Towards explanation of airglow variation by ML techniques

Simon Mackovjak
Slovak Academy of Sciences

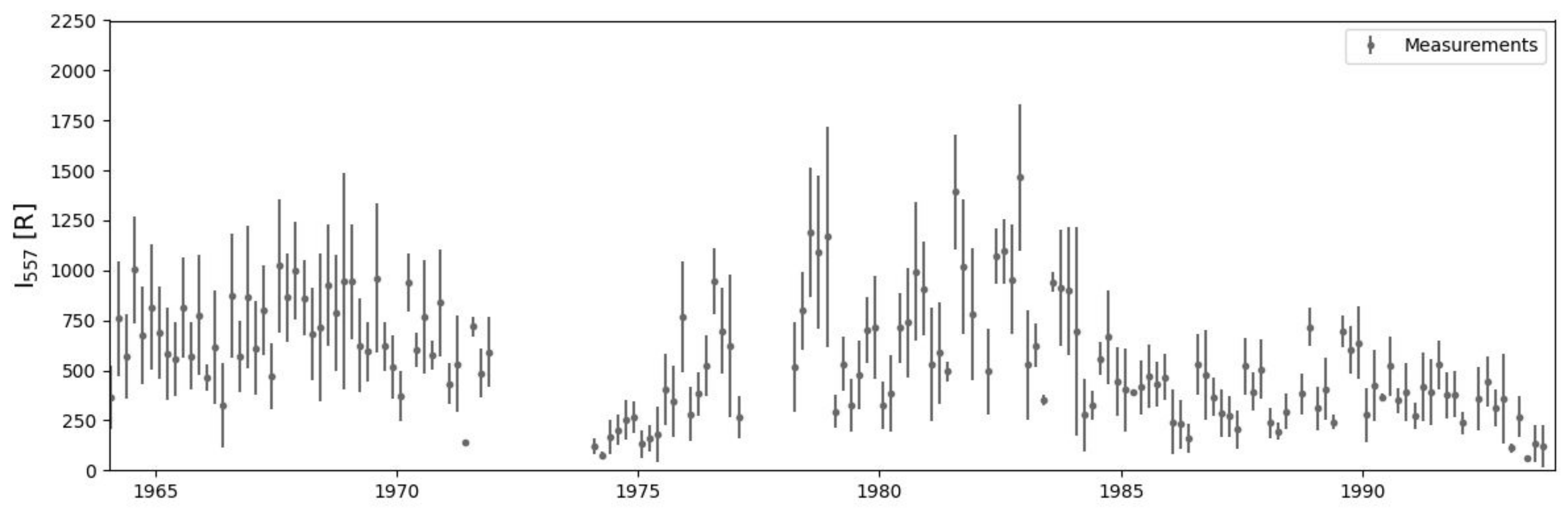
Airglow

an interface between Space and Earth

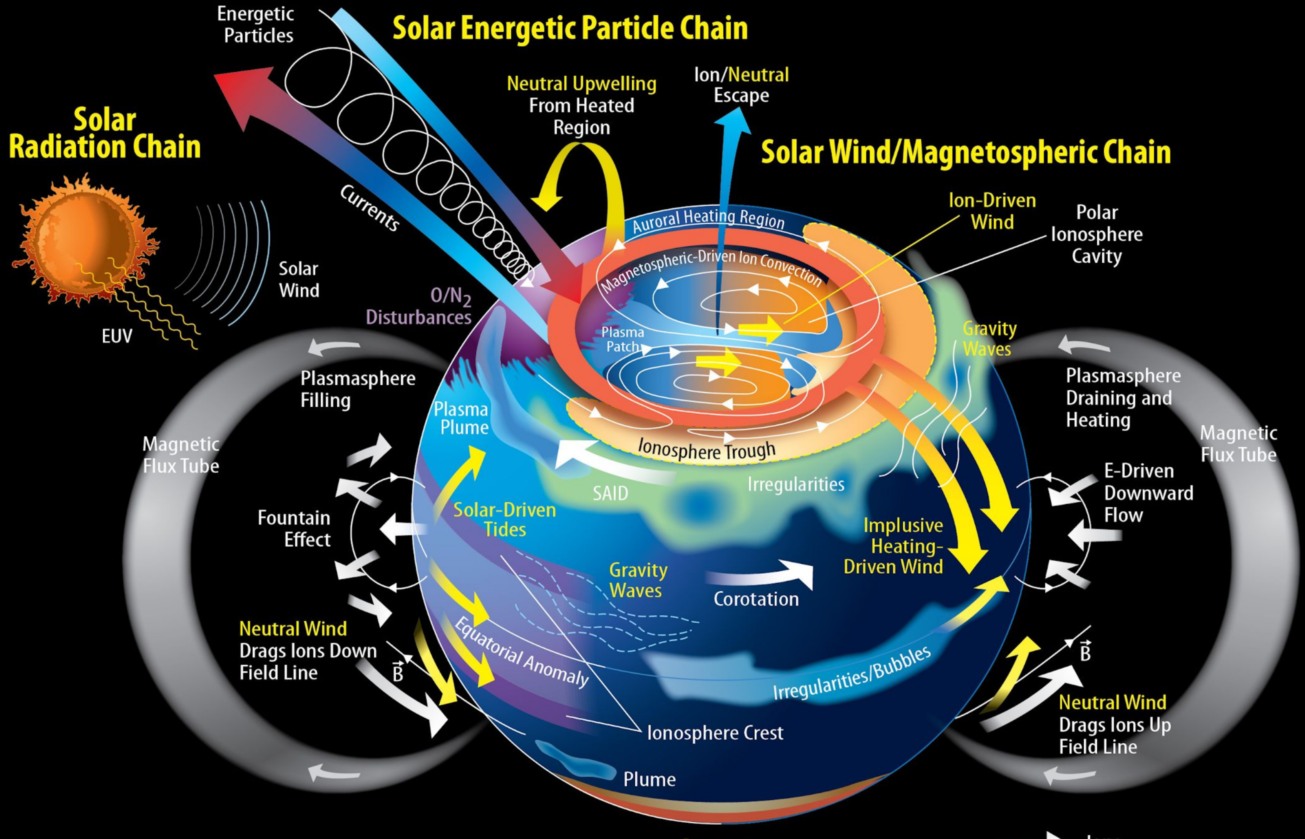
Image by: Tomáš Slovinský, Slovakia

Airglow data from Abastumani (Georgia)

Airglow data from Abastumani (Georgia)

