Geoeffectiveness of CMEs estimated with NNs

Uwamahoro, J.[1] McKinnell, L. A. [2] Habarulema P. J.[2]

[1]Kigali Institute of Education [KIE]

[22]South African National Space Agency [SANSA]

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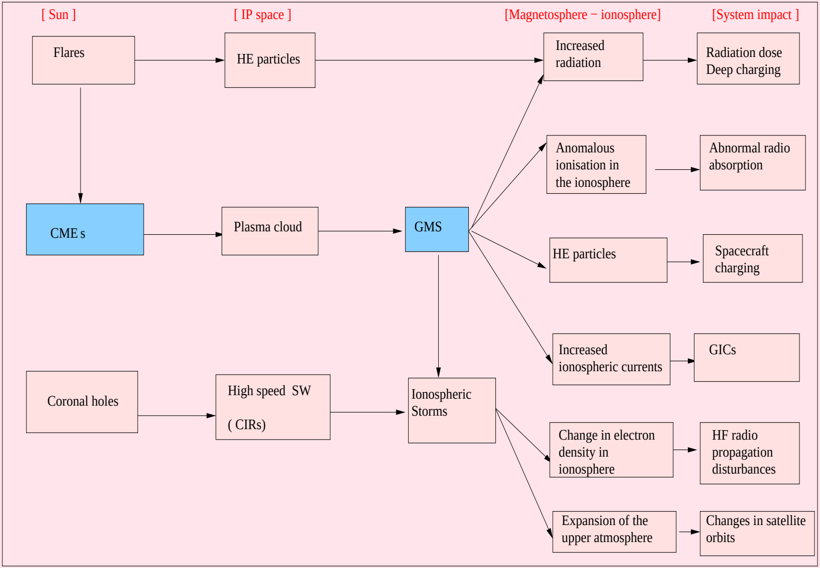
Outline

- Solar and IP signatures of geoeffective halo CMEs
- Neural networks inputs + NN optimasation
- Results

Coronal mass ejections: halo CMEs

- Huge explosive solar phenomena
- ... SDO ....E.F
- 360^0 angular width
- Appear to envelop the Sun, forming a halo
- Mostly geoeffective if earth-directed
- But no one to one relationship between CMEs and GMS.
- Less than 2.5% of all CMEs produced GMS during SC 23.

CMEs, GMS and Space weather



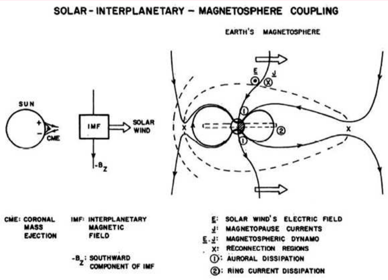


Figure 1 – Diagram of the interplanetary-magnetosphere coupling, showing the reconnection process and energy injection into the nightside magnetosphere, which leads to the formation of the storm-time ring current (Gonzalez & Tsurutani, 1992).

Figure:

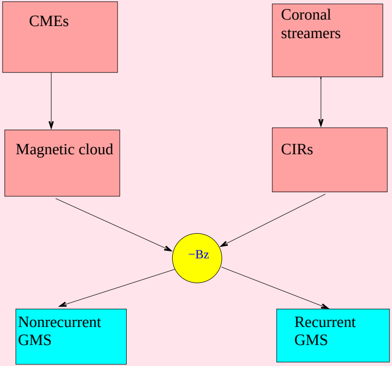
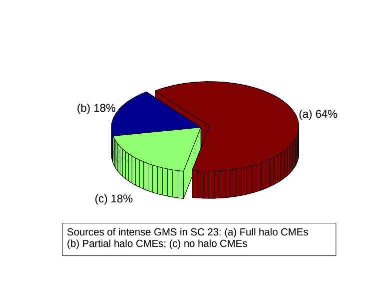


Figure:

Halo CMEs, GMS relationships



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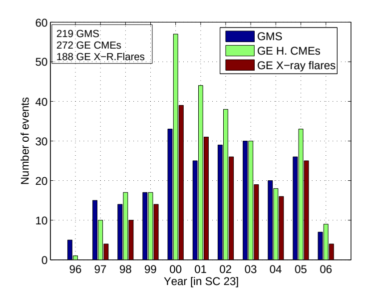
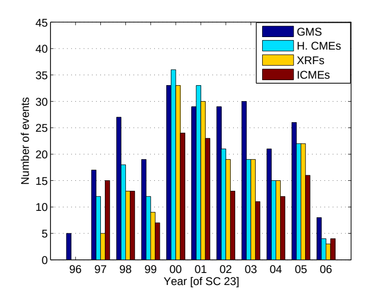


Figure:

Geoeffective CMEs properties

1. Their ability to produce geomagnetic storms: In this study, only $Dst \leq -50$ nT.
2. halo CMEs: appear to surround the occulting disk of the observing coronagraphs
3. Generally fast and wide and mostly associated with powerful flares (Class X and M)
4. Full halo CMEs: apparent width (W) of 360^0
5. partial halo CMEs: apparent width (W) of $120^0 \leq W \leq 360^0$.
6. But still not very clear what kind of CMEs produce GMS, some halo and front-sided CMEs do not have a geomagnetic impact (Cane and Richardson, 2003)
7. For improving model prediction: Need to consider interplanetary manifestations of CMEs

