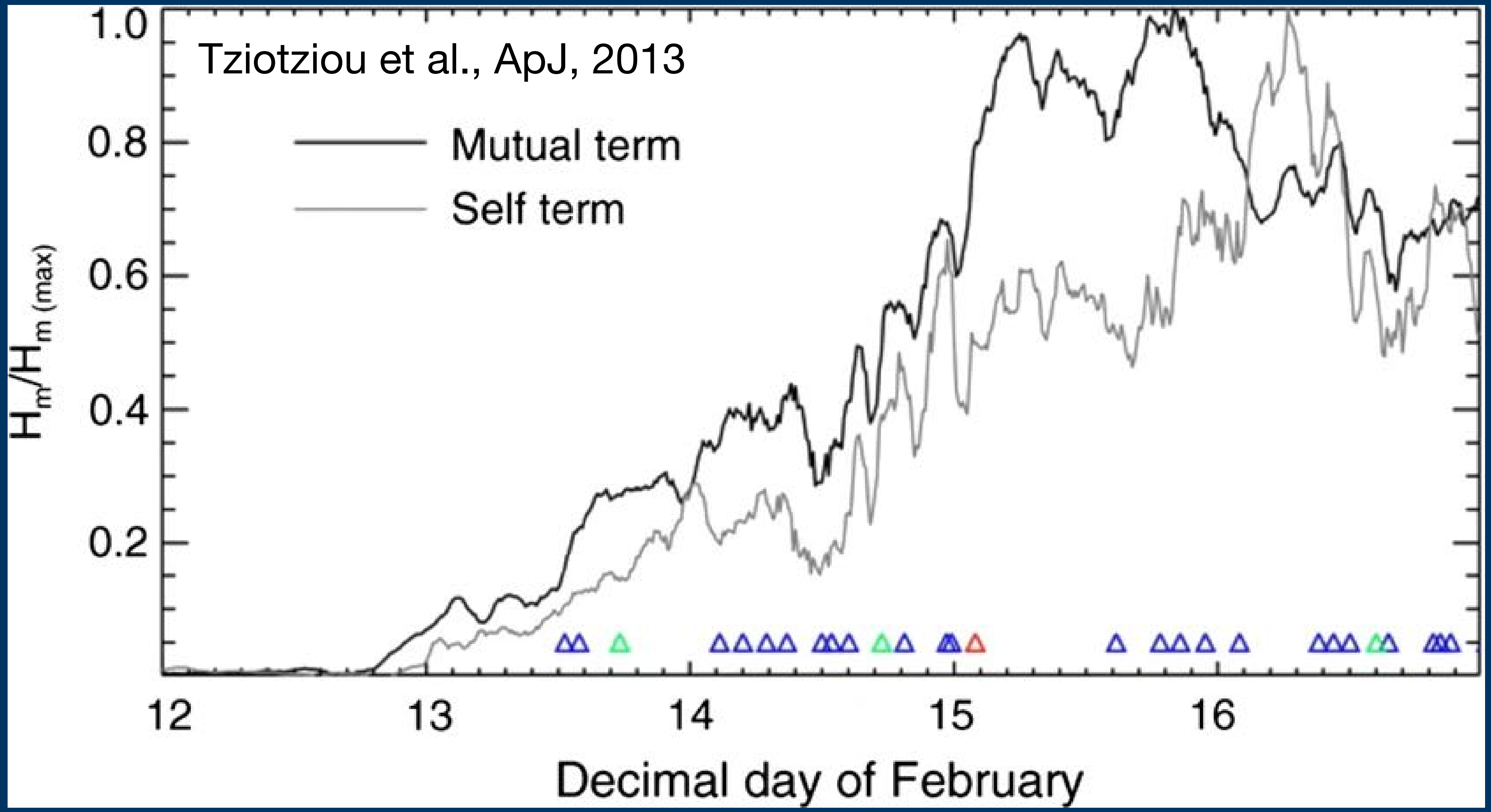
An emerging paradigm: time dependence

" Our key conclusion is that the differentiation of pre-eruptive configurations in terms of SMAs and MFRs seems artificial. Both observations and modeling can be made consistent if the pre-eruptive configuration exists in a hybrid state that is continuously evolving from an SMA to an MFR. Thus, the 'dominant' nature of a given configuration will largely depend on its evolutionary stage (SMA-like early on, MFR-like near the eruption)", Patsourakos et al., SSR, 2020



Resistive formation (i.e., via a confined flare) of a hot, pre-eruption flux rope

Patsourakos et al., ApJ, 2013

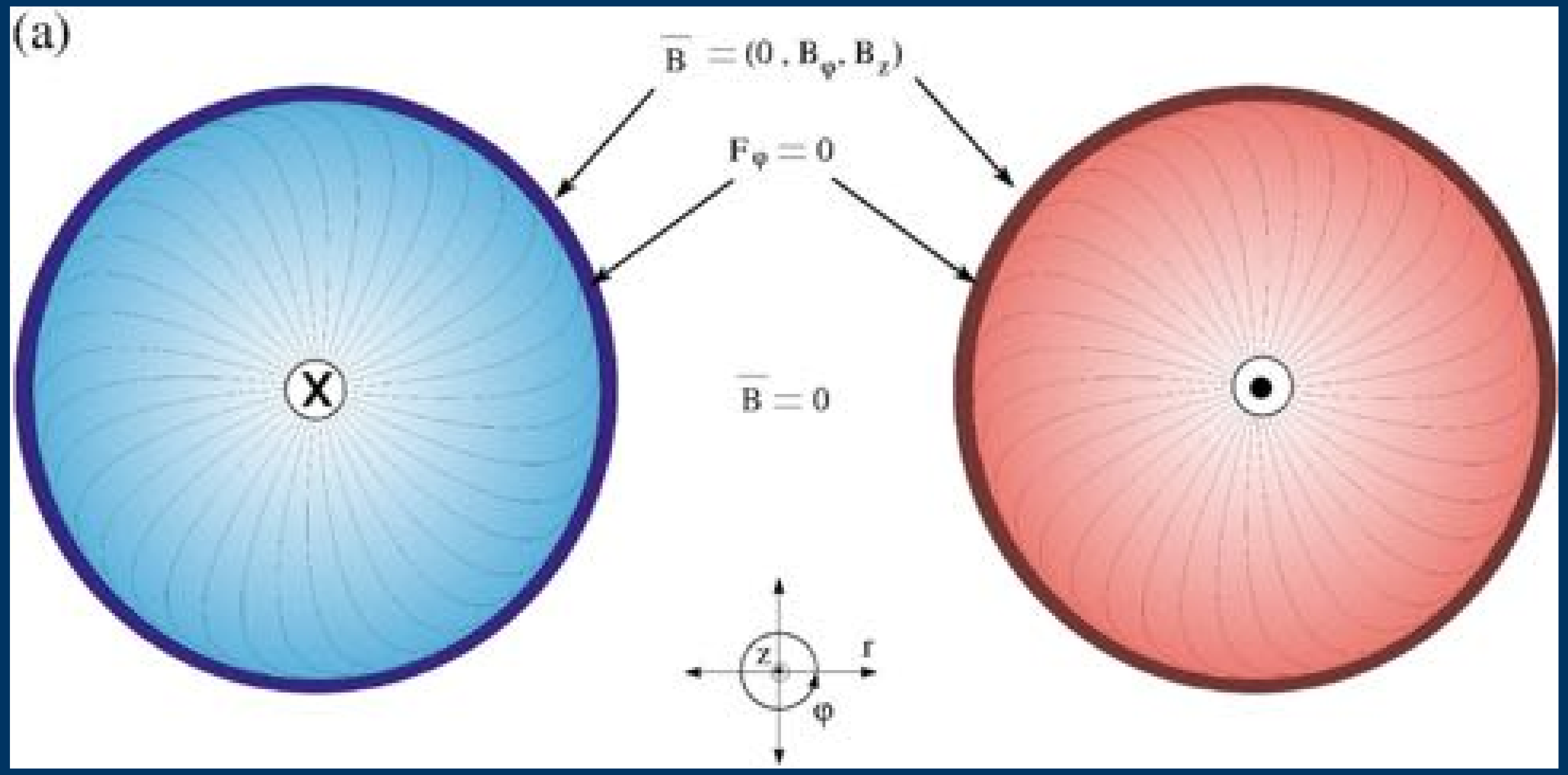


Resistive development of self-magnetic helicity through helicity conservation and mutual-to-self helicity conversion

$$\mathscr{H} = (twist + writhe)\,\Phi^2 + \mathscr{H}_{mutual}$$

Bringing magnetic helicity into the picture, in relation to PILs

- Velocity and magnetic shear develops invariably along a strong (i.e., flux-massive) PIL
- Shear seems to be due to the Lorentz tension force along the strong PILs - not so along well-separated ones

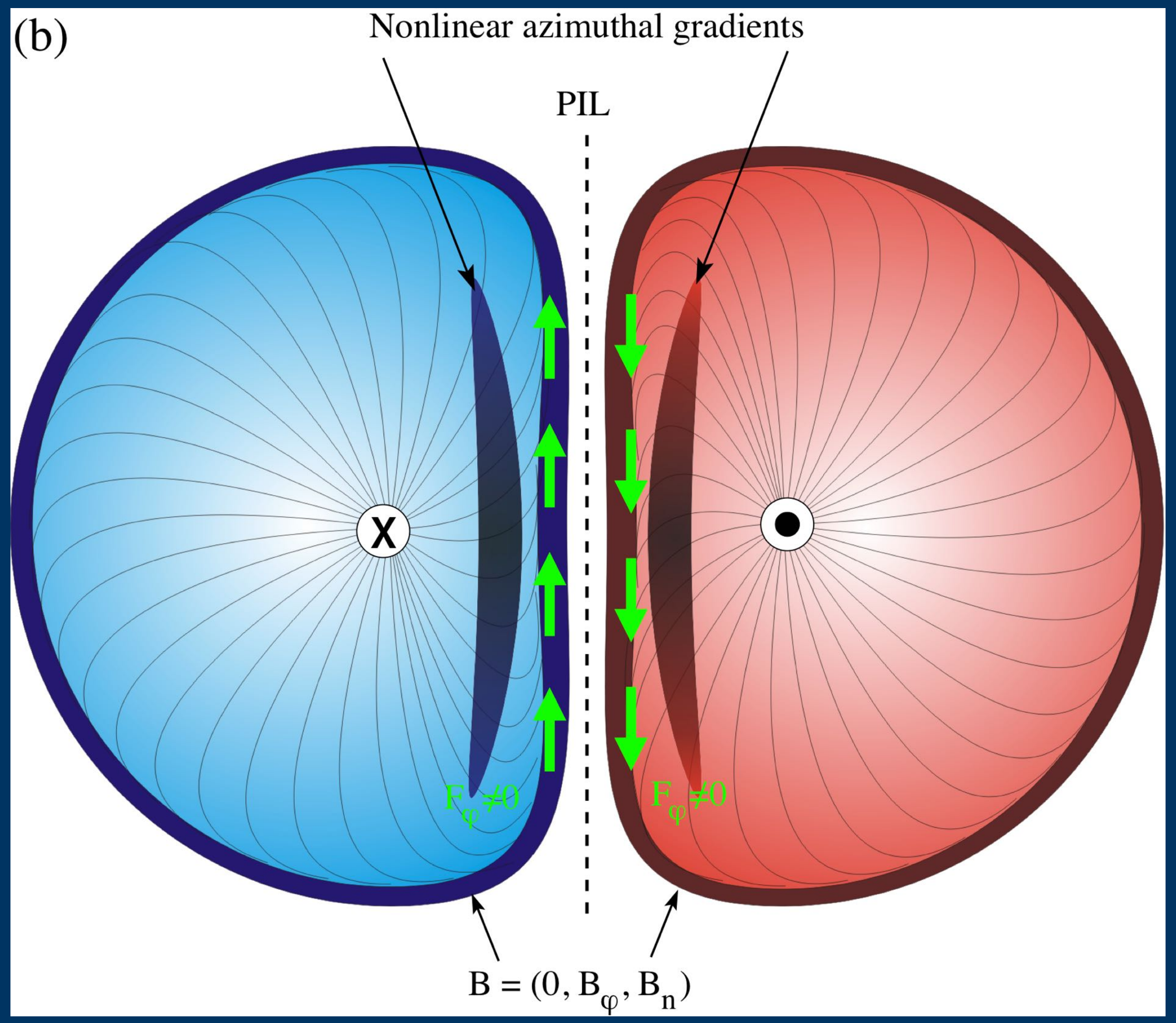


$F_\phi \simeq 0$

Georgoulis et al., ApJ, 2012

Azimuthal component of the Lorentz force:

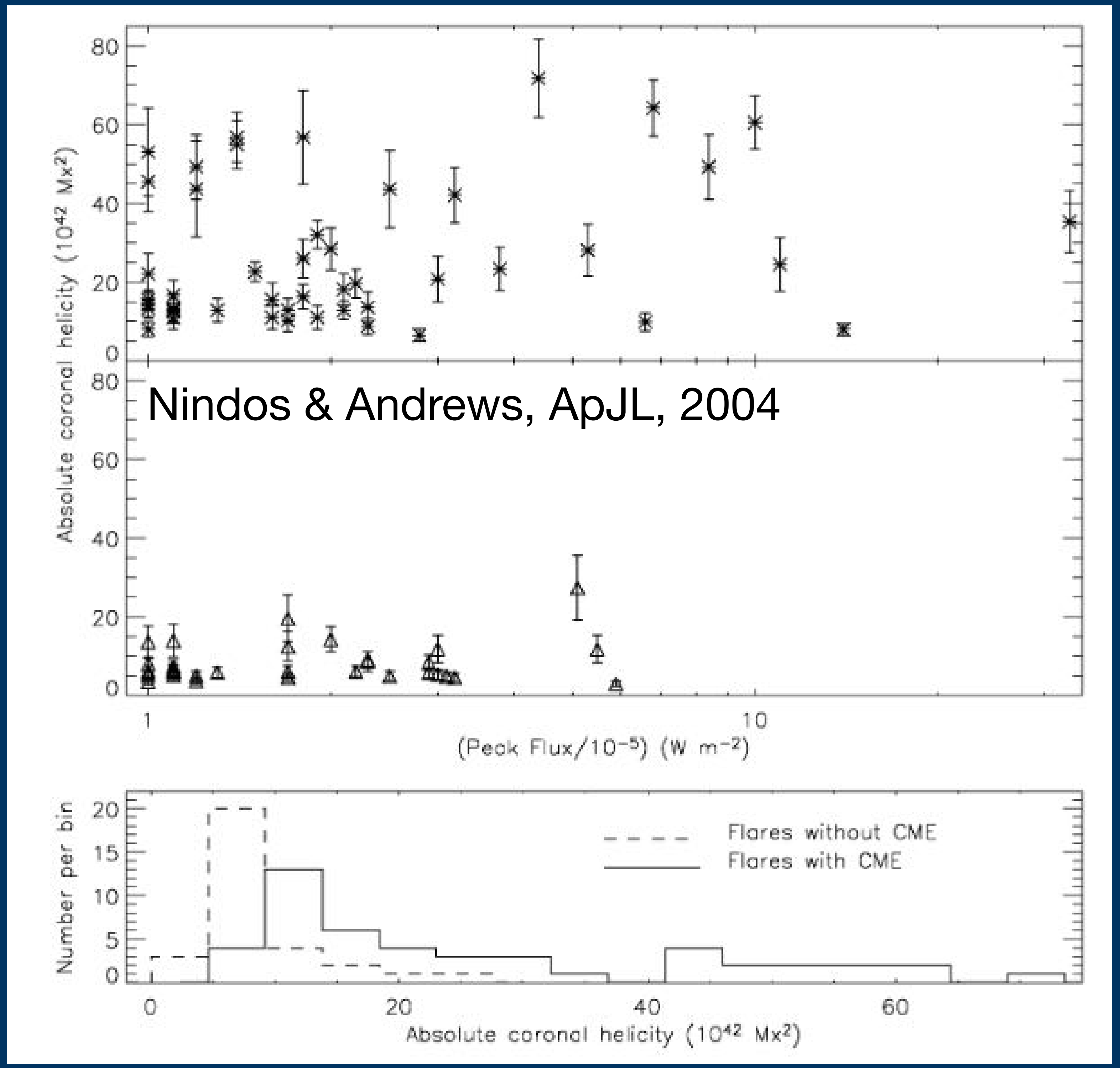
$$F_\phi = \frac{B_n}{4\pi}\left(-\frac{1}{r}\frac{\partial B_n}{\partial \phi} + \frac{\partial B_\phi}{\partial n}\right)$$



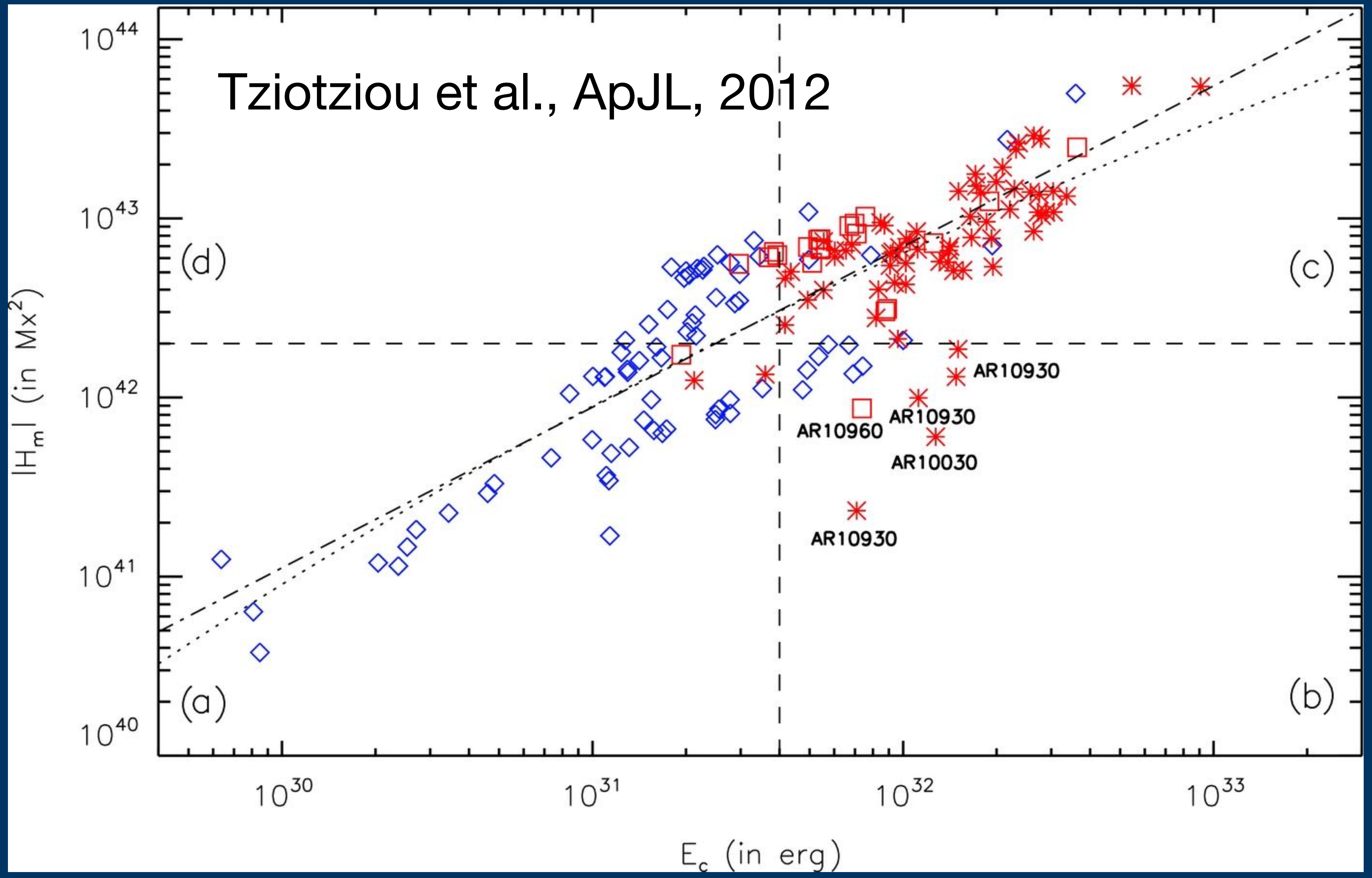
$F_\phi \neq 0$

- If field stregth along the PIL is above the equipartition value in the photosphere, then this Lorentz force can move the otherwise line-tied magnetic field and cause shear
- Shear gives rise to confined reconnection along the PIL, converting mutual to self magnetic helicity, hence causing a helical pre-eruption flux rope
- Confined reconnection releases energy and relaxes mutual helicity but does not change the roughly conserved total magnetic helicity, hence increasing its self-term

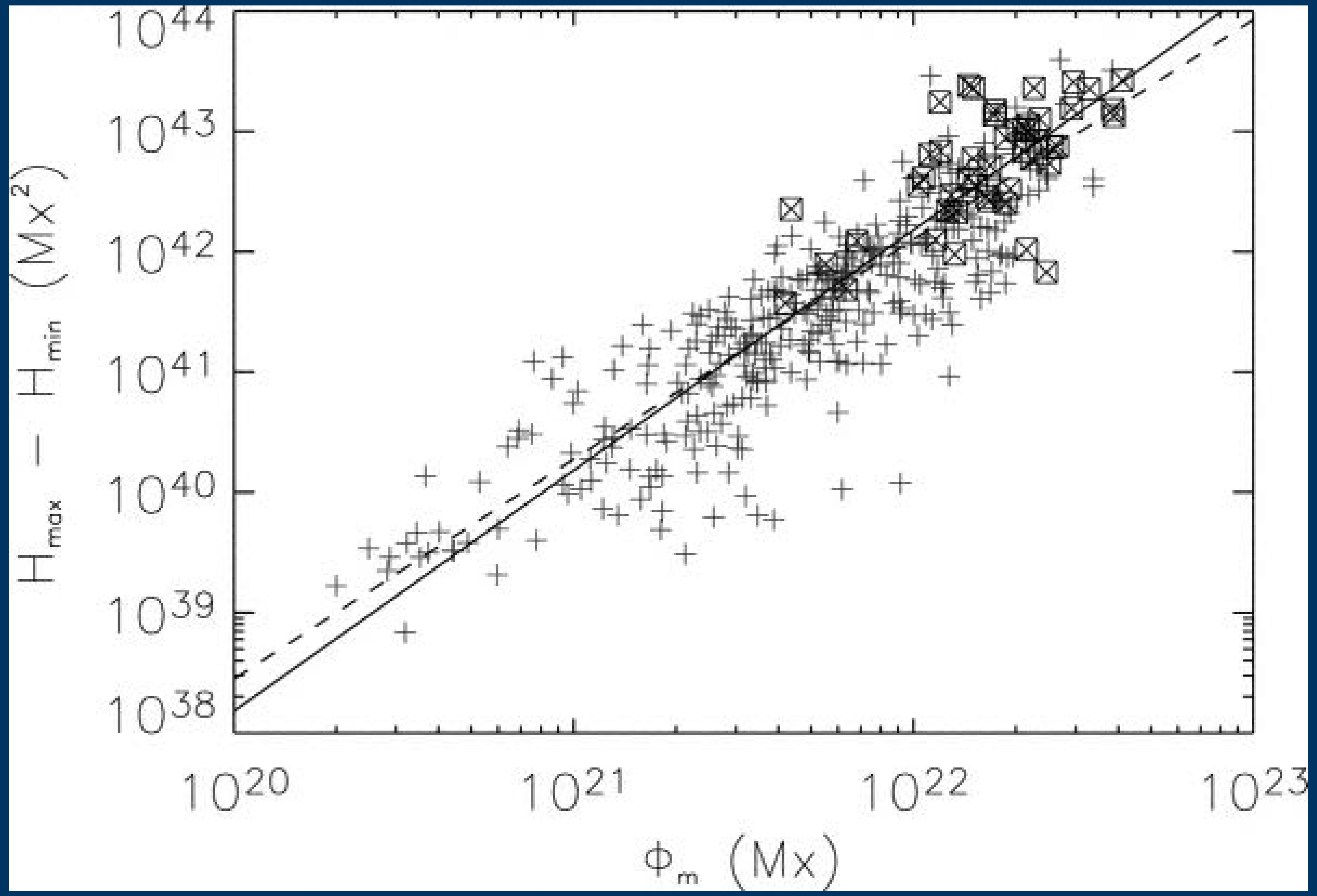
More helical active regions are more likely to erupt

