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Deep Learning Reconstruction of Sunspot Vector Magnetic Fields for Forecasting Solar Storms

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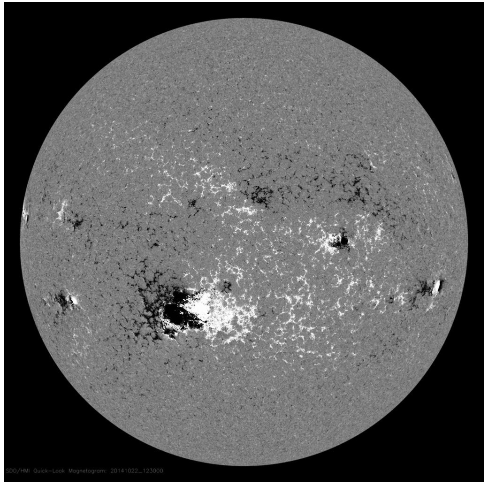
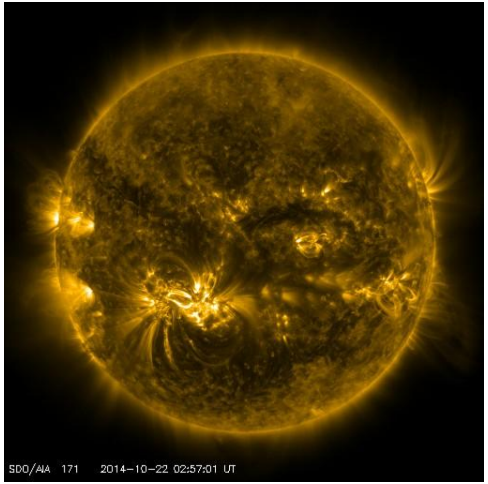
Solar activity is defined by dynamics of photospheric and coronal active region magnetic fields.

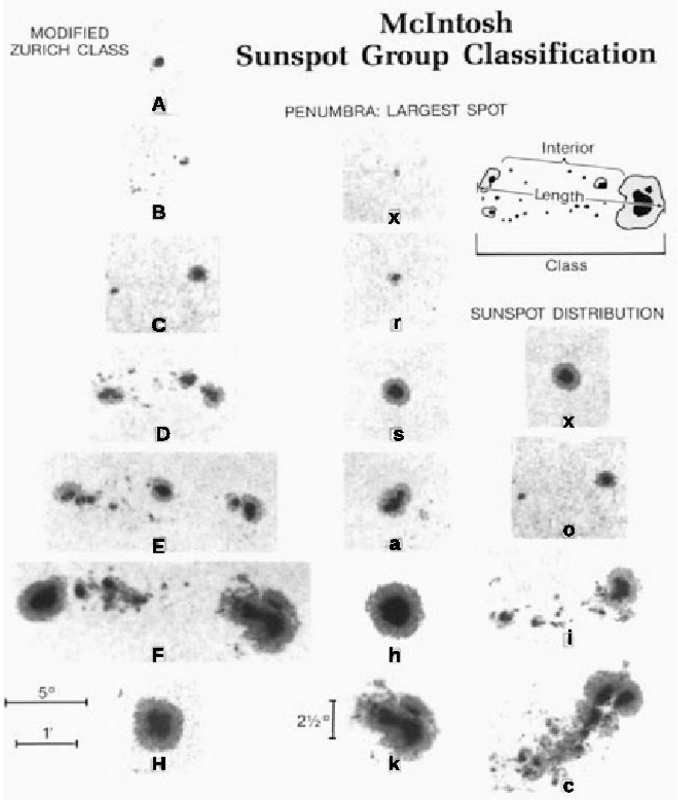
- ➔ Buoyantly rising flux tubes form active regions (ARs).
- ➔ Flows impact morphology of ARs e.g. twists and rotations.
- ➔ Twisted magnetic fields accumulate non-potential energy and become unstable.
- ➔ Unstable AR magnetic fields are responsible for flares and CMEs.