IP medium: in situ ICMEs



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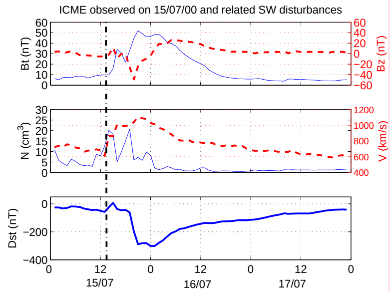
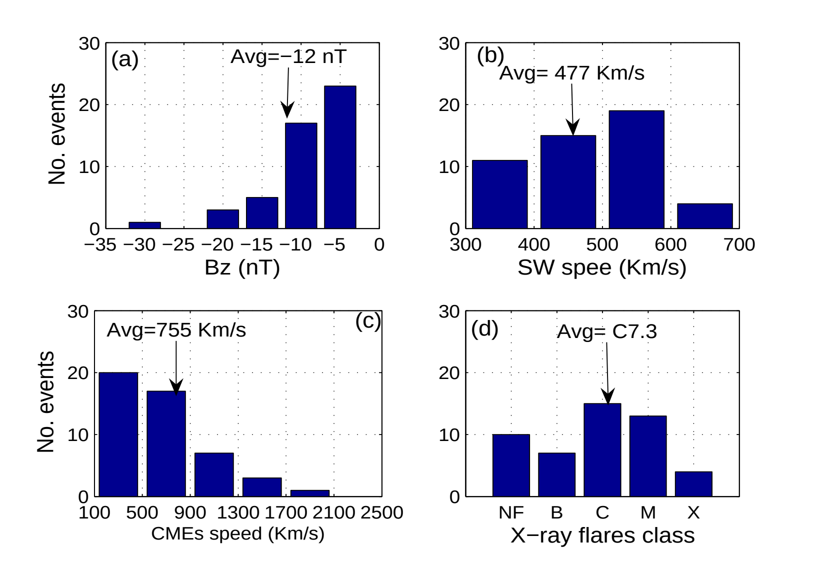


Figure:

In situ SW parameters



ANN prediction techniques

- An interconnected assembly of processing elements, called units or neurons
- Can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements.
- The network can deal with unseen patterns and generalize from the training set.
- Commonly used: three layer feed forward ANN.

On the NN algorithms

- If input, hidden and output layers are denoted by k, j and i respectively, the net output can be described according to Lundstedt,1994.

The output value of the NN is computed...

$$O_i^\mu = g_0 \left(\sum_j W_{ij} g_h \left(\sum_k W_{jk} \xi_k^\mu \right) \right), \quad (1)$$

- W_{jk} and W_{ij} represent the weights from the input to hidden layer and from hidden to the output layer respectively.
- ξ_k^μ represents the input parameters used in this study

ANN algorithms

- Activation functions are needed to introduce the non-linearity into the network. In this study, a logistic sigmoid activation function ranging between 0 and 1 was used and for both inputs and hidden and output nodes; represented by

Sigmoid activation function

$$g(o) = g_h(x) = \frac{1}{1 + exp(-x)}, \tag{2}$$

- inputs can be either binary or continuous values
- allow the outputs to be given a probabilistic interpretation

ANN algorithms

- During the training process, the input ξ_k^μ is presented to the network together with its corresponding known output O^μ and the network system learns the relationship that exists between the two by adjusting the weights.
- The training proceeds until the network error (E) is minimized according to the relation.

$$E = \frac{1}{2}\sum_{\mu}(0^{\mu} - T^{\mu})^2\,, \tag{3}$$

- Where T is the desired output and the sum is over all the outputs in the training pattern.

Solar and IP input parameters

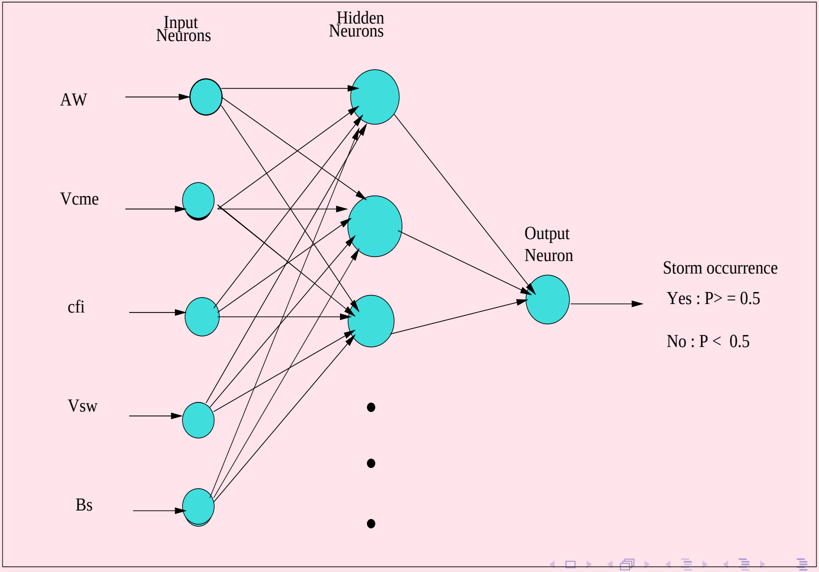
Table:

