Predicting Active Region Emergence Using an LSTM Machine Learning Model

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Introduction

Importance:

Active Regions (ARs) are the source of Solar Flares, CMEs and SEPs, therefore early prediction of ARs will assist with the prediction of these solar weather phenomena. Such phenomena can affect the near-earth environment, degrade high frequency (HF) radio communications, incapacitate satellites, expose airline passengers to elevated radiation levels and even endanger life in outer space.

Research Goals:

a) Understand the physics behind the emergence and evolution of solar ARs
b) Create and publish a ML-ready dataset of emerging ARs
c) Define the time of emergence of ARs
d) Detect 12 hours ahead the decrease in continuum intensity (emergence of ARs) using ML

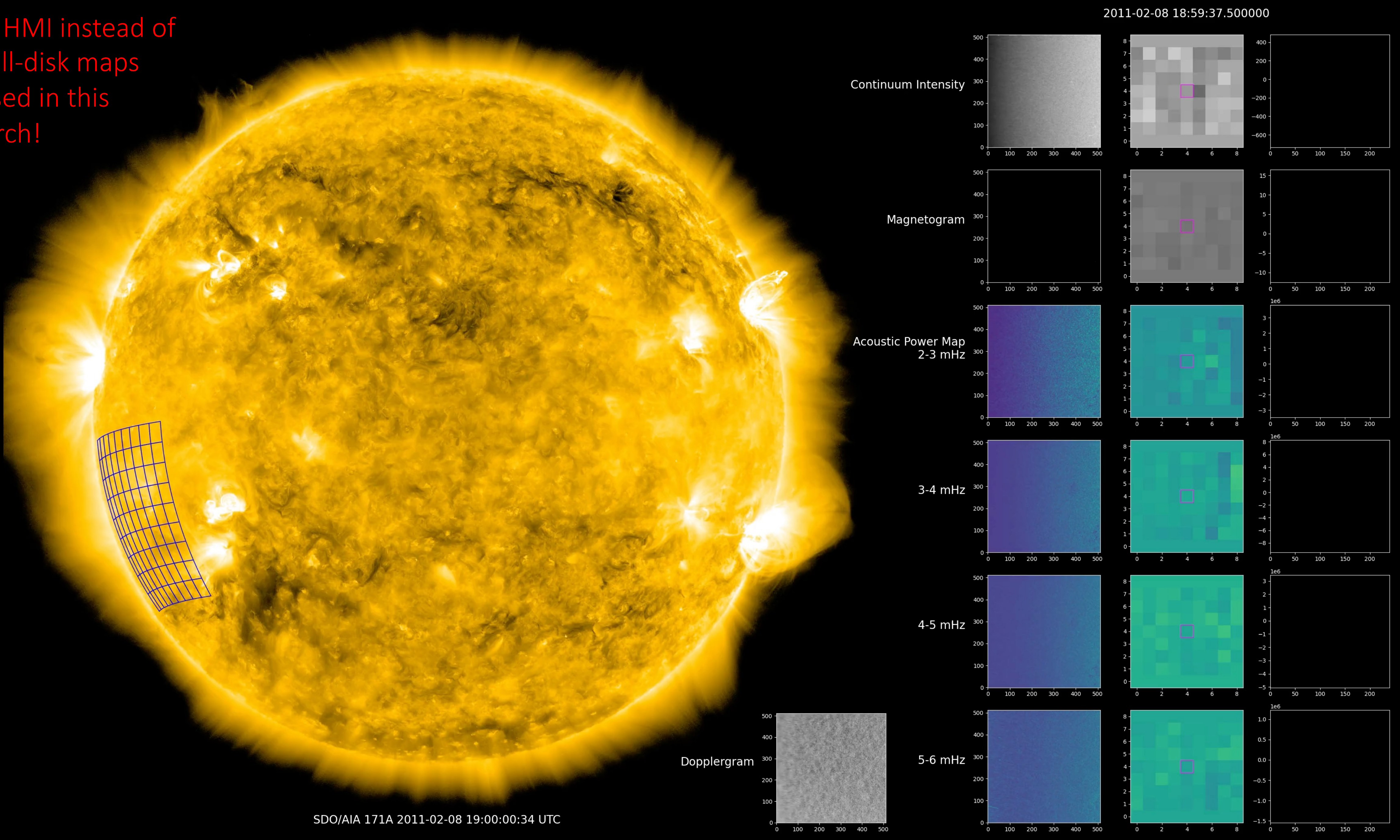
Emergent ARs Dataset

- We tracked 512 by 512 pixels (30.66° x 30.66°) SDO/HMI patches of 45 ARs before, during and after emergence for the:
  a) Doppler velocity V_D
  b) Line-of-sight magnetic flux Φ_m
  c) Continuum intensity I_c
- Each selected AR appeared on the solar surface within 30° longitude from the central meridian, between March 1st 2010 and June 1st 2023, persisted for more than 4 days, and reached a total area of 200 millionths of the solar hemisphere.
- The Φ_m and I_c maps are used as-is. The Dopplergrams (V_D maps) are used to generate acoustic power P_a maps for four frequency ranges: 2–3, 3–4, 4–5, and 5–6 mHz.