From: Solar Dynamics Observatory (SDO)

Characterisation of AR magnetic field complexity — Heuristics vs Modelling.



Coronal magnetic-field extrapolation

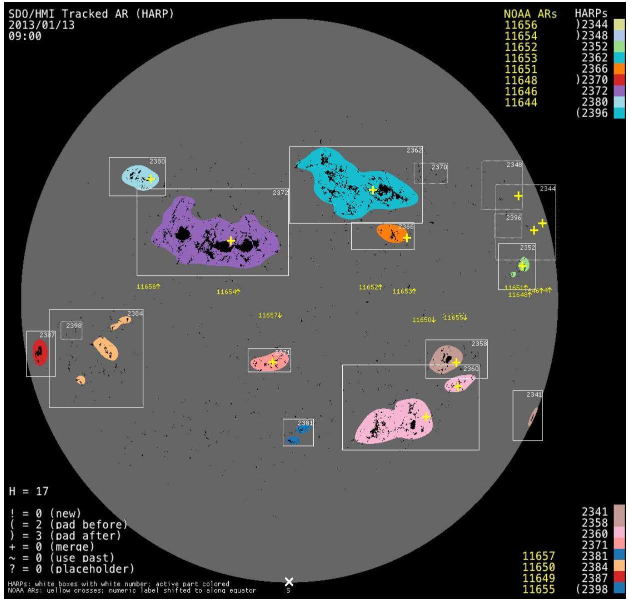
$$\nabla \times \mathbf{B} = \alpha B$$

$$\alpha = \frac{1}{B_z}\left(\frac{\partial B_y}{B_x} - \frac{\partial B_x}{B_y}\right)$$

(at the photosphere boundary)

- Potential field extrapolation
- Linear/non-linear force free field extrapolation

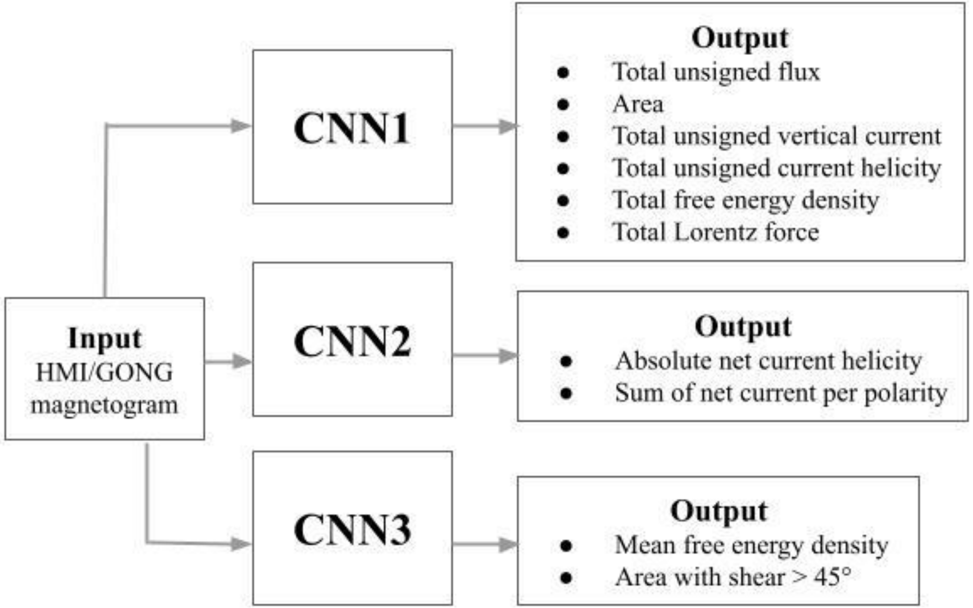
Photospheric Vector-magnetic-field features are indicative of the imminent flare-productivity of an AR.