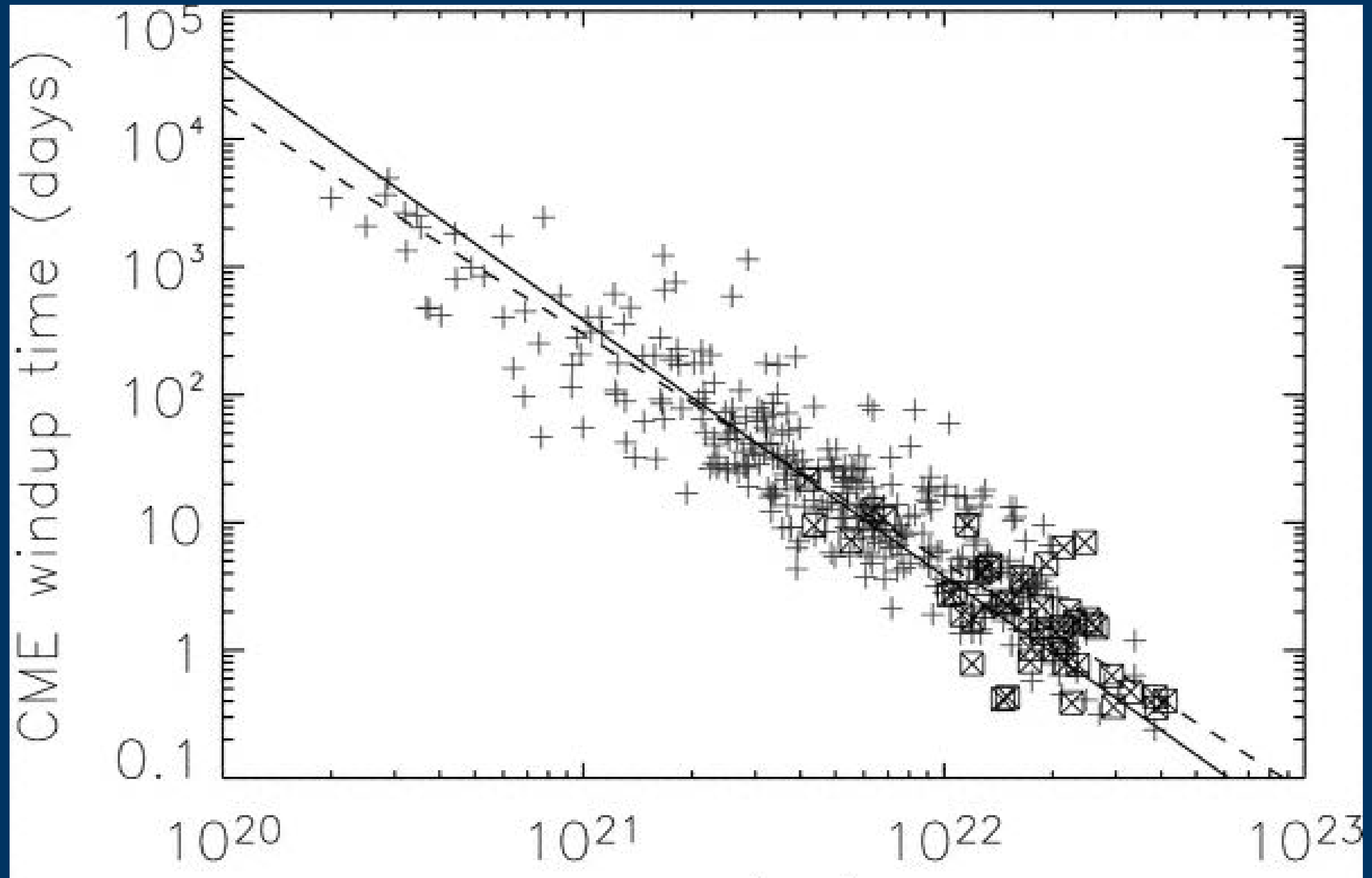


Nindos & Andrews, ApJL, 2004

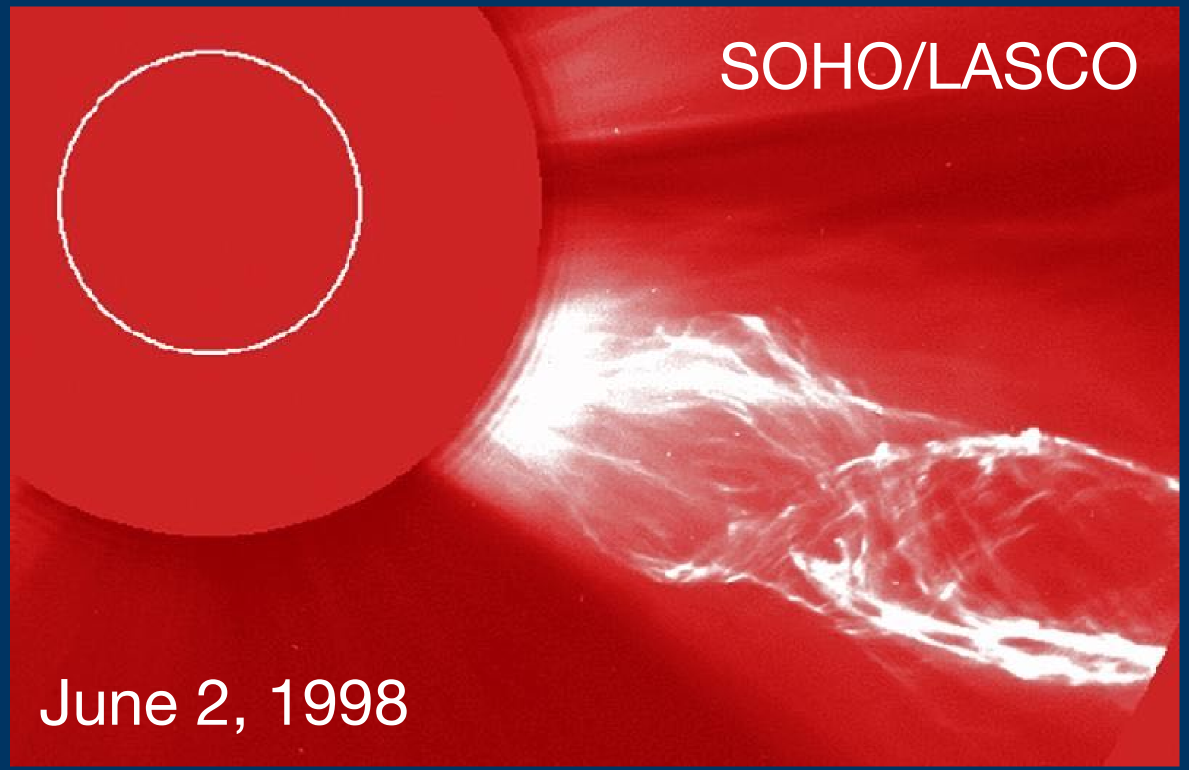


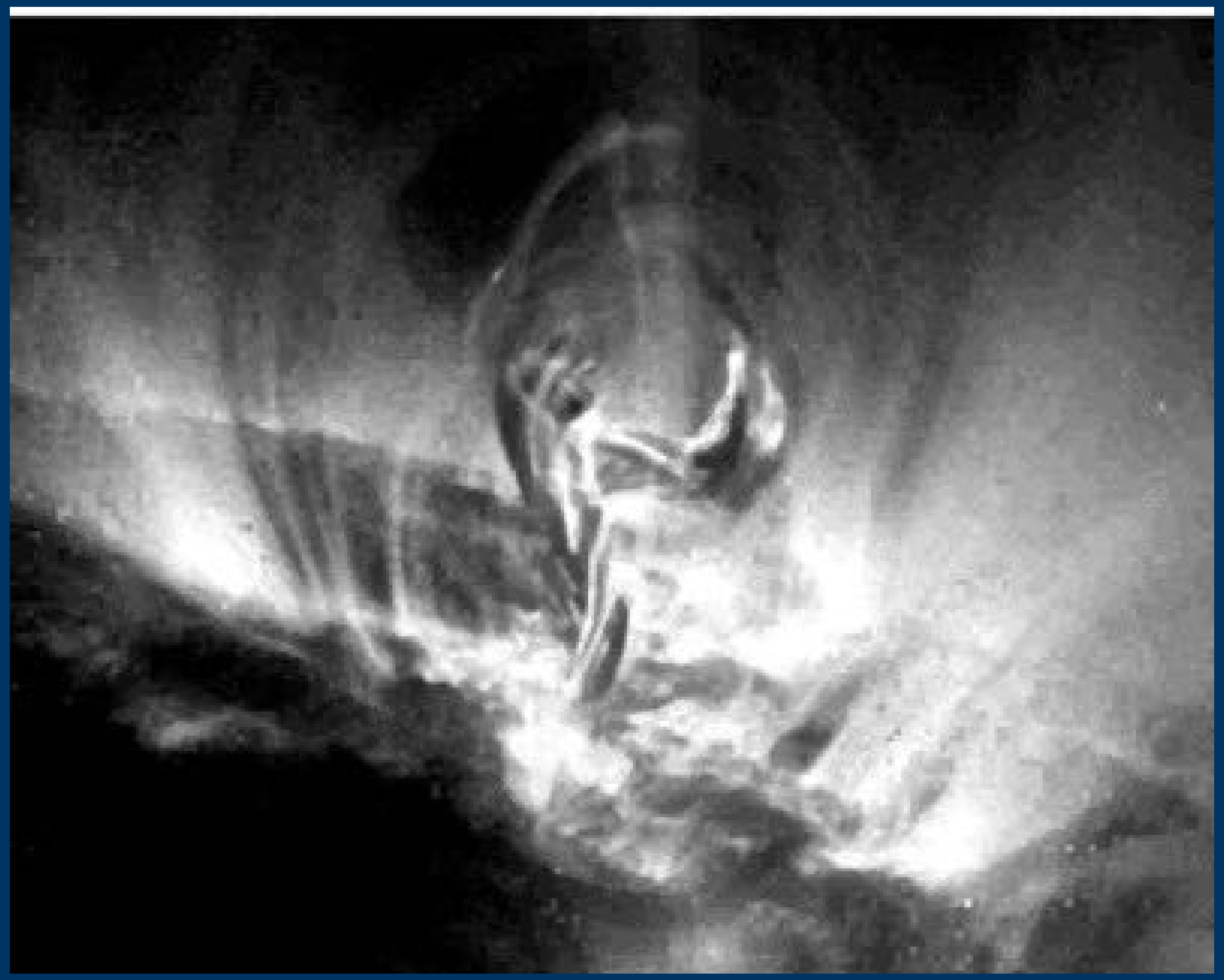
Tziotziou et al., ApJL, 2012





LaBonte et al., ApJ, 2007




Rust & LaBnte, ApJL, 2004

Heuristic active region evolution and the point of no return

Continuing as needed

Active region (flux) emergence

PIL formation

Net currents: strong PIL formation

Lorentz tension force

Shear

Magnetic helicity accumulation / self helicity conversion

Eruption!

Active region dissolution

Irreversibility!

adapted from Georgoulis et al. (2019)

Weak, unsheared PIL: mainly confined, microflaring activity or an eruption purely due to flux emergence

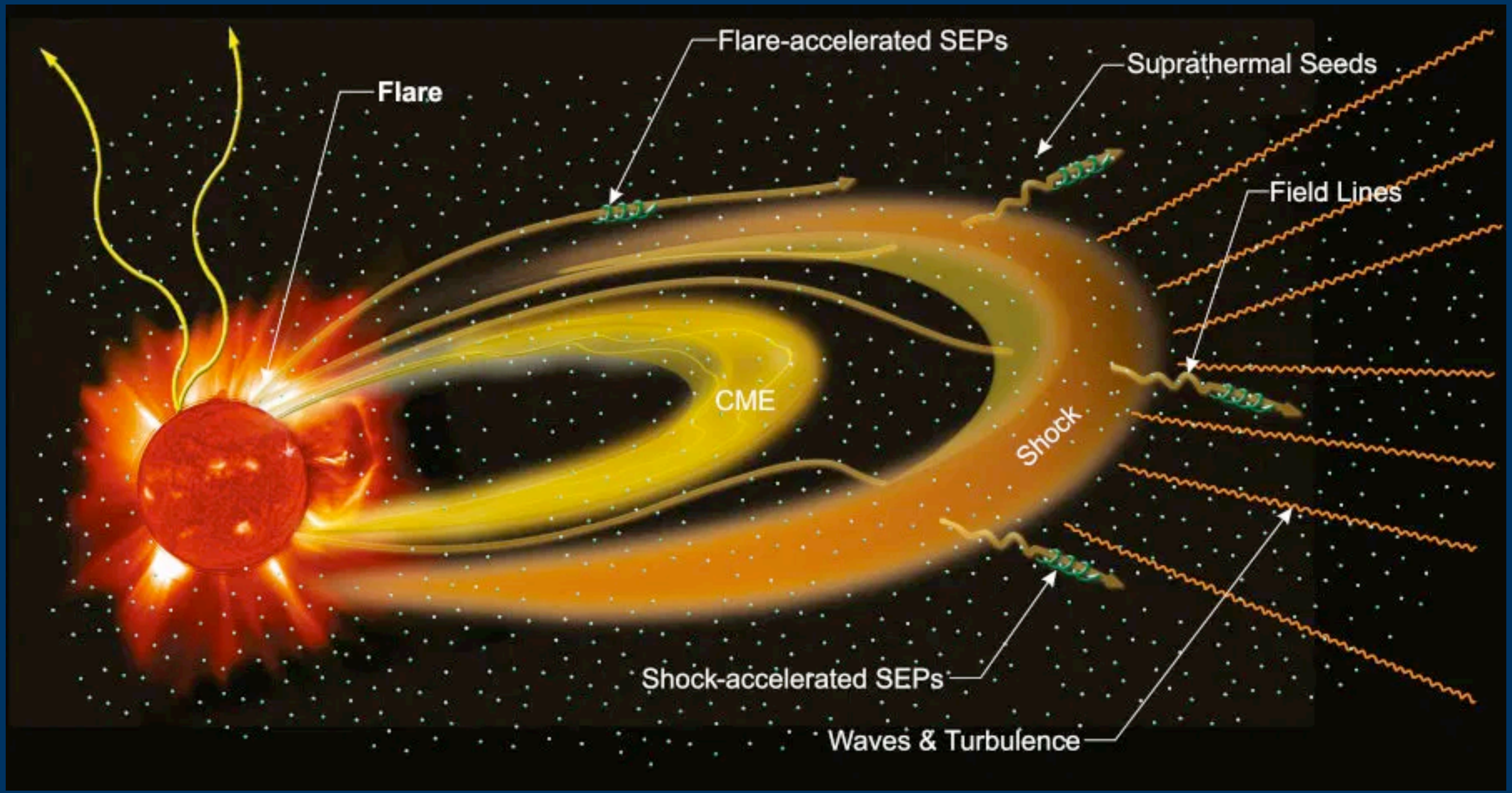
Active region dissolution

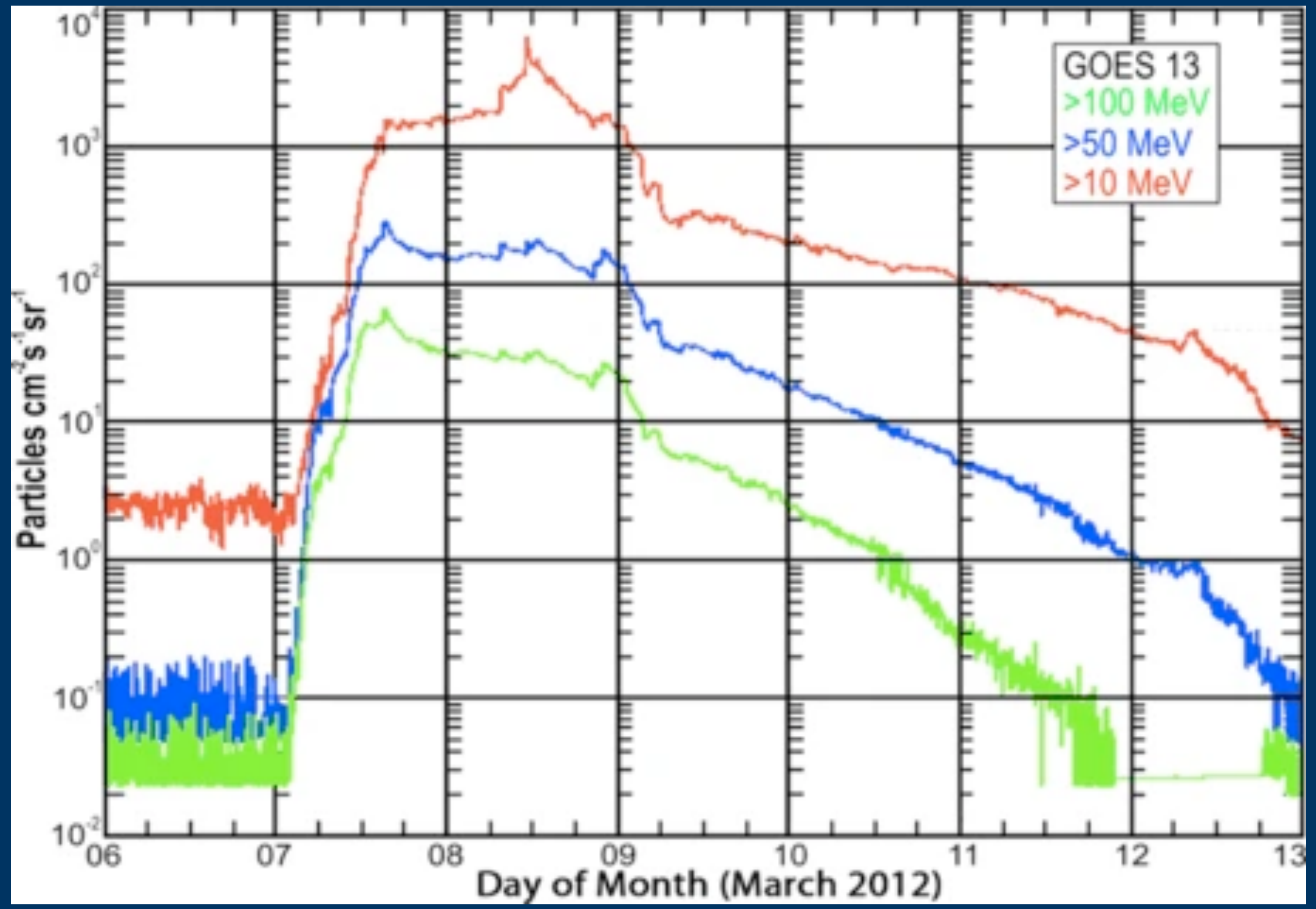
NOAA AR 12673, Sep 2017

The majority of active regions do not make it past the first two steps.
The third step is a ‘point of no return’ for eruptions

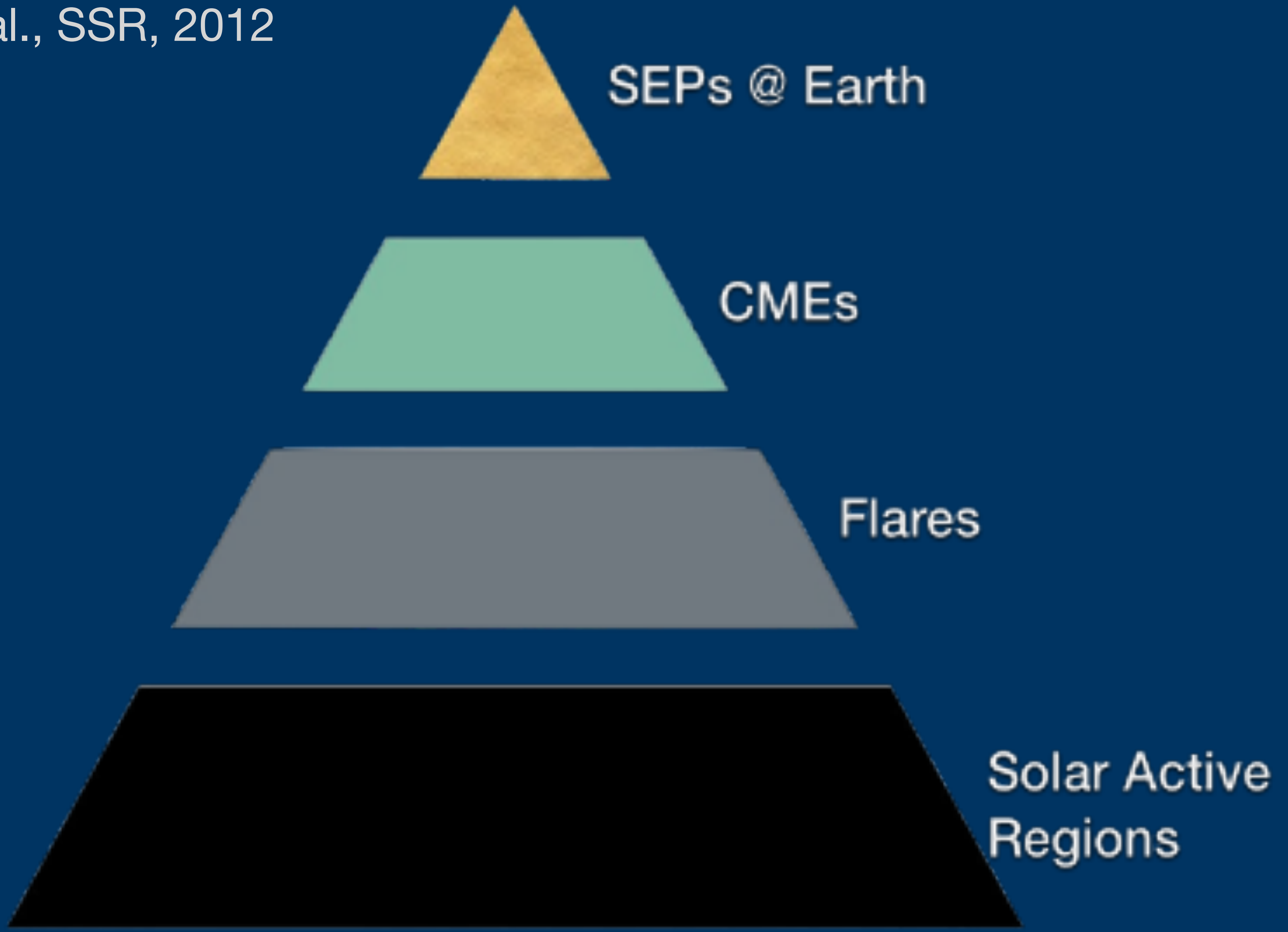
However, there's more than flares: eruptive flares (i.e., CMEs); SEPs

