Forecasting High-Energy Proton and Electron Fluxes at LEO Orbits

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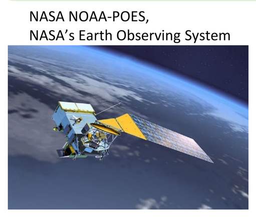
Introduction



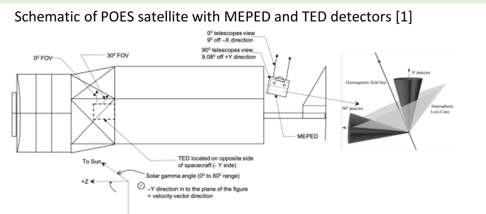
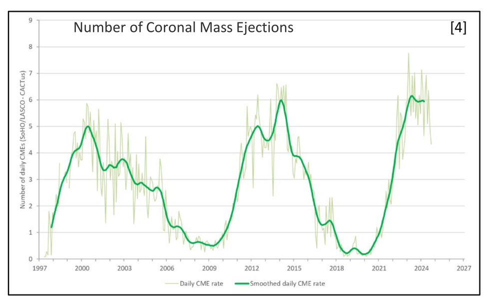


Table 1. Energy thresholds of the MEPED proton detector (SEM-2). [2]

Channel	Nominal energy range of protons (keV)
P1	30–80
P2	80–250
P3	250–800
P4	800–2500
P5	2500–6900
P6	>6900



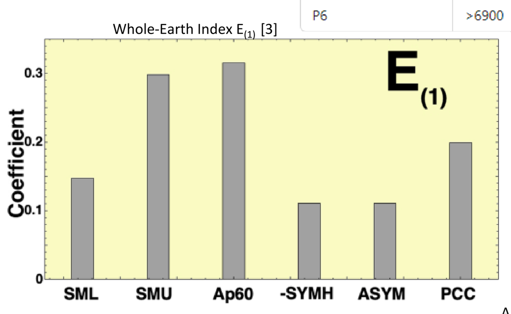
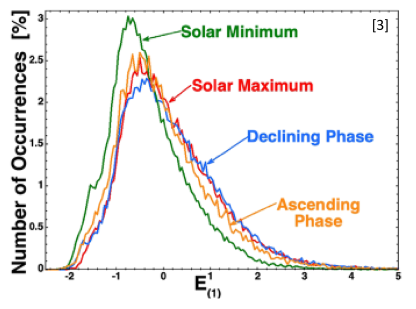
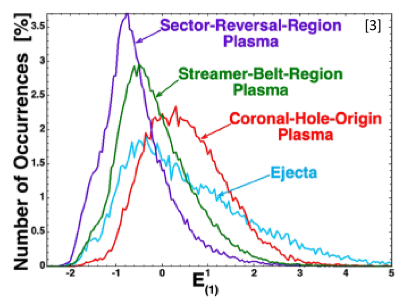
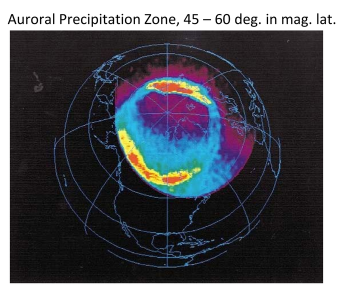


Table 2 Standardizing the variables for the 1997–2020 dataset [XX units]. [3]