Feature	Formula
McIntosh (1989)	
Area of the active region	$\propto \sum \text{Pixels}$
Leka and Barnes (2006)	
Total unsigned current helicity	$\propto \sum \lvert B_z \cdot J_z \rvert$
Absolute value of the net current helicity	$\propto \lvert \sum B_z \cdot J_z \rvert$
Photospheric magnetic free energy	$\propto \sum \left(\mathbf{B}^{obs} - \mathbf{B}^{pot}\right)^2$
Total unsigned flux	$\propto \sum \lvert B_z \rvert dA$
Total unsigned vertical current	$\propto \sum \lvert J_z \rvert dA$
Sum of the modulus of the net current per polarity	$\propto \lvert \sum^+ J_z \rvert dA + \lvert \sum^- J_z \rvert dA$
Fraction of Area with shear $> 45^\circ$	
Mean free Energy	
Schrijver (2007)	
Sum of flux near polarity inversion line	
Fisher et, al, (2012)	
Total magnitude of Lorentz force	$\propto \sum B^2 dA$
Sum of z-component of Lorentz force	$\propto \sum \left(B_x^2 + B_y^2 - B_z^2\right) dA$

- Space-weather HMI Active Region Patches (SHARPs) Vector-magnetic field features (Bobra et al. 2014)
- Quantify AR magnetic field complexity and extensively used for flare forecasting

We use deep learning to quantify AR complexity from LOS magnetograms in terms of SHARPs vector-field-features.



- ➔ Purely "data-driven modelling" of AR vector-fields - more sophisticated than heuristics, less rigorous than true modelling.
- ➔ "Improving" the historical ground-/ space-based LOS magnetic field observations

  Kitt Peak 1974 - present
  GONG 1995 - present
  MDI 1996 - 2011
  HMI 2010-2011

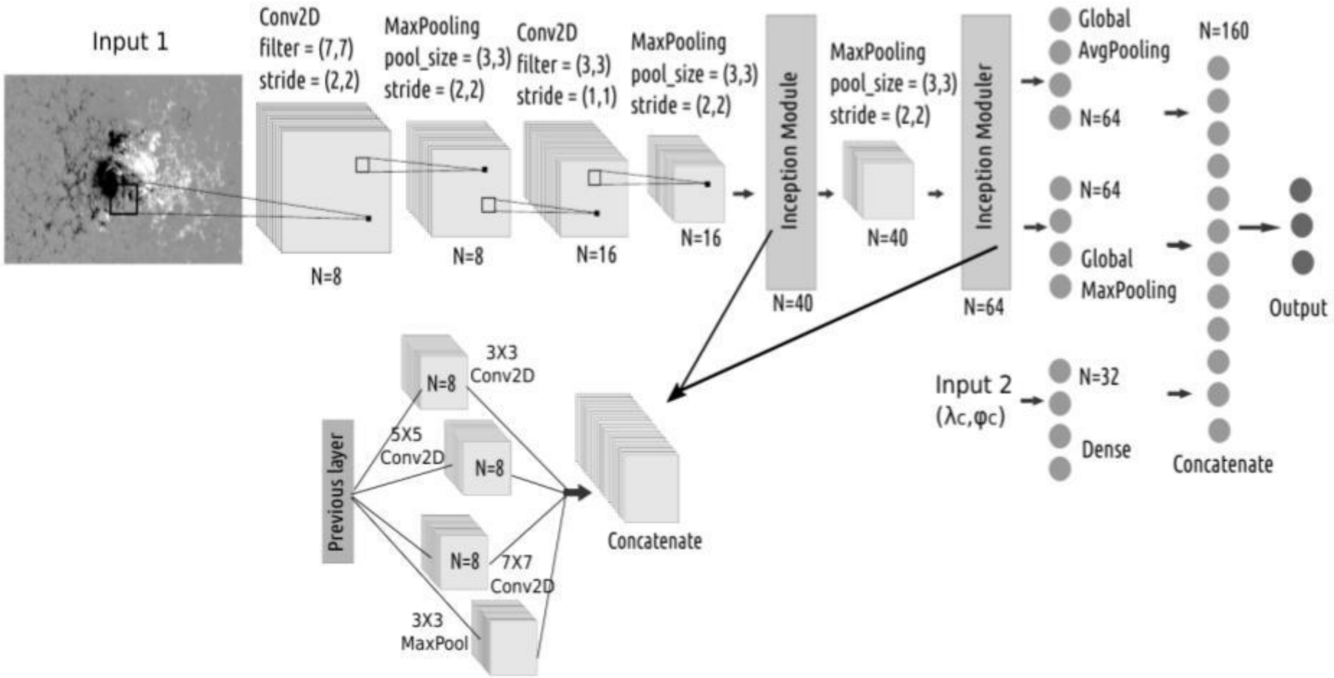
- ➔ Allowing for robust space-weather forecasting models.