Desai & Burgess, JGR, 2008



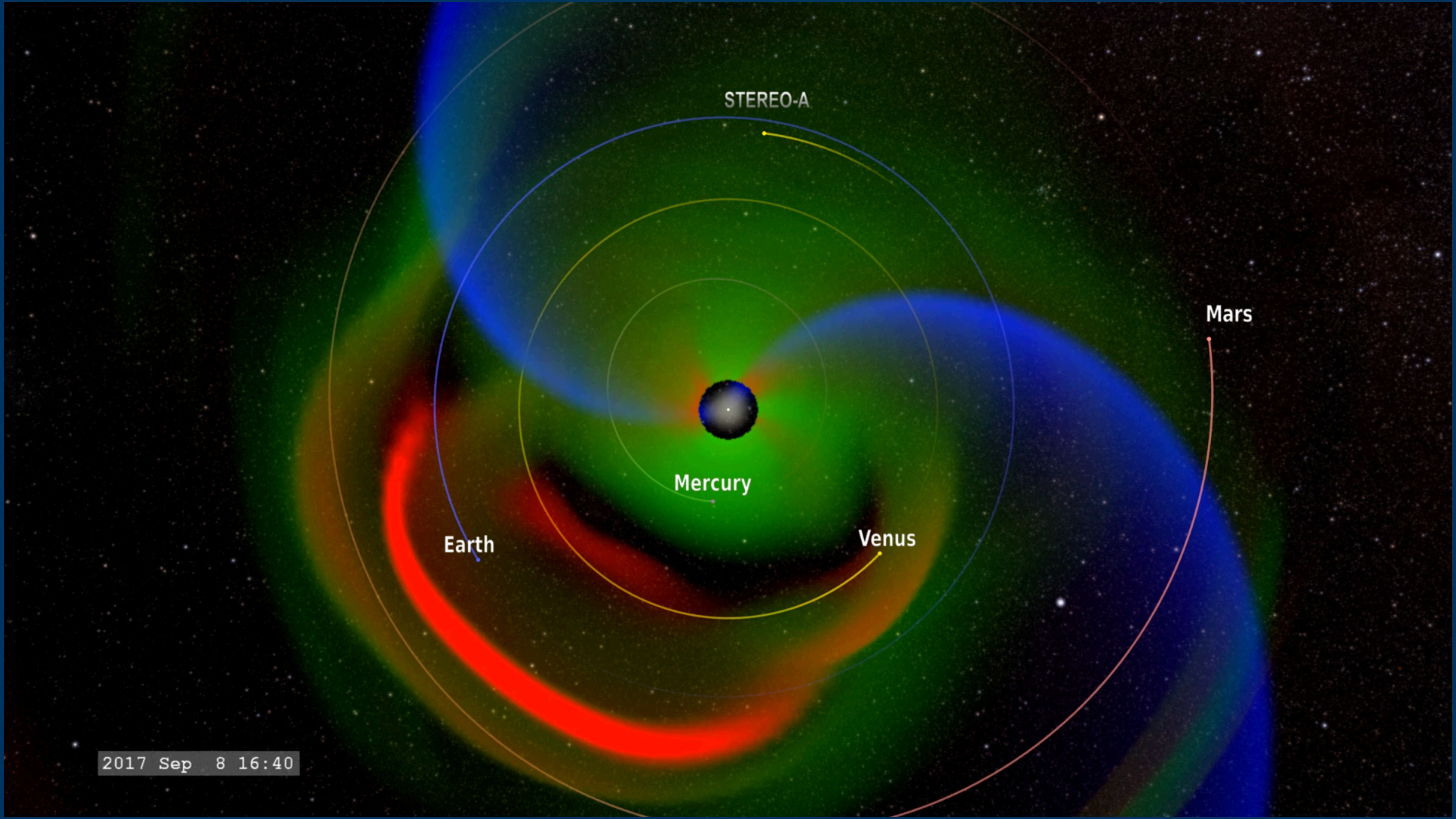


Hassler et al., SSR, 2012



- Larger flares are more frequently associated with coronal mass ejections (CMEs)
- Fast, shock-fronted CMEs generate solar energetic particle (SEP) events
- Four SEP event "populations" — Reames, SSR, 2020

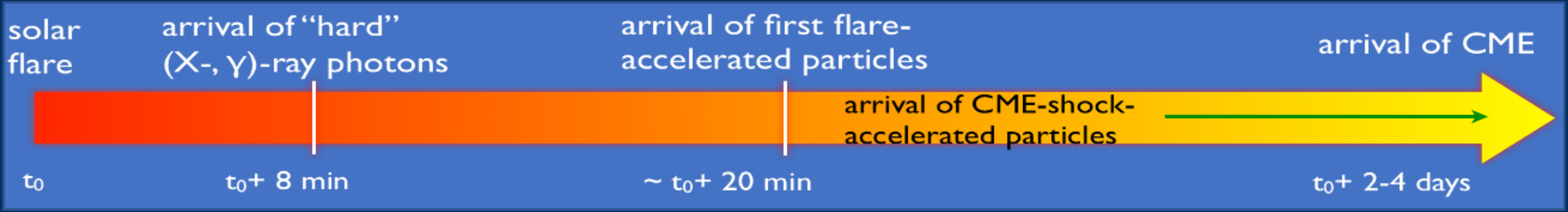
Putting it all together : heliospheric space weather

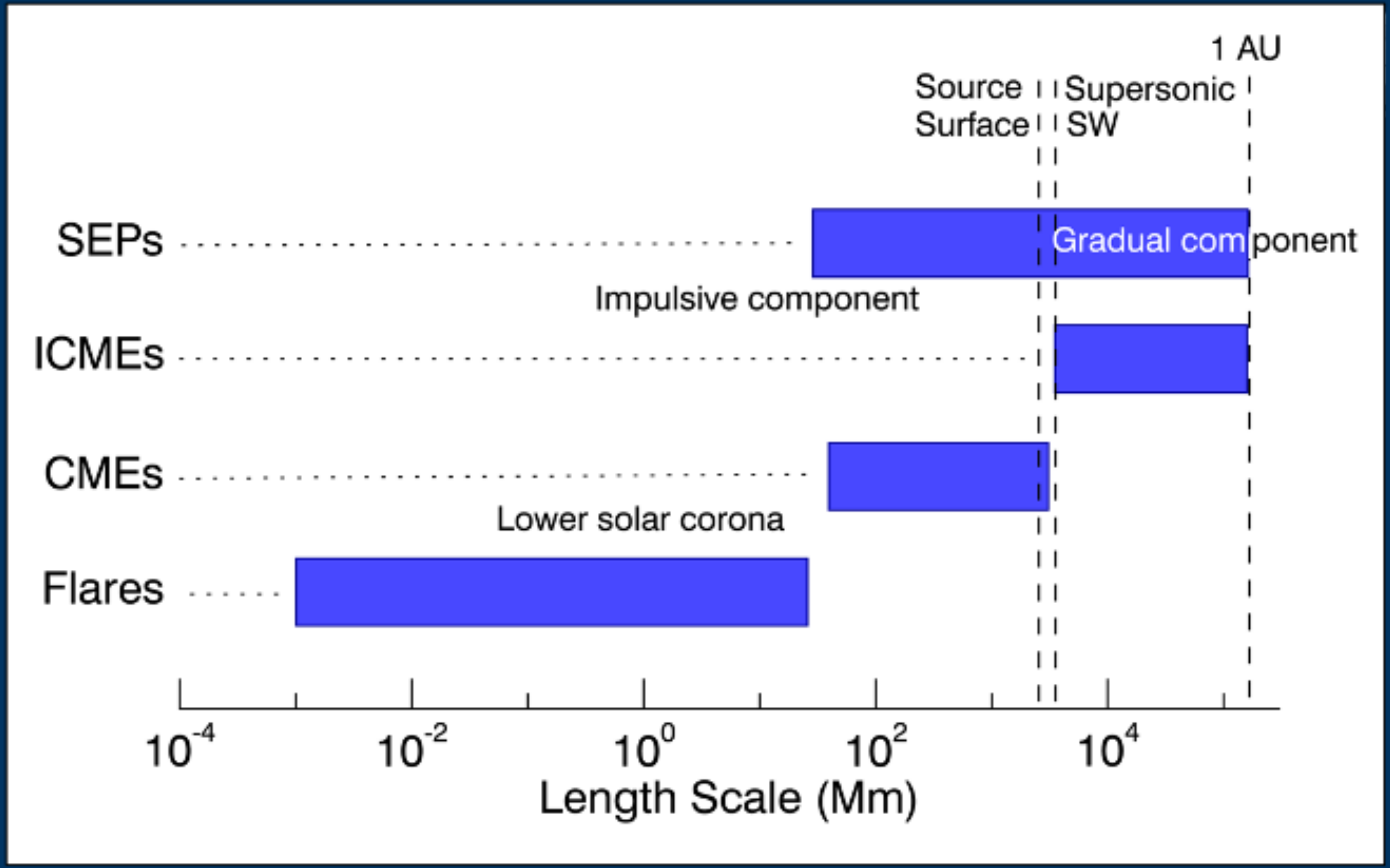


Source: NASA Scientific Visualization Studio

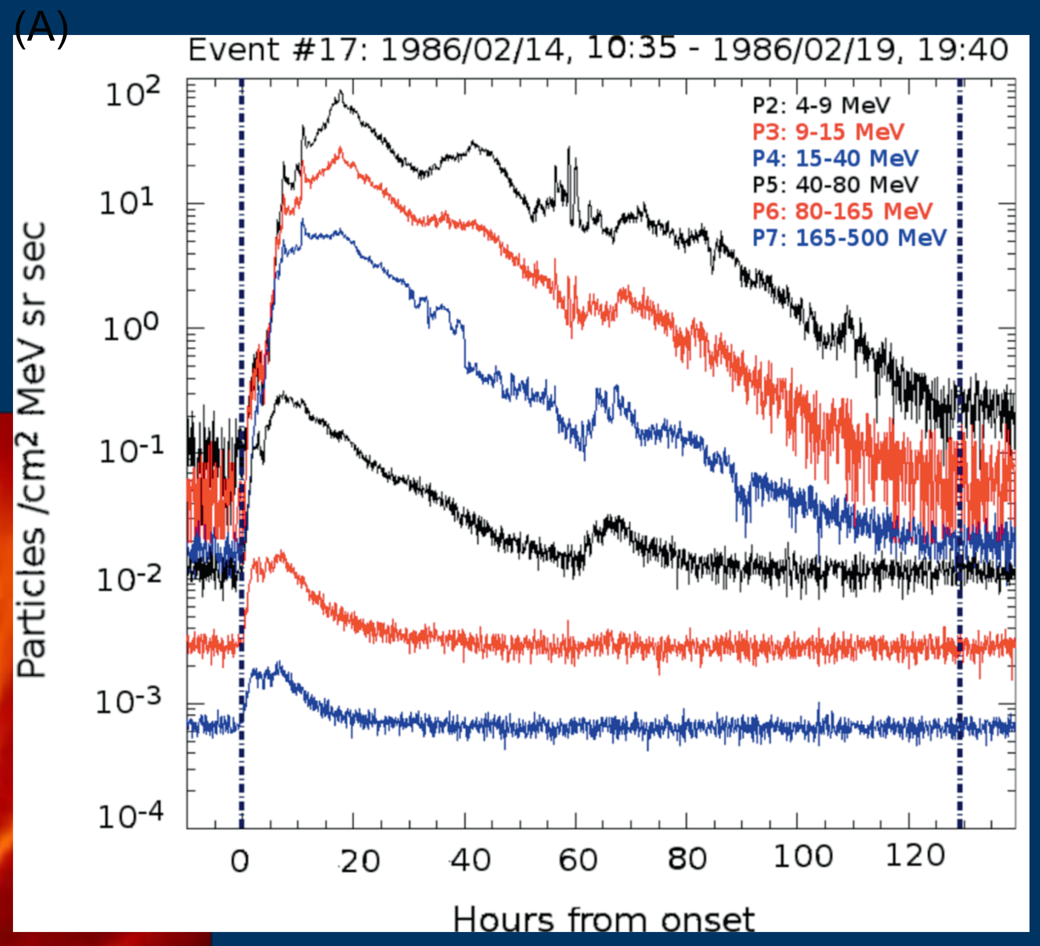
No directionality in flares (i.e., photons), but a clear directionality in CMEs and SEP events

A tangled, intertwined evolution

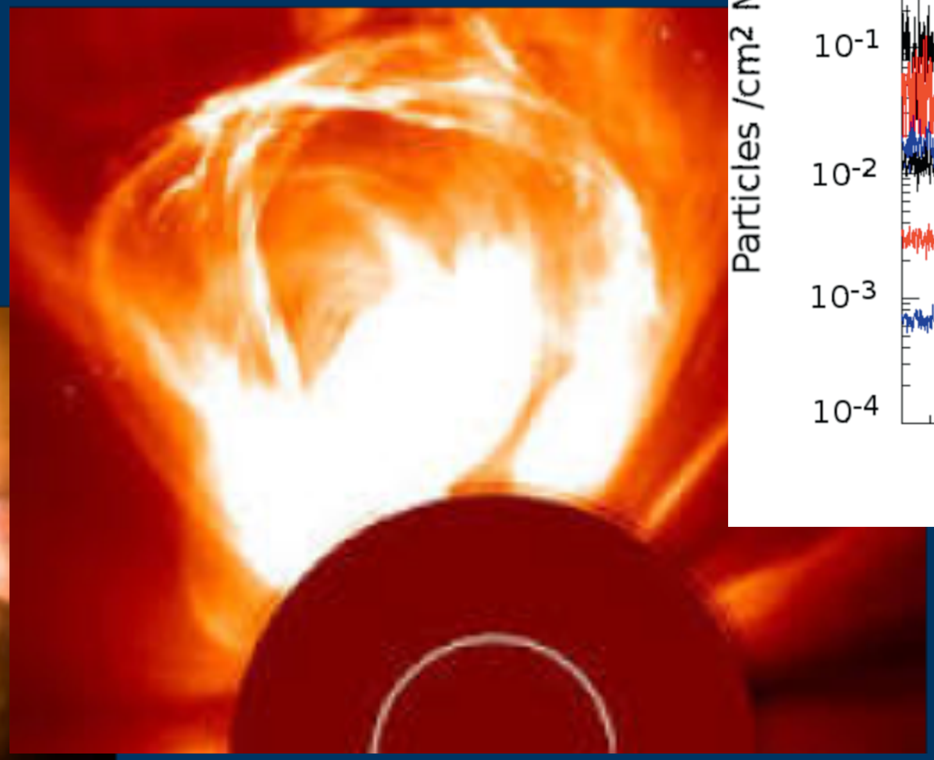




A problem spanning 8 orders of magnitude in both space and time



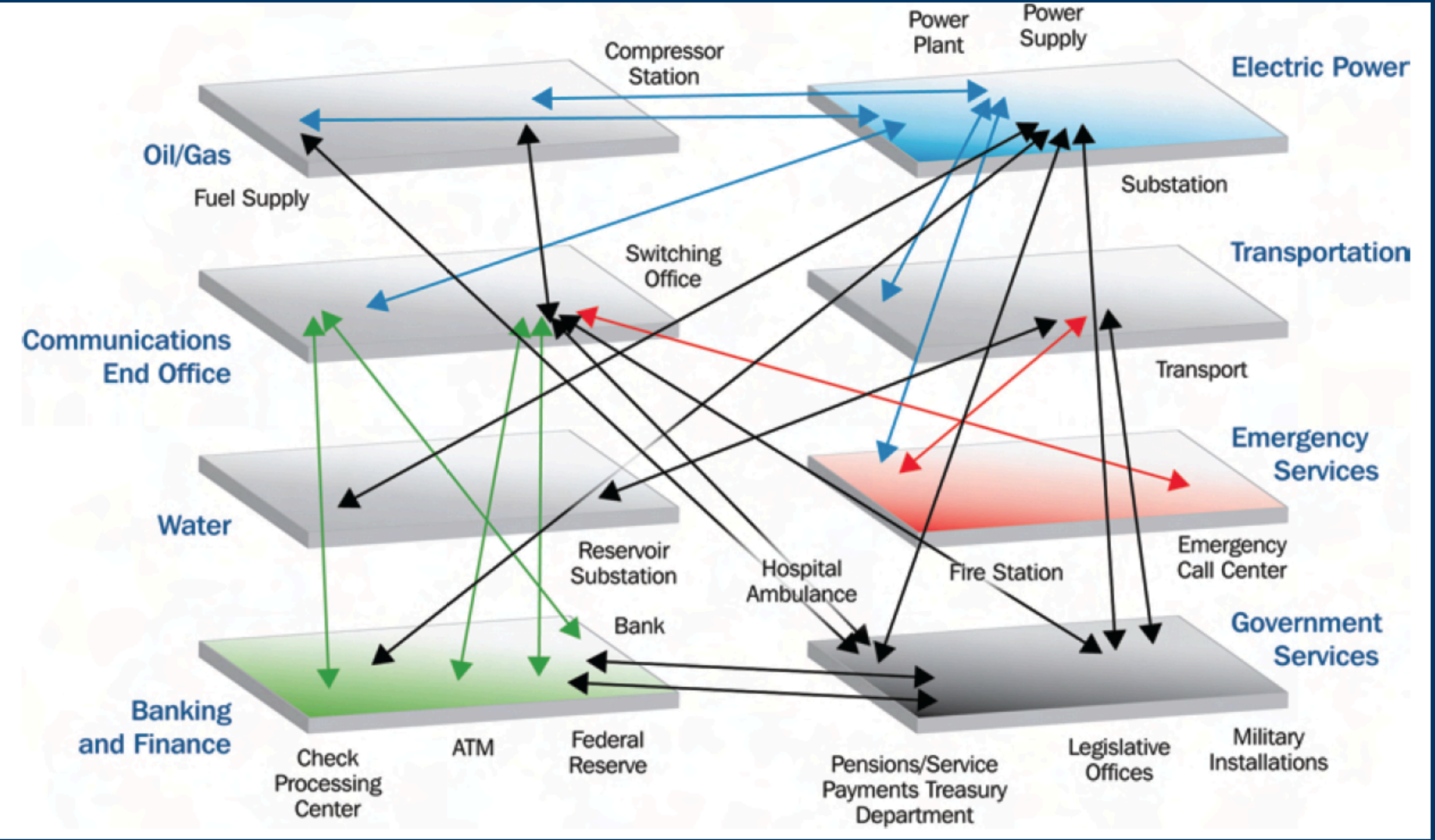
SEP event



CME

Flare

Repercussions of intense / extreme space weather : technology



Source: Severe Space Weather Events: Understanding Societal and Economic Impacts, NAS Press (2008)

Nonlinearly interconnected societal infrastructures. If an infrastructure goes down, others will be affected virtually instantly in a hardly predictable manner.

For example, a significant GPS disruption may not allow you to withdraw cash from an ATM because the ATM itself will not be able to verify its position, hence will not 'know' whether it is where it should be…

For projections of socio-economic impact, see Oughton et al., SWx, 2017; RiskAn, 2019; Eastwood et al., RiskAn, 2017; Riley et al., SSR, 2017 and others

Repercussions of intense / extreme space weather : biological

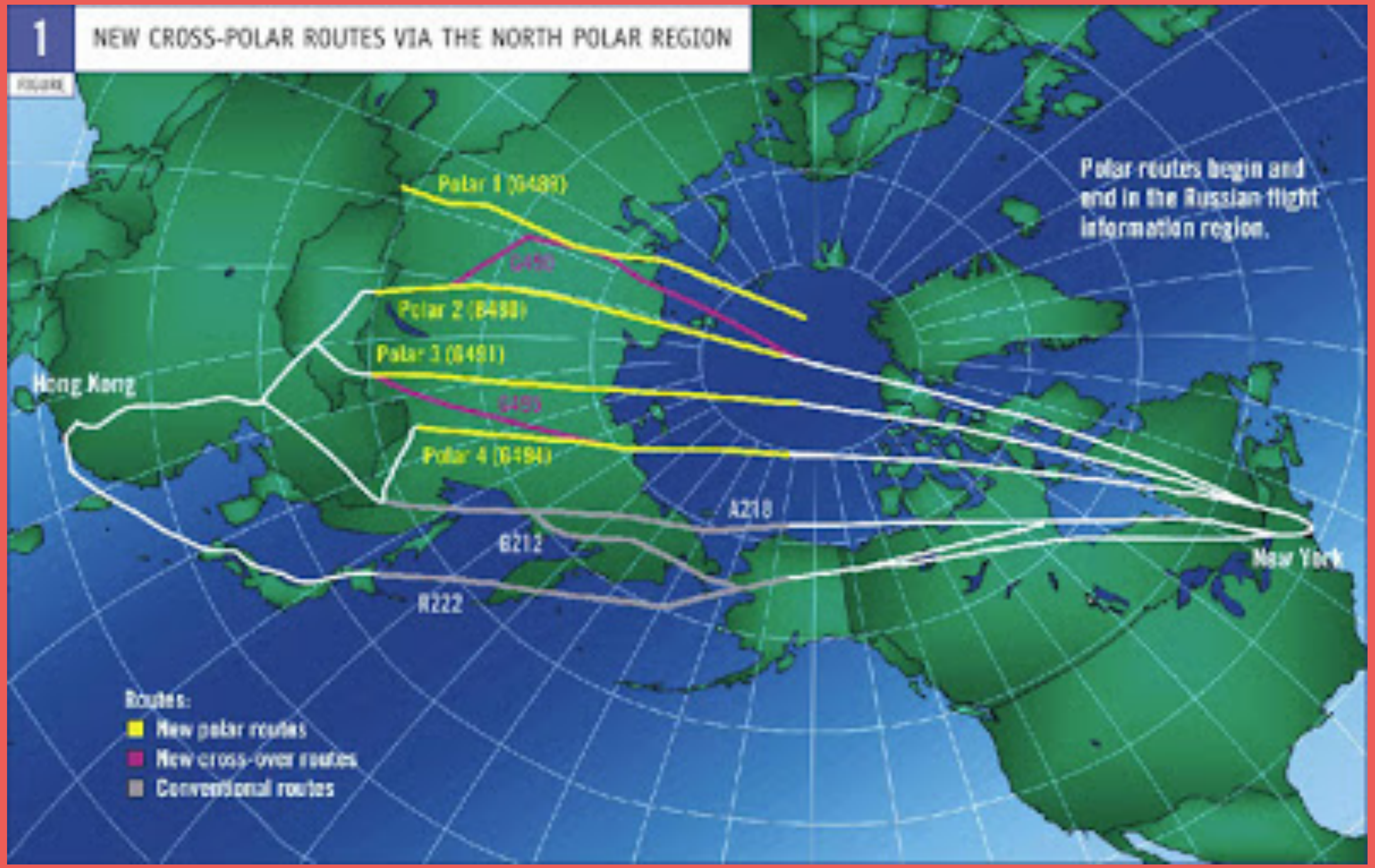
ISS extravehicular activities (present)

Lunar outposts / moonvilage (near future)

Space travel (future)

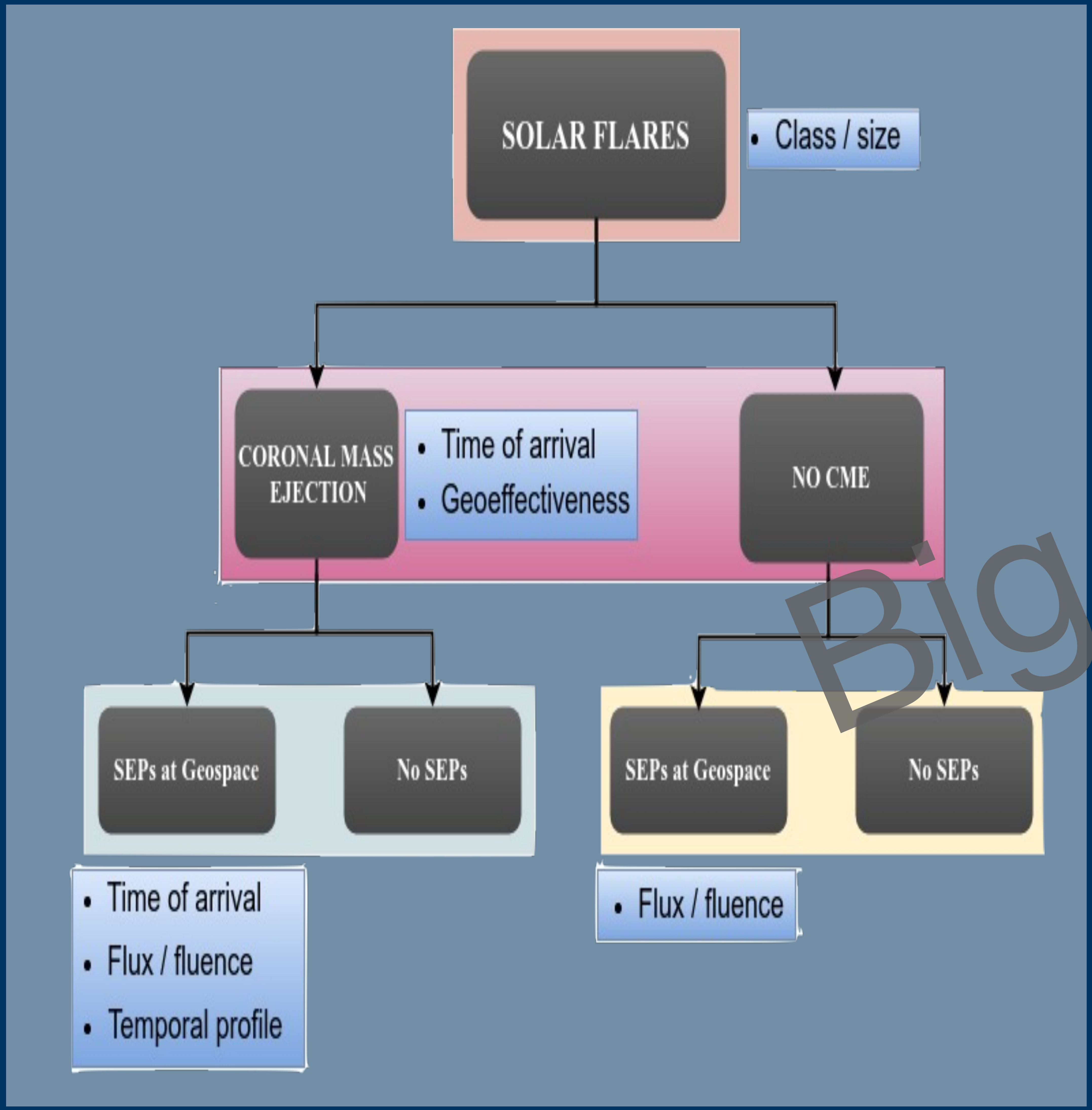
Martian outposts (future)