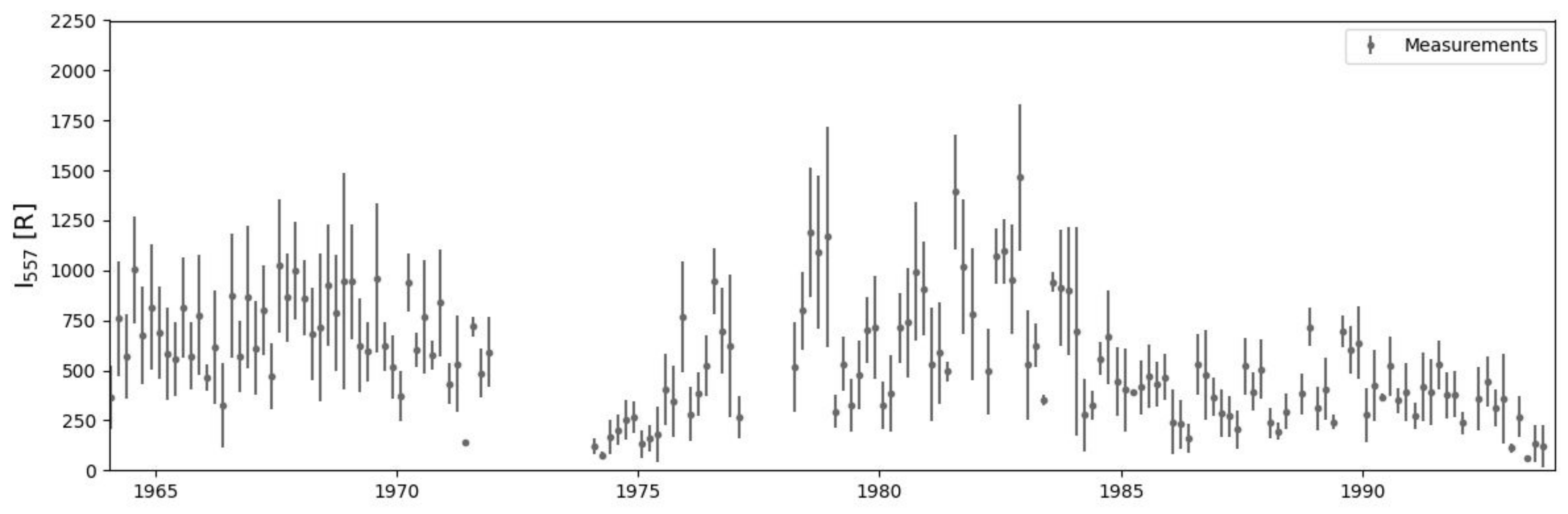


Terrestrial Atmospheric ITM Processes



Credit: NASA / J. Grobowsky

Airglow data from Abastumani (Georgia)



➔ Only ~8% of all possible dark night hours

15

parameters

30

years

1

hour step

Table 1

The Selected Features for Machine Learning Techniques to Model Airglow Intensities

Feature	Units	Description	Source
F10.7 index	SFU	Solar radio flux per frequency ($\lambda = 10.7$ cm)	OMNIWeb[a]
Kp index		Geomagnetic planetary K-index	OMNIWeb[a]
Dst index	nT	Geomagnetic equatorial index	OMNIWeb[a]
Neutral Temperature	K	Temperature of neutral atmosphere	NRLMSISE-00[b]
Total Mass Density	g/cm^3	Total mass density of neutral atmosphere	NRLMSISE-00[b]
O	N/cm^3	Atomic oxygen density	NRLMSISE-00[b]
O_2	N/cm^3	Molecular oxygen density	NRLMSISE-00[b]
N	N/cm^3	Atomic nitrogen density	NRLMSISE-00[b]
N_2	N/cm^3	Molecular nitrogen density	NRLMSISE-00[b]
H	N/cm^3	Atomic hydrogen density	NRLMSISE-00[b]
T_e	K	Temperature of electrons	IRI-2016[c]
n_e	N/m^3	Density of electrons	IRI-2016[c]
h_mF_2	km	F_2 layer peak height	IRI-2016[c]
N_mF_2	N/m^3	F_2 layer peak density	IRI-2016[c]
Sun-Earth	AU	Sun-Earth distance	PyEphem[d]

[a]Available at: https://omniweb.gsfc.nasa.gov/form/dx1.html King and Papitashvili (2005). [b]Available at: https://ccmc.gsfc.nasa.gov/modelweb/models/nrlmsise00.php Picone et al. (2002). [c]Available at: https://ccmc.gsfc.nasa.gov/modelweb/models/iri2016\text{_}vitmo.php Bilitza et al. (2017). [d]Available at: https://pypi.org/project/pyephem.

$$MAE(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|,$$

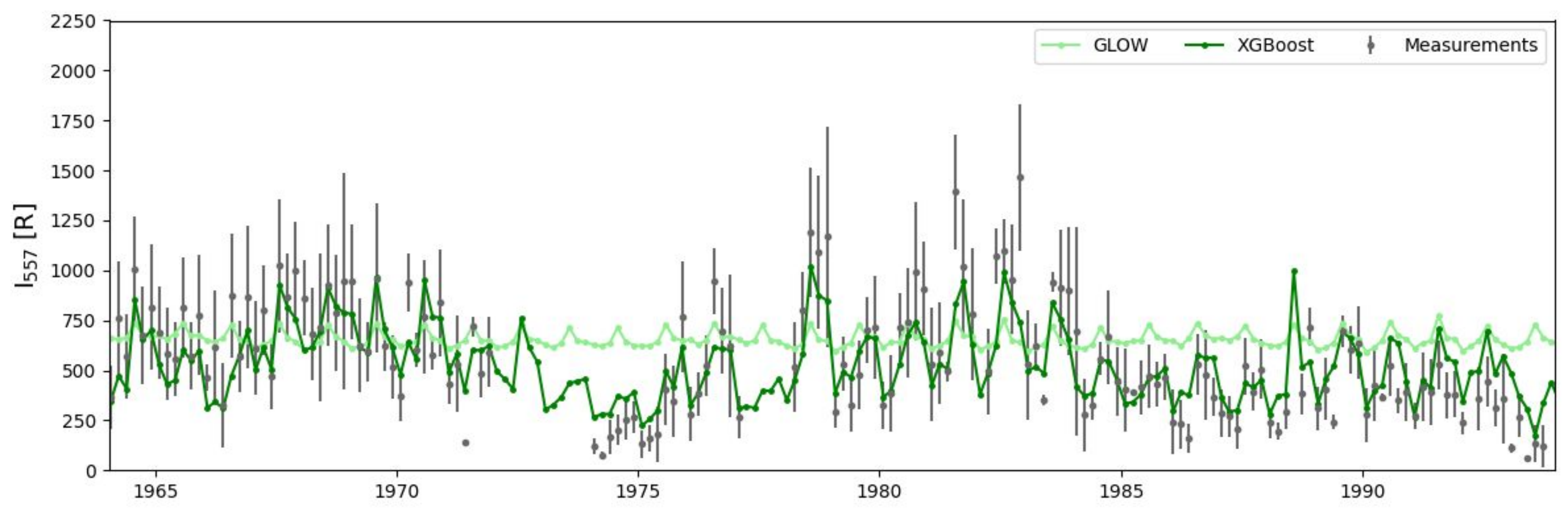
$$MAPE(y,\hat{y}) = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}$$

Table 2

The Performance of Machine Learning Techniques Used for Modeling of Green (557.7 nm) and Red (630.0 nm) Airglow Lines Intensities

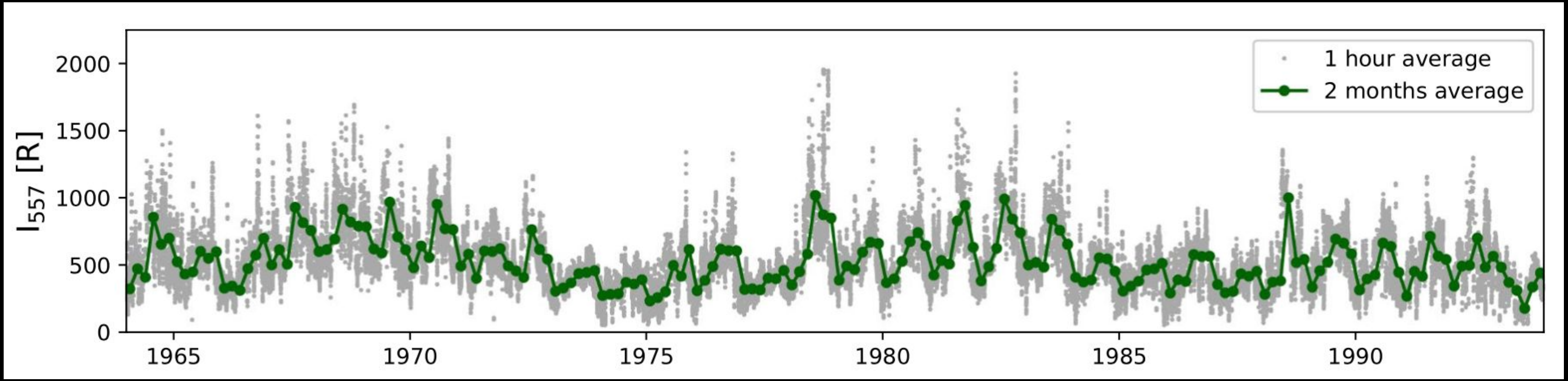
	I 557		I 630	
	MAE	MAPE	MAE	MAPE
Baseline	265 R	78 %	84 R	86 %
Lin. Regression	247 R	65 %	77 R	72 %
Neural Network	146 R	95 %	63 R	90 %
Random Forest	102 R	23 %	53 R	41 %
XGBoost	88 R	16 %	48 R	32 %