We use SDO/HMI as well as GONG LOS magnetograms to obtain SHARPs features.

- ➔ HMI - 0.5 arcsec per pixel, GONG - 2.5 arcsec per pixel (**no explicit cross-calibration**)
- ➔ AR magnetograms are remapped to CEA - hmi.sharps_cea_720s
- ➔ We consider only observations that are within ±45° of the central meridian
- ➔ We include only relatively large ARs - maximum area > 25 Mm^2
- ➔ 2:1 - Training:Validation AR split, 10 times (**no mixing of observations from same ARs between training, validation and test sets**).
- ➔ Six hourly samples are drawn from each AR

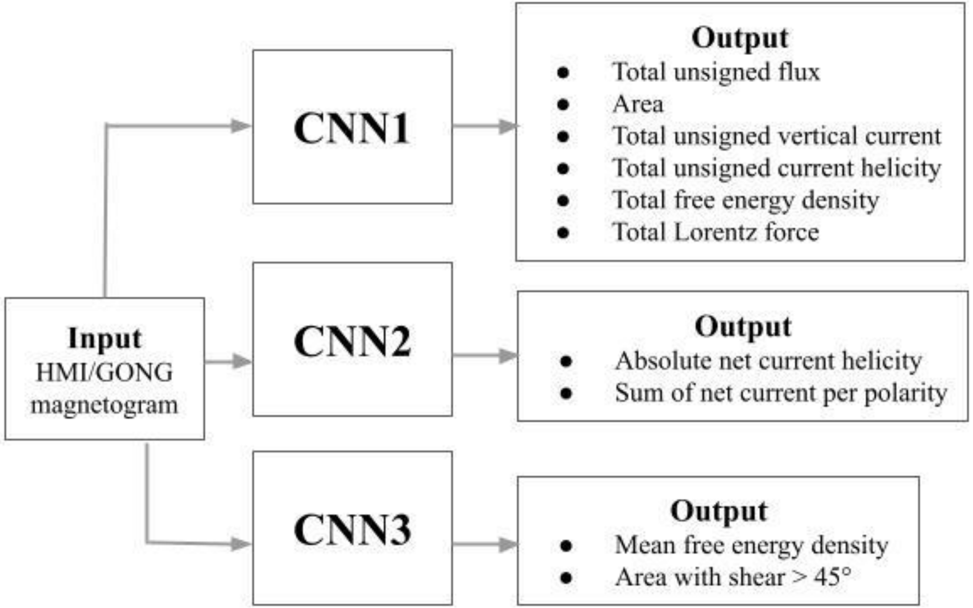
	Train & Val May'10 - Sep'15	Test Oct'15 - Aug'18
# HMI ARs	848	194
# HMI Samples	124633	26820
# GONG ARs	848	145
# GONG Samples	114443	13454