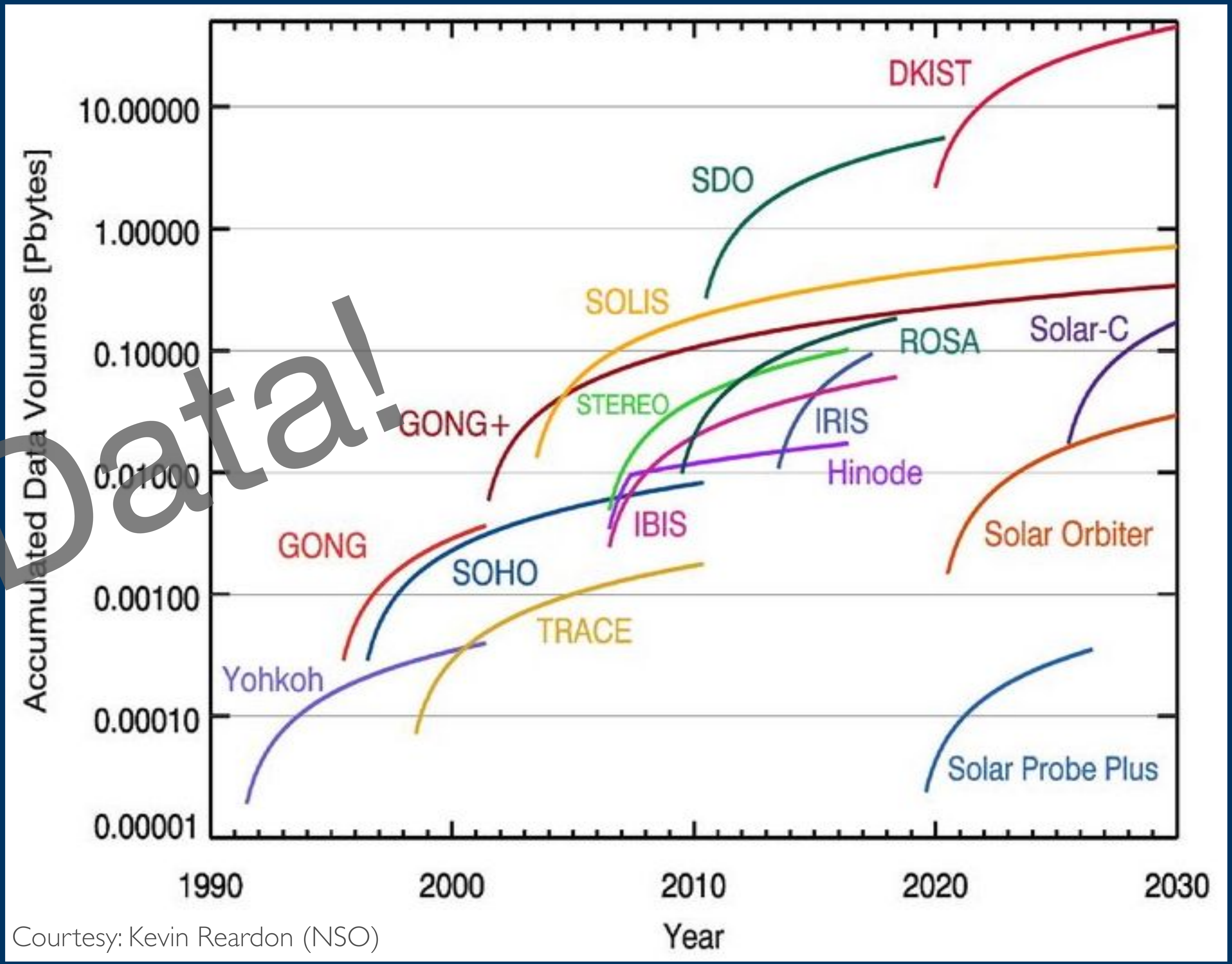
Transpolar flights (present)



The Hows

Predicting solar weather: the undertaking





Capacity increased by ~7 orders of magnitude within 40 years!

Conventional statistical treatment (non-exhaustive)

The objective: a boolean (YES/NO) or occurrence probability (0 < P < 1) of a given forecast event

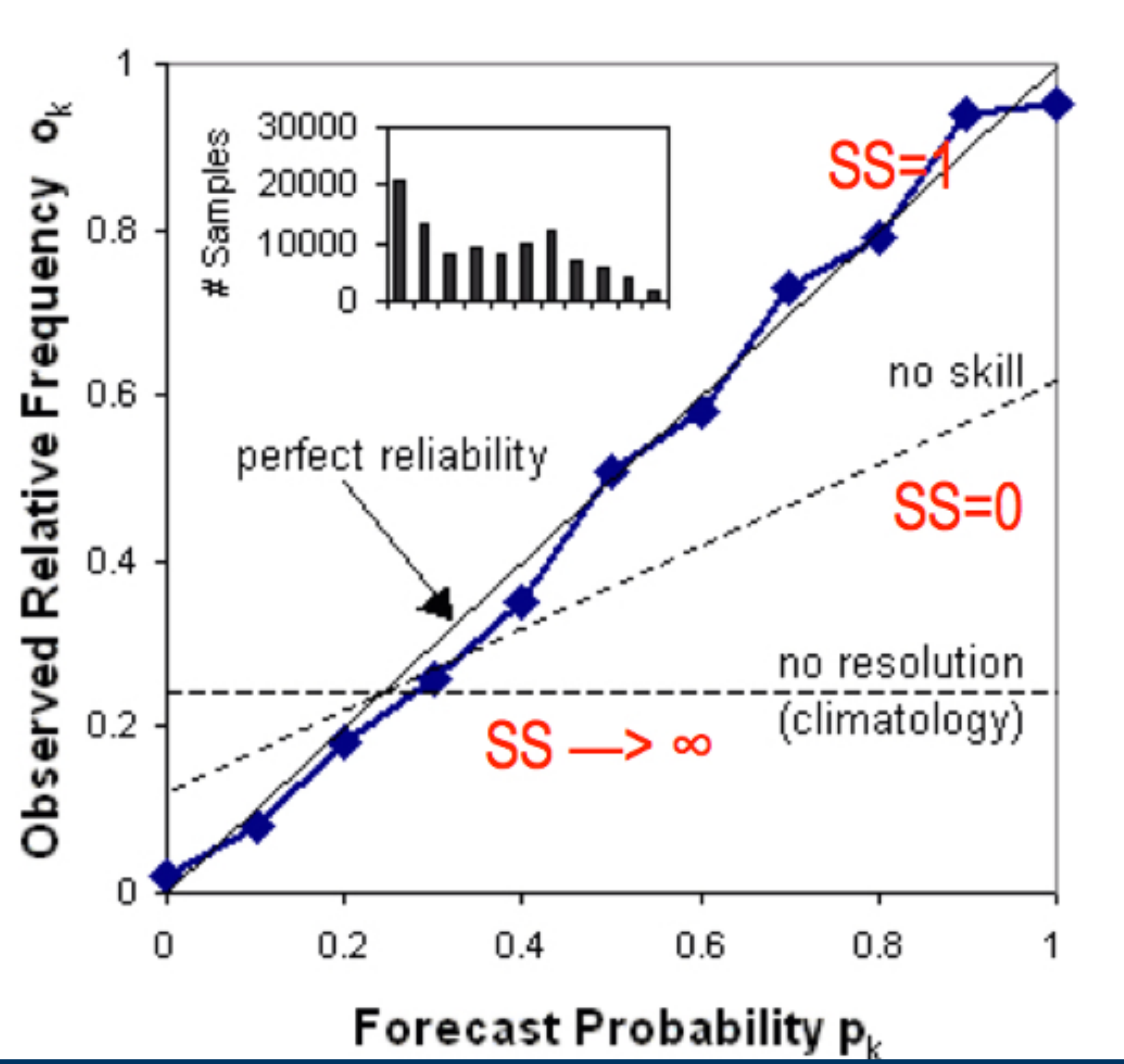
— Binary Prediction

- Issuing a YES or a NO
- Doing this many times
- Checking how you have done

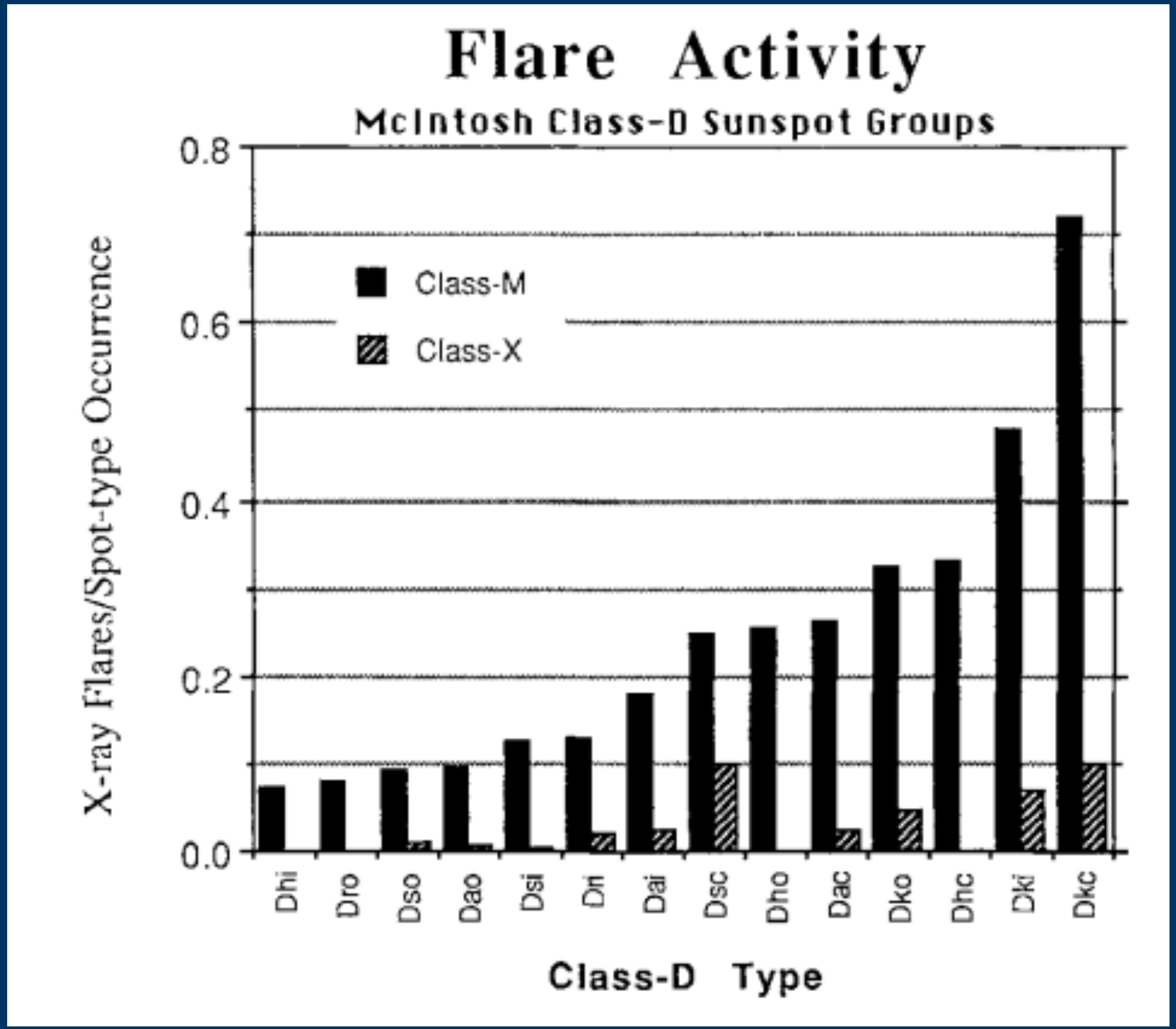
Event Observed / Event Predicted	YES	NO
YES	True Positive (TP)	False Positive (FP)
NO	False Negative (FN)	True Negative (TN)

— Probabilistic Prediction

- Issuing $P \in (0,1)$
- Doing this many times
- Checking how you have done



First systematic flare prediction methods



McIntosh, SoPh, 1990

Flare occurrence probability vs. McIntosh sunspot Class D and Types thereof - any lead time (no 24 hours assigned)

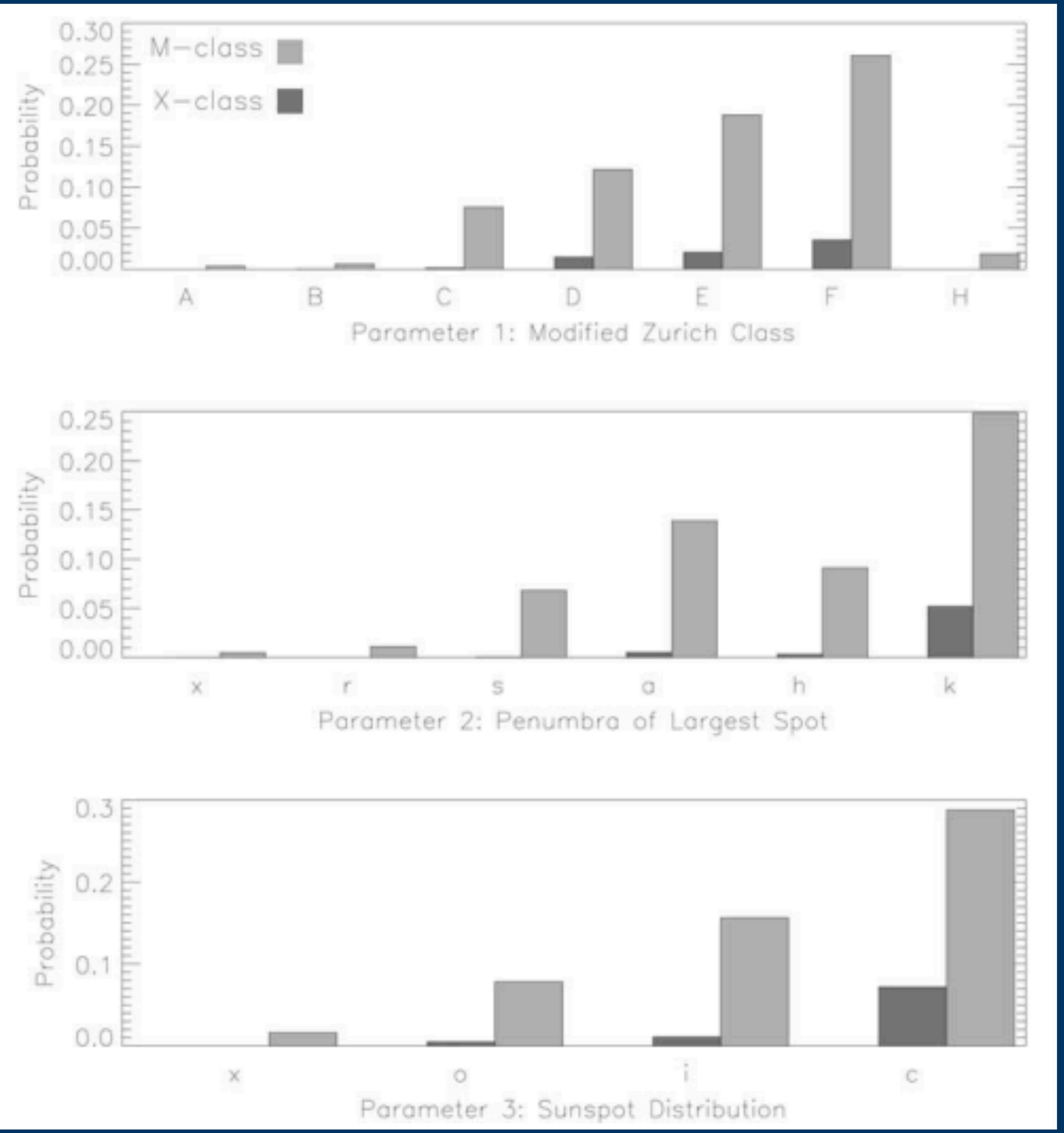
- Poisson flare distribution:

$$P_{\mu}(N) = \frac{\mu^N}{N!} e^{-\mu}$$

— μ : mean flare occurrence rate

— N : numbers of flares

- Varying μ for different sunspot classes for N = 1, one obtains a 24-hour flare probability



Gallagher et al., SoPh, 2002

24-hour flare probabilities per McIntosh Class, assuming Poisson distribution of flare occurrence

Conventional statistical treatment (non-exhaustive)

The objective: distinguish flaring from non-flaring active region distributions

Bayes' analysis

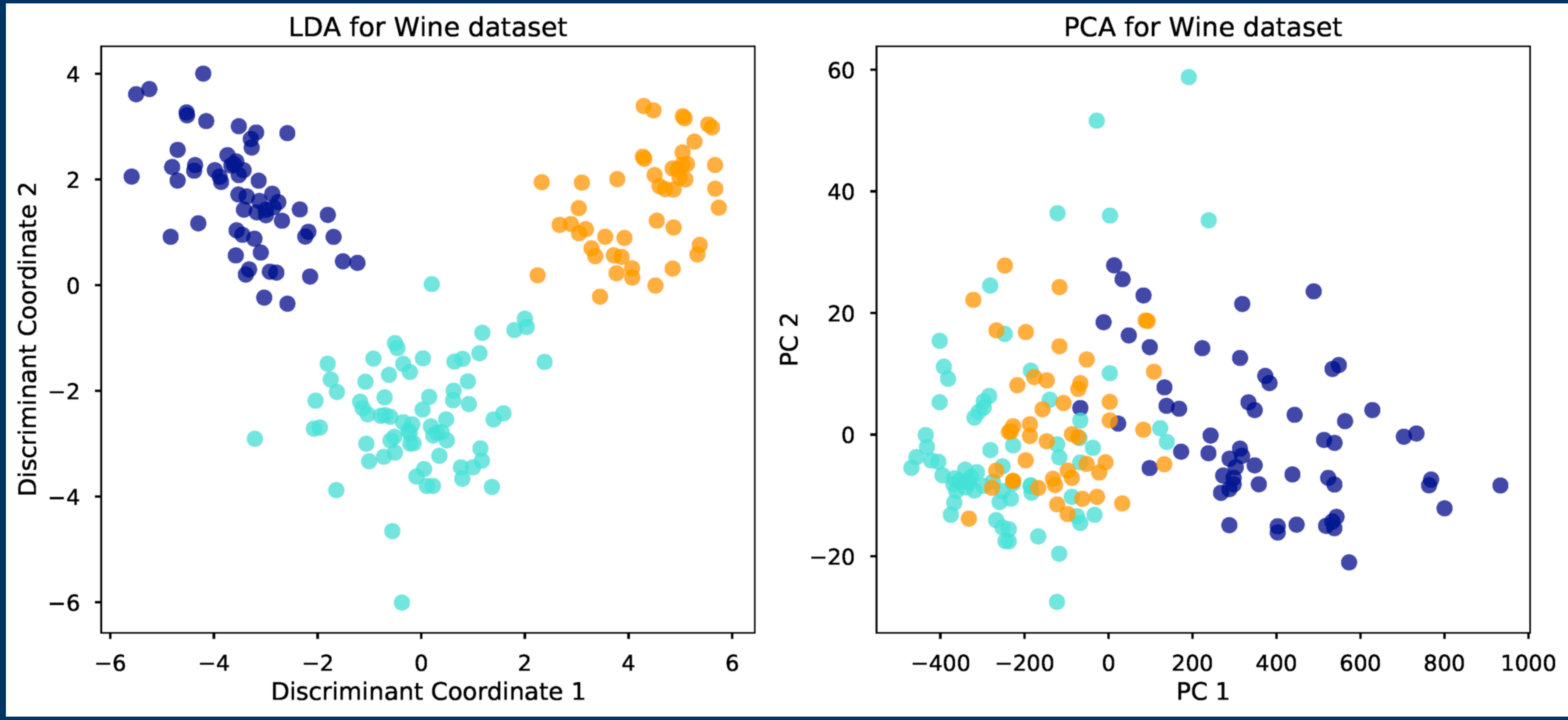
Bayesian Inference:

$$P(H|E) = \frac{P(E|H) \times P(H)}{P(E)}$$

Laplace's rule of succession:

$$P(F|p_{thres}) = \frac{(F+1)|_{p_{thres}}}{(N+2)|_{p_{thres}}}$$

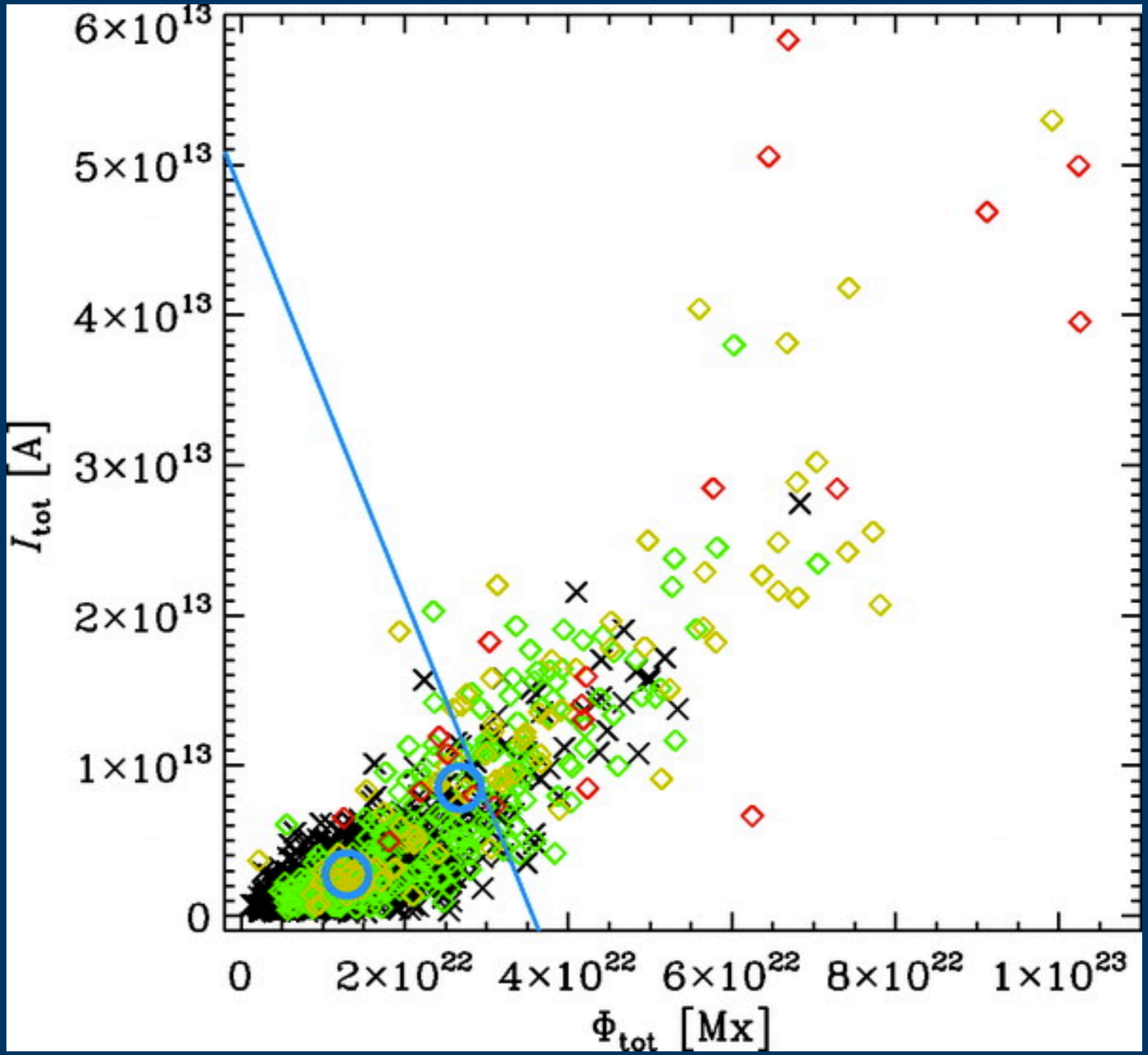
(Linear) Discriminant analysis   Principal component analysis