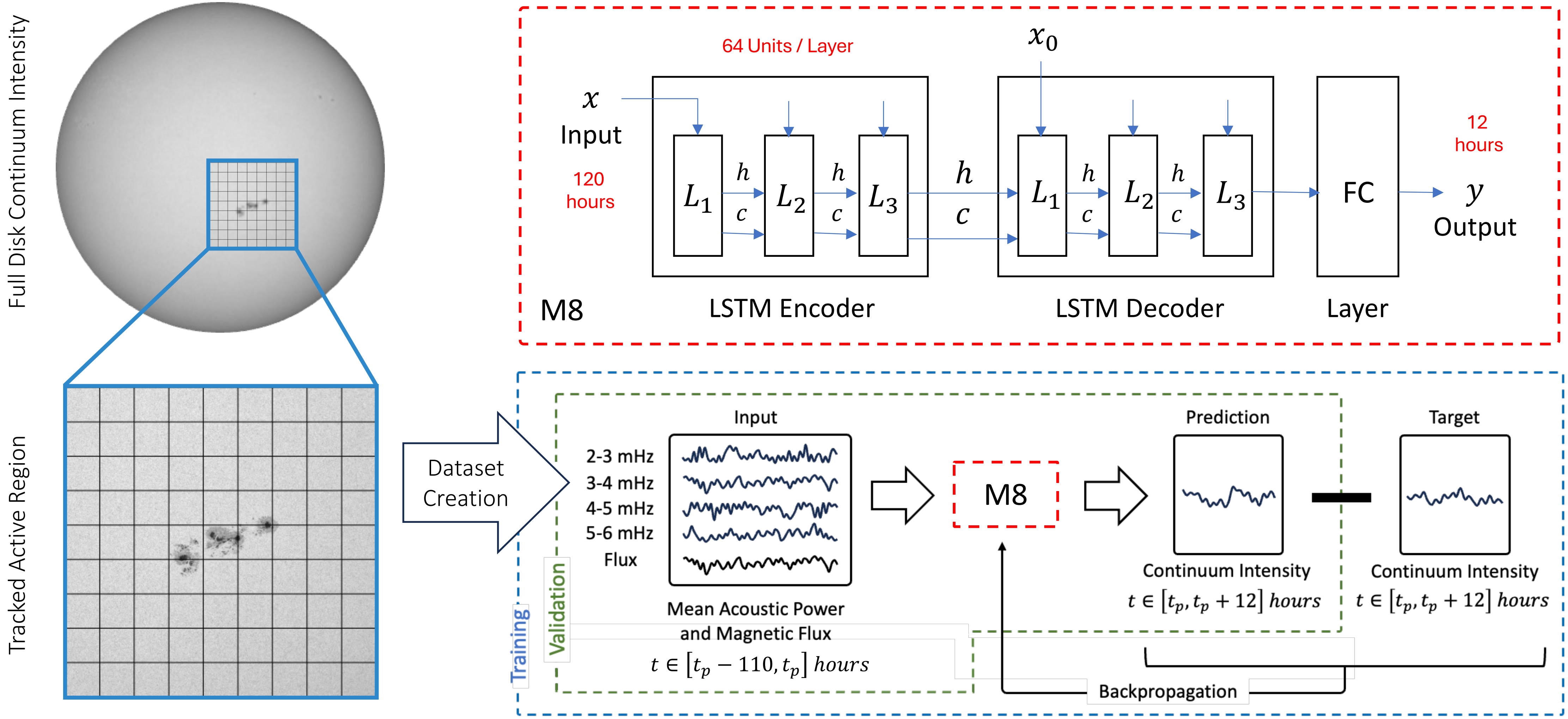
	Mean ϕ	Mean Traveled λ	Mean A_{max}	NOAA Record Span	Number
Training ARs	9.3 ± 16.58	87.6 ± 18.16	318.0 ± 169.91	6.6 ± 1.52	40
Testing ARs	-5.9 ± 17.53	79.8 ± 15.35	424.0 ± 332.08	5.8 ± 1.10	5
Entire Dataset	7.6 ± 17.17	86.7 ± 17.89	329.8 ± 191.70	6.5 ± 1.49	45
Units	degrees	degrees	$\frac{1}{10^6}$ of Hemisphere	days	

* AR latitude is ϕ, longitude is λ and area is A

Note: HMI instead of AIA full-disk maps are used in this research!



Training



Full Disk Continuum Intensity
Tracked Active Region
Dataset Creation
64 Units / Layer
x
Input
120 hours
x_0
L_1 h c L_2 h c L_3
h
c
L_1 h c L_2 h c L_3
FC
12 hours
y
Output
M8
LSTM Encoder
LSTM Decoder
Layer
Training
Validation
Input
2-3 mHz
3-4 mHz
4-5 mHz
5-6 mHz
Flux
Mean Acoustic Power and Magnetic Flux
$t \in [t_p - 110, t_p]$ hours
M8
Prediction
Continuum Intensity
$t \in [t_p, t_p + 12]$ hours
Target
Continuum Intensity
$t \in [t_p, t_p + 12]$ hours
Backpropagation

Testing

Testing is performed on 5 tracked emerging ARs...

AR#	First Record	Last Record	ϕ	λ_{Carr}	λ_s	λ_e	A_s	A_e	A_{max}	A_{max} Date	McIntosh	Hale
11698	2013.03.15	2013.03.19	-19.5	117.0	29.0	86.0	20	200	200	2013.03.18	Eao	β
11726	2013.04.20	2013.04.27	13.0	327.0	-7.0	93.0	20	600	1000	2013.04.26	Fkc	$\beta\gamma\delta$
13165	2022.12.12	2022.12.18	-20.0	277.5	10.0	88.0	20	150	340	2022.12.16	Ekc	$\beta\delta$
13179	2022.12.30	2023.01.05	13.5	43.0	11.0	92.0	30	80	380	2023.01.03	Dko	β
13183	2023.01.06	2023.01.12	-16.5	309.0	8.0	91.0	30	50	200	2023.01.08	Dso	$\beta\delta$

...using two testing methods.