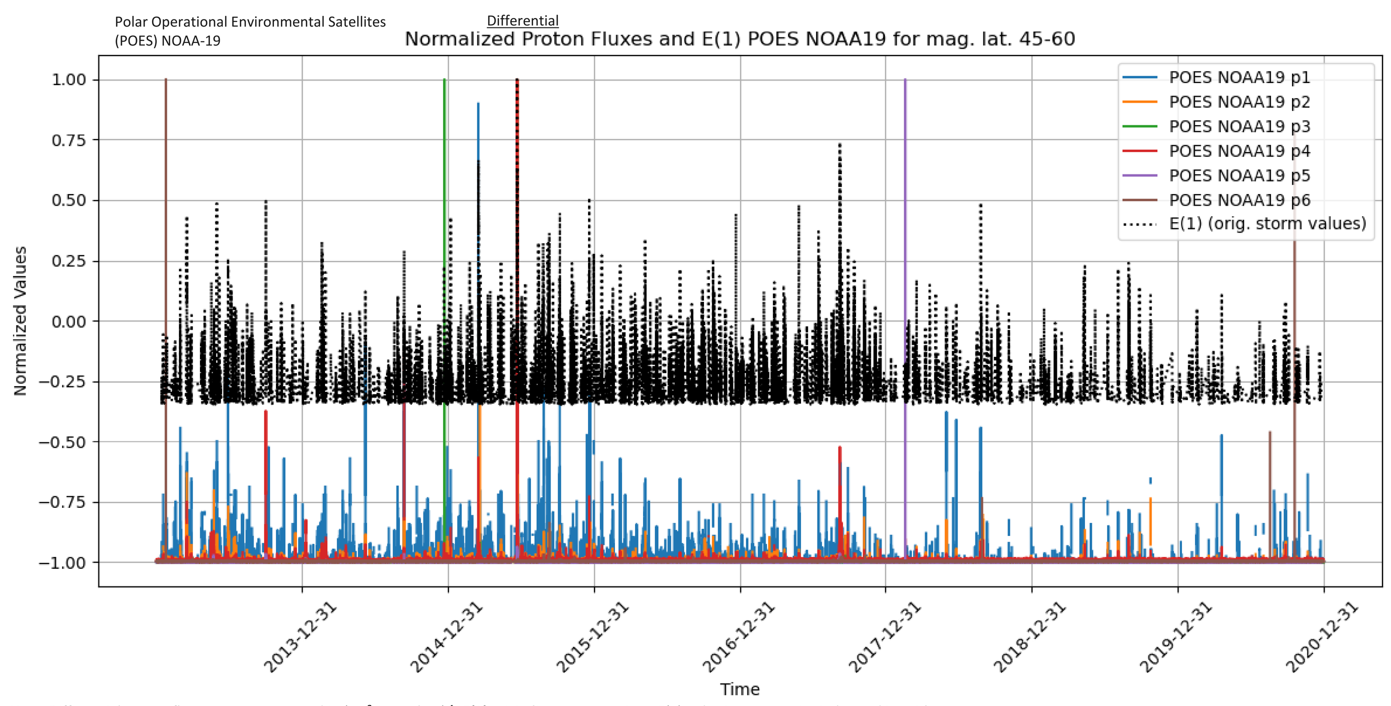
#	Variable	Mean value	Standard deviation
	Magnetospheric indices		
1	$\log_{10}(1+\lvert SML\rvert)$	1.9160	0.40865
2	$\log_{10}(1+\lvert SMU\rvert)$	1.8089	0.31363
3	$\log_{10}(1+Ap60)$	0.83552	0.38671
4	SYMH	-11.273	18.119
5	ASYM	19.560	14.274
6	PCC	1.2537	1.2858