Credit: towardsdatascience.com

… plus other means of regression, extrapolation or classification, including linear or nonlinear models

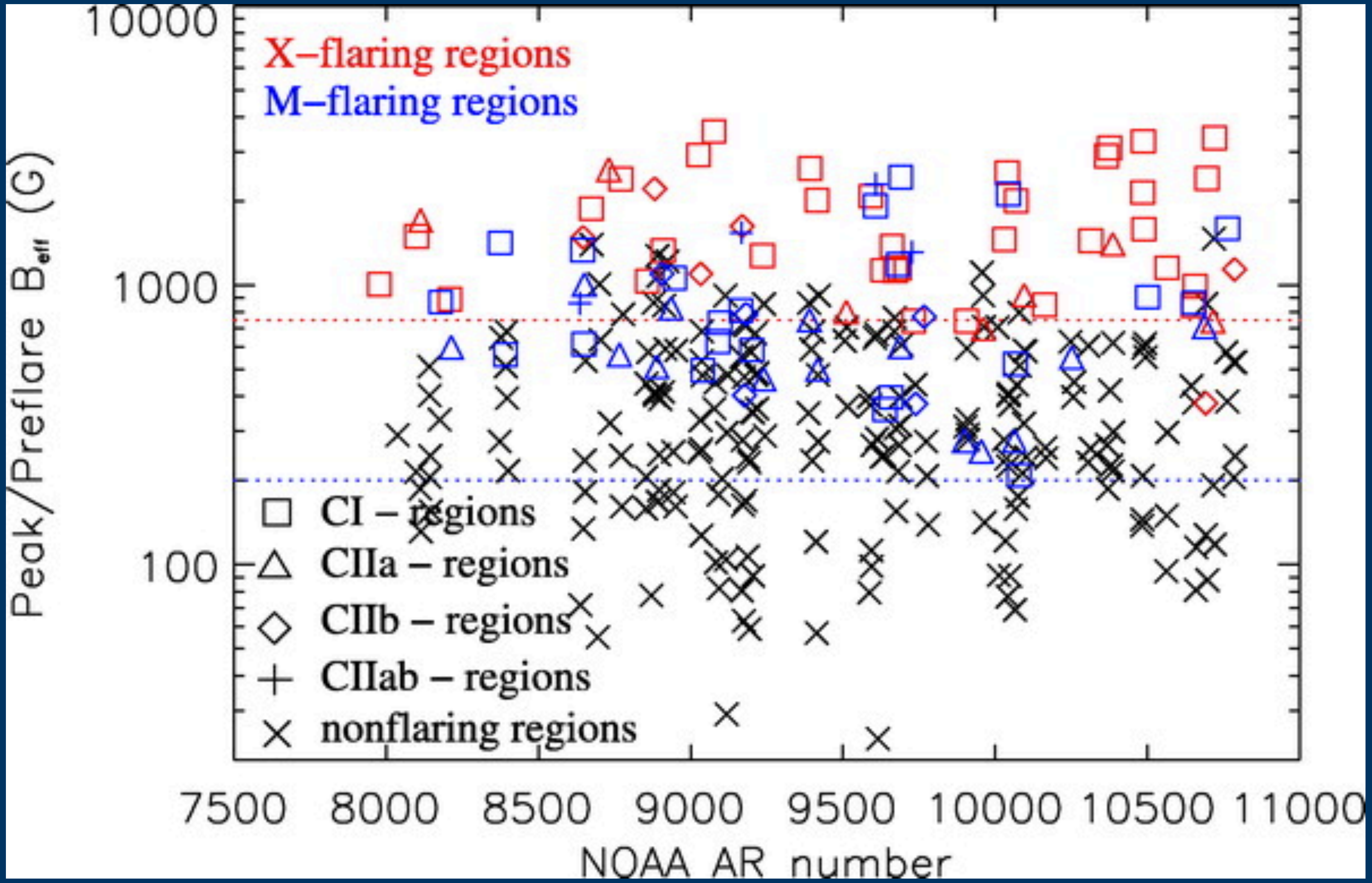
Some initial results, far from ideal



Leka & Barnes, ApJ, 2007

Two-variable discriminant analysis and function for different flare classes

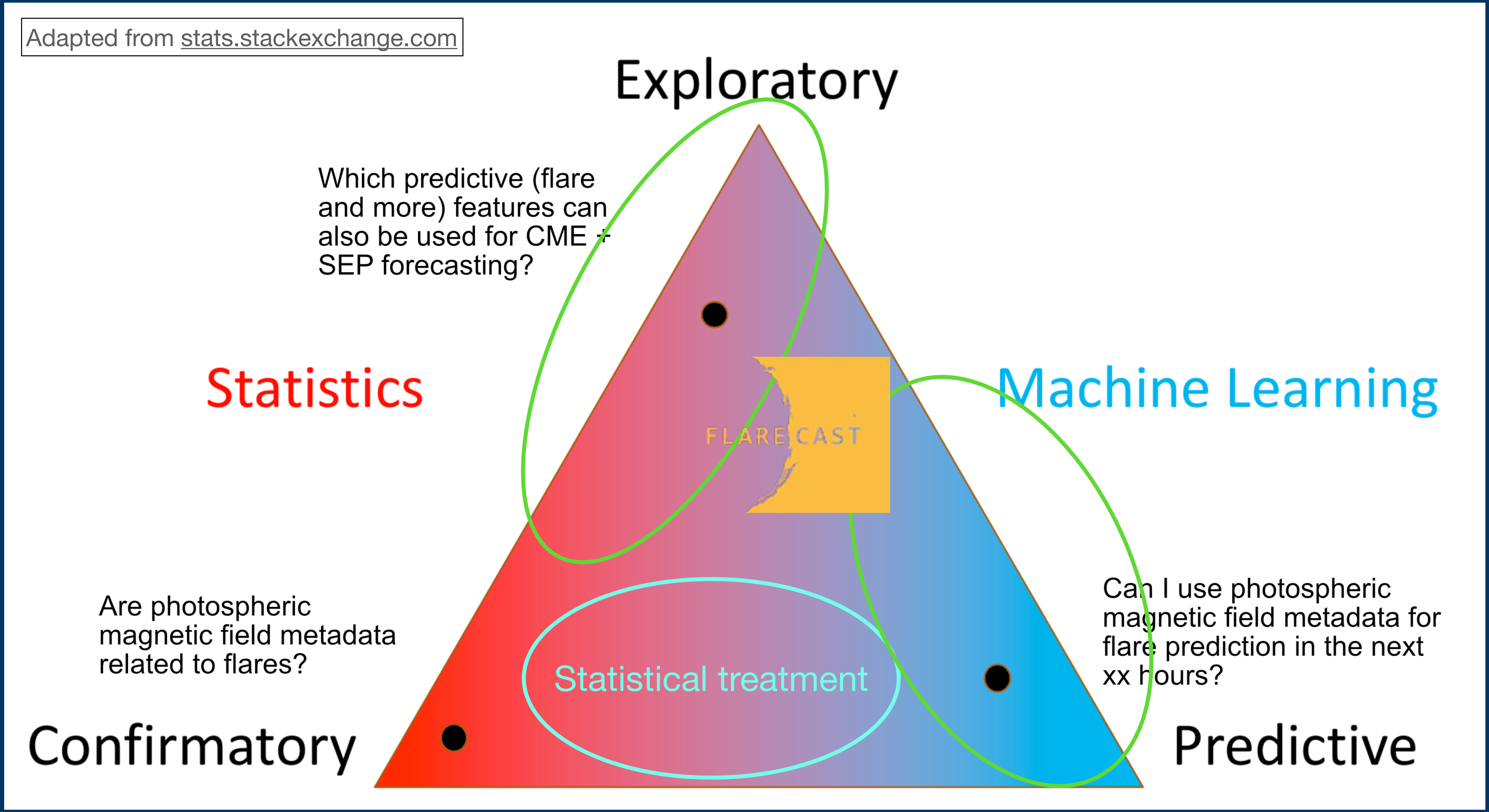
Objective: distinguish flaring from non-flaring active region populations



Georgoulis & Rust, ApJL, 2007

Single parameter using Laplace's rule of succession

A top-level concept from data science, adapted for flares



Machine learning seems to be a natural treatment for forecasting tasks

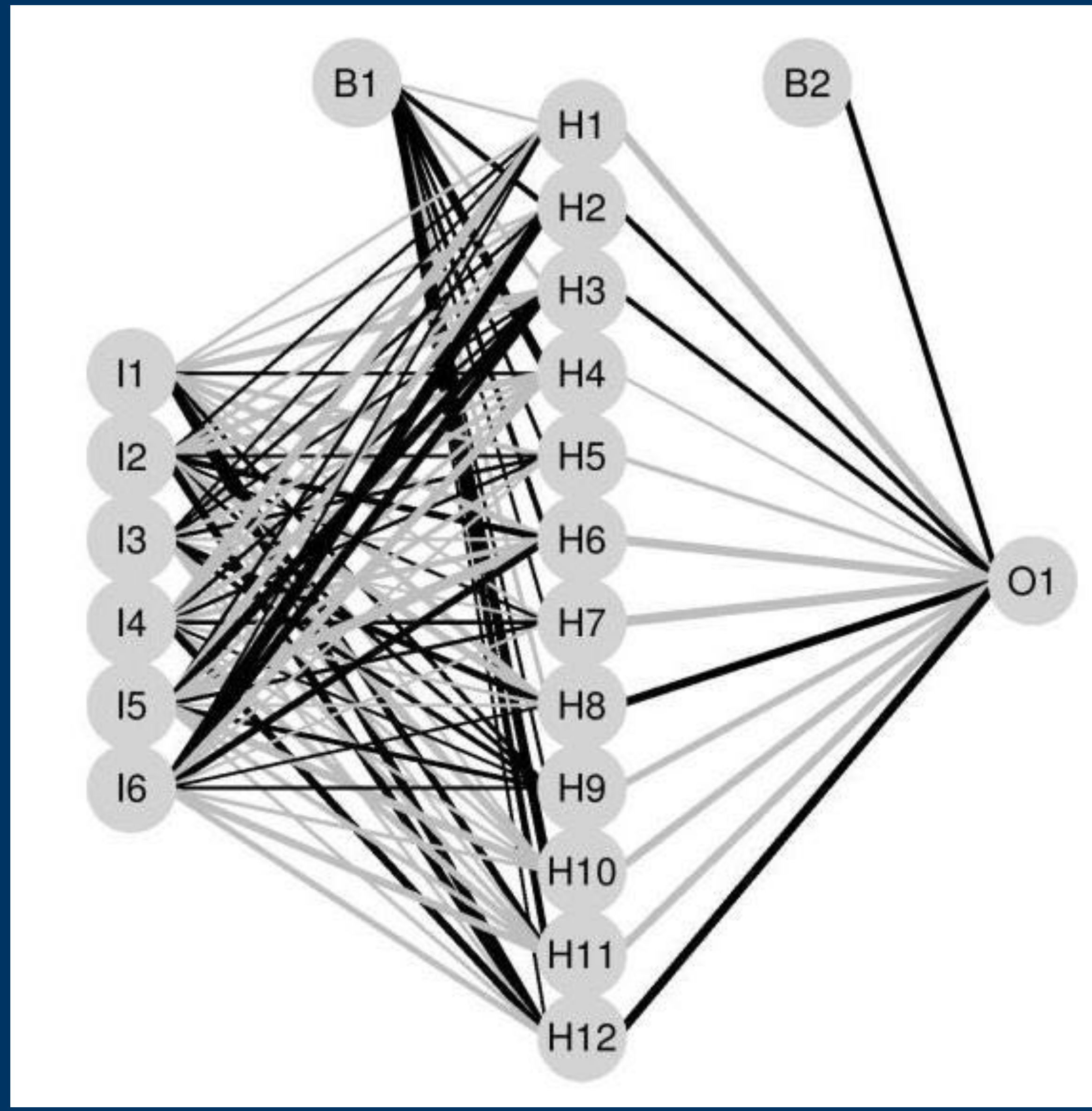
Data Mining: Machine Learning

<u>A definition</u>: **Machine learning** is a natural outgrowth of the intersection of Computer Science and Statistics that seeks to answer the following question:

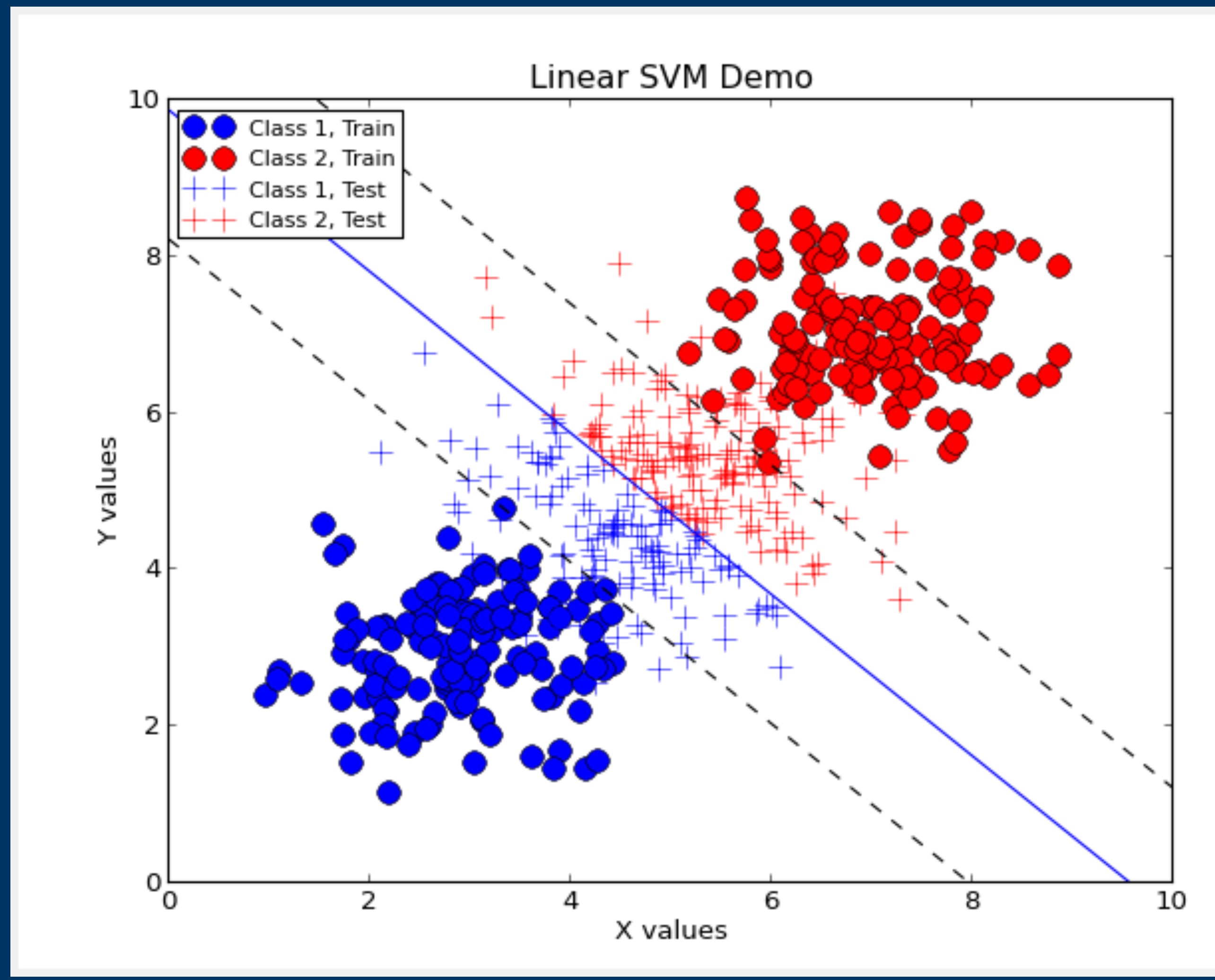
'How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?'

Tom M. Mitchell's *'The Discipline of Machine Learning'*

(Carnegie Mellon U., 2006)



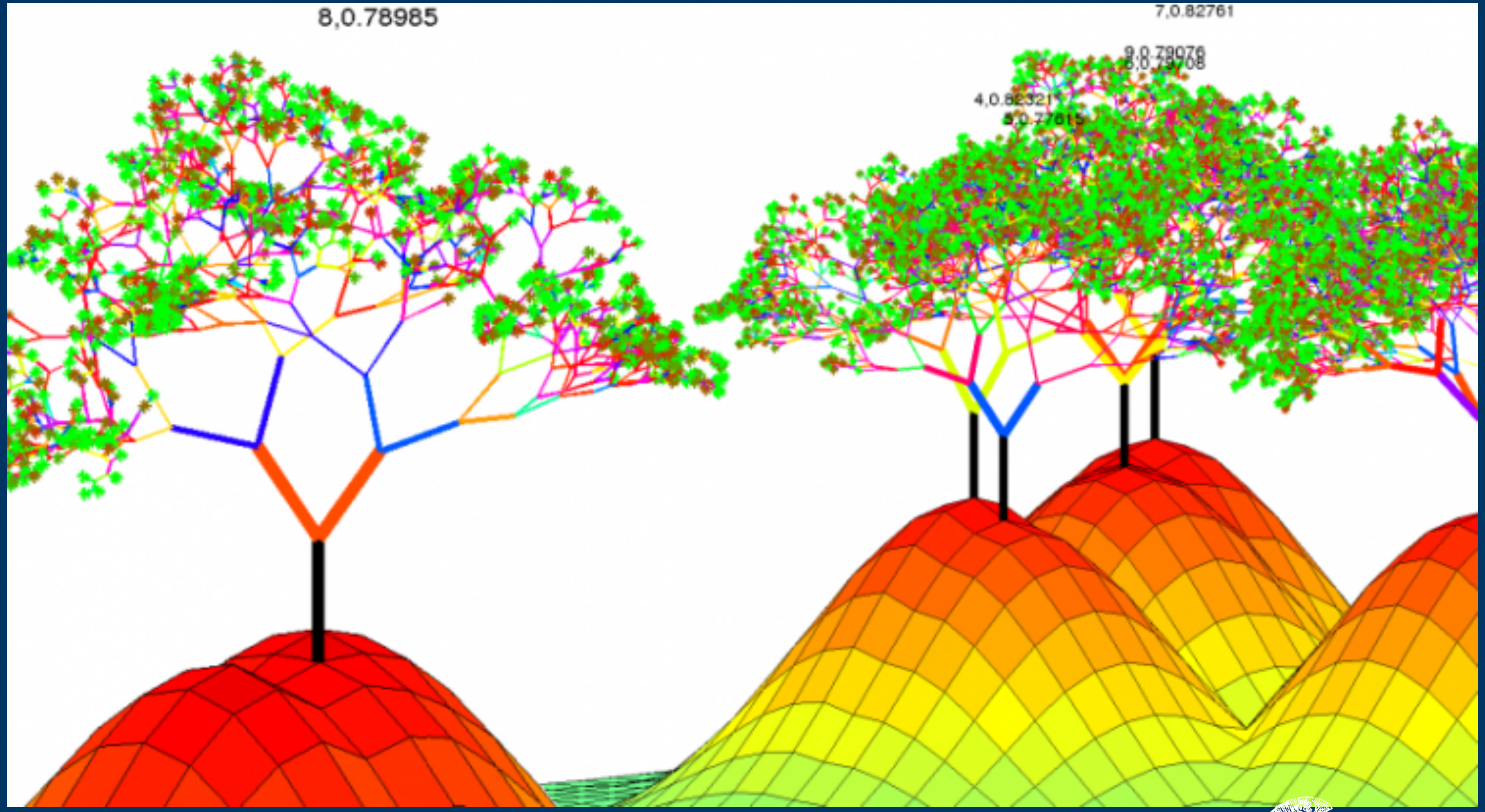
Multi-Layer Perceptron



Support Vector Machines

Supervised / Unsupervised / Hybrid

Random Forests



Credit: paolaelefante.com

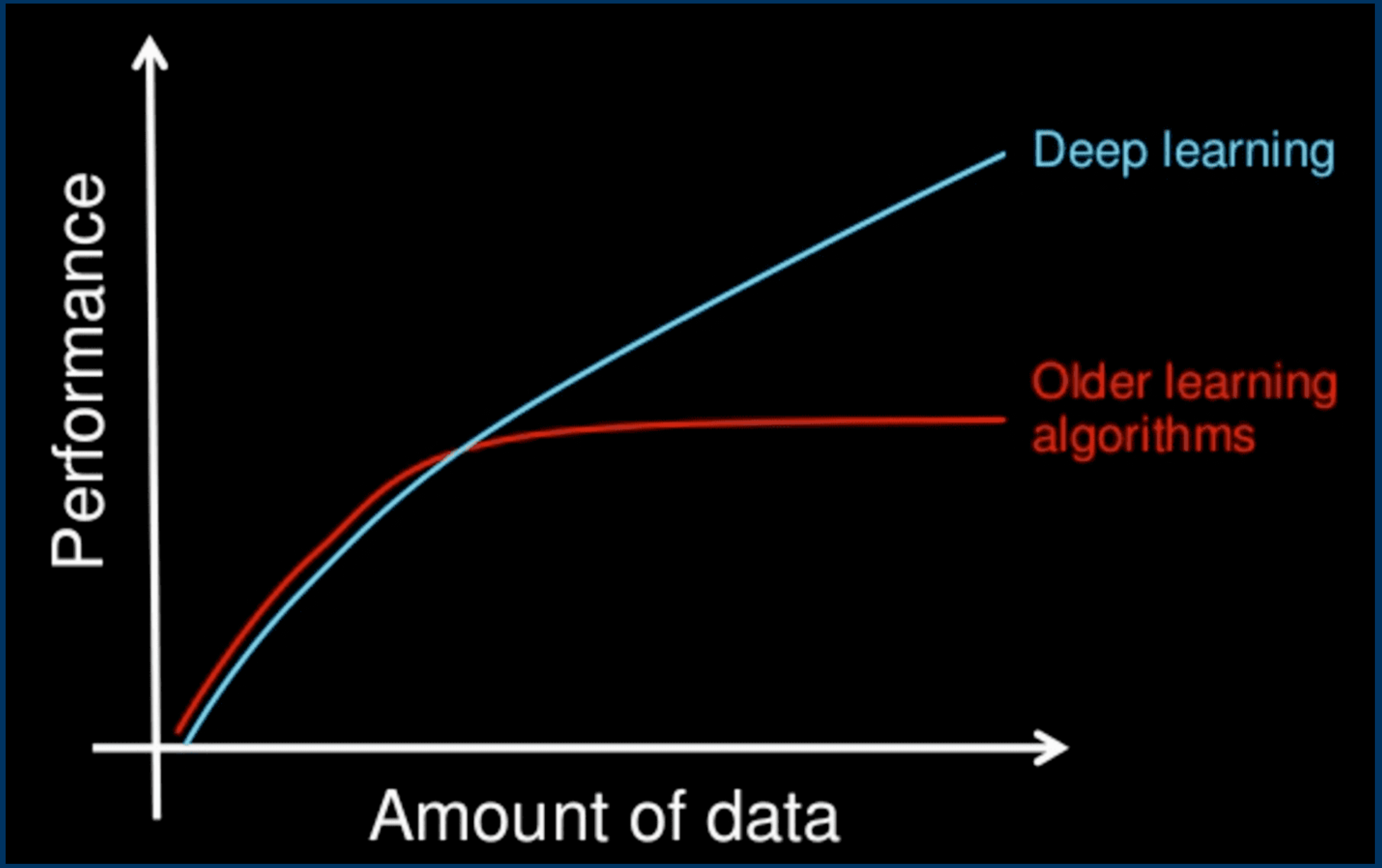
Data Mining: Deep Learning

A definition: **Deep learning** is a particular kind of machine learning that achieves great power and flexibility by representing the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones.

Goodfellow, Bengio & Courville 'Deep *Learning*'
(MIT Press, 2016)

Unsupervised, hard to interpret

Why Deep Learning?