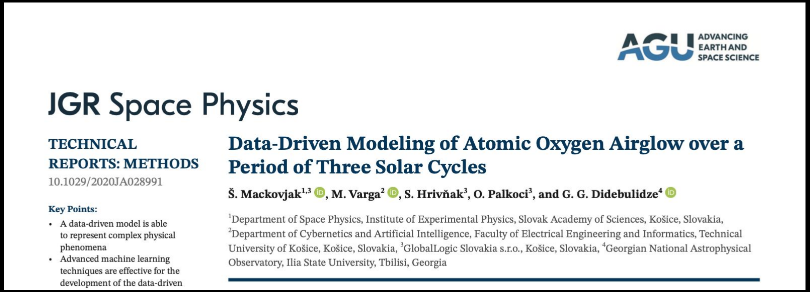
MAE, mean absolute error; MAPE, mean absolute percentage error; XGBoost, Extreme Gradient Boosting.



GLOW
XGBoost
Measurements
I_{557} [R]
2250
2000
1750
1500
1250
1000
750
500
250
0
1965
1970
1975
1980
1985
1990

Results of data-driven model




AGU ADVANCING EARTH AND SPACE SCIENCE

JGR Space Physics

TECHNICAL REPORTS: METHODS
10.1029/2020JA028991

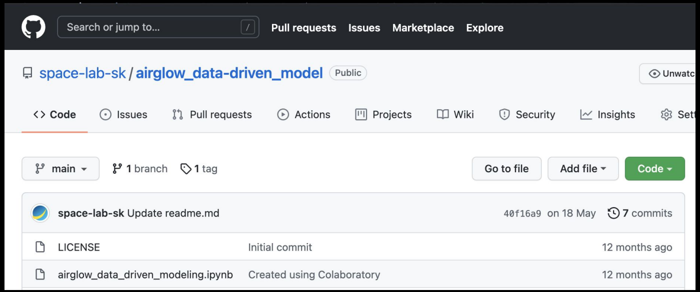
Key Points:
- A data-driven model is able to represent complex physical phenomena
- Advanced machine learning techniques are effective for the development of the data-driven

Data-Driven Modeling of Atomic Oxygen Airglow over a Period of Three Solar Cycles

Š. Mackovjak[1,3], M. Varga[2], S. Hrivňak[3], O. Palkoci[3], and G. G. Didebulidze[4]

[1]Department of Space Physics, Institute of Experimental Physics, Slovak Academy of Sciences, Košice, Slovakia, [2]Department of Cybernetics and Artificial Intelligence, Faculty of Electrical Engineering and Informatics, Technical University of Košice, Košice, Slovakia, [3]GlobalLogic Slovakia s.r.o., Košice, Slovakia, [4]Georgian National Astrophysical Observatory, Ilia State University, Tbilisi, Georgia

https://doi.org/10.1029/2020JA028991

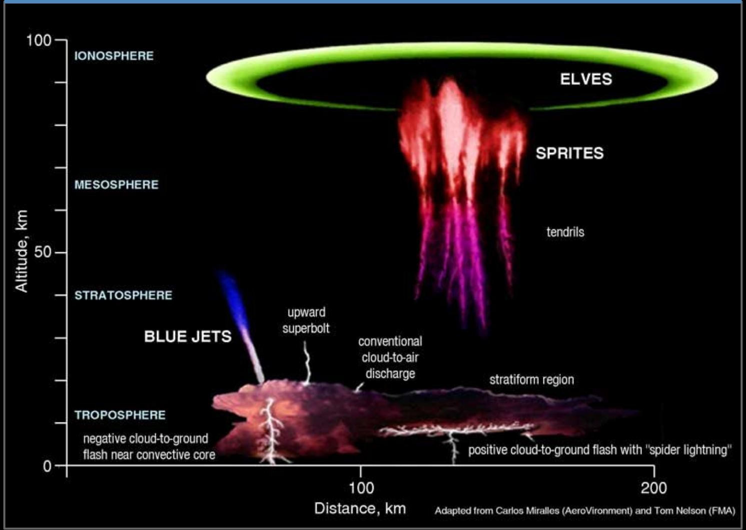


https://github.com/space-lab-sk

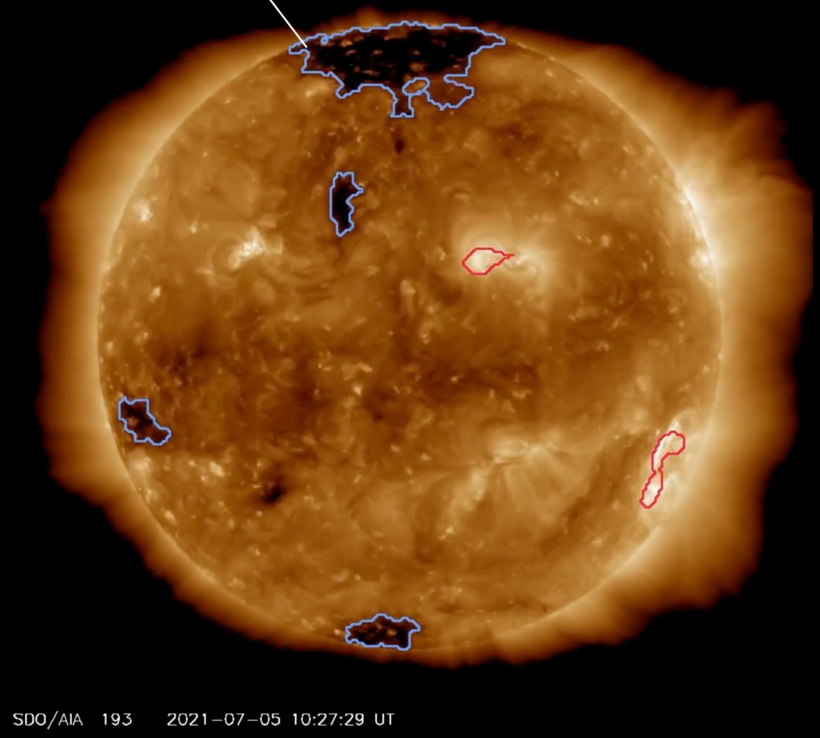
Local effects need to be considered for understanding of **airglow variations**