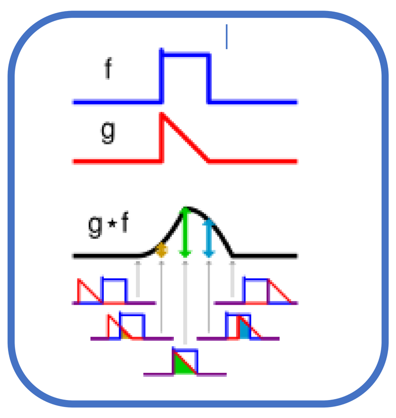
Data



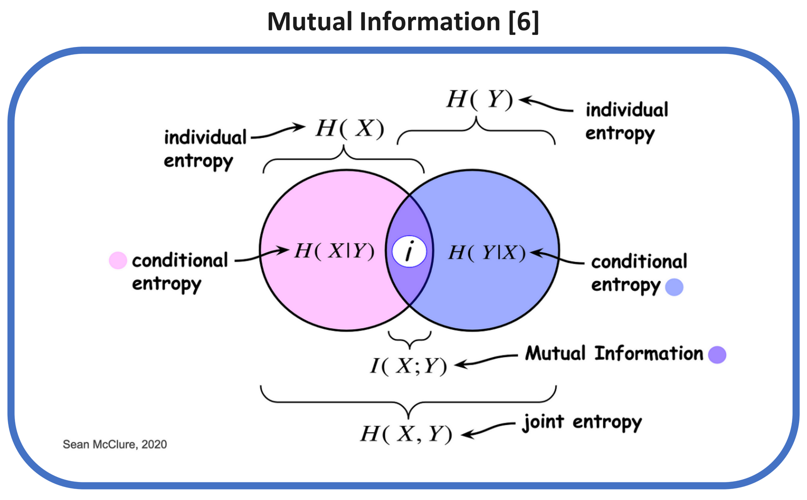
Note: Differential proton flux energy is measured in $(cm^2\text{-s-ster-keV})^{-1}$. **E(1) > 1 indicates storm time.** E(1) index is a composite index and is unitless. For sake of convenience in the above to display the six differential proton energies along with E(1), all values were normalized between [-1,+1].

Proposed Approaches

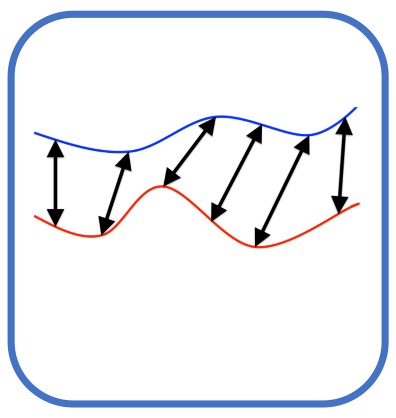
Cross-Correlation Analysis



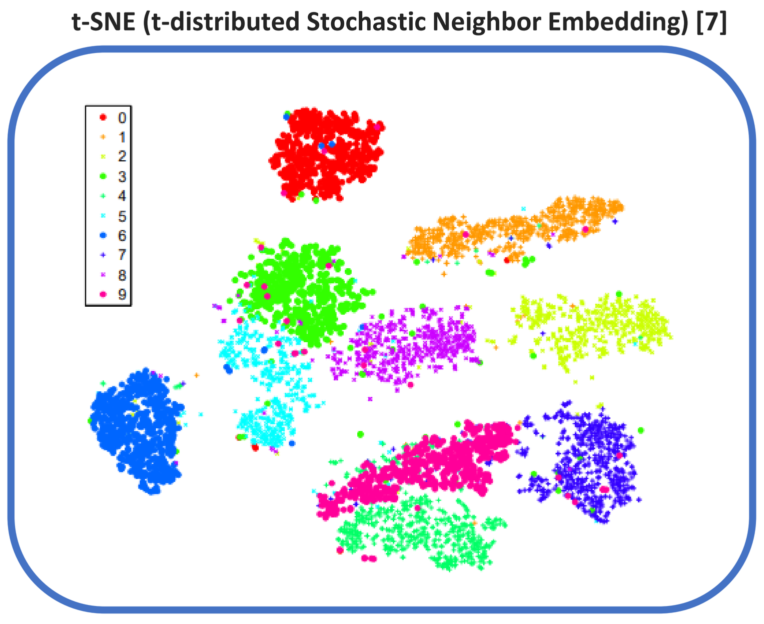
Mutual Information [6]



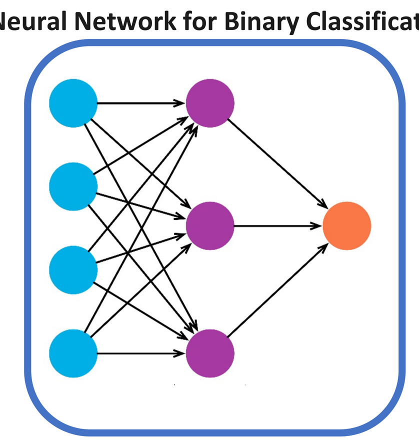
Dynamic Time Warping (DTW) [5]