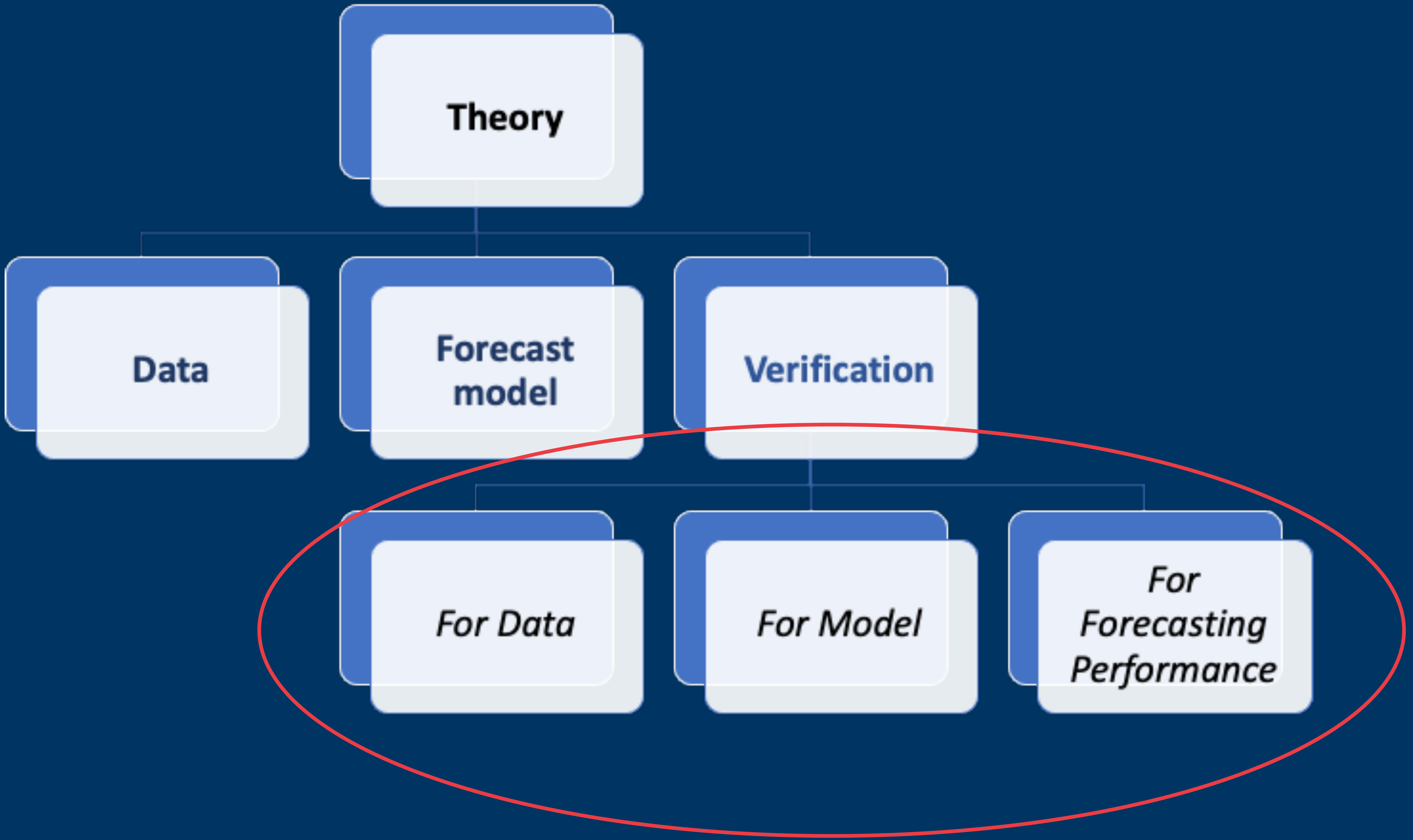


Credit: Andrew Ng

The nagging questions:
- Do we have enough data?
- How to interpret?

How to: a bigger picture emerges

A theory analog:



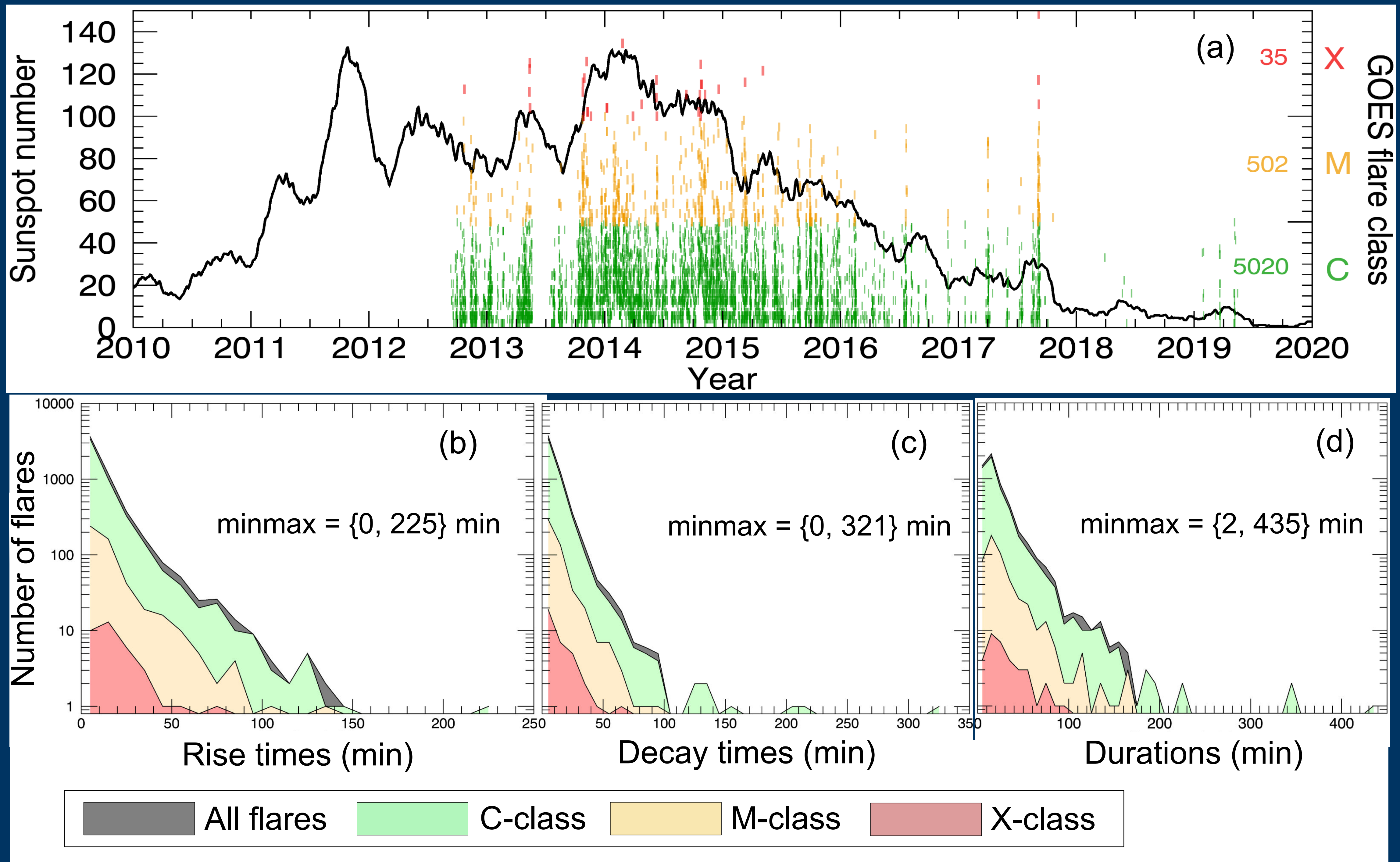
Does it work?

- To test the theory (the hypothesis-based idea), one needs:
  - ML / DL-ready data (curated; preprocessed)
  - The ML / DL (or pure statistical) model to feed the data to
  - Verification at three different levels:
    - o Data verification
    - o Model verification
    - o Performance verification (validation)
- Interpretation of the performance, via parameter (i.e. predictor) ranking

Why does it work?

Data verification via benchmark datasets: train & test on identical conditions

- FLARECAST Predictor Database
  (near-realtime SDO / HMI SHARPs)



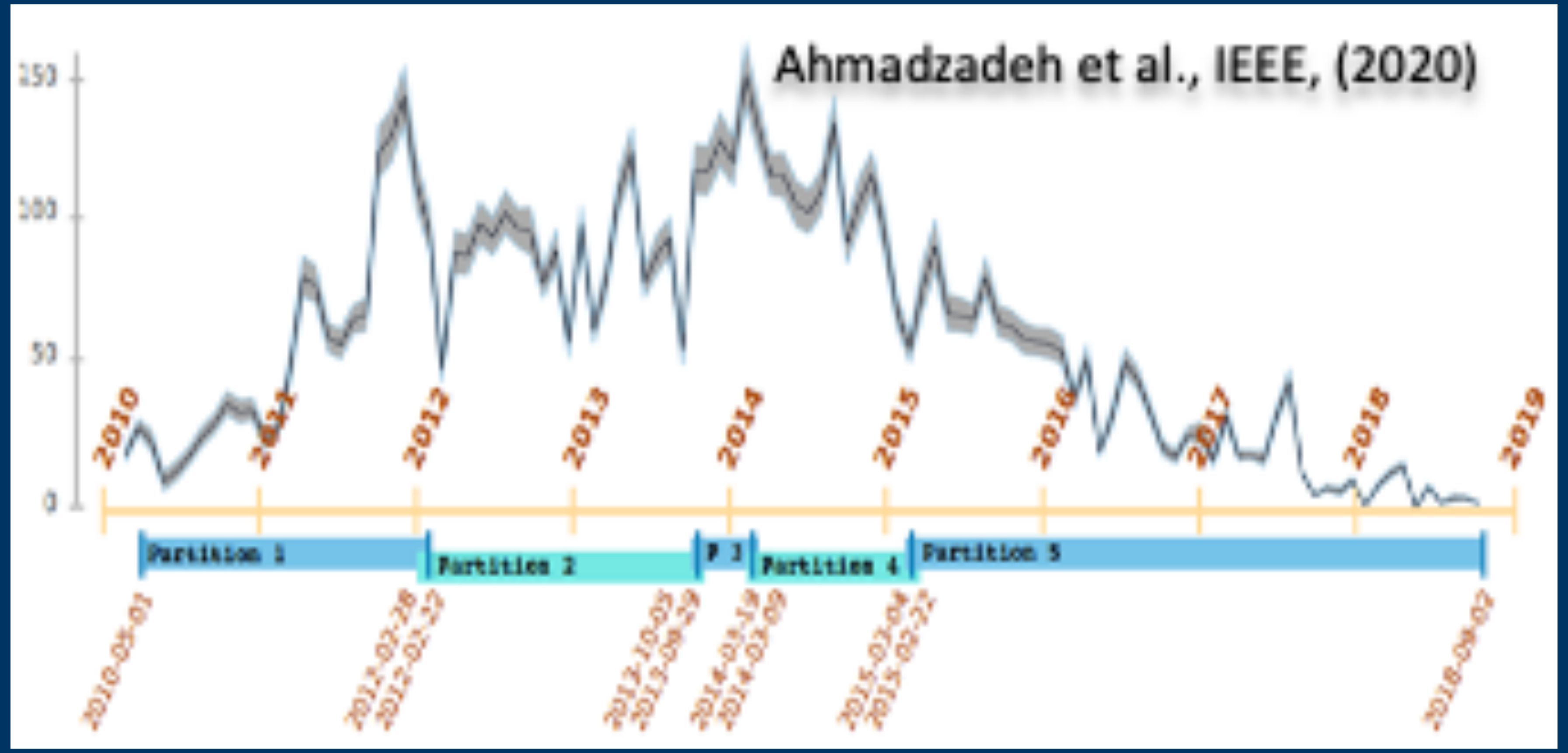
Georgoulis et al., JSWSC, 2021

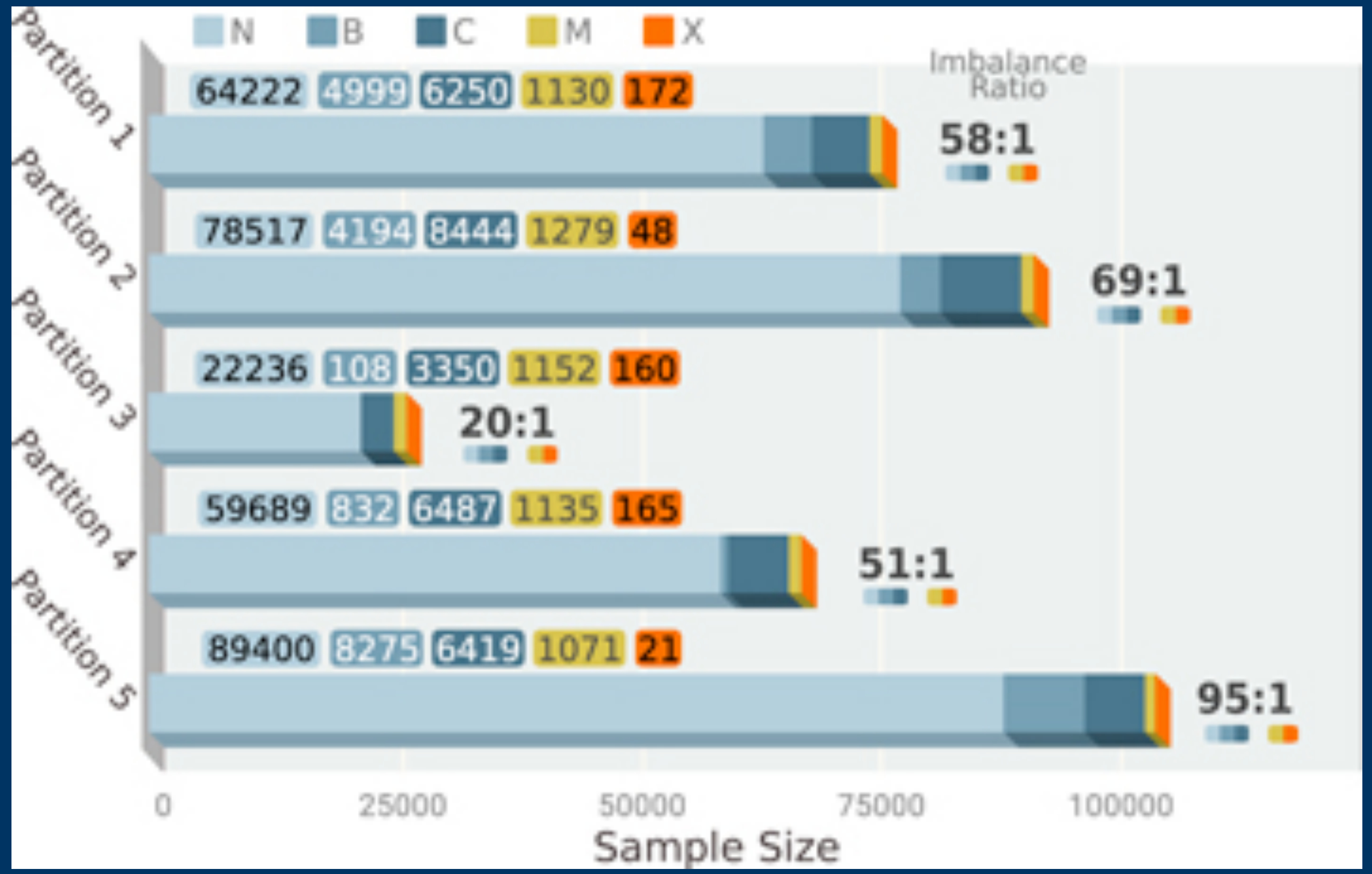
Numbers of verified GOES flares:

* C-class: 5020
* M-class: 502
* X-class: 35

Accessible at FLARECAST property database: https://api.flarecast.eu/property/ui

- Space Weather Analytics for Solar Flares (SWAN-SF)
  (definitive SDO / HMI SHARPs)





Angryk et al., NatSciData, 2020

Numbers of verified GOES flares:

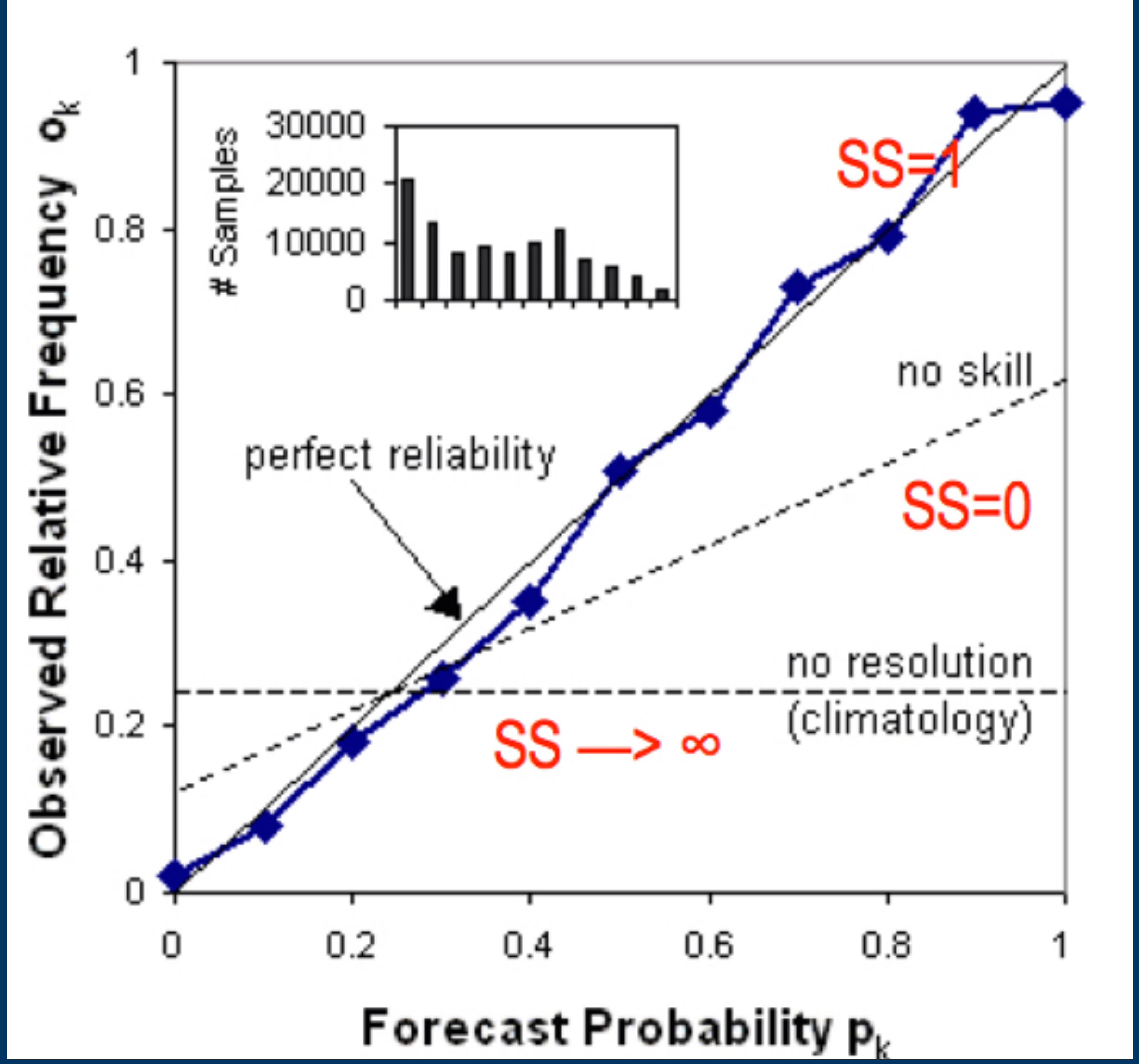
* A-/B-class: 5305
* C-class: 7556
* M-class: 730
* X-class: 50

Accessible at Harvard Dataverse: https://bit.ly/3wjHBli

Performance verification: know the nature of your data

2 x 2 contingency table

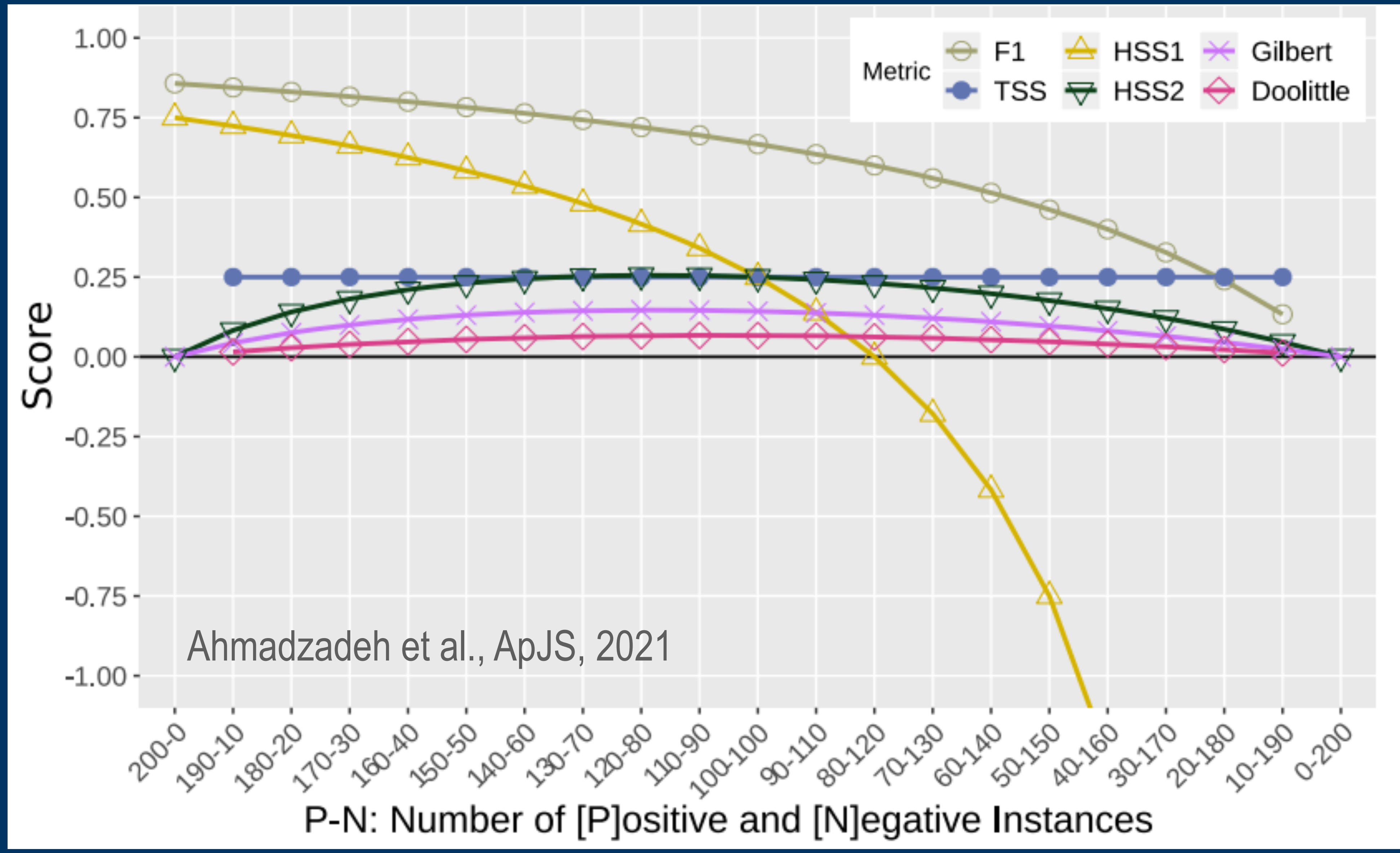
		Flaring Observed	
		Yes	No
Flaring Predicted	Yes	True Positive (TP)	False Positive (FP)
	No	False Negative (FN)	True Negative (TN)



Reliability diagram

Name	Notation	Formula	Range
Accuracy	ACC	$\frac{TP+TN}{N}$	[0,1]
False alarm ratio	FAR	$\frac{FP}{TP+FP}$	[0,1]
Bias	BIAS	$\frac{TP+FP}{TP+FN}$	[0,∞]
Threat score	TS	$\frac{TP}{TP+FN+FP}$	[0,1]
Equitable threat score	ETS	$\frac{TP-R_{ETS}}{TP+FN+FP-R_{ETS}}$	[$-\frac{1}{3}$,1]
		using $R_{ETS} = \frac{(TP+FN)(TP+FP)}{N}$	
Probability of detection	POD	$\frac{TP}{TP+FN}$	[0,1]
Probability of false detection	POFD	$\frac{FP}{FP+TN}$	[0,1]
Odds ratio	OR	$\frac{TP \cdot TN}{FN \cdot FP}$	[0,∞]
Odds ratio skill score	ORSS	$\frac{(TP \cdot TN)-(FN \cdot FP)}{(TP \cdot TN)+(FN \cdot FP)}$	[-1,1]
Heidke skill score	HSS	$\frac{TP+TN-R_{HSS}}{N-R_{HSS}}$	[-1,1]
		using $R_{HSS} = \frac{(TP+FN)(TP+FP)+(TN+FN)(TN+FP)}{N}$	
True skill statistic	TSS	POD − POFD	[-1,1]
Symmetric extremal dependence index	SEDI	$\frac{\log(POFD)-\log(POD)-\log(1-POFD)+\log(1-POD)}{\log(POFD)+\log(POD)+\log(1-POFD)+\log(1-POD)}$	[-1,1]
Appleman's discriminant	AD	$\frac{TN-FN}{FP+TN}$ if $(TP+FN) > (FP+TN)$	[$-\frac{FN}{FP}$,1]
		$\frac{TP-FP}{FN+TP}$ if $(TP+FN) < (FP+TN)$	[$-\frac{FP}{FN}$,1]

Performance verification: know the nature of your data



Class-imbalance: rare events; TN >> {TP, FP, FN}

- Accuracy is practically useless $$ACC = \frac{TP+TN}{TP+TN+FP+FN} \simeq 1$$
- TSS is largely immune $$TSS = \frac{TP}{TP+FN} - \frac{FP}{FP+TN}$$
- HSS and F1-score are largely not immune

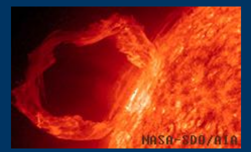
$$HSS = \frac{TP+TN-R_{HSS}}{TP+FN+FP+FN-R_{HSS}} \qquad R_{HSS} = \frac{(TP+FN)(TP+FP)+(TN+FN)(TN+FP)}{TP+FP+TN+FN}$$

$$F1 = \frac{2TP}{2TP+FP+FN}$$

- For extreme class imbalance, namely $TN \simeq TP+FP+TN+FN$

$$HSS \simeq F1$$

One should always experiment on the efficiency of performance verification metrics and compare in controlled conditions



Keeping it modular and expandable: an example of ‘horizontal’ expansion

No	Source ID	Time stamp	Properties’ vector	Event
1	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_N\}$	-
2	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_N\}$	+
k	. . .	. . .	. . .	. . .