From Above

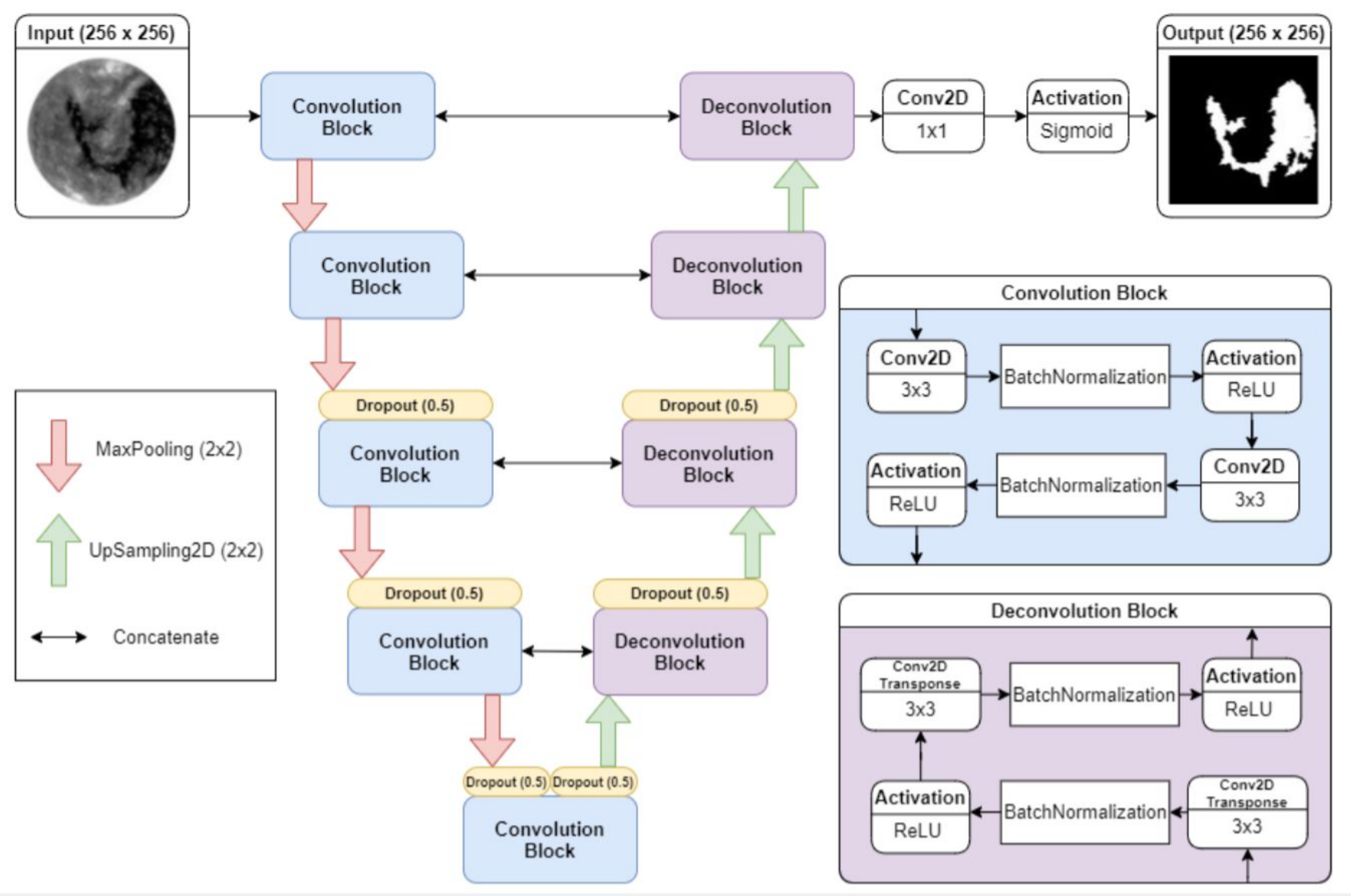
From Below



Our deep learning model for
automatic segmentation
of solar corona



SCSS-Net

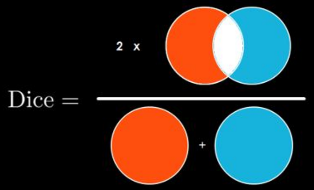


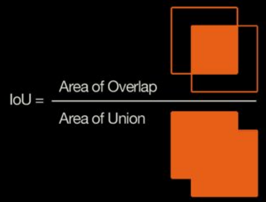
python™

TensorFlow

Keras
A deep learning library

Train dataset	Test set	Dice	IoU
Custom	353	0.83	0.71
SPoCA	353	0.43	0.28
CHIMERA	353	0.85	0.73
Region Growth	353	0.88	0.78





$$\mathrm{Dice} = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$

CH

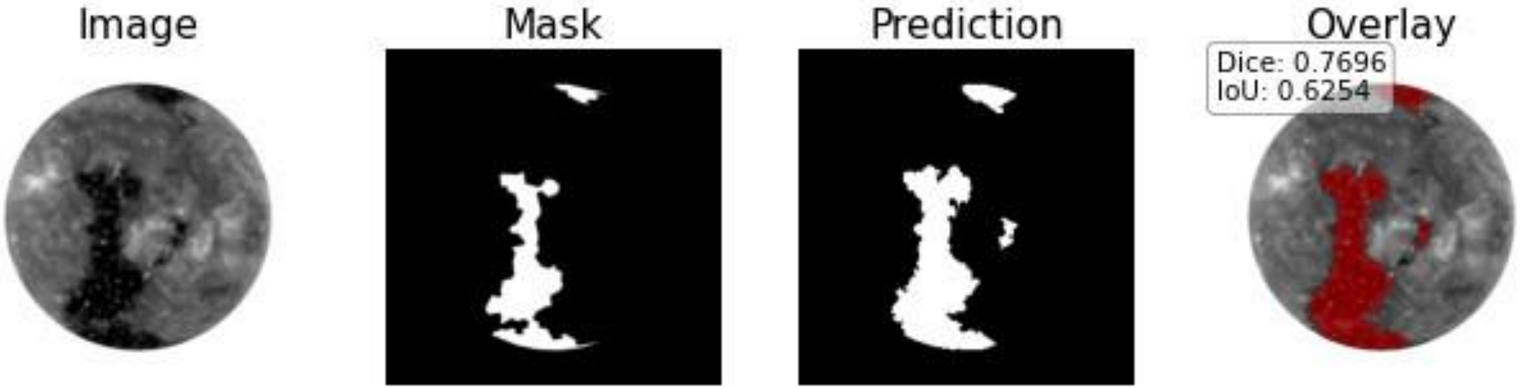
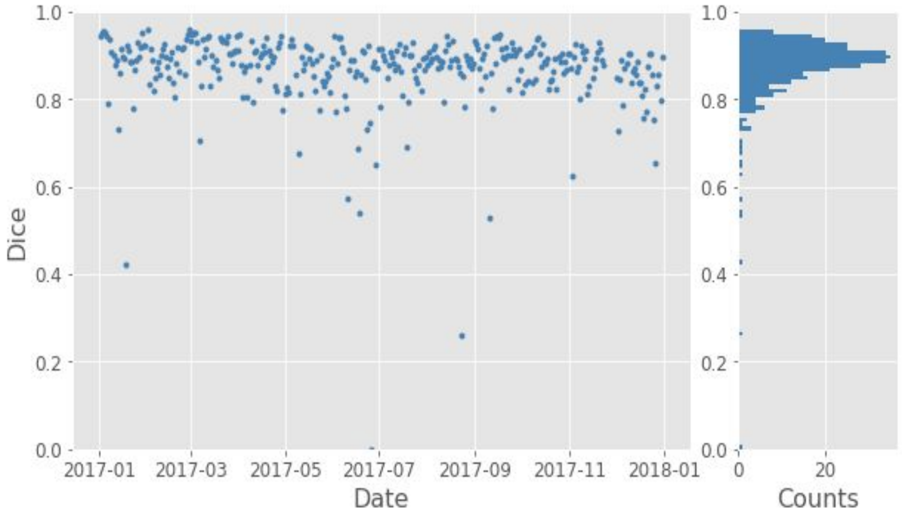
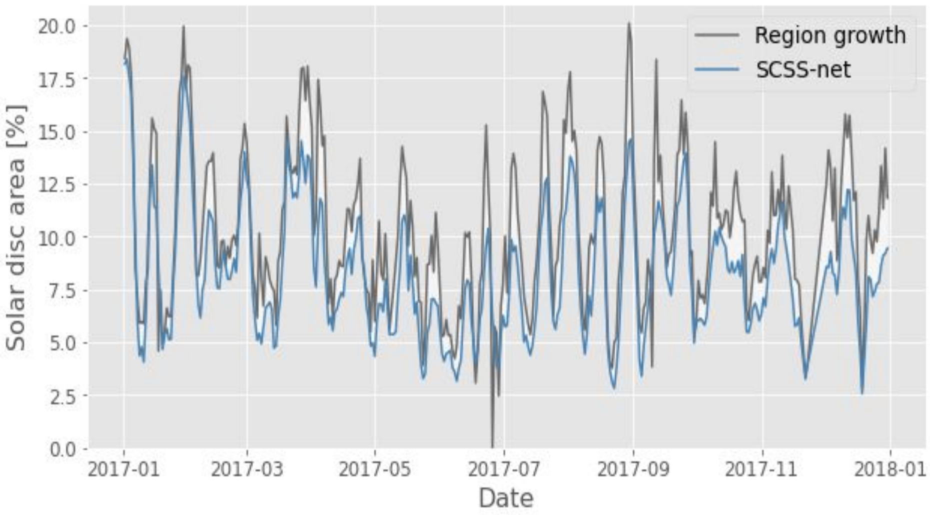