Root Mean Squared Error

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Emergence Criterion

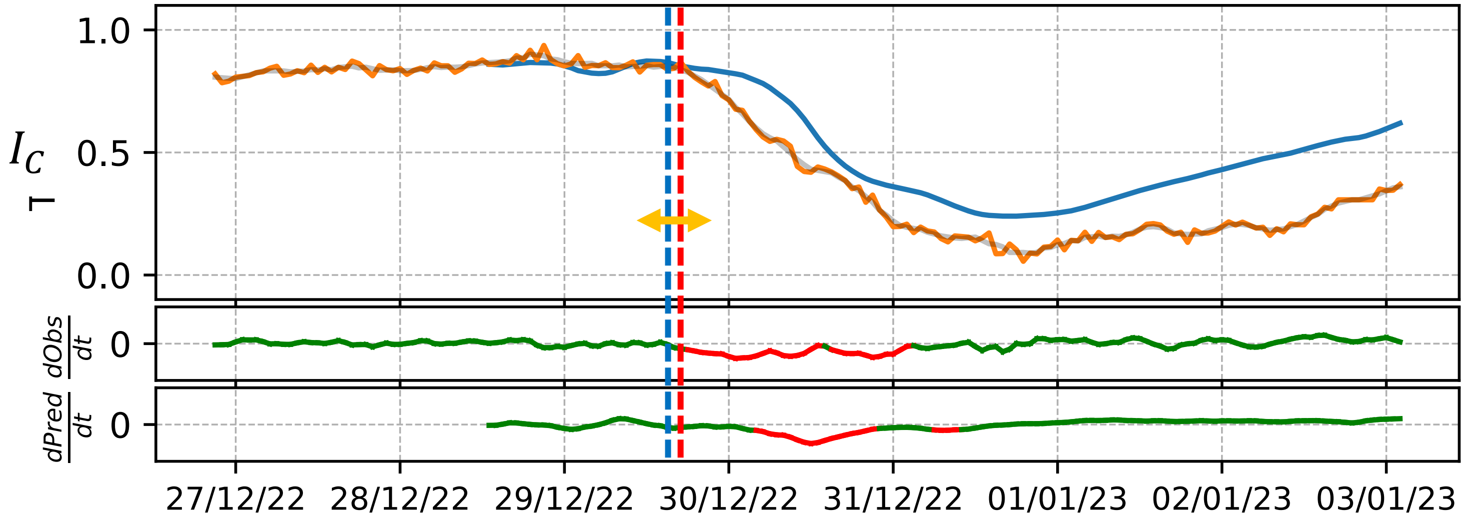
$$\frac{dI_c}{dt} < -0.01 \quad \text{for} \quad t_{sus} > 3 \text{ hours}$$

Results (RMSE)

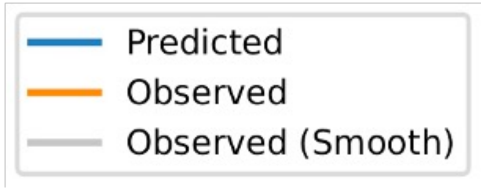
Model	Model Parameters						Average Testing RMSE for 12h Prediction					
Model	In	Out	LN	U	E	LR	AR11698	AR11726	AR13165	AR13179	AR13183	**Avg**
M1	110	5	3	64	1000	0.01	0.106	0.084	0.107	0.140	0.115	0.110
M2	110	8	3	64	1000	0.01	0.130	0.092	0.113	0.145	0.107	0.117
M3	120	12	3	32	1000	0.001	0.118	0.111	0.122	0.160	0.115	0.125
M4	120	12	3	64	1000	0.001	0.125	0.106	0.128	0.150	0.118	0.125
M5	120	12	3	64	1000	0.0005	0.121	0.105	0.121	0.161	0.116	0.125
M6	120	12	4	64	1500	0.0005	0.126	0.105	0.121	0.152	0.144	0.130
M7	110	12	3	128	1000	0.01	0.124	0.090	0.111	0.125	0.100	0.110
M8	**110**	**12**	**3**	**64**	**1000**	**0.01**	**0.128**	**0.108**	**0.127**	**0.158**	**0.125**	**0.130**
M9	110	18	3	64	1000	0.01	0.136	0.099	0.125	0.181	0.122	0.133
M10	110	24	3	64	1000	0.01	0.136	0.100	0.128	0.153	0.136	0.131
					AR	Average	0.125	0.101	0.120	0.153	0.120	0.124

Results (Emergence Criterion – Single Tile)

