



### Plasma-Sheet Bubble Identification Using Multivariate Time Series Classification

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### 1 Background

- ② Bubble Criteria and Dataset
- ③ Multivariate Time Series Classification (MTSC) Models

### ④ Results

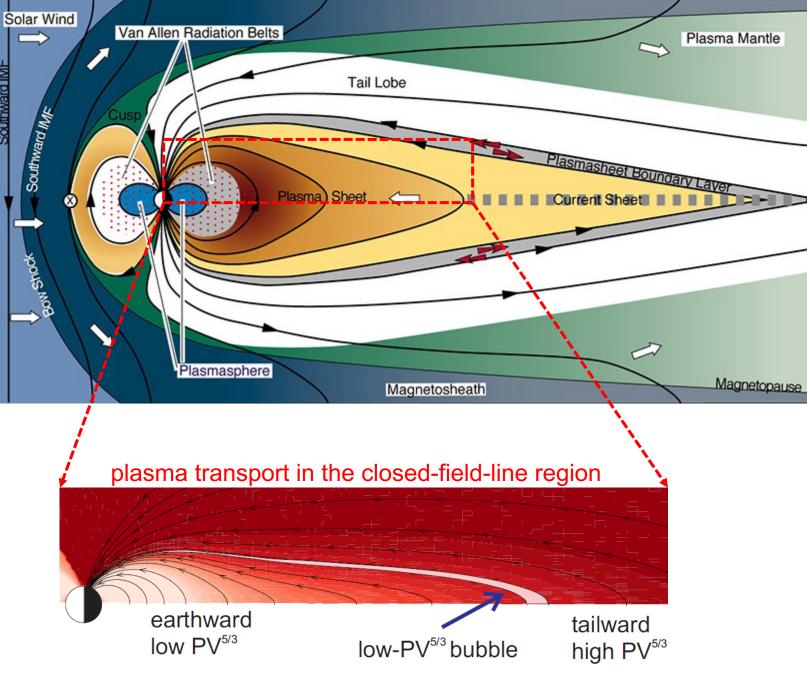
### **5** Summary

# 1. Background

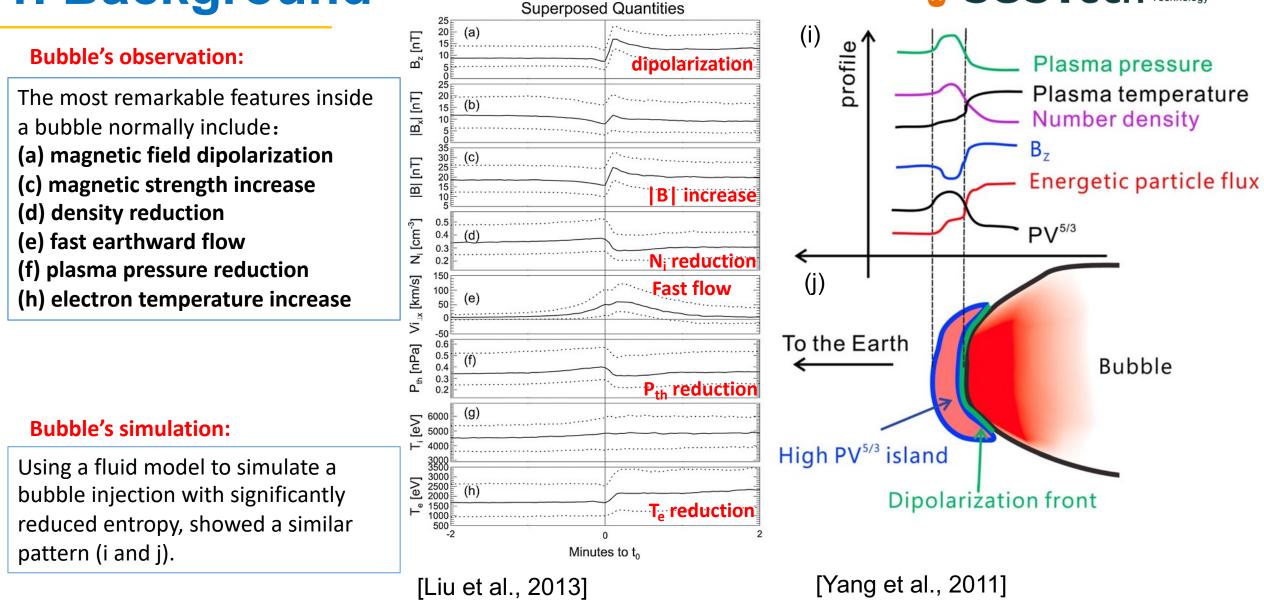
### What is a **plasma-sheet Bubble?**

Bubble?

- A plasma-sheet bubble is a flux tube in the nightside magnetotail with its entropy lower than its neighbors [Pontius and Wolf, 1990].
- (2) Bubbles are also referred to as bursty bulk flows (BBFs) in observation [Angelopoulos et al., 1992; Wolf et al., 2009].