Image
Mask
Prediction
Overlay
Dice: 0.7696
IoU: 0.6254


Dice
Date
Counts
1.0
0.8
0.6
0.4
0.2
0.0
2017-01
2017-03
2017-05
2017-07
2017-09
2017-11
2018-01
0
20


Region growth
SCSS-net
Solar disc area [%]
Date
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2017-01
2017-03
2017-05
2017-07
2017-09
2017-11
2018-01

AR

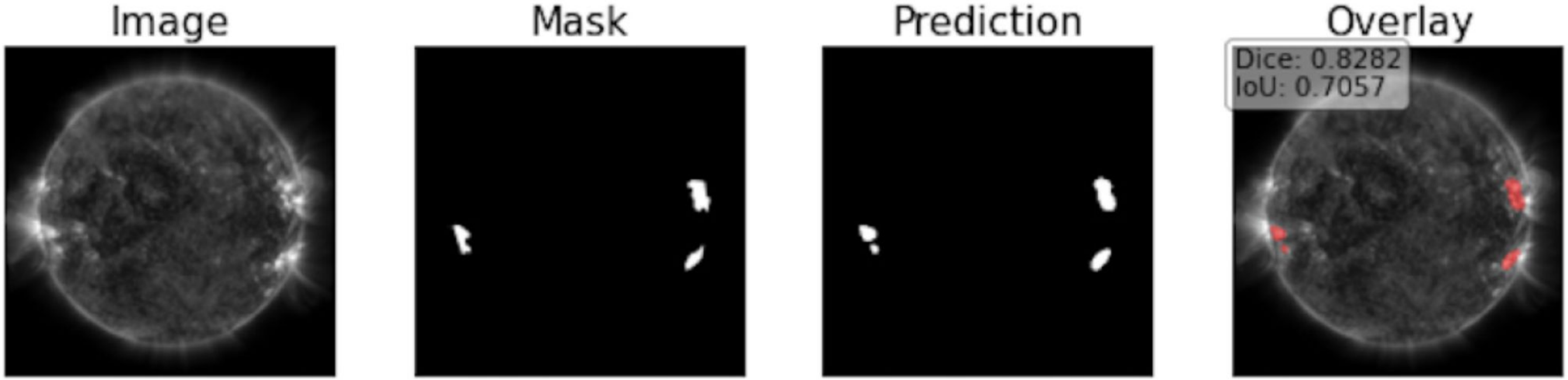
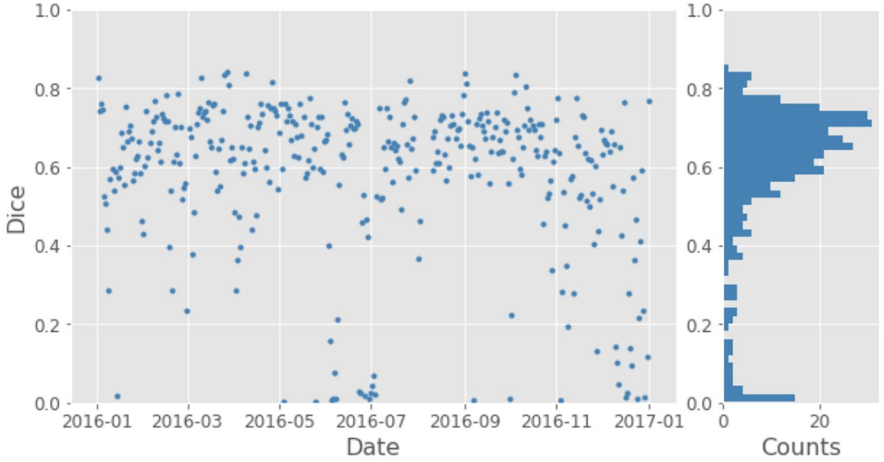
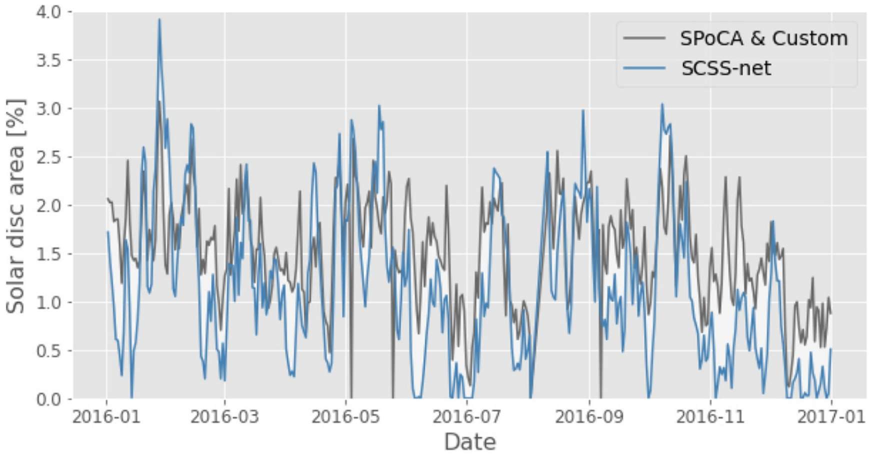
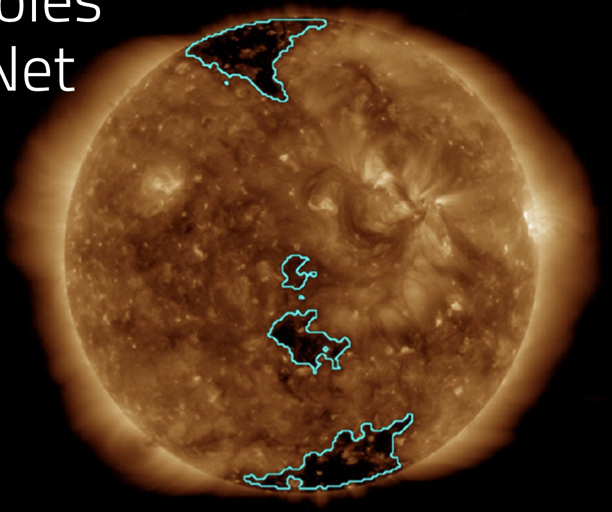