AR13179
Tile 42
RMSE = 0.105

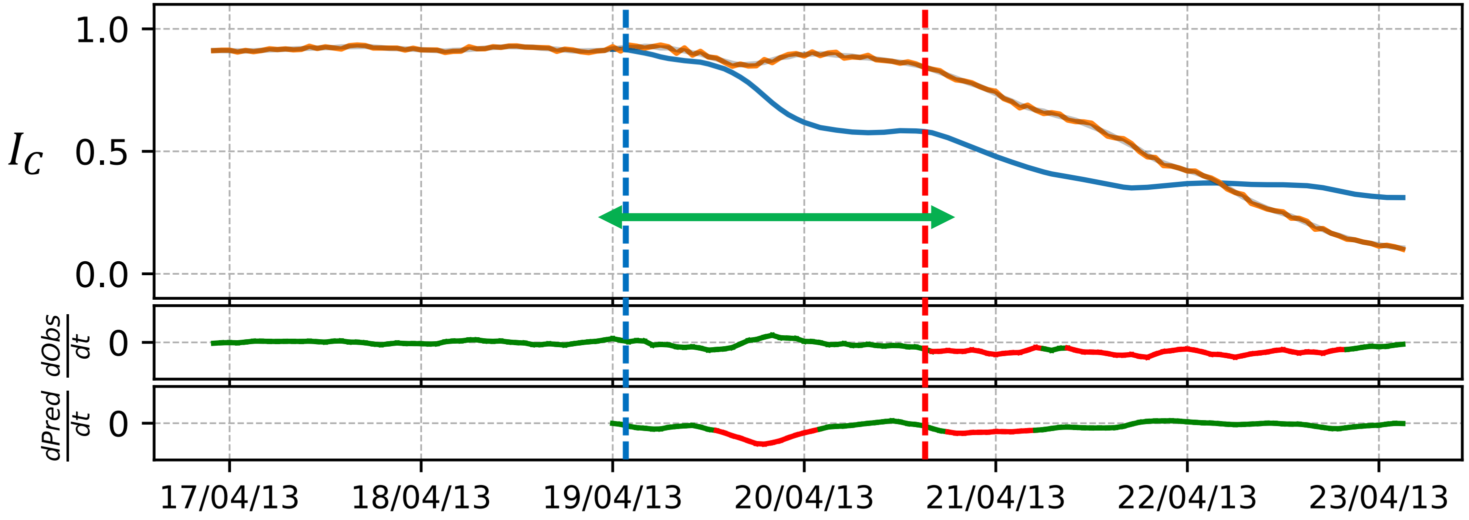


First Alarm
-
Emergence Start
=
2 hours



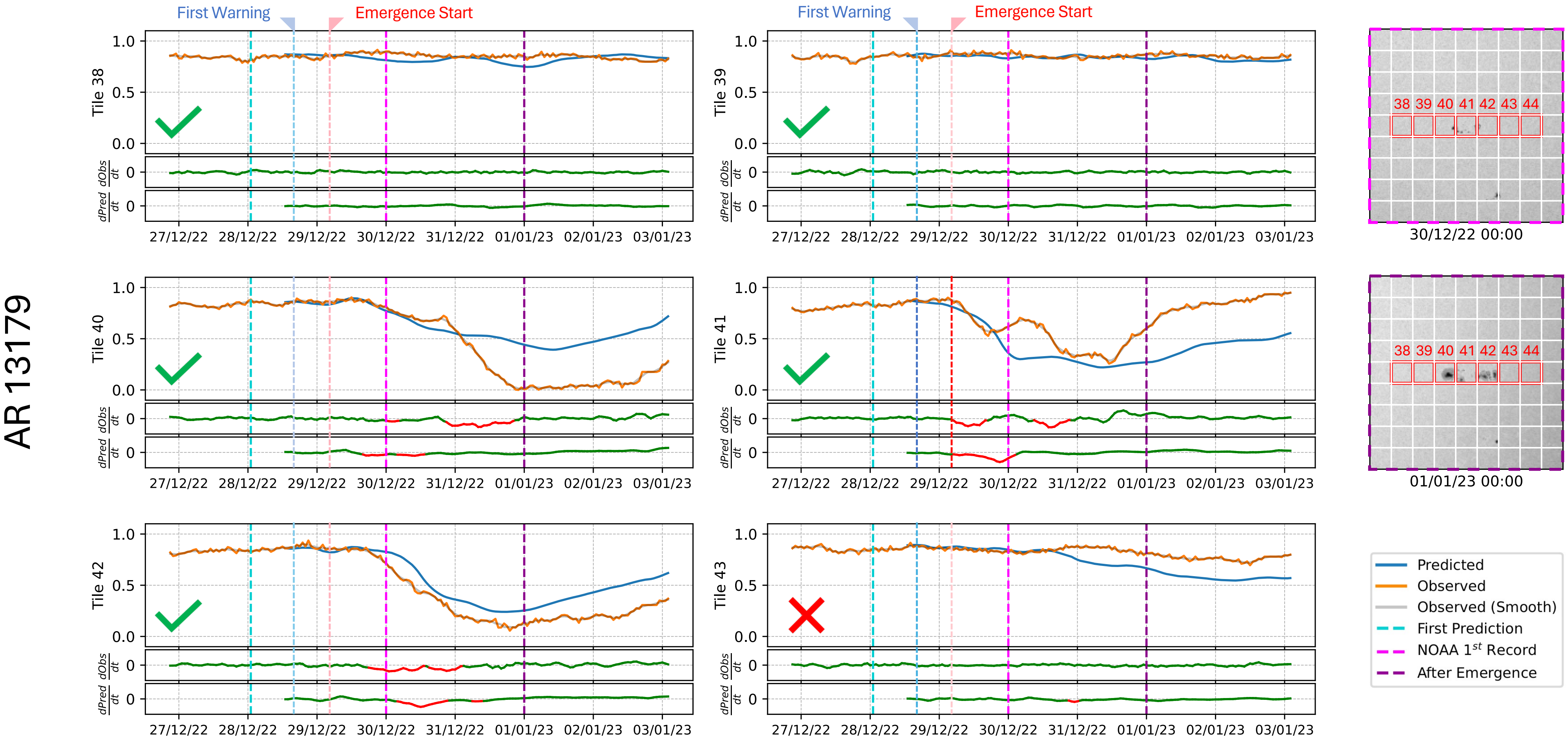
$$\frac{dI_c}{dt} < -0.01 \quad \text{for} \quad t_{sus} > 3 \text{ hours}$$

AR11726
Tile 41
RMSE = 0.124



First Alarm
-
Emergence Start
=
39 hours

Results (Emergence Criterion – Full AR)



Results (Operational)

	Independent Tile Prediction							Full AR Prediction
Tile Type	Quiet	Quiet	Quiet	Q/A	Active	Active	Active	Experimental
AR11698	Tile 47	Tile 48	Tile 50	Tile 53 (Q)	Tile 49	Tile 51	Tile 52	Tiles 49/49
	Quiet	Quiet	FA	Quiet	4h Alarm	12h Alarm	1h Alarm	4h Alarm
AR11726	Tile 38	Tile 39	Tile 40	Tile 41 (A)	Tile 42	Tile 43	Tile 44	Tiles 42/41
	Quiet	Quiet	Quiet	39 h Alarm	9h Alarm	39h Alarm	18h Alarm	17h Alarm
AR13165	Tile 29	Tile 30	Tile 35	Tile 31 (A)	Tile 32	Tile 33	Tile 34	Tiles 32/32
	Quiet	Quiet	Quiet	35h Alarm	36h Alarm	7h Alarm	55h Alarm	36h Alarm
AR13179	Tile 38	Tile 39	Tile 43	Tile 44 (Q)	Tile 40	Tile 41	Tile 42	Tiles 41/41
	Quiet	Quiet	FA	Quiet	20h Alarm	12h Alarm	2h Alarm	12h Alarm
AR13183	Tile 38	Tile 39	Tile 44	Tile 40 (A)	Tile 41	Tile 42	Tile 43	Tiles 41/41
	Quiet	Quiet	Quiet	-2h Alarm	5h Alarm	4h Alarm	11h Alarm	5h Alarm

Failed Prediction   Operationally Failed Prediction   Successful Prediction

Conclusions and Future Work

- Our LSTM model succeeded in predicting the emergence of all 5 testing ARs in an experimental setting and 3/5 in an operational setting (AR11726, AR13165 and AR13179).

- Although 45 emerging ARs are used in this research, 61 ARs have been tracked and the entire dataset will be published, along with the ML-ready data produced.

- Improvement suggestions in the dataset production process can be derived, such as the optimal frequency range, integration time range, tile arrangement and normalization methods.

- Improvements in the LSTM training methods and the use of more advanced ML methods such as transformers.

- Creation of a universal AR emergence definition which can be used in different works.

Kasapis, S., Kitiashvili, I.N., Kosovichev, A.G., Stefan, J.T. and Apte, B., 2024. Predicting the Emergence of Solar Active Regions Using Machine Learning. arXiv preprint arXiv:2402.08890.