Model parameter type	parameter name	variable type	measure	value
Inputs	CME A.W	Numeric	$\geq 120^0$	-
[A]				
	CME speed	Numeric	value in km/s	-
	cfi	Numeric	-	-
	Vsw	Numeric	value in km/s	-
[B]				
	Bs	Numeric	value in nT	-
Outputs	No storm	Binary	$Dst > -50$ nT	0
	storm	Binary	$Dst \leq -50$ nT	1

Data sources

- SOHO/LASCO CMEs catalogue list: http://cdaw.gsfc.nasa.gov/CME_list
- ftp://ftp.ngdc.noaa.gov/STP/GEOMAG/dst.html
- fttp://ftp.ngdc.noaa.gov/ STP/SOLAR_DATA/SOLAR_FLARES_INDEX
- http://www.ssg.sr.unh.edu/mag/ace/ACElists/obs_list.html

Simplified FFNN architecture



Model development

- The model developed behaves like a function that estimates the probability of storm occurrence an can be written as:

$$P = f(AW_{cmes}, V_{cmes}, cfi, B_s, V_{sw}) \quad (4)$$

- Any output with value ≥ 0.5 was considered likelihod of occurrence of a storm following a halo CME eruption.

NN optimization

- The best NN architecture is obtained by considering the minimum RMSE value computed over the validation data set:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{obs} - P_{pred})^2}, \quad (5)$$

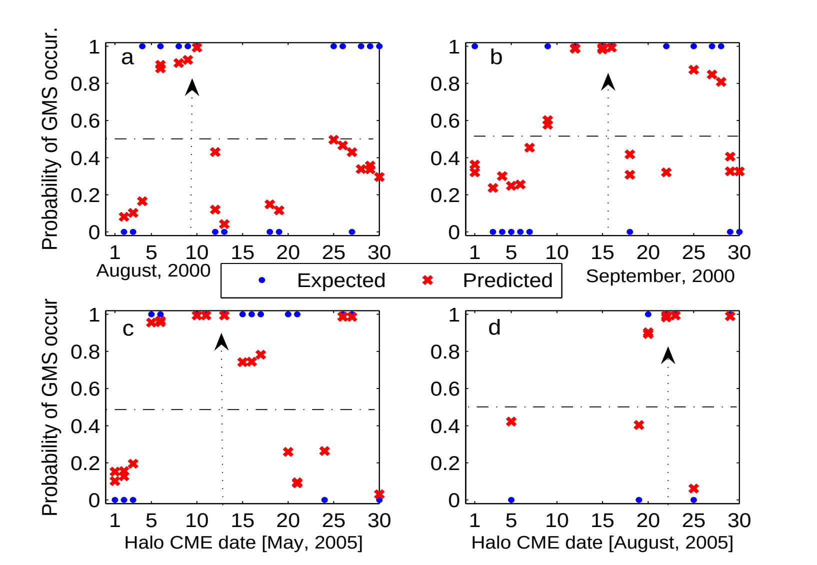
- where P_{obs} (e.g.0 or 1) and P_{pred} represent the observed and predicted probability.
- Optimum NN obtained for only solar inputs [A] and combined solar and IP inputs [A+B] as follows:

NN optimization

Table: [A]+[B] inputs improve the estimate of the probability of storm occurrence

Inputs	NN architecture	RMSE
[A]	**3:3:1**	**0.5126**
	3:4:1	0.5137
	3:5:1	0.5147
	3:6:1	0.5155
[A]+[B]	5:5:1	0.3225
	5:6:1	0.3396
	5:7:1	0.3366
	5.8:1	0.3376

Prediction performance: some typical examples



Model validation

- The NN model was validated on 43 CME-driven storms, not part of the training data set.
- The percentage of correctly predicted storms is calculated as follows:.

$$\frac{PE}{OE} \times 100 \qquad (6)$$

- where PE is the number of correctly predicted storms and OE the total number of observed GMS.
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Table: Prediction performance:Validation of the model

Data set	Storm category	Observed	Correct predictions	False alarms
Training	Intense storms	53	51 [96%]	
	Moderate storms	59	42 [71%]	
	Total	112	93 [83%]	32
Validation	Intense storms	19	19 [100%]	
	Moderate storms	24	18 [75%]	
	Total	43	37 [86%]	8

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7. Srivastava (2005): 77.7% using logistic regression model.

References

1. Ref: F. Valash et al. *Solar energetic particle enhancement as a pedictor of geomagnetic acitvity in a neural network-based model*, Space Weather, VOL.7,2009
2. Ref: N. Srivastava *A logistic regression model for predicting the occurrence of intense geomagnetic storms*, Ann.Geoph., 23,2969-2974, 2005.
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