Image
Mask
Prediction
Overlay
Dice: 0.8282
IoU: 0.7057

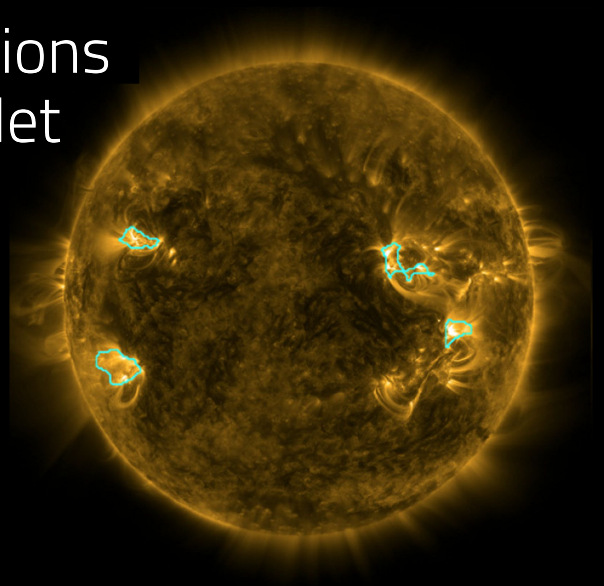

Dice
Date
Counts
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01

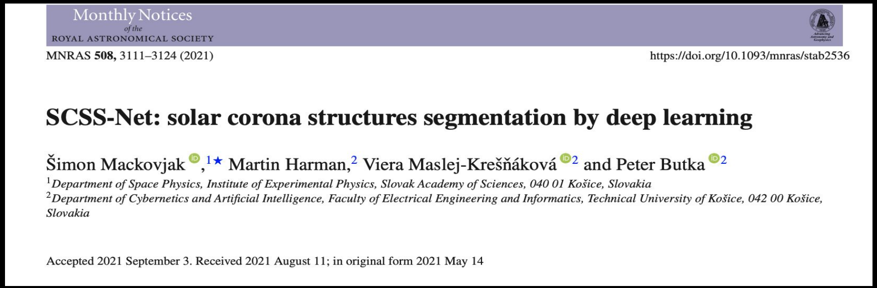

SPoCA & Custom
SCSS-net
Solar disc area [%]
Date

Coronal Holes by SCSS-Net



Active Regions by SCSS-Net





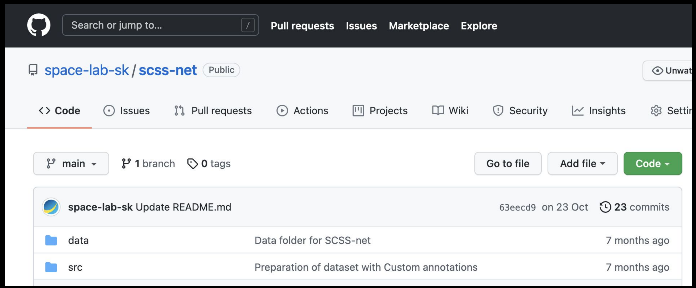
Monthly Notices of the ROYAL ASTRONOMICAL SOCIETY
MNRAS **508,** 3111–3124 (2021) https://doi.org/10.1093/mnras/stab2536

SCSS-Net: solar corona structures segmentation by deep learning

Šimon Mackovjak [1★], Martin Harman,[2] Viera Maslej-Krešňáková [2] and Peter Butka [2]
[1] *Department of Space Physics, Institute of Experimental Physics, Slovak Academy of Sciences, 040 01 Košice, Slovakia*
[2] *Department of Cybernetics and Artificial Intelligence, Faculty of Electrical Engineering and Informatics, Technical University of Košice, 042 00 Košice, Slovakia*