Thank you for your attention!

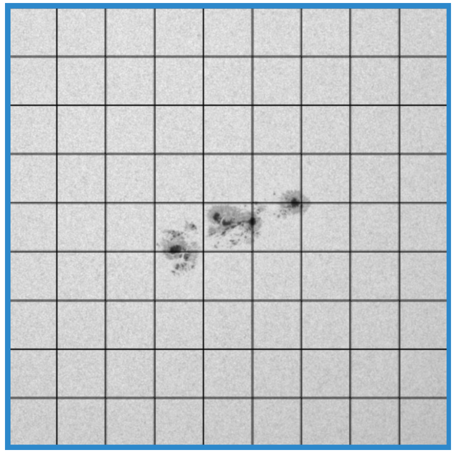
Kasapis et al. (2024)

Training

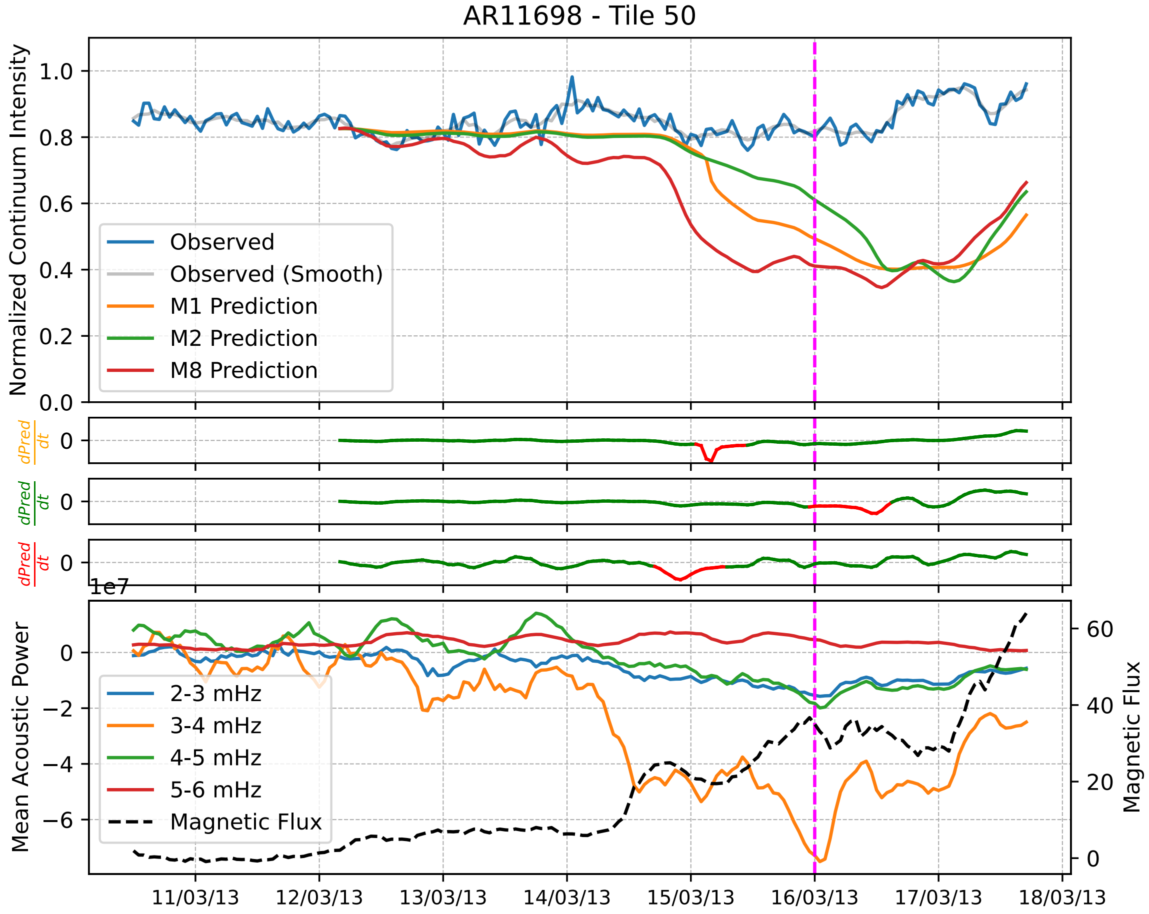
Algorithm 2 LSTM Training Process

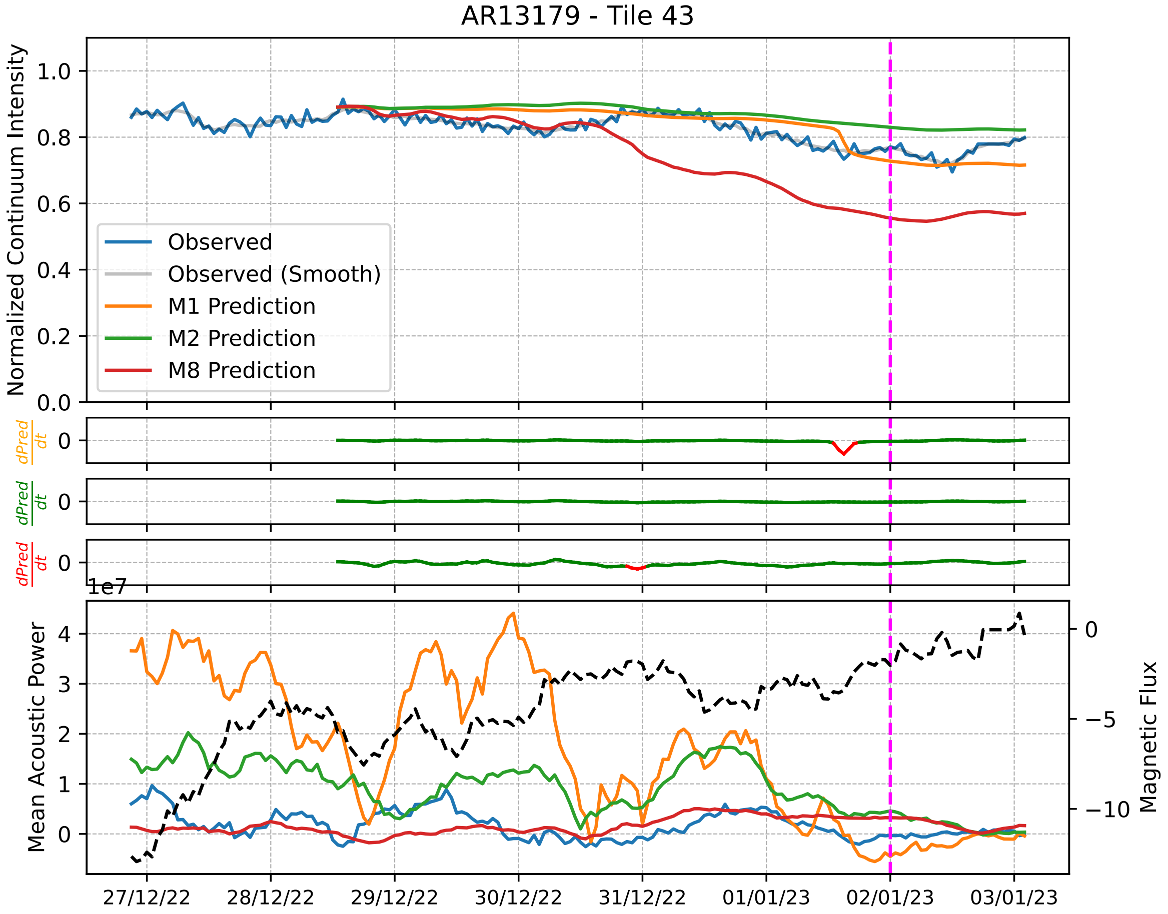
```
Set Hyperparameters and Initialize LSTM Model
Load ML-Ready Dataset
Remove Active/Quiet Tile Imbalance
Split in Training and Testing
Initialize Optimizer
for Active Region in Training Dataset do
    for Tile in AR Grid do
        Split in Input and Target
        Process the Timelines to Sliding Window Form
        Move Data to GPU