- Number of rows: k
- Number of predictors: N

‘Horizontally’ expanded dataset

No	Source ID	Time stamp	Properties’ vector	Event
1	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_{N'}\}$	-
2	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_{N'}\}$	+
k’	. . .	. . .	. . .	. . .

- Number of rows: k’ > k
- Number of predictors: N’ > N

In this respect one adds more sources and / or more predictors to improve statistics for the <u>same</u> problem

Keeping it modular and expandable: an example of ‘vertical’ expansion

No	Source ID	Time stamp	Properties	Event
1	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_N\}$	-
2	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_N\}$	+
k	…	…	…	…

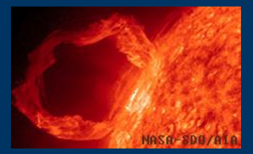
- Number of rows: k
- Number of predictors: N

In this case one adds extra column(s) to train and test the model on the initial and additional event(s)

‘Vertically’ expanded dataset

No	Source ID	Time stamp	Properties	Event	Event association with other event
1	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_N\}$	-	-
2	ID no.	UT	$\vec{P} = \{P_1, P_2, ..., P_N\}$	+	YES/NO
k	…	…	…	…	…

- Number of rows: k
- Number of predictors: N



Consistency is important: from flares …

Flare				
Date	UTime	Class	AR	Location
2003-Nov-2	17:03	X8.3	10486	S17 W63
2003-Nov-4	19:29	X17.4	10486	S17 W90
2004-Jul-25	14:19	M1.1	10652	N08 W35
2004-Sep-12	00:56	M4.8	10672	N04 E42
2004-Sep-19	16:46	M1.9	10672	N06 W59
2004-Nov-1	03:04	M1.1	10691	N13 W42
2004-Nov-7	15:42	X2.0	10696	N08 W18
2004-Nov-10	01:59	X2.5	10696	N13 W50
2005-Jan-15	05:54	M8.6	10720	N13 W04
2005-Jan-15	22:25	X2.6	10720	N13 W17
2005-Jan-17	06:59	X3.8	10720	N13 W30
2005-Jan-20	06:36	X7.1	10720	N14 W70
2005-May-13	16:13	M8.0	10759	N12 E10
2005-Jun-16	20:01	M4.0	10775	N09 W90
2005-Jul-13	14:39	M5.2	10786	N17 W90
2005-Jul-17	12:57	–	10789	–
–	–	–	–	–
2005-Aug-22	16:46	M5.6	10798	S10 W60
2005-Sep-7	17:17	X17	10808	S10 E90
2005-Sep-13	19:19	X1.5	10808	S11 E05
2006-Dec-5	10:18	X9.0	10930	S06 E90
2006-Dec-13	02:14	X3.4	10930	S05 W23

Georgoulis et al., JSWSC, 2018

For brevity, the Table omits the vector of predictors and includes only positive-sample (i.e., flare) events

…to eruptive (i.e., CME-associated) flares + SEP events

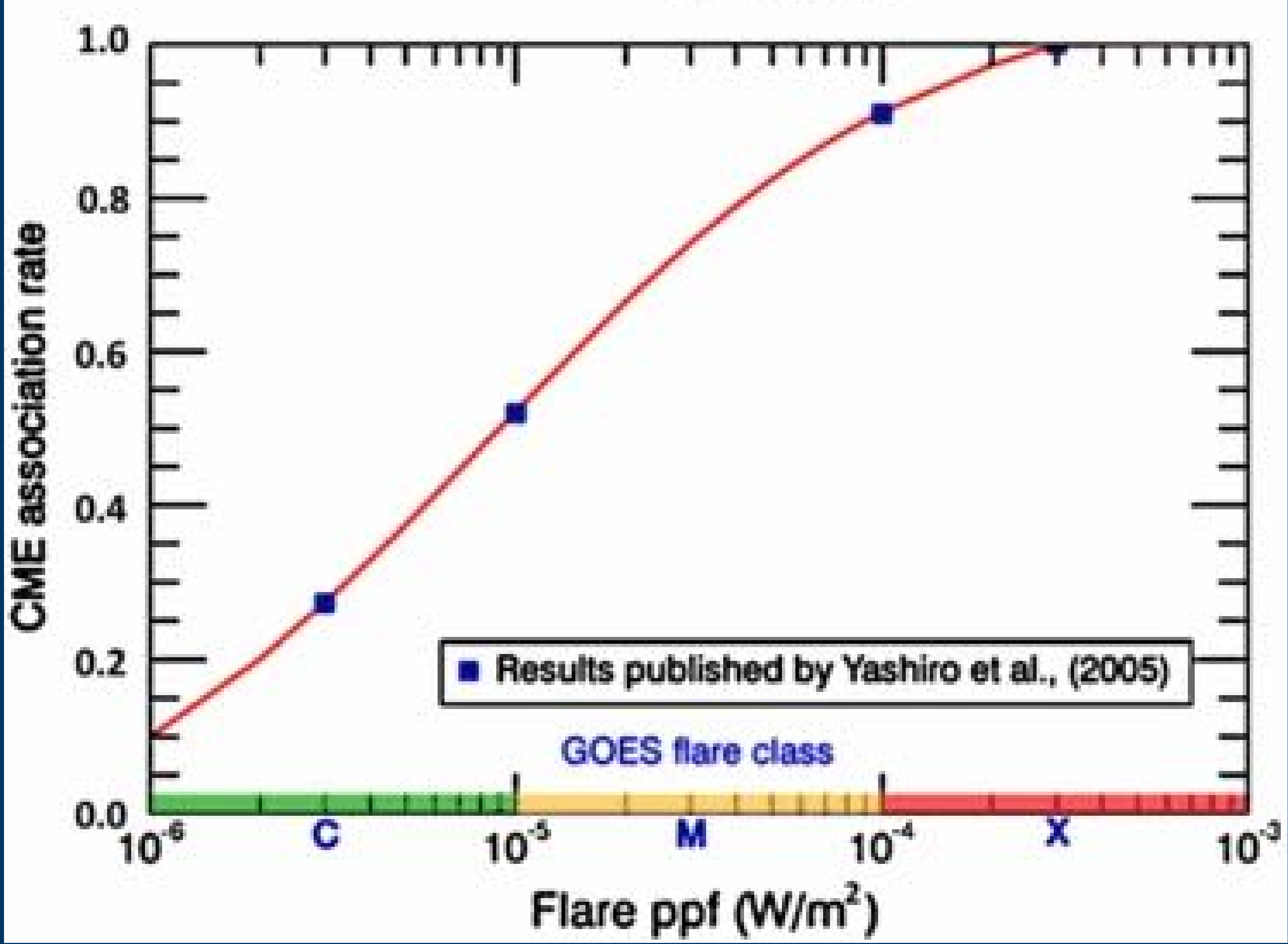
IDs		Flare					CME				
		Date	UTime	Class	AR	Location	Date	UTime	Position angle (°)	Speed (km/s)	Shock
I1		2003-Nov-2	17:03	X8.3	10486	S17 W63	2003-Nov-2	17:15	Halo	2554–2598	Y
I2		2003-Nov-4	19:29	X17.4	10486	S17 W90	2003-Nov-4	19:38	Halo	2657–3284	Y
I3		2004-Jul-25	14:19	M1.1	10652	N08 W35	2004-Jul-25	14:32	Halo	1333–1366	Y
I4		2004-Sep-12	00:56	M4.8	10672	N04 E42	2004-Sep-12	00:21	Halo	1328–1484	Y
I5		2004-Sep-19	16:46	M1.9	10672	N06 W59	–	–	99	365	Y
I6	R1	2004-Nov-1	03:04	M1.1	10691	N13 W42	2004-Nov-1	05:25	266	720–925	Y
I7		2004-Nov-7	15:42	X2.0	10696	N08 W18	2004-Nov-7	16:16	Halo	1696–1759	Y
I8	R2	2004-Nov-10	01:59	X2.5	10696	N13 W50	2004-Nov-10	02:05	Halo	3142–3387	Y
I9	R3	2005-Jan-15	05:54	M8.6	10720	N13 W04	2005-Jan-15	05:57	Halo	1926–2049	Y
I10	R4	2005-Jan-15	22:25	X2.6	10720	N13 W17	2005-Jan-15	22:36	Halo	2596–2861	Y
I11	R5	2005-Jan-17	06:59	X3.8	10720	N13 W30	2005-Jan-17	09:00	Halo	2094	Y
I12	R6	2005-Jan-20	06:36	X7.1	10720	N14 W70	2005-Jan-20	05:55	Halo	882–940	Y
I13	R7	2005-May-13	16:13	M8.0	10759	N12 E10	2005-May-13	16:40	Halo	1689	Y
I14	R8	2005-Jun-16	20:01	M4.0	10775	N09 W90	–	–	–	–	Y
I15	R9	2005-Jul-13	14:39	M5.2	10786	N17 W90	2005-Jul-13	14:04	Halo	1423	Y
I16		2005-Jul-17	12:57	–	10789	–	2005-Jul-17	11:11	Halo	1527–1814	Y
I17	R10	–	–	–	–	–	2005-Jul-26	04:11	Halo	1246–1458	?
I18	R11	2005-Aug-22	16:46	M5.6	10798	S10 W60	2005-Aug-22	17:00	Halo	2378–2612	Y
I19	R12	2005-Sep-7	17:17	X17	10808	S10 E90	–	–	–	–	Y
I20	R13	2005-Sep-13	19:19	X1.5	10808	S11 E05	2005-Sep-13	19:36	Halo	1866–1915	Y
I21	R14	2006-Dec-5	10:18	X9.0	10930	S06 E90	–	–	–	–	Y
I22		2006-Dec-13	02:14	X3.4	10930	S05 W23	2006-Dec-13	02:18	Halo	1622–1774	Y

Georgoulis et al., JSWSC, 2018

For brevity, the Table omits the vector of predictors and includes only positive-sample (i.e., flare) events

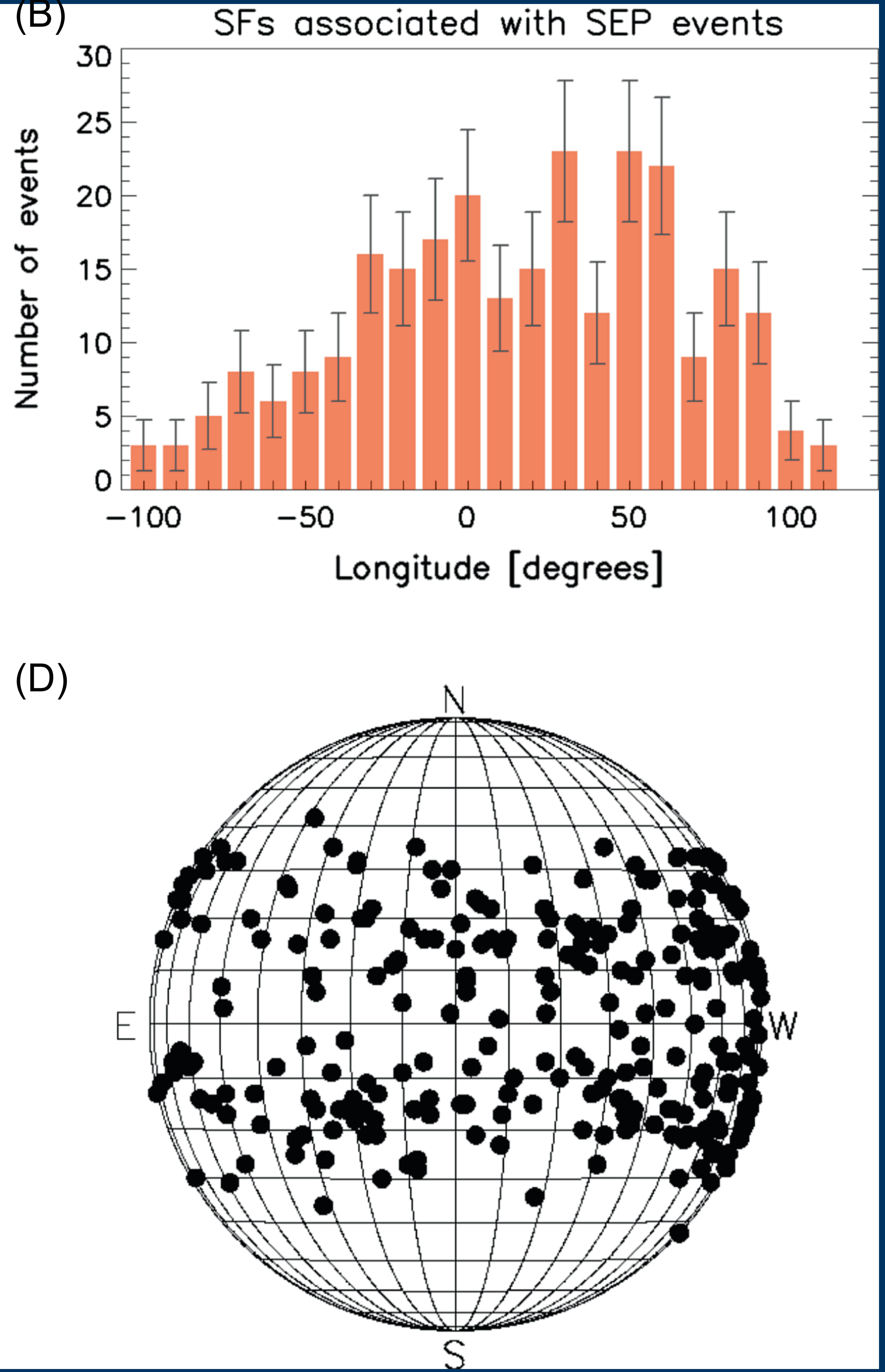
Now the table relates flares to CME information, if any

Event rarity, from flares, to CMEs to SEP events



Anastasiadis et al., SoPh, 2017

Flare-to-CME association



Papaioannou et al., JSWSC, 2016

Eruptive flare to SEP event association

Period: 04/1997 – 11/2017

- 23,129 flares, any size
- 29,390 CMEs, any properies
- 206 SEP events

Overall flare and SEP association regardless of heliographic location:

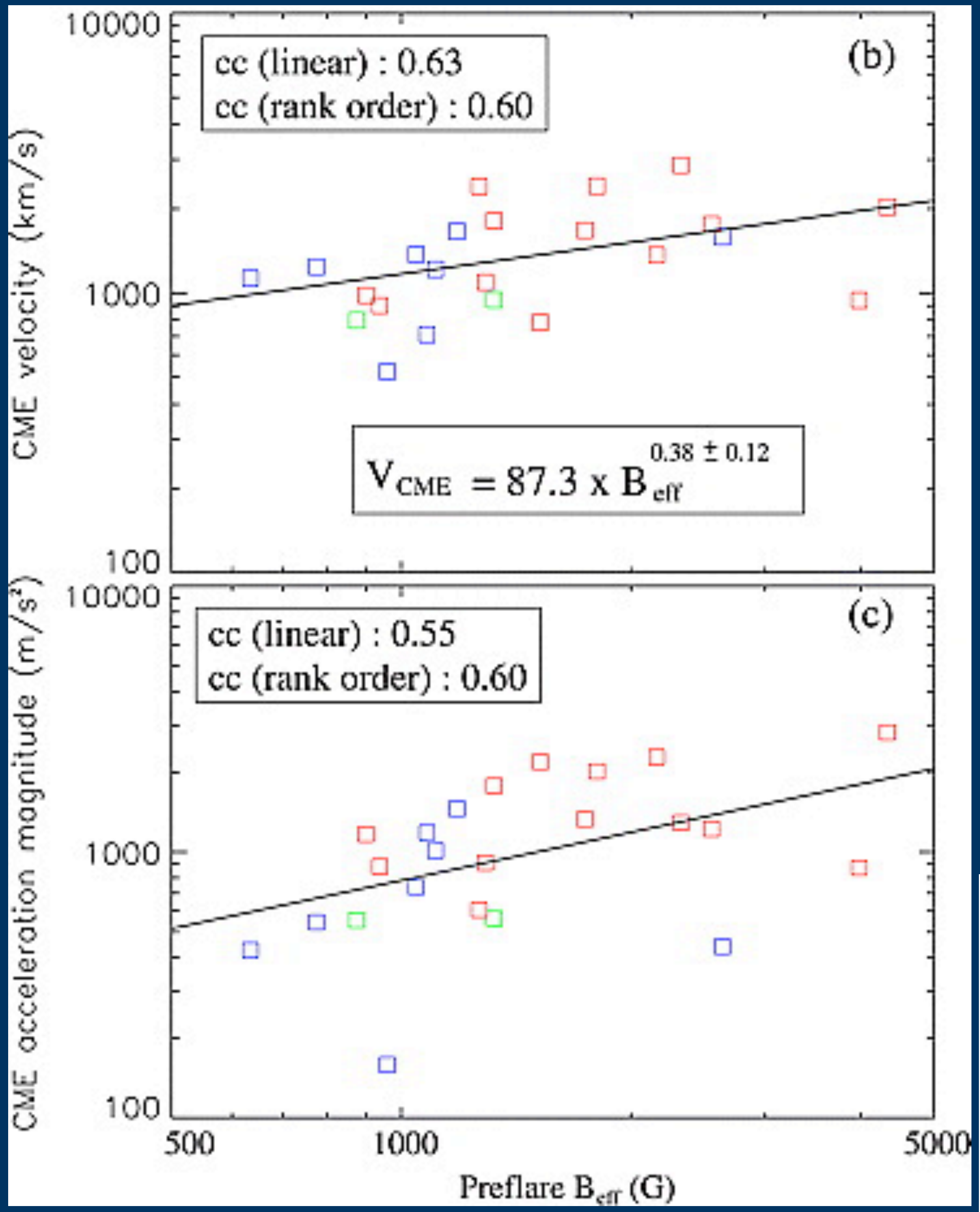
- ❑ C-class flares: **1 : 634**
- ❑ M-class flares: **1 : 24**
- ❑ X-class flares: **1 : 3**

Overall CME and SEP association regardless of heliographic location:

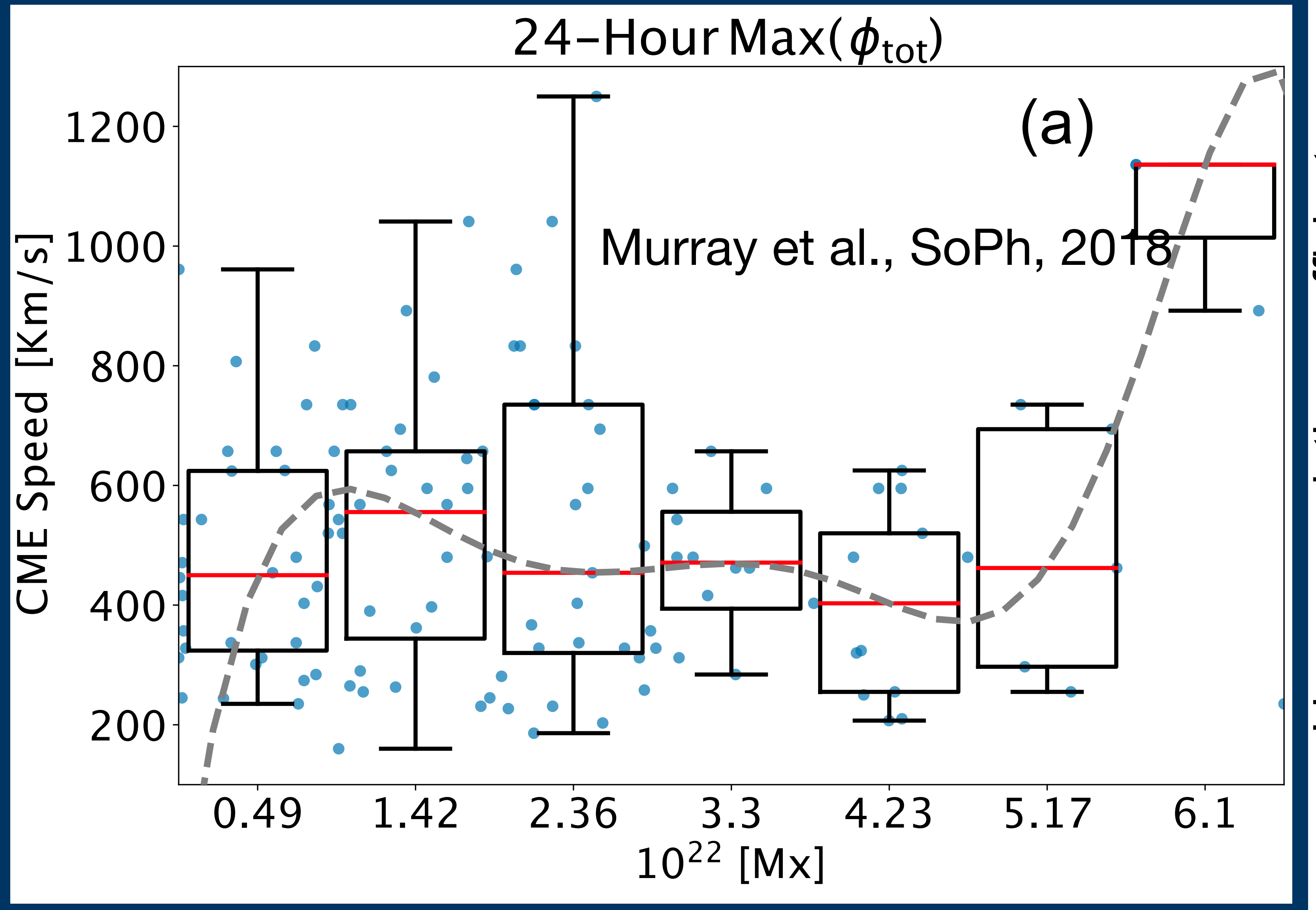
- ❑ Non-halo CMEs: **1 : 630**
- ❑ Fast CMEs (>750 km/s): **1 : 12**
- ❑ Halo CMEs: **1 : 6**
- ❑ Fast & halo CMEs: **1 : 1.8**