Accepted 2021 September 3. Received 2021 August 11; in original form 2021 May 14

https://doi.org/10.1093/mnras/stab2536

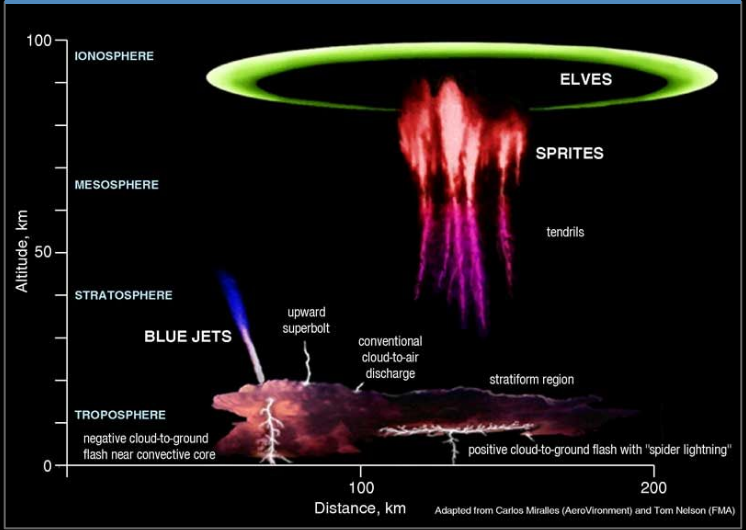


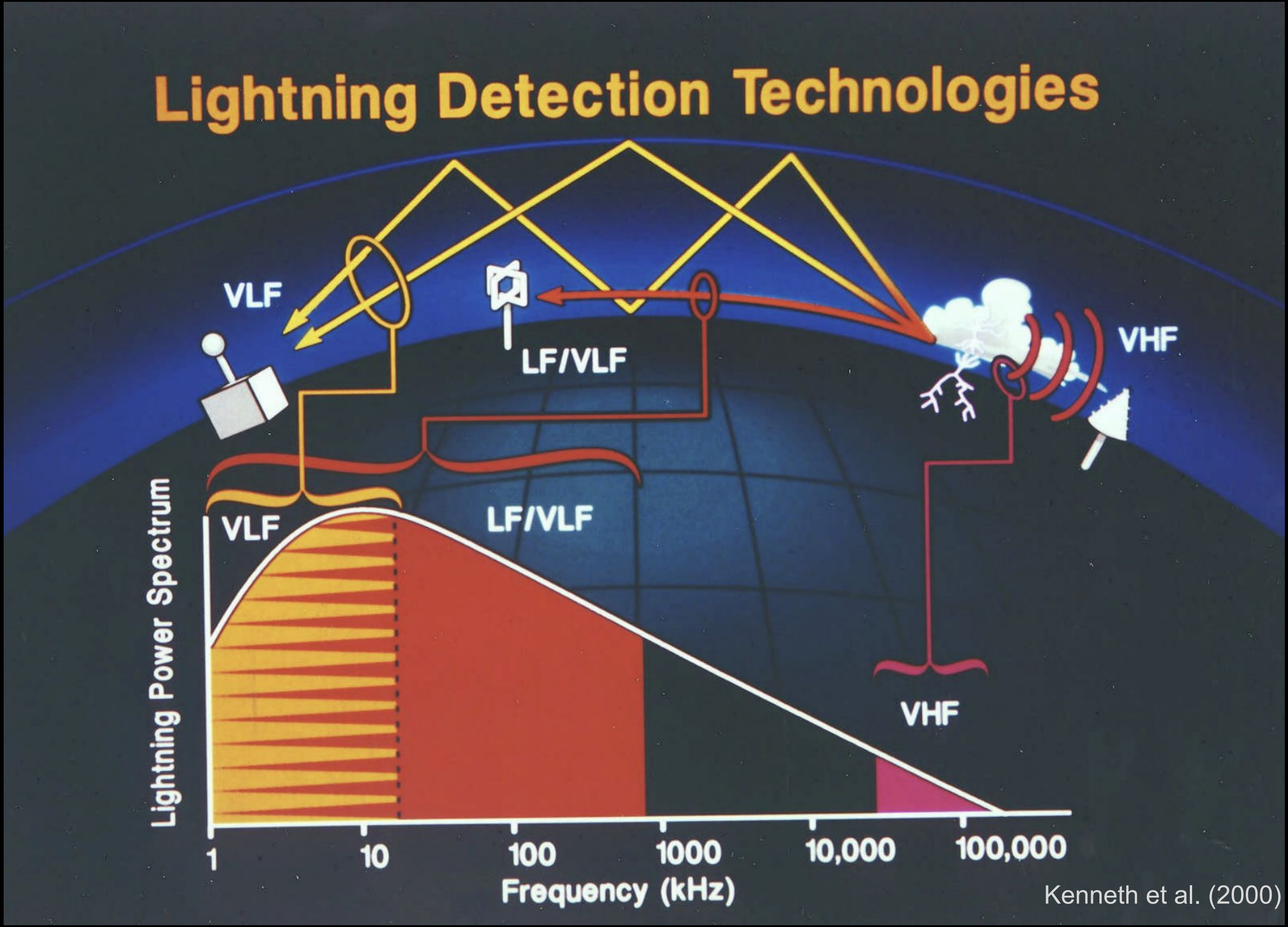
https://github.com/space-lab-sk

Local effects need to be considered for understanding of **airglow variations**

From Above

From Below




Lightning Detection Technologies
VLF
LF/VLF
VHF
Lightning Power Spectrum
VLF
LF/VLF
VHF
1
10
100
1000
10,000
100,000
Frequency (kHz)
Kenneth et al. (2000)

Automatic detection by Deep Learning

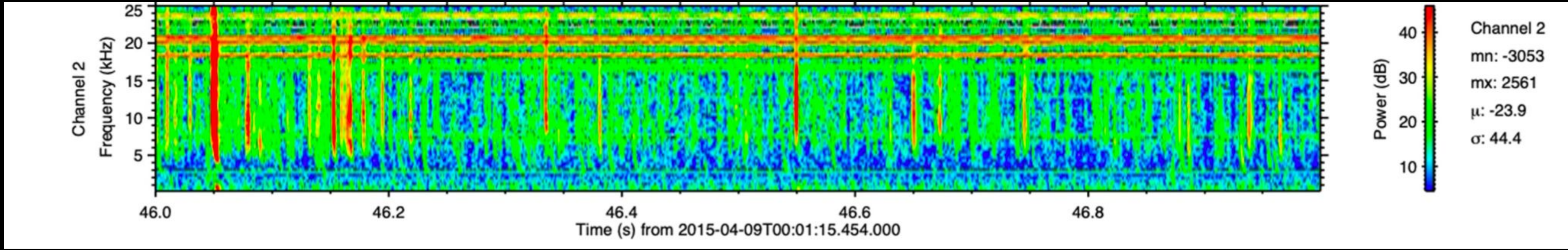
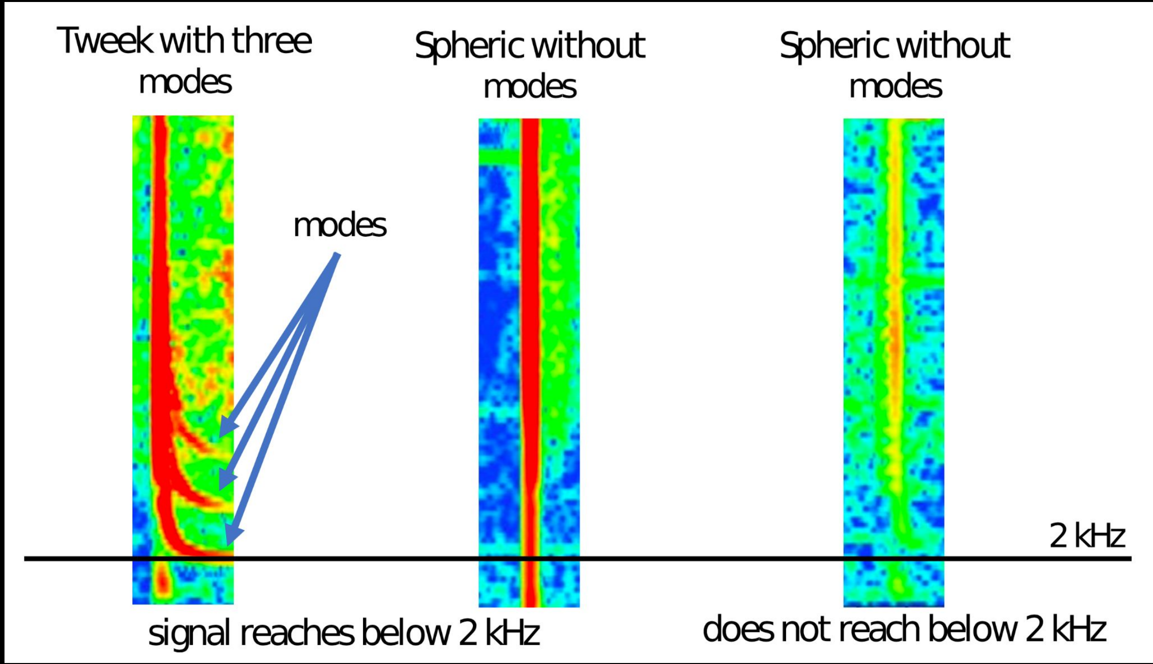


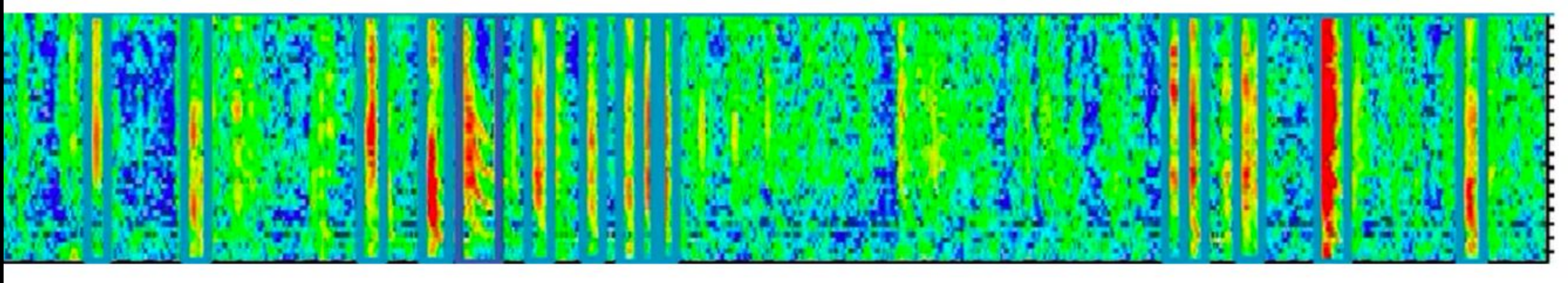
image	event	date	second	milisecond	tweek	f_min<2kHz
8	1	20150902_231933	102	100	1	1
8	2	20150902_231933	102	129	1	1
8	3	20150902_231933	102	153	0	1
8	4	20150902_231933	102	190	1	1
8	5	20150902_231933	102	246	1	1
8	6	20150902_231933	102	417	0	0
8	7	20150902_231933	102	786	0	1
8	8	20150902_231933	102	813	0	1
8	9	20150902_231933	102	864	0	1