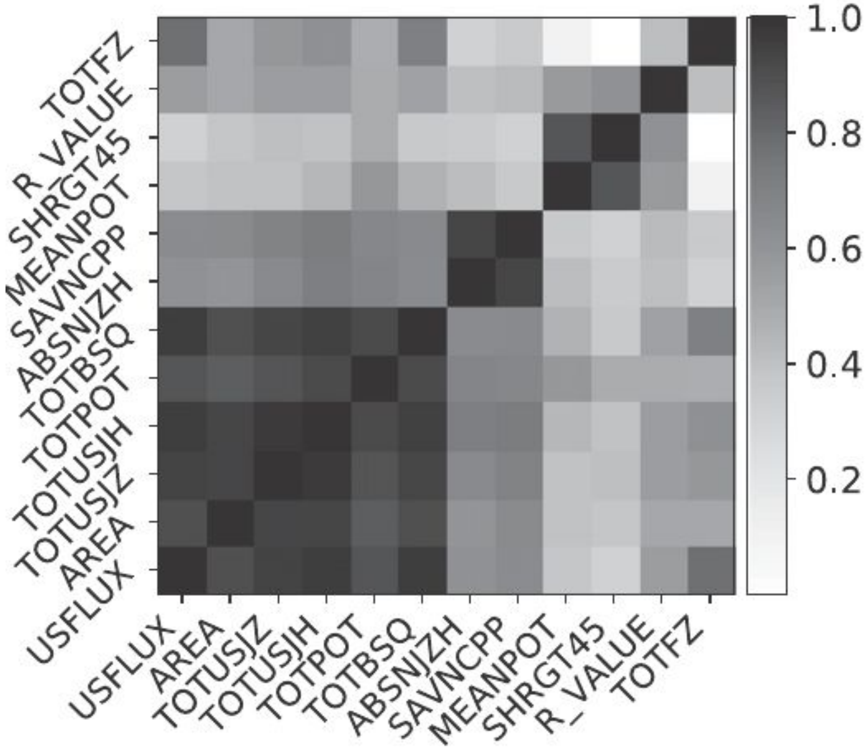
We use an inception-based CNN architecture.



- ➔ Outputs are N SHARPs vector-field features
- ➔ No fully connected layers, the input magnetograms are of variable sizes. Prevents spurious effects as a consequence of resizing (Bhattacharjee et al 2020).

We develop three different CNNs to obtain SHARPs features from different mutually correlated groups.