        Set Scheduler (and Learning Rate Decay)
        for Current Epoch in Total Epochs Number do
            Forward Pass the Training Data through the LSTM Model to Obtain Output
            Zero the Gradients of the Optimizer
            Calculate Loss Using Output and Targets
            Backpropagate Loss
            Take Gradient Step Using LR and Update Model Weights
            Perform Validation
        end for
    end for
end for
```

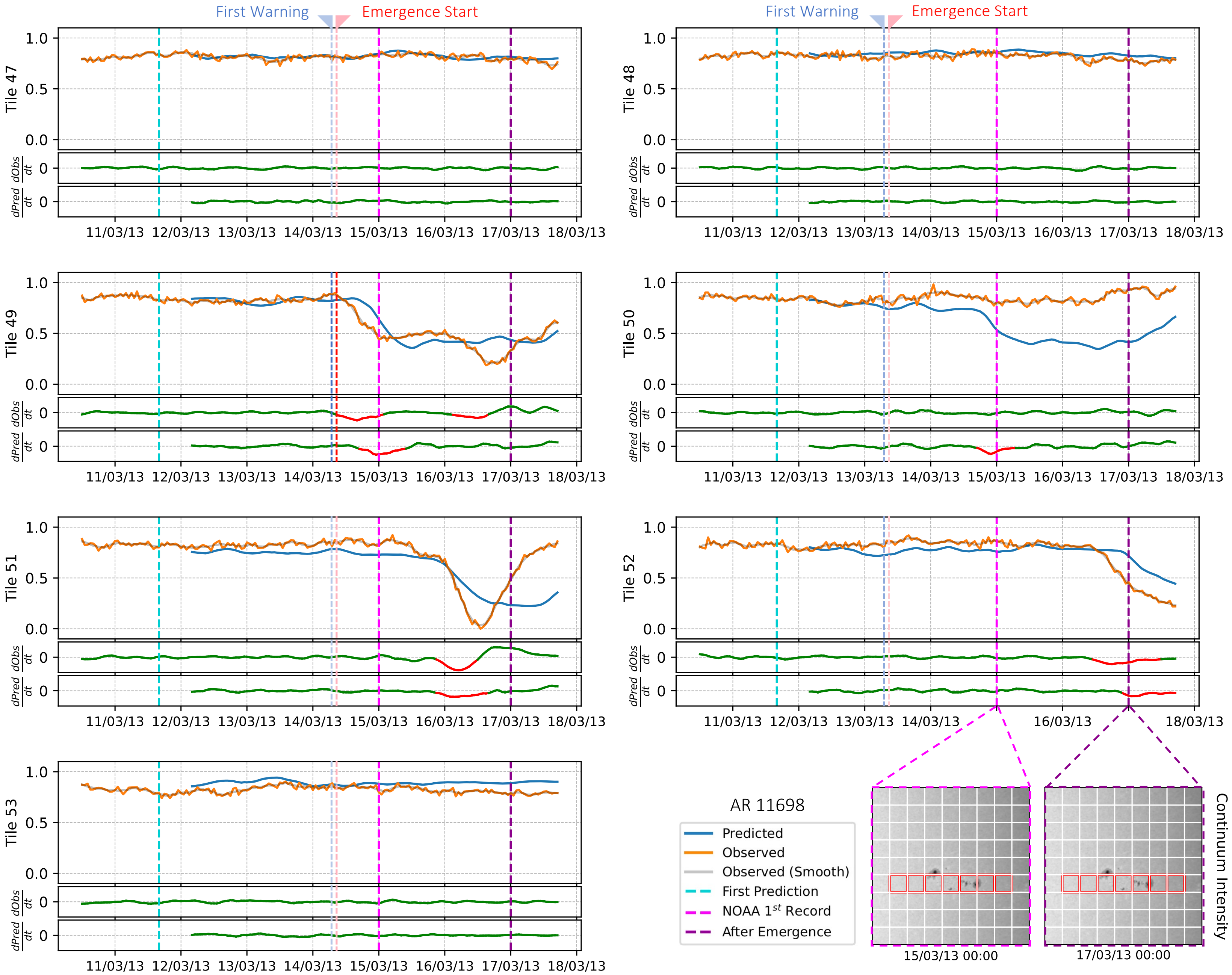
Standard ML Process Sequence
1000 Epochs, LR = 0.01