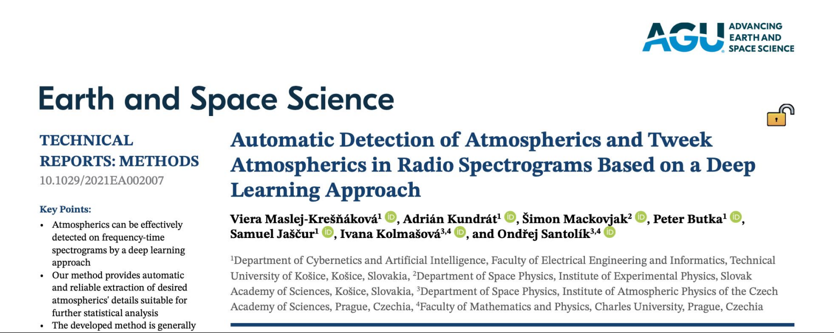


Class	Images	Events	Precision	Recall	F1 score
Sferic	219	1,890	0.74	0.68	0.71
Tweek	219	245	0.58	0.56	0.57
Total	219	2,135	0.72	0.66	0.69

Class	Events	Precision	Recall	F1 score
Over 2 kHz	1,053	0.93	0.96	0.94
Below 2 kHz	914	0.95	0.91	0.93
Total	1,967	0.94	0.94	0.94

Results of atmospherics detection and classification





ADVANCING EARTH AND SPACE SCIENCE

Earth and Space Science

TECHNICAL REPORTS: METHODS

10.1029/2021EA002007

Automatic Detection of Atmospherics and Tweek Atmospherics in Radio Spectrograms Based on a Deep Learning Approach

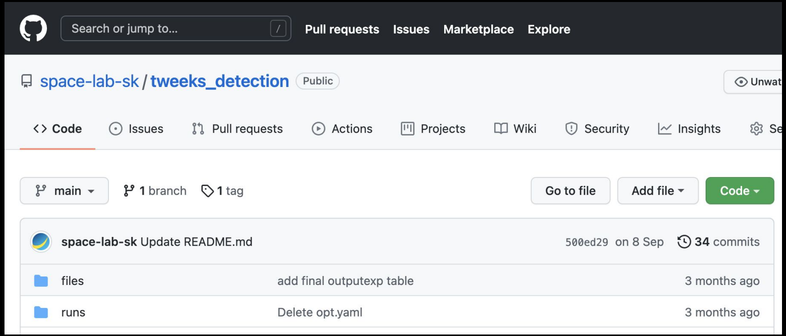
Viera Maslej-Krešňáková[1], Adrián Kundrát[1], Šimon Mackovjak[2], Peter Butka[1], Samuel Jaščur[1], Ivana Kolmašová[3,4], and Ondřej Santolík[3,4]

[1]Department of Cybernetics and Artificial Intelligence, Faculty of Electrical Engineering and Informatics, Technical University of Košice, Košice, Slovakia, [2]Department of Space Physics, Institute of Experimental Physics, Slovak Academy of Sciences, Košice, Slovakia, [3]Department of Space Physics, Institute of Atmospheric Physics of the Czech Academy of Sciences, Prague, Czechia, [4]Faculty of Mathematics and Physics, Charles University, Prague, Czechia

Key Points:

- Atmospherics can be effectively detected on frequency-time spectrograms by a deep learning approach
- Our method provides automatic and reliable extraction of desired atmospherics' details suitable for further statistical analysis
- The developed method is generally

https://doi.org/10.1029/2021EA002007



https://github.com/space-lab-sk

ML techniques for:

- automatic data reduction
- autonomous operation

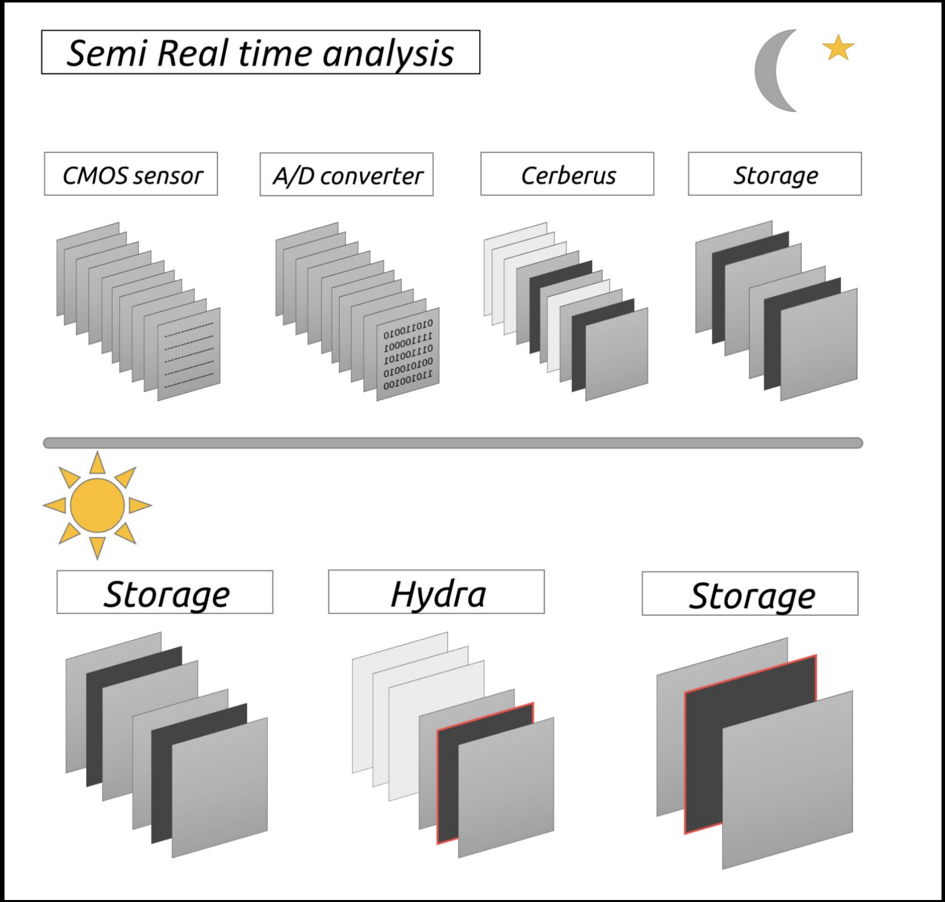

JINST
Published by IOP Publishing for Sissa Medialab
Received: October 4, 2021
Revised: November 30, 2021
Accepted: December 8, 2021
Published: December 21, 2021

TECHNICAL REPORT

Design and construction of hardware and software for autonomous observations of Transient Luminous Events

S. Amrich,[a,b,*] Š. Mackovjak,[b] I. Strhárský,[b] J. Baláž[b] and M. Hančikovský[c]

[a] Charles University, Faculty of Mathematics and Physics, Ke Karlovu 3, 121 16 Praha 2, Czech Republic
[b] Department of Space Physics, Institute of Experimental Physics, Slovak Academy of Sciences, Košice, Slovakia
[c] Faculty of mechanical engineering, Technical University of Košice, Košice, Slovakia



https://doi.org/10.1088/1748-0221/16/12/T12016

Main Goal:

To add Slovakia to ESA SWE network

Conclusions

- Physics is embedded in data
- Data-driven models need a lot of data
- ML techniques automate research

Next steps:

- Put obtained data together and recognize sources of airglow variations

All code, data, papers: https://github.com/space-lab-sk

Disclaimer

The airglow studies are supported by the government of Slovakia through ESA contracts under the PECS (Plan for European Cooperating States).