- (3) Bubbles/BBFs are the primary carrier for substorm-time particle injection from the plasma sheet to the inner magnetosphere [Yang et al., 2011].



# 1. Background

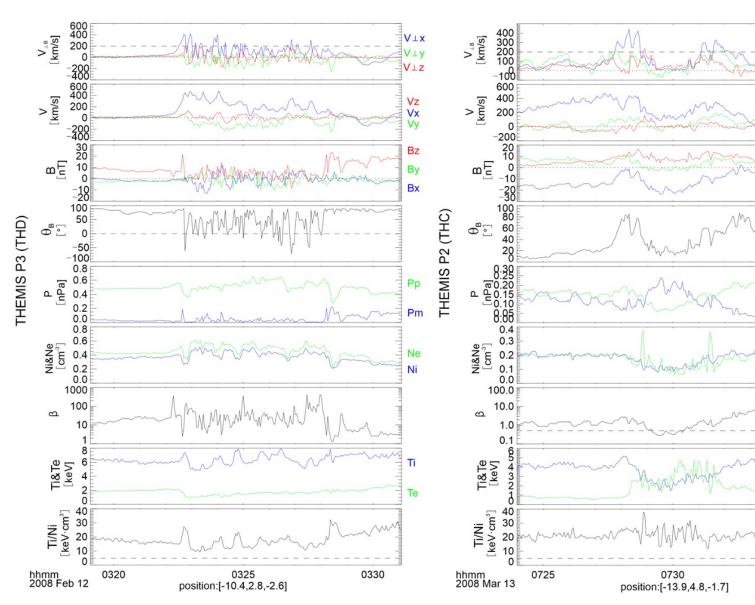


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# 1. Background

### Why using machine learning?

- a) the rapid **development** of machine learning **techniques**
- b) Abundant data
- c) Alleviate the manual inspection workload on scientists
- d) Traditional recognition can easily
   confuse plasma-sheet bubbles
   with other categories of events
- e) Provide a list of bubbles obtained by machine learning methods