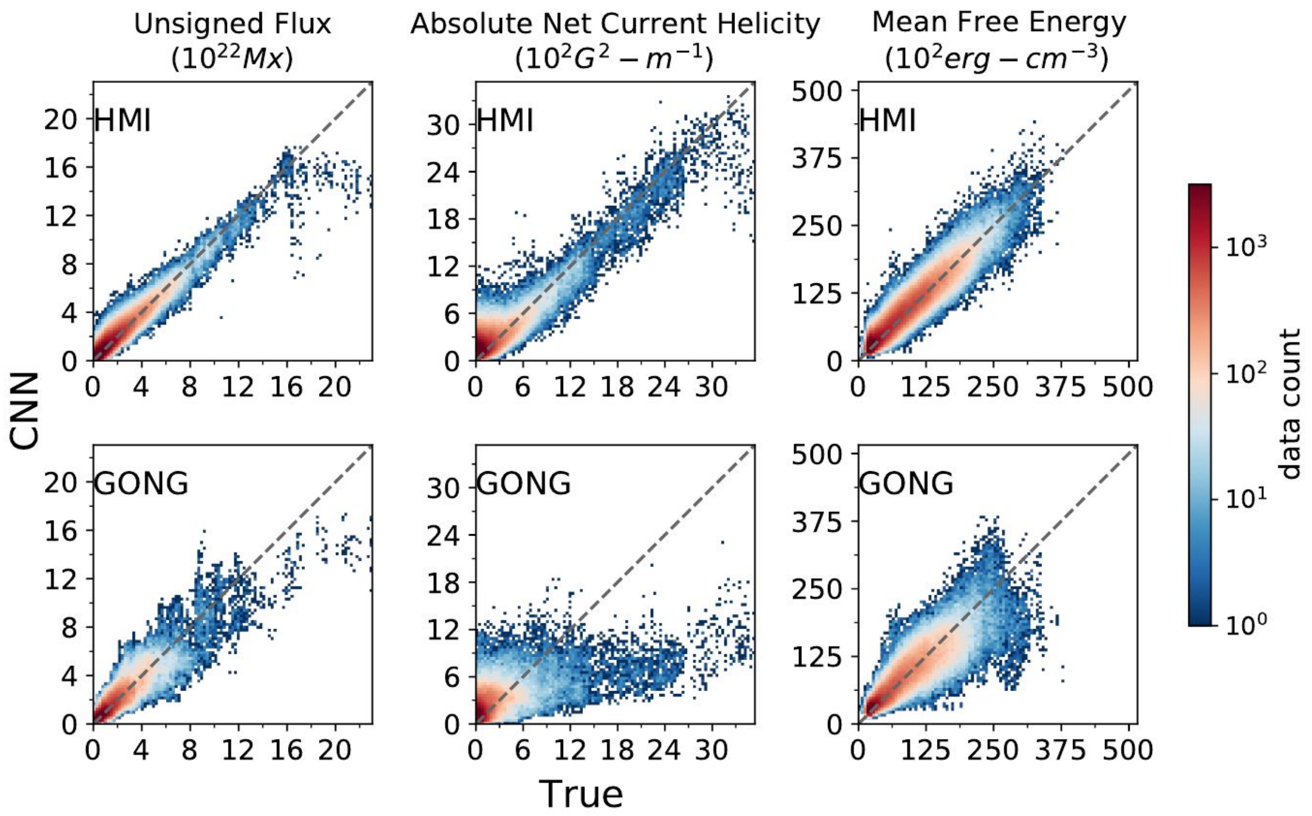




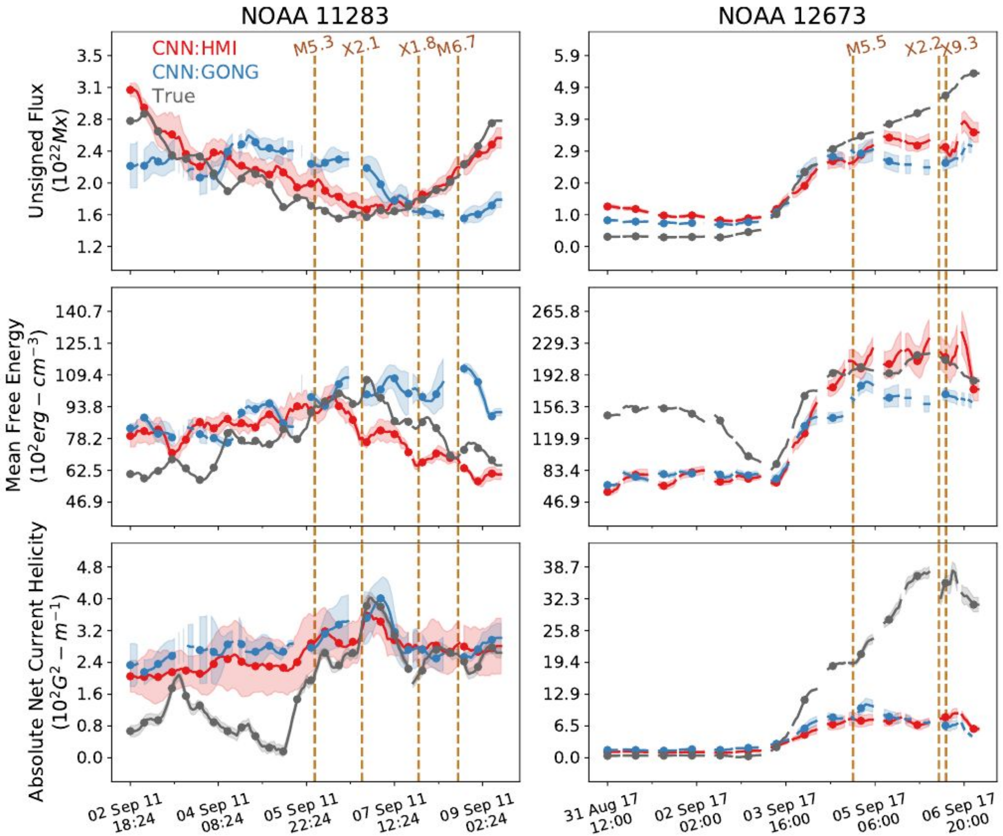
True and CNN estimated SHARPs features are strongly correlated.

