

# Can Machine Learning solve the „Bz Problem“ in solar coronal mass ejections?

**Martin A. Reiss**

Austrian Academy of Sciences,  
Space Research Institute (IWF), Graz

**Christian Möstl**  
IWF Graz

**Rachel Bailey**  
ZAMG Vienna

**Hannah Rüdiger**  
Know-Center GmbH