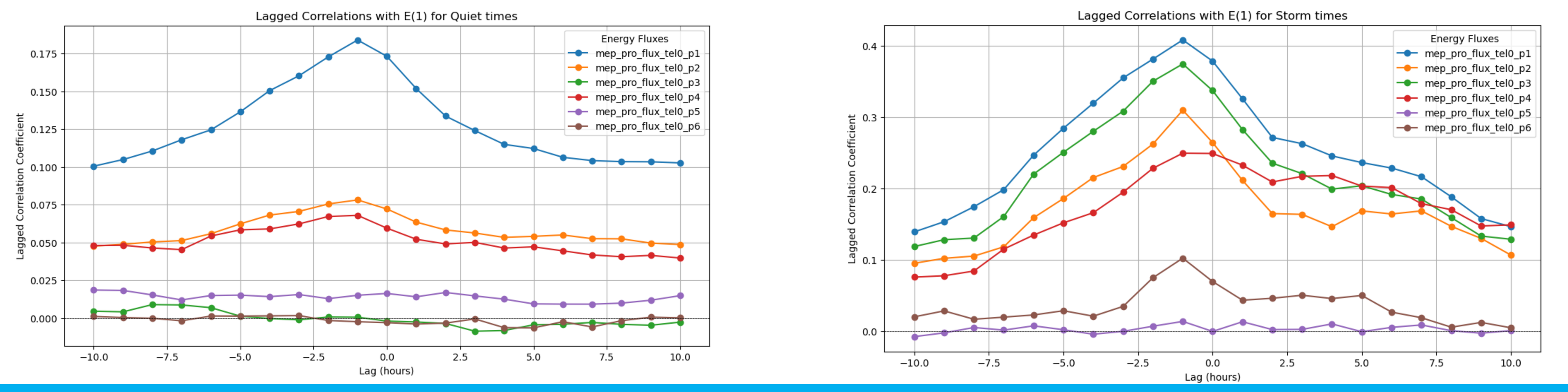
t-SNE (t-distributed Stochastic Neighbor Embedding) [7]