V⊥x

V⊥y

V⊥z

Vz

Vx

Vv

Bz

By

Bx

Pp

Pm

Ni

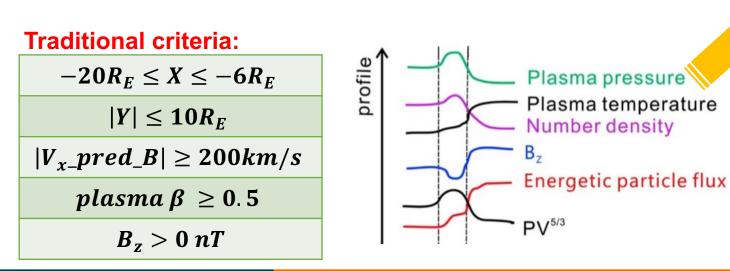
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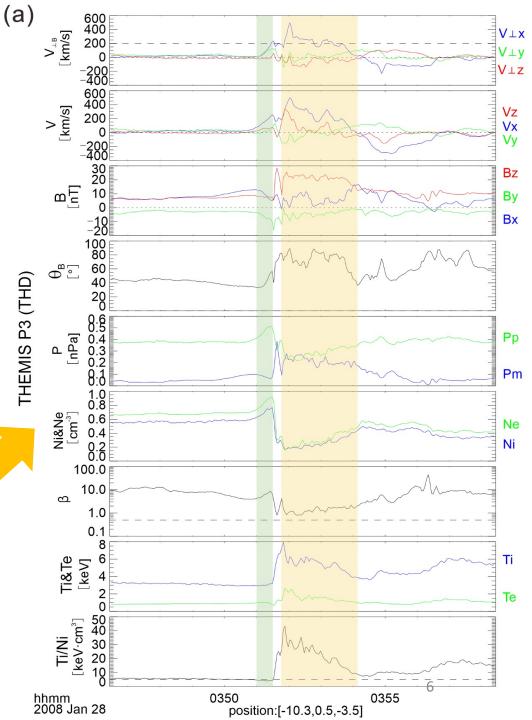
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### 2. Bubble Criteria and Dataset

- Data: THEMIS measurements in the magnetosphere from FGM, ESA, and SST instruments.
- **Time Duration**: from year 2007 to 2021;
- Resolution: 3 seconds;
- 12 minutes data is taken as one sample;
- 18 variables:  $B_{\chi}, B_{y}, B_{z}, \theta_{B}(\arctan \frac{B_{z}}{|B_{\chi}|}), N_{i}, N_{e}, plasma \beta,$   $P_{m}, P_{p}, T_{i}, T_{e}, V_{\chi}, V_{y}, V_{z}, (V \perp B)_{\chi}, (V \perp B)_{y}, (V \perp B)_{z},$  $T_{i}/T_{i}$





### 2. Bubble Criteria and Dataset



**Dataset**: Positive negative samples ratio is **1:40** (1:1, 1:3, 1:10,1:20 had been tested)

- Positive samples: 2668 bubbles (identify bubbles between 2007 and 2020 using traditional criteria and manual inspection)
- Negative samples: 106,720 non-bubbles(consists of non-bubbles that are manually excluded and non-bubble that are randomly selected at other times).

### Train-validation-test dataset split: 6:2:2

**Normalization:** maximum-minimum normalization

Prediction dataset: 82,152 12-minute intervals data from 2021

# **3. MTSC Models**



### **3.1 MINIROCKET**

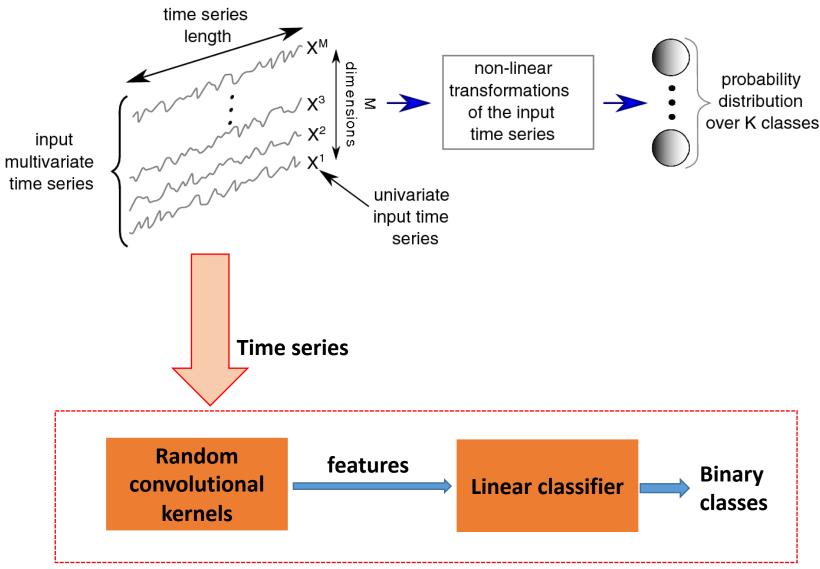
• MINIROCKET achieves state-of-theart accuracy for time series classification by transforming input time series using **random convolutional kernels**, and using the **transformed features** to train a **linear classifier** [Angus Dempster, 2021].