	Training & Validation		Test	
SHARPs Features	HMI	GONG	HMI	GONG
Total unsigned flux	95.18 ± 00.63	90.83 ± 01.95	89.97 ± 02.78	87.66 ± 01.60
Area	95.91 ± 00.46	95.03 ± 00.84	92.23 ± 01.87	92.95 ± 00.87
Total unsigned vertical current	94.83 ± 00.72	91.83 ± 01.69	89.04 ± 02.70	87.20 ± 01.87
Total unsigned current helicity	95.77 ± 00.50	91.66 ± 01.76	88.46 ± 02.78	83.34 ± 02.32
Total free energy density	96.22 ± 00.78	92.63 ± 01.60	90.28 ± 02.35	91.52 ± 01.23
Total Lorentz force	96.69 ± 00.45	94.95 ± 00.98	90.79 ± 02.48	92.90 ± 01.07
Absolute net current helicity	90.43 ± 03.28	63.51 ± 03.95	58.32 ± 09.36	57.33 ± 07.18
Sum of net current per polarity	89.61 ± 02.58	64.28 ± 03.71	62.53 ± 08.37	58.95 ± 07.10
Mean free energy density	95.15 ± 01.02	89.86 ± 00.75	92.20 ± 01.89	91.62 ± 00.64
Area with shear $> 45^\circ$	95.02 ± 00.80	89.96 ± 01.18	90.56 ± 01.53	90.51 ± 00.40

The CNN-estimated mean free energy values from HMI magnetograms are in good agreement with true values.



The CNN-estimated values capture the time-evolution of AR magnetic fields reasonably well except at the extreme values.



Pearson correlations between time derivatives of true and CNN-estimated features for trend comparison.

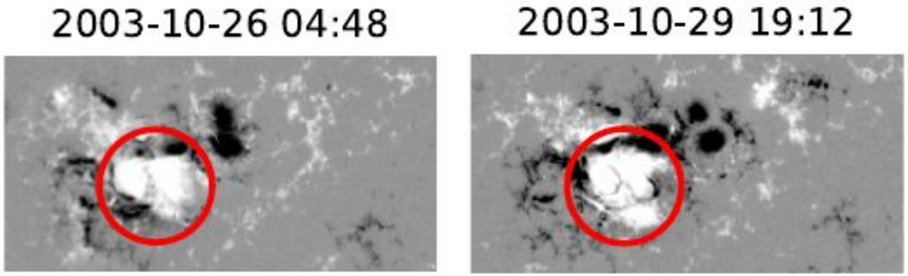
		Total unsigned flux		Absolute net current helicity		Mean free energy density	
		Spline Fit	Time Derivative	Spine Fit	Time Derivative	Spline Fit	Time Derivative
Training & Validation	HMI	97.45 ± 0.36	84.82 ± 02.53	95.07 ± 02.01	78.00 ± 12.23	98.55 ± 00.38	89.75 ± 02.53
	GONG	91.57 ± 01.94	24.36 ± 07.76	65.91 ± 04.02	32.96 ± 05.60	92.06 ± 07.38	75.51 ± 02.29
Test	HMI	90.73 ± 02.68	75.84 ± 07.26	60.66 ± 09.68	33.19 ± 19.11	94.21 ± 01.61	81.95 ± 02.99
	GONG	88.84 ± 01.67	17.84 ± 05.96	59.44 ± 07.36	25.76 ± 08.10	93.57 ± 00.63	70.32 ± 02.19

Forecasting performance of >M flares using CNN obtained SHARPs features with support vector machines is consistent with true SHARPs.