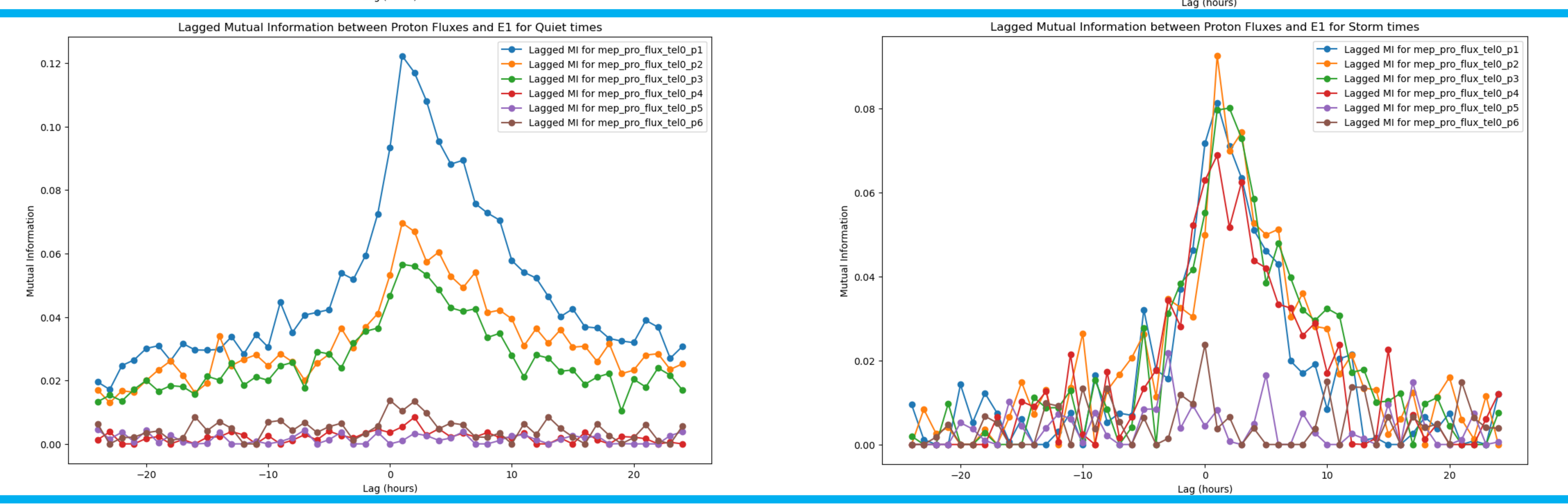


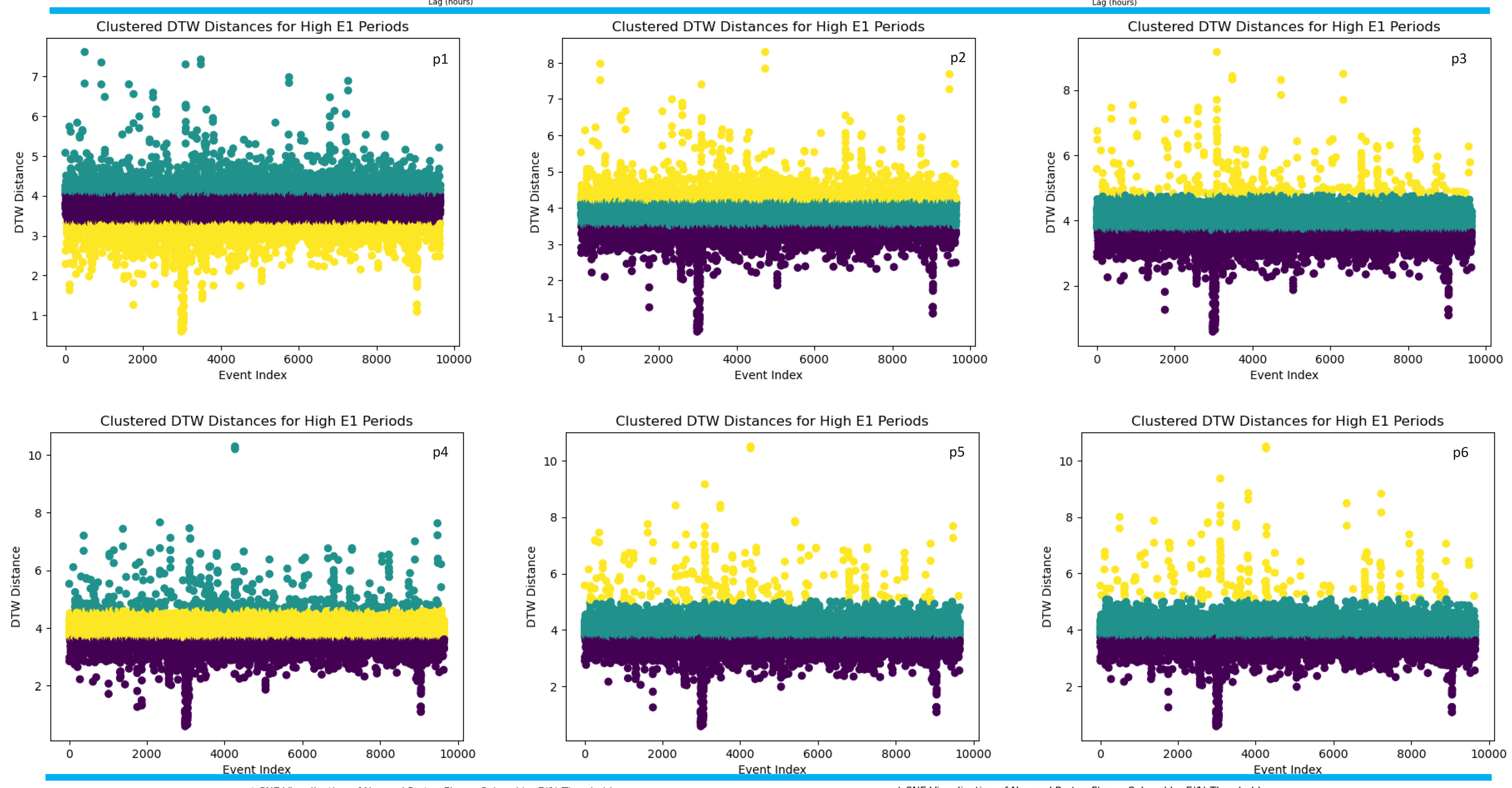
Neural Network for Binary Classification