#### •Transformed features:

•Each input time series is convolved with 10000 random convolutional kernels. Kernels with random length, weights, bias, dilation, and padding.

#### **Linear Classifier:**

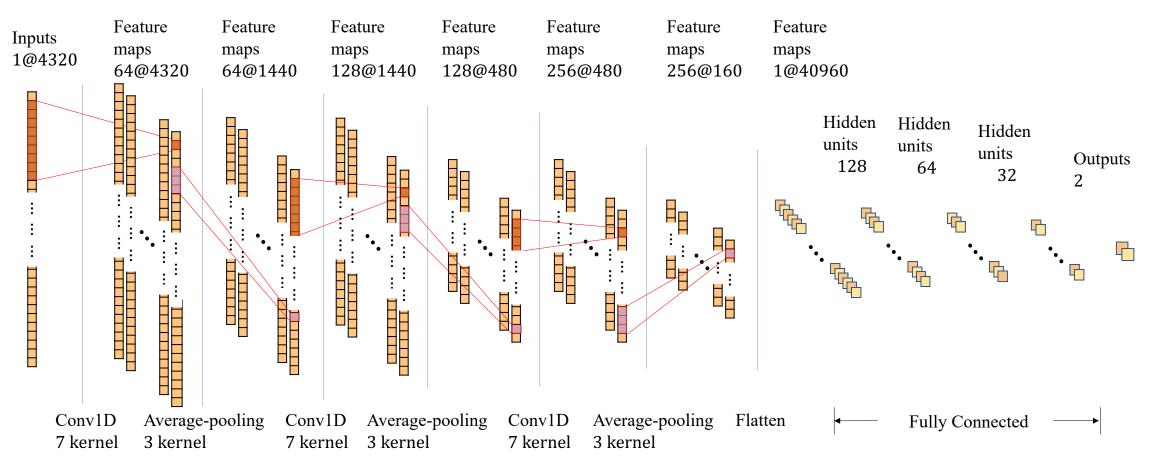
•The model uses logistic regression as classifier.



# 3.2 1D-CNN



- The convolutional layer slides a filter across the time series of the plasma bubble, which is known as the 'convolutional kernel'.
- > Each sample is **flattened** into a single column to serve as input for the model.



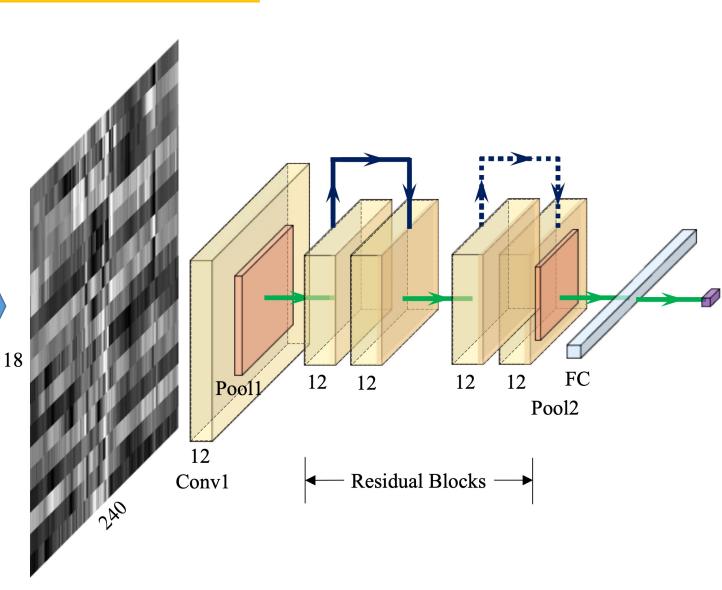
# **3.3 The residual network**



Residual Network (ResNet), which has shown success in **image recognition** [*He et al.*, 2016].