Flare forecasting using CNN obtained SHARPs features				
Number of observations				
# Positives	338			
# Negatives	6011			
	accuracy	recall(+)	recall(-)	TSS
True SHARPs	0.843 ± 0.030	0.854 ± 0.044	0.990 ± 0.002	0.696 ± 0.046
CNN:HMI	0.818 ± 0.028	0.861 ± 0.053	0.991 ± 0.003	0.676 ± 0.038
CNN:GONG	0.821 ± 0.033	0.801 ± 0.064	0.990 ± 0.003	0.623 ± 0.058
True SHARPs (Bobra & Couvidat 2015)	0.924 ± 0.007	0.832 ± 0.042	0.929 ± 0.008	0.761 ± 0.039

- ➔ We explicitly separate training and test sets based on ARs.
- ➔ We do not consider ARs with maximum area <= 25Mm^2 (all non-flaring).
- ➔ Flare forecasting using LDA of individual SHARPs is also consistent.

The evolution CNN estimated features during Halloween 2003 storms is qualitatively consistent with that obtained using explicit modelling.



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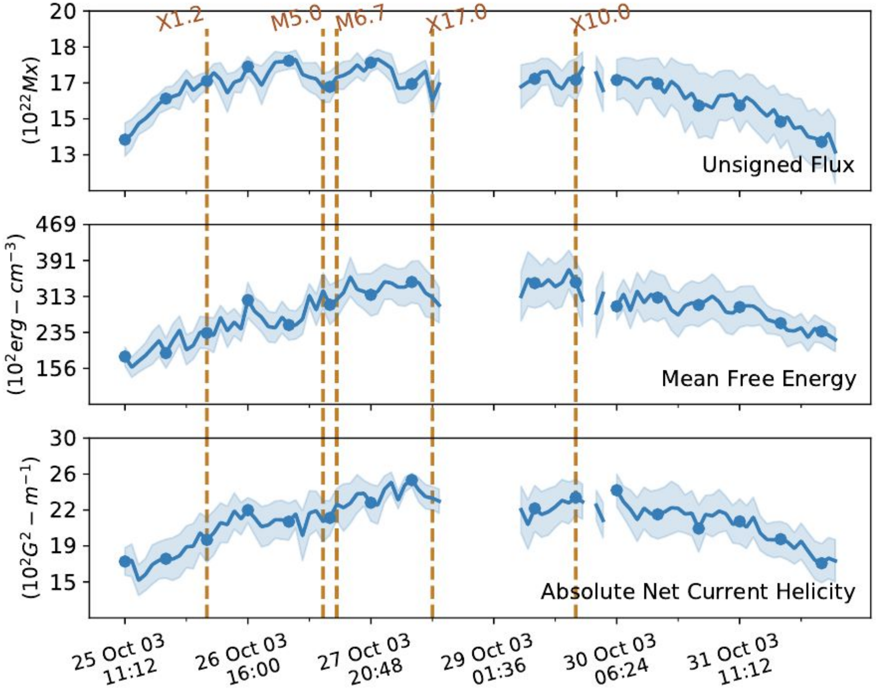

Other Modelling Approaches:

- Magnetic virial theorem (Metcalf et. al. 2005, Régnier & Priest 2007)
- Force-free field extrapolation (Régnier & Priest 2007)
- Minimum current corona model (Kazachenko et al. 2010)

Summary and outlook

- ➔ We obtained a reliable reconstruction of vector-field-features important for space-weather forecasting, particularly mean free energy. Our method can be extended to historical LOS observations.
- ➔ The SHARPs features estimated here are not exclusive, rather to be thought of as placeholders for any AR vector-magnetic-field feature important for understanding solar activity and improving space weather forecasting.
- ➔ Many improvements are necessary and possible - explicit cross-calibration, improved regression with more data, super-resolution.
- ➔ Generative deep learning algorithms (e.g. cGANs) to obtain the complete full vector-magnetograms.
- ➔ More rigorous treatment using physics based loss functions and physics informed models [**Interpretation**].

D. Dhuri, S. Bhattacharjee, S. Hanasoge and S. Mahapatra, *under review*

THANK YOU