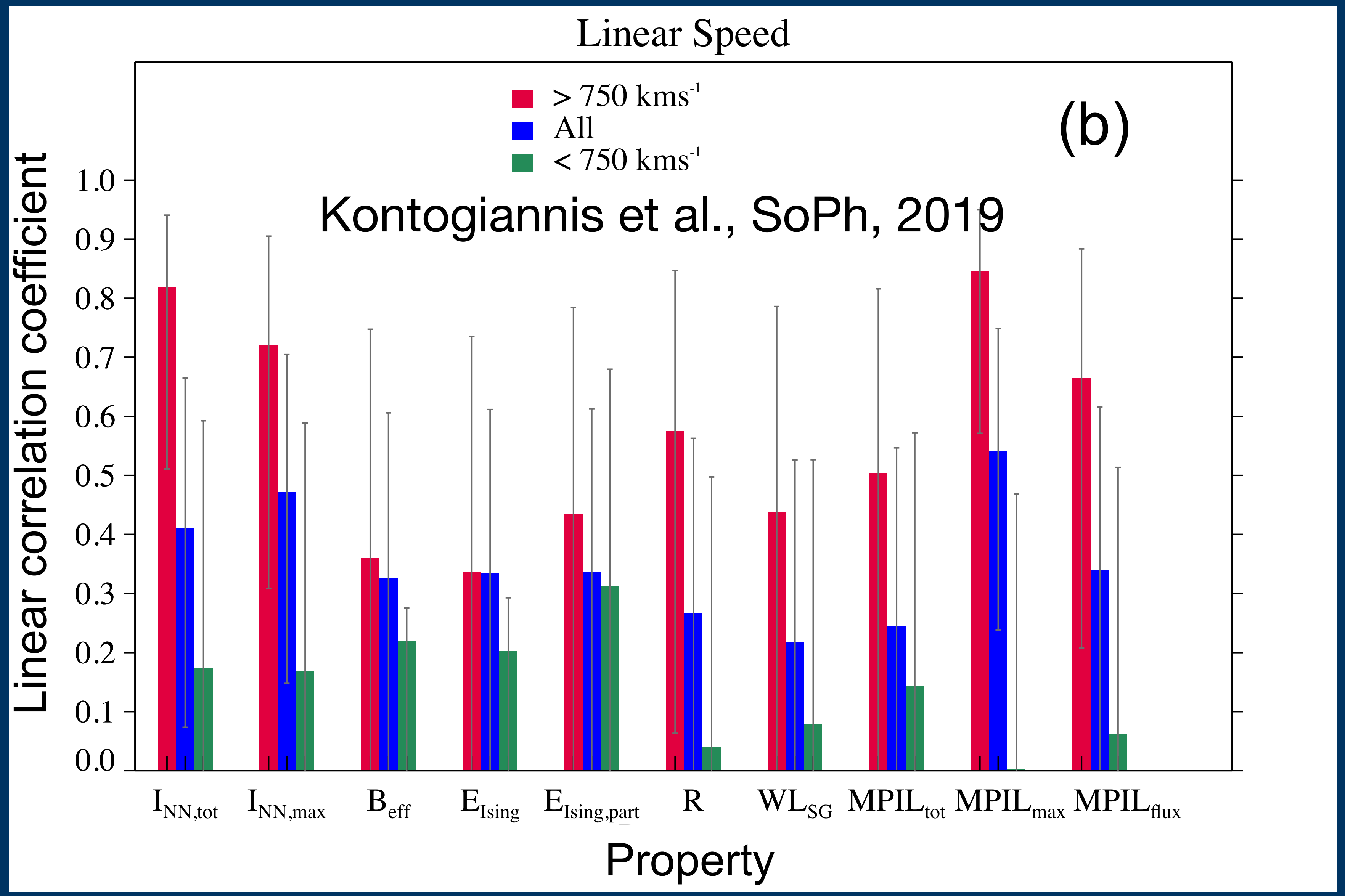
Courtesy: GSU/DMLab

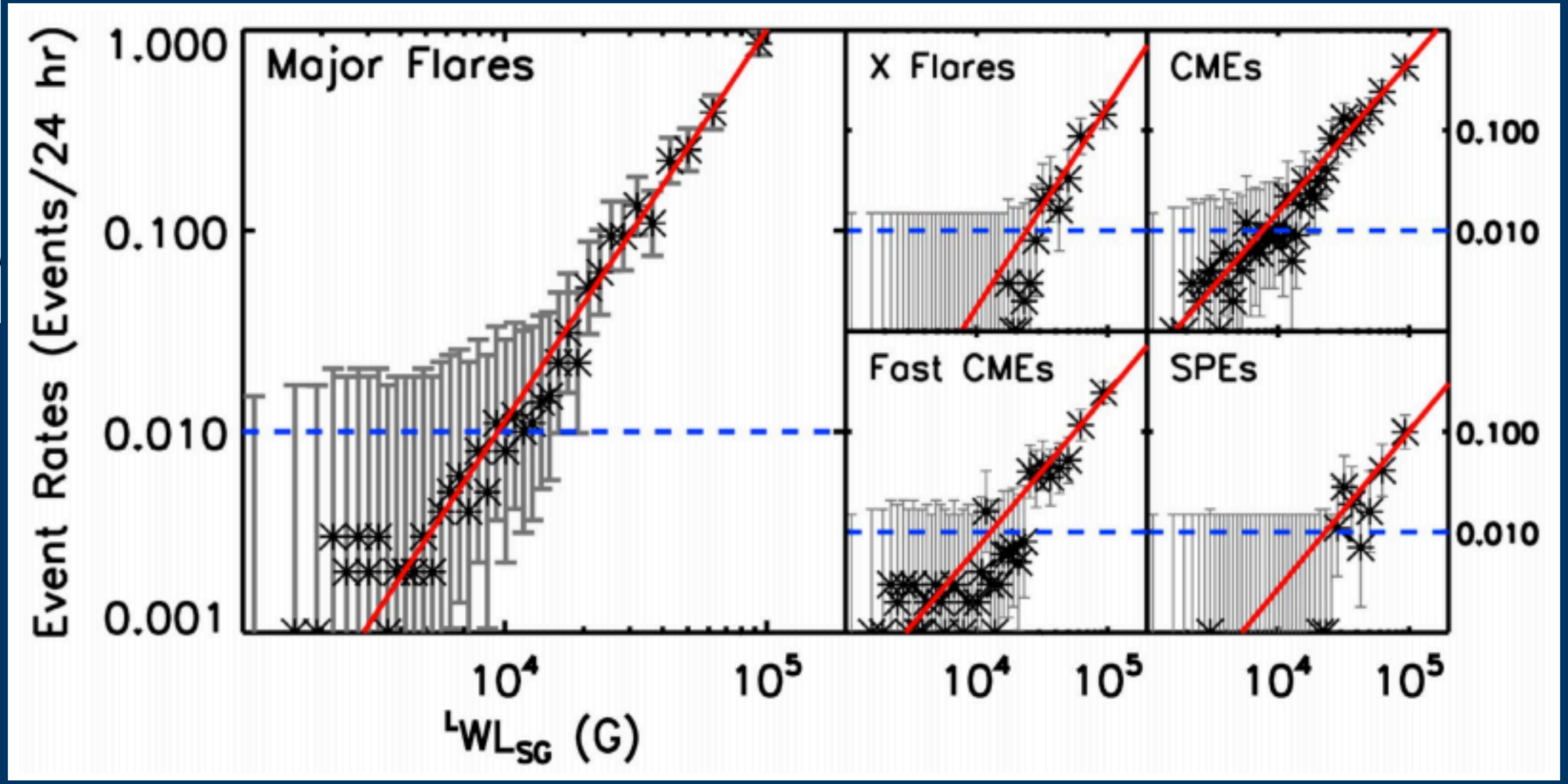
Physical clues to extend from flares, to CMEs, to SEP events



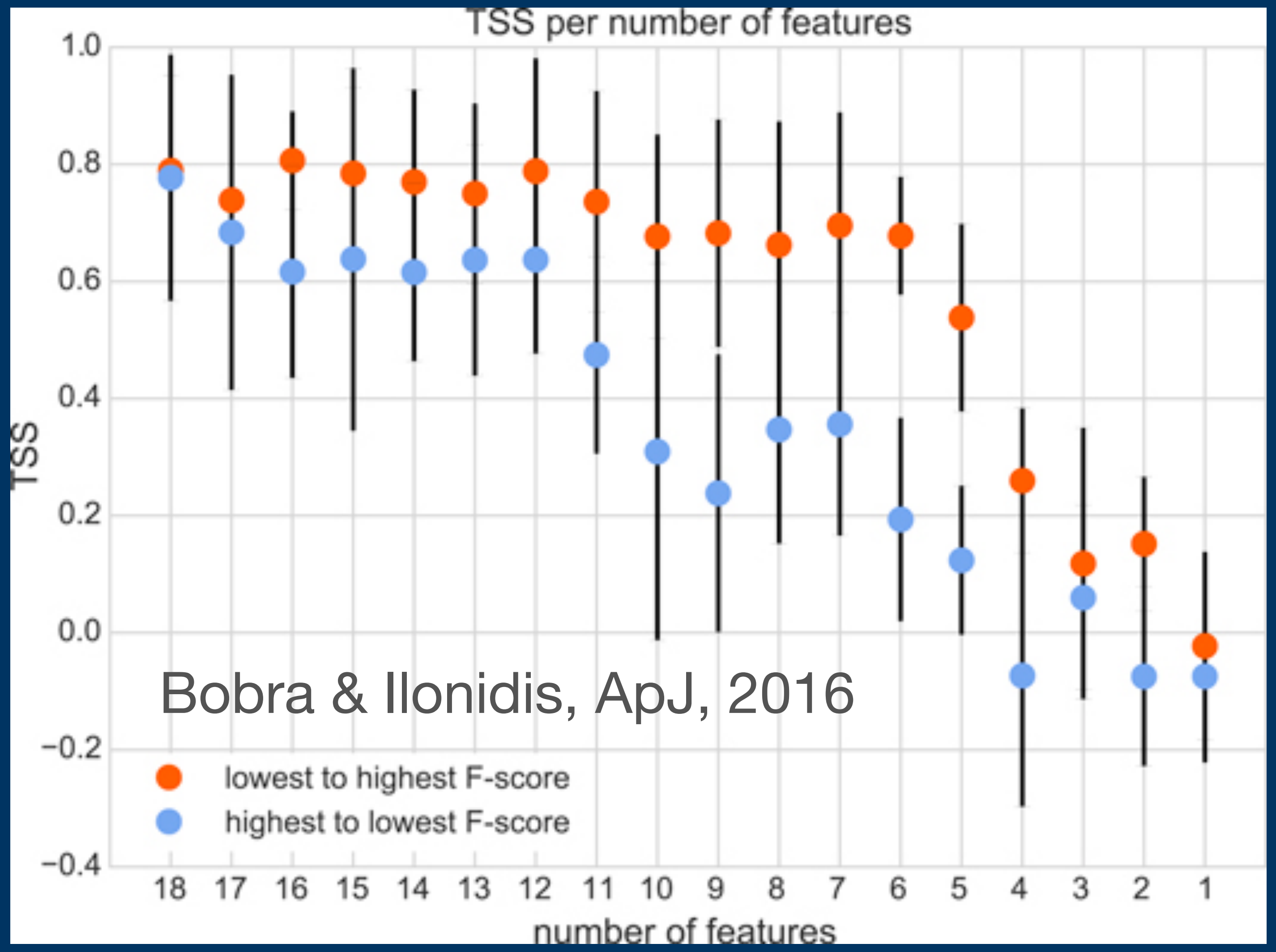
Georgoulis et al., GRL, 2008







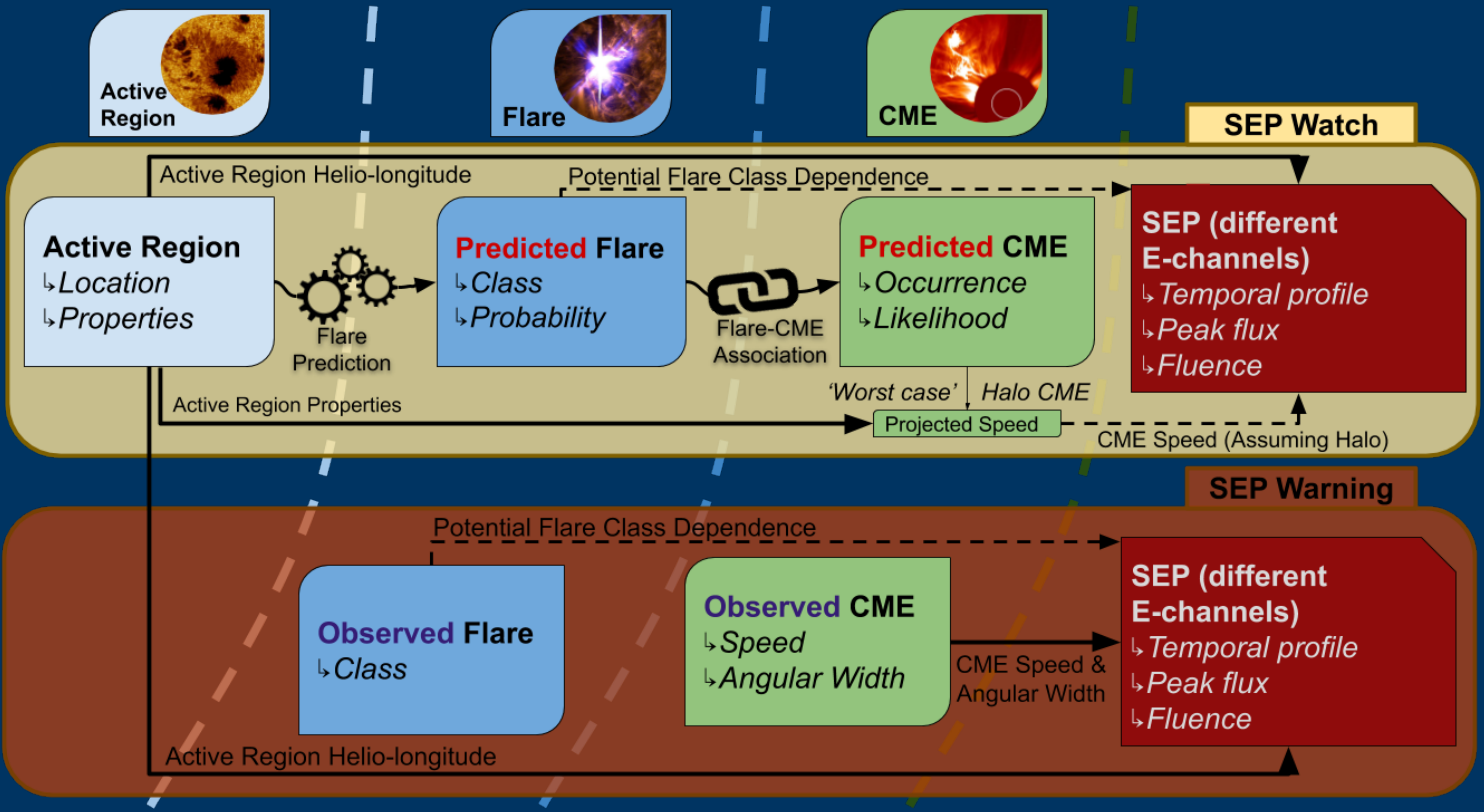
Falconer et al., Space Wea. 2011



Correlating photospheric (active region) metadata to all eruptive manifestations

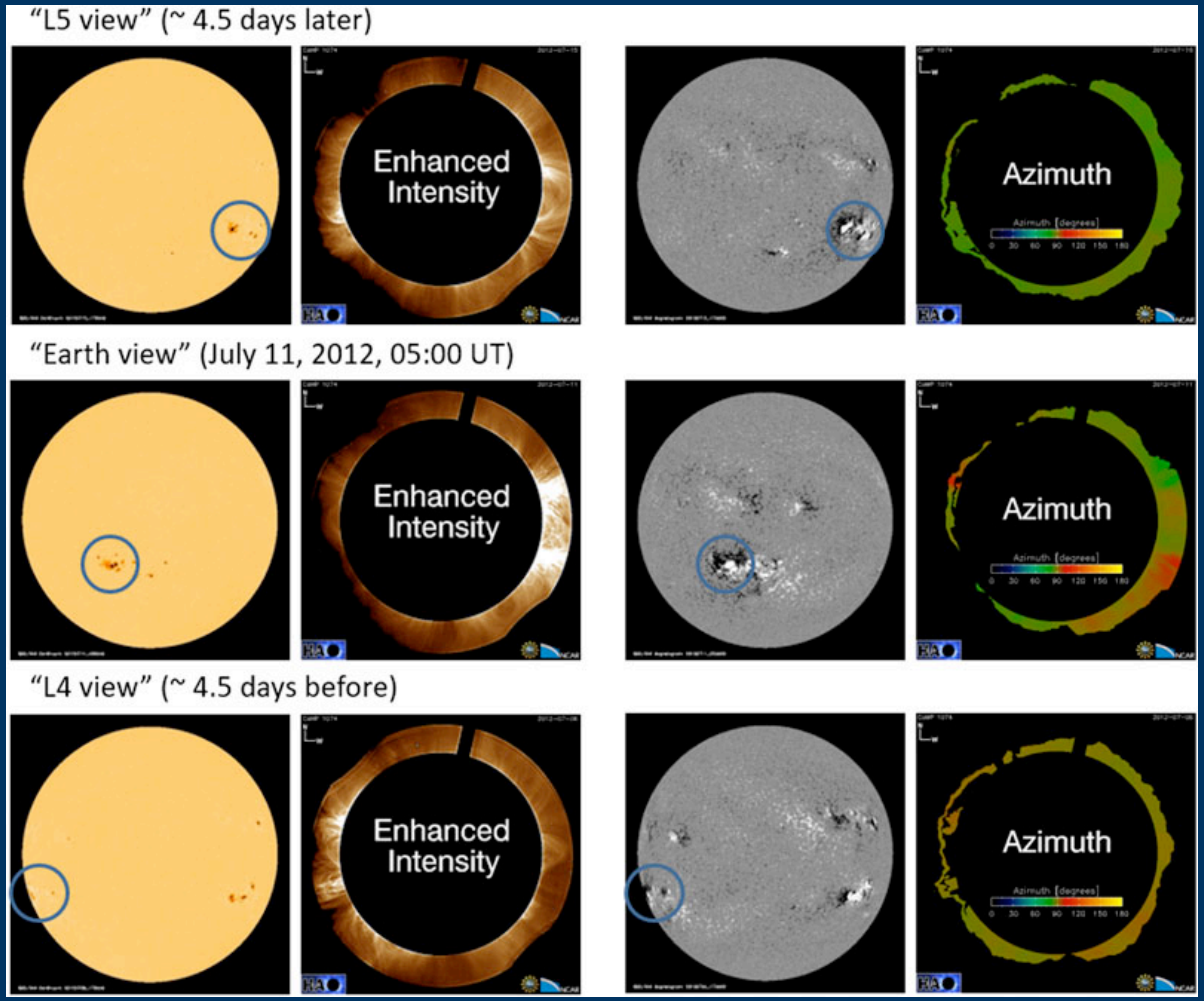
An example of consistent flare / CME / SEP event prediction frameworks

In prep. at GSU's DMLab, in a collaboration with NASA / SRAG



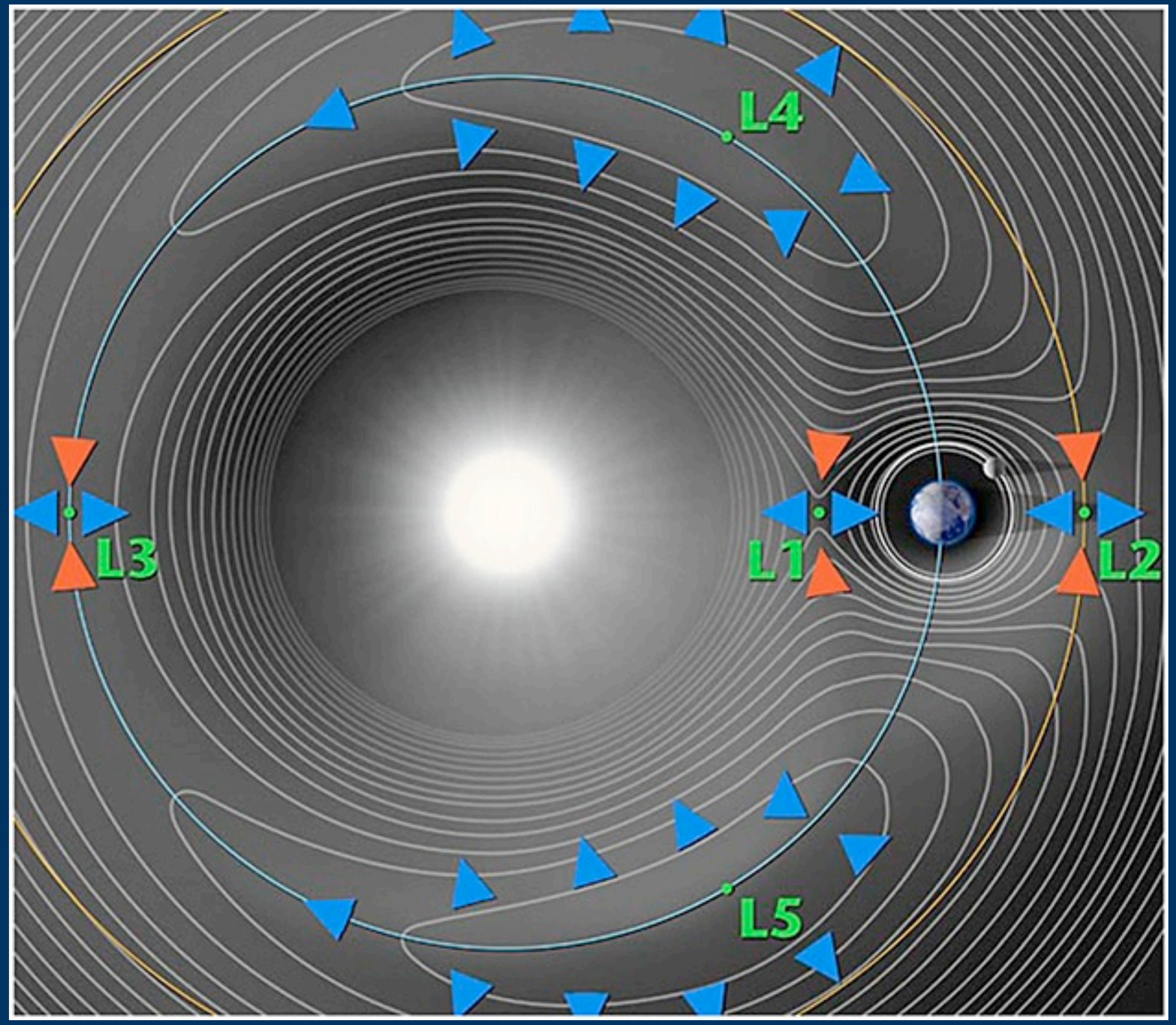
- Two-tier SEP event forecasting
- *SEP Watch* & *SEP Warning* tiers
- SEP Watch means conditions are ripe for a SEP-triggering solar eruption in at least one active region
- SEP Warning means an eruption (flare + CME) has occurred
- Self-consistent projected SEP properties in both foecasting (Watch) and nowcasting (Warning) tiers

The future: solar eruption forecasting beyond the Sun-Earth line



Bemporad, Frontier, 2021

Twin L4 / L5 mission concept



Vourlidas, Space Wea., 2015

L5 mission concept

- L5 - Carrington mission (UKSA)
- L5 - Lagrange / Vigil mission (ESA)
- Potential NASA / NOAA move on a L4 mission (Posner et al., SWx, 2021)

Conclusions

- Firmly rooted in (solar) physics, we need to go a step further in order to benefit society and space exploration efforts

- This next step is too important to leave to solar physicists alone: an osmosis of expertise is needed from:
  - — **Data scientists:** to bring the Big Data landscape to exploitable, verifiable ends
  - — **Computer scientists:** to assess, implement & verify ML and DL forecasting models
  - — **Statisticians:** to perform a meaningful performance verification

- Predicting solar eruptions goes all the way back to the Sun (photospheric magnetic fields)

- Predicting solar eruptions takes self-consistency (horizontal / vertical expansion) and a seamless transition through different spatial and temporal scales

This is a wide open, interdisciplinary field. Things may change. The proposed course of action is but a possibility that seems to bear promise