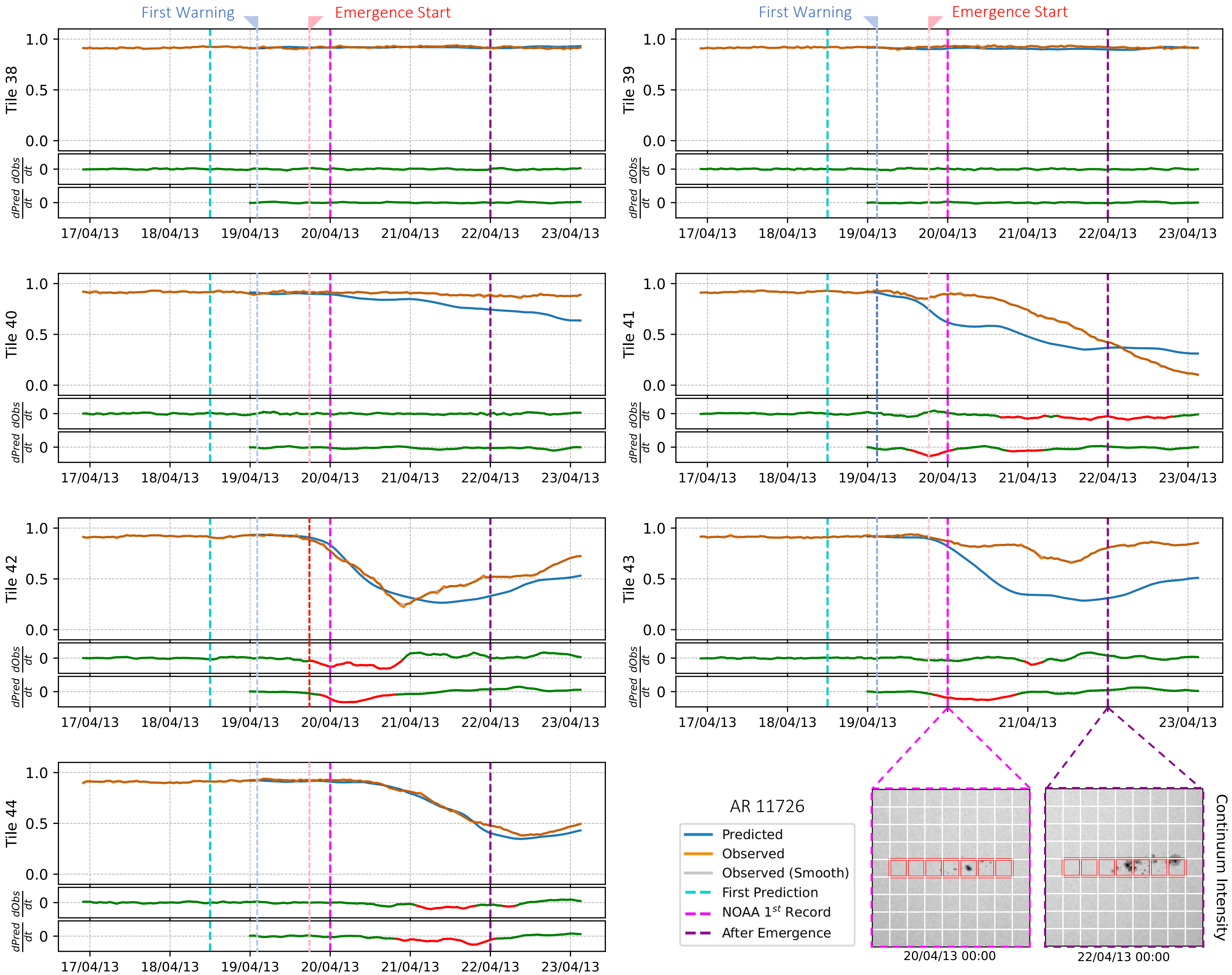
False Alarms



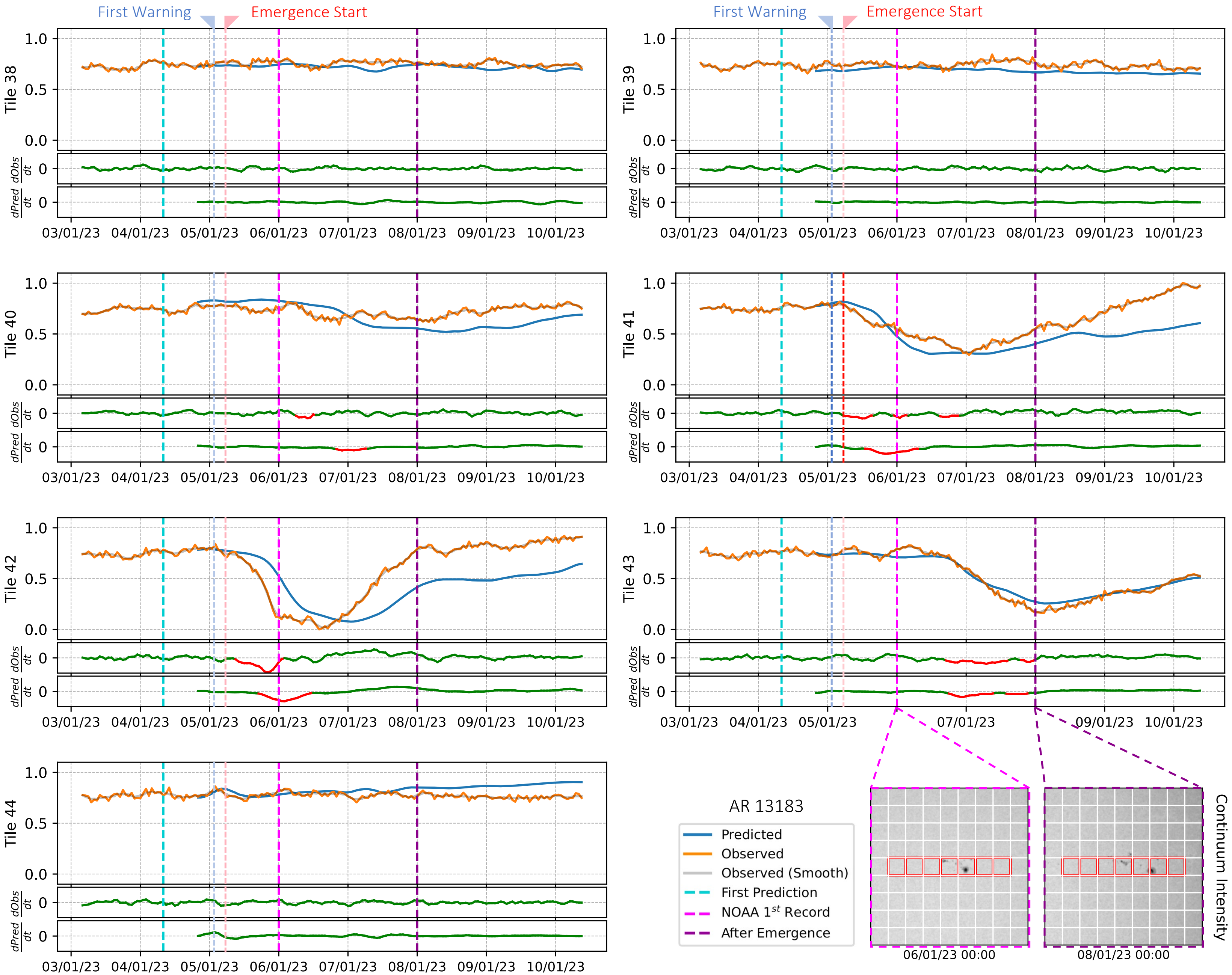




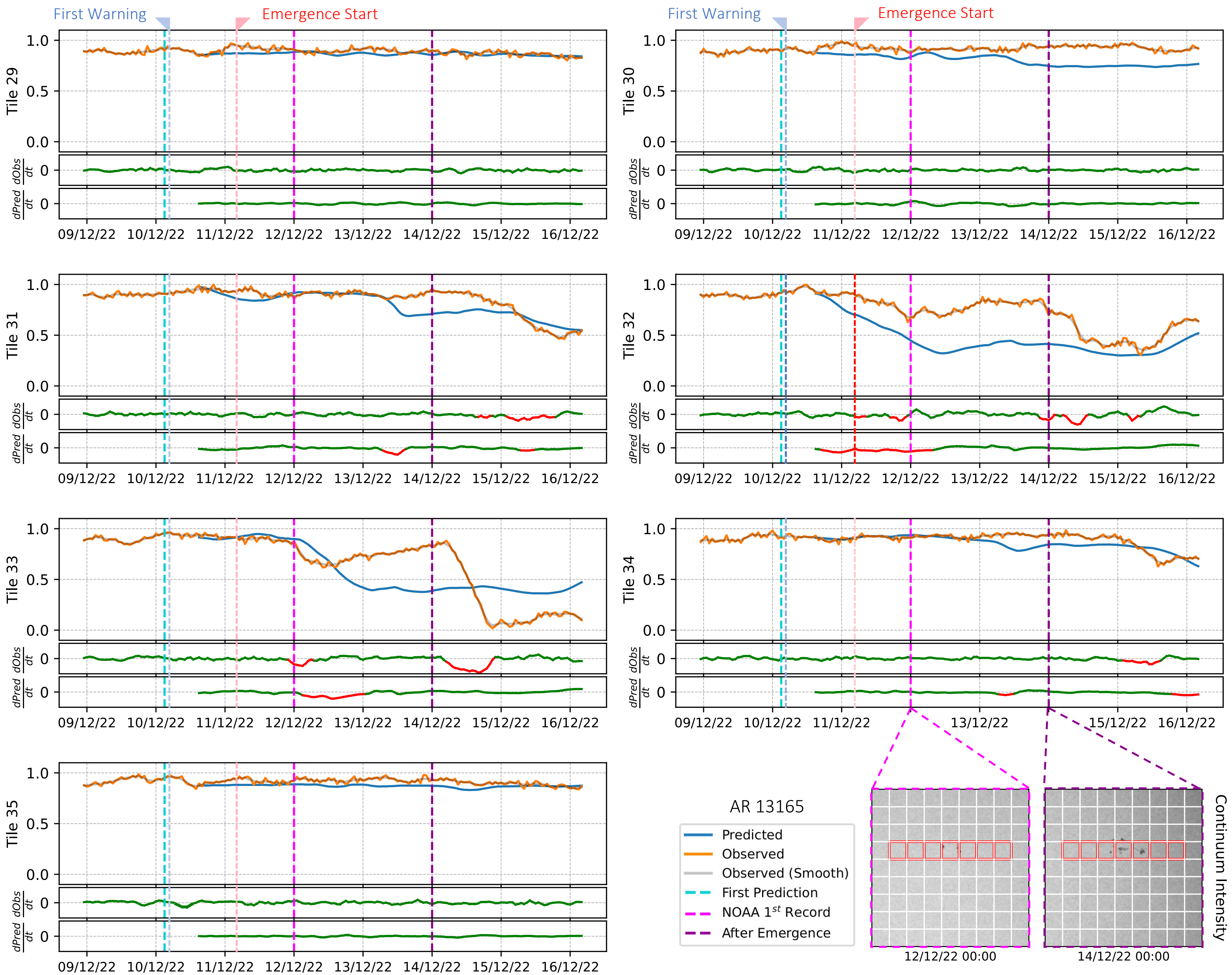
Average metrics for all tiles plotted: MAE = 0.098, MSE = 0.024, RMSE = 0.126, RMSLE = 0.079, $R^2 = -5.295$



Average metrics for all tiles plotted: MAE = 0.097, MSE = 0.025, RMSE = 0.116, RMSLE = 0.073, $R^2 = -9.5$



Average metrics for all tiles plotted: MAE = 0.1, MSE = 0.02, RMSE = 0.119, RMSLE = 0.073, $R^2 = -2.179$



Average metrics for all tiles plotted: $\mathrm{MAE}=0.112$, $\mathrm{MSE}=0.026$, $\mathrm{RMSE}=0.134$, $\mathrm{RMSLE}=0.082$, $R^2=-3.931$