The input time series of the bubble can be converted to **grayscale image** data.

Layer name	Output size	6-layer
conv1	120×9	7×7,12, <i>stride</i> 2
	120×9	3×3 max pool, stride 2
Conv2	60×5	$\begin{bmatrix} 3\times3, 12\\ 3\times3, 12\end{bmatrix} \times 2$
Pool2	59×4	Average pooling
FC1- Softm ax	2×1	Fully-Connected, Softmax



# 4.1 Results – model training



Confusion matrices	Pred. Null	Pred. Event
Obs. Null	tn	fp
Obs. Event	fn	tp

MINIROCK	CK Train		Train Validation			Test		
ET		Pred. Null	Pred. Event		Pred. Null	Pred. Event	Pred. Null	Pred. Event
Obs. Null		63947	116		21251	66	21253	87
Obs. Event		126	1443		81	480	106	432

1D-CNN	Train			Validation			Test		
ID-CININ	Pred. Null	Pred. Event		Pred. Null	Pred. Event		Pred. Null	Pred. Event	
Obs. Null	63865	198		21246	71		21245	95	
Obs. Event	110	1459		64	497		78	460	

Resnet2D		Train			Validation			Test		
Kesnet2D		Pred. Null	Pred. Event		Pred. Null	Pred. Event		Pred. Null	Pred. Event	
Obs. Null		63762	301		21211	106		21229	111	
Obs. Event		178	1391		76	485		89	449	

## 4.1 Results – model training

- All three models exhibit over 99% accuracy, with precision and recall rates exceeding 80%. Moreover, their F<sub>2</sub> scores are above 80%.
- The F<sub>2</sub> score for MINIROCKET, 1D-CNN, and ResNet in test sets are 81%, 85%, and 83%, respectively.

$$\begin{aligned} Accuracy &= \frac{TP + TN}{TP + FP + TN + FN}, \\ Precision &= \frac{TP}{TP + FP}, \\ Recall &= \frac{TP}{TP + FN}, \\ and F_{\beta} &= (1 + \beta^2) \cdot \frac{Precision \cdot Recall}{(\beta^2 \cdot Precision) + Recall}. \end{aligned}$$

$F_2$ score	Train	Validation	Test
MINIROCKET	0.9209	0.8602	0.8087
1D-CNN	0.9196	0.8837	0.8496
2D-ResNet	0.8729	0.8554	0.8278



## 4.2 Results - prediction in 2021



We utilized observed data from P3(THD), P4(THE), and P5(THA) in the year 2021.

Only traditional	20	021	MINIROCKET	2021			
Crateria	Pred. Null	Pred. Event	MINIKUCKEI	Pred. Null	Pred. Event		
Obs. Null	81782	181	Obs. Null	81880	83		
Obs. Event	0	189	Obs. Event	93	96		
CNIN1D	20	021	DesNet	20	)21		
CNN1D	20 Pred. Null	<b>D21</b> <i>Pred. Event</i>	ResNet	20 Pred. Null	21 Pred. Event		
CNN1D Obs. Null			ResNet Obs. Null				

To improve the recall rate (detectable rate) of bubbles identified by the three models, we combined their respective prediction results using intersection and union.

Intersection	20	)21	Union	2021			
Intersection	Pred. Null	Pred. Event	Union	Pred. Null	Pred. Event		
Obs. Null	81928	35	Obs. Null	81682	281		
Obs. Event	123 66		Obs. Event	63	126		

### 4.2 Results - prediction in 2021



Due to the **extremely unbalanced** sample in 2021, which has a ratio of 435 non-bubbles to bubbles, the model can detect about half of the actual bubbles.