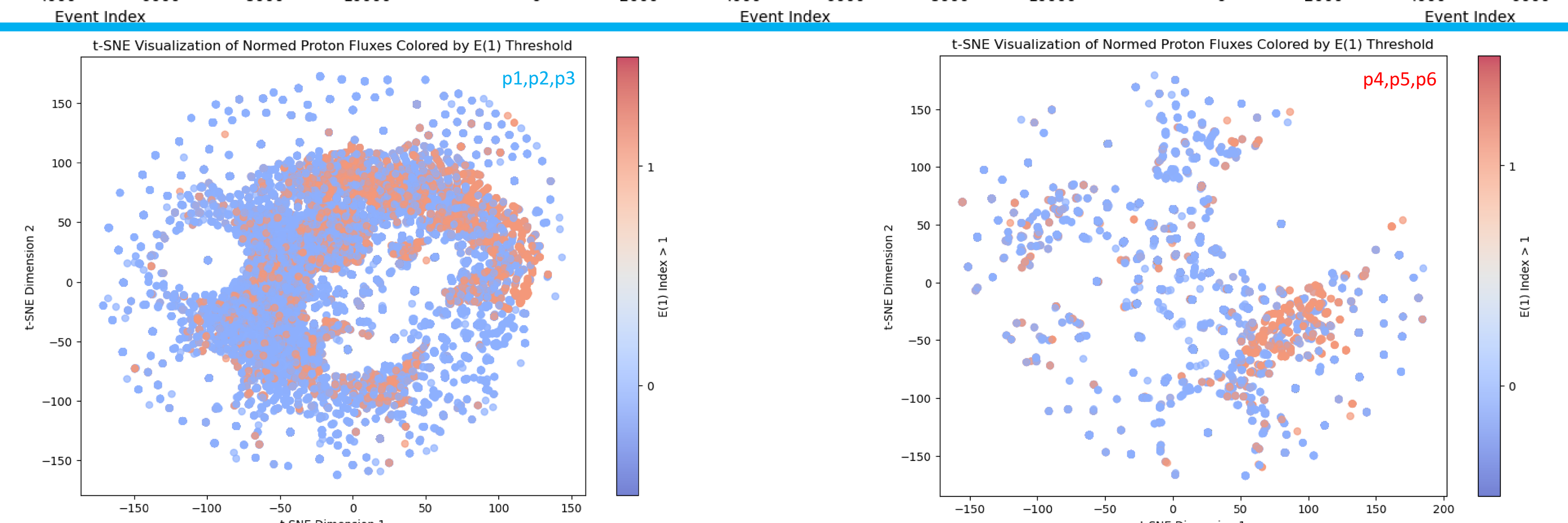


Experimental Results

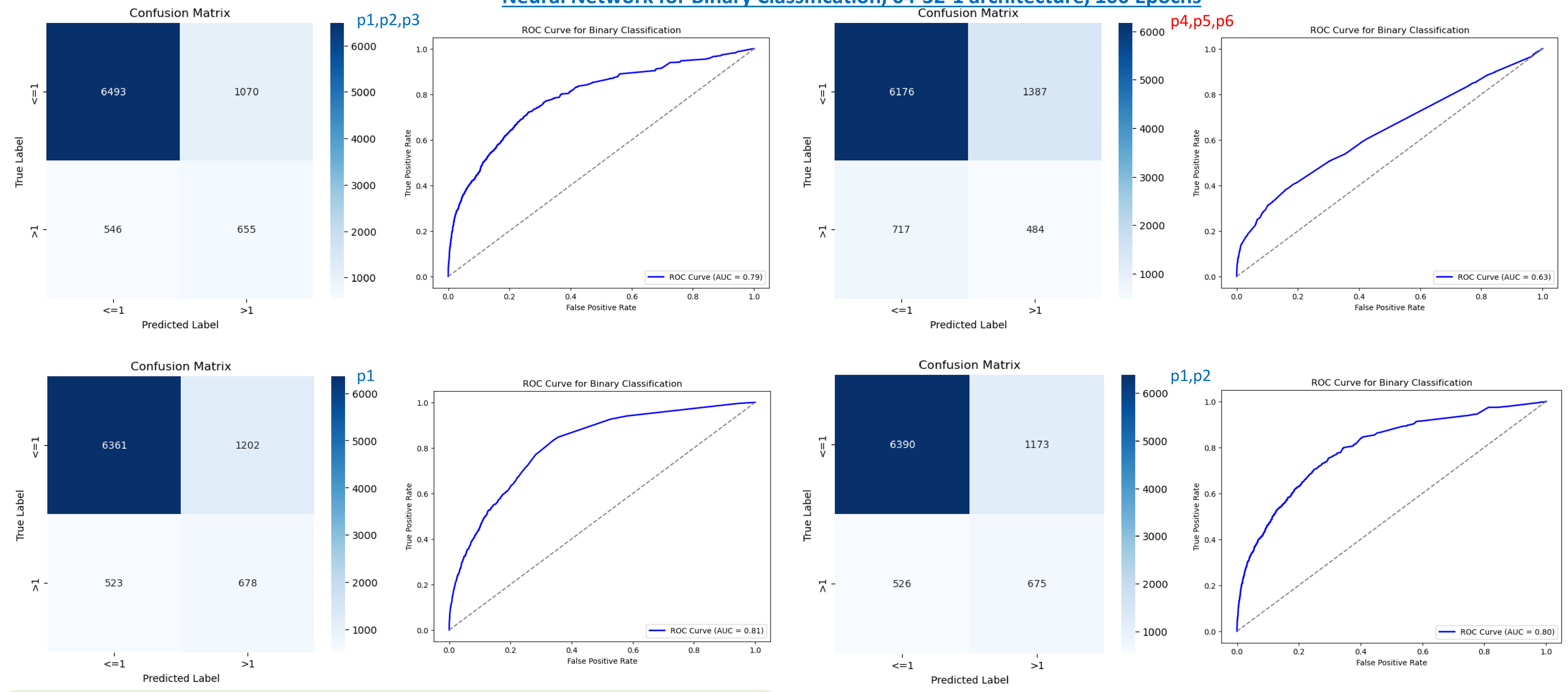








Neural Network for Binary Classification, 64-32-1 architecture, 100 Epochs



References

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Conclusion

1. Consistently, the set of the three lowest energies (i.e., p1,p2,p3) which are all less than 1 MeV, seems most significant for E(1) prediction than the set of the three highest energies (i.e., p4,p5,p6).
2. Recasting the prediction of E(1)>1 for storm times as a binary classification problem and using a neural network with two hidden layers with balanced classes, the ROC AUC = 0.79 of the set (p1,p2,p3) outperforms the AUC = 0.63 of the set (p4,p5,p6). In fact, taking all six proton differential flux energies gives an AUC of 0.77 which is less than that of the (p1,p2,p3) set. Furthermore, p1 alone gives the best AUC performance with AUC = 0.81 and 56.5% true positive rate (TPR) for the storm class. All fluxes taken together gave TPR=59.3%.
3. Cross-correlation analysis and lagged mutual analysis both show a ~1 hour lag time with the (p1,p2,p3) set giving the highest values for storm times, respectively.
4. In terms of DTW clustering, the sets (p1,p2) and (p3,p4,p5,p6) can be visually seen as being more similar, respectively. Three clusters were selected for the K-Means algorithm. It is unsupervised.
5. t-SNE analysis shows different morphologies for local behavior between the two sets (p1,p2,p3) and (p4,p5,p6) with the (p1,p2,p3) exhibiting more cyclic underlying patterns. No clear clustering is observed.