Methods	Only Traditional Criteria	MINIRO CKET	CNN-1D	ResNet	Intersectio n	Union
Precision	0.5108	0.5363	0.4335	0.3106	0.6535	0.3096
Recall	1.0000	0.5079	0.4656	0.5291	0.3492	0.6667
$F_2$ score	0.8393	0.5134	0.4588	0.4638	0.3851	0.5417

- $\succ$   $F_2$  score indicates that the highest score is obtained when the union set is used, suggesting that it provides the best identification of bubbles.
- Based on the recall rate of the union results, we can identify two-thirds (126 out of 189) of the bubbles in 2021.

Where the term "intersection" refers to a situation where all three models predict a bubble, resulting in the final combination also being classified as a bubble. The term "union" means that the event is classified as a bubble if at least one of the three models predicts it as such.

# 5. Summary

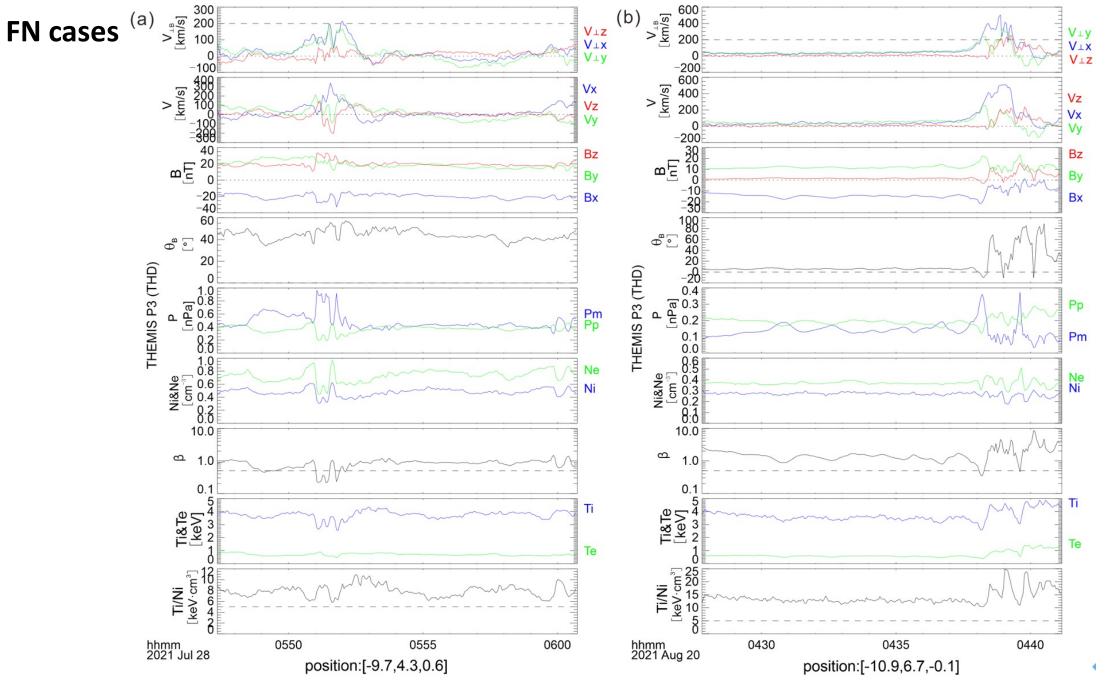


- 1. This study utilized a plasma-sheet bubble dataset that was created through a combination of traditional criteria and manual inspection with an imbalanced ratio of 1:40.
- 2. Bubble identification: (defined as multivariate time series classification). The models included MINIROCKET, a traditional machine learning method, 1D-CNN, a deep learning technique, and ResNet, a two-dimensional deep learning technique typically used for image recognition.
- >3. All three models were effective in recognizing bubbles, with precision, recall, and  $F_2$  score reaching 80% on the training-validation-test set.
- ≻4. When predicting in 2021, combining the results of three models to create a union set improved the accuracy of predicted results, increasing the recall rate and F<sub>2</sub> score.

The data and model files are available at <a href="https://github.com/pinecypressfxd/Bubble\_Identification\_MTS15">https://github.com/pinecypressfxd/Bubble\_Identification\_MTS15</a>



## •Thanks for your attention!



a few data points' velocities exceed 200km/s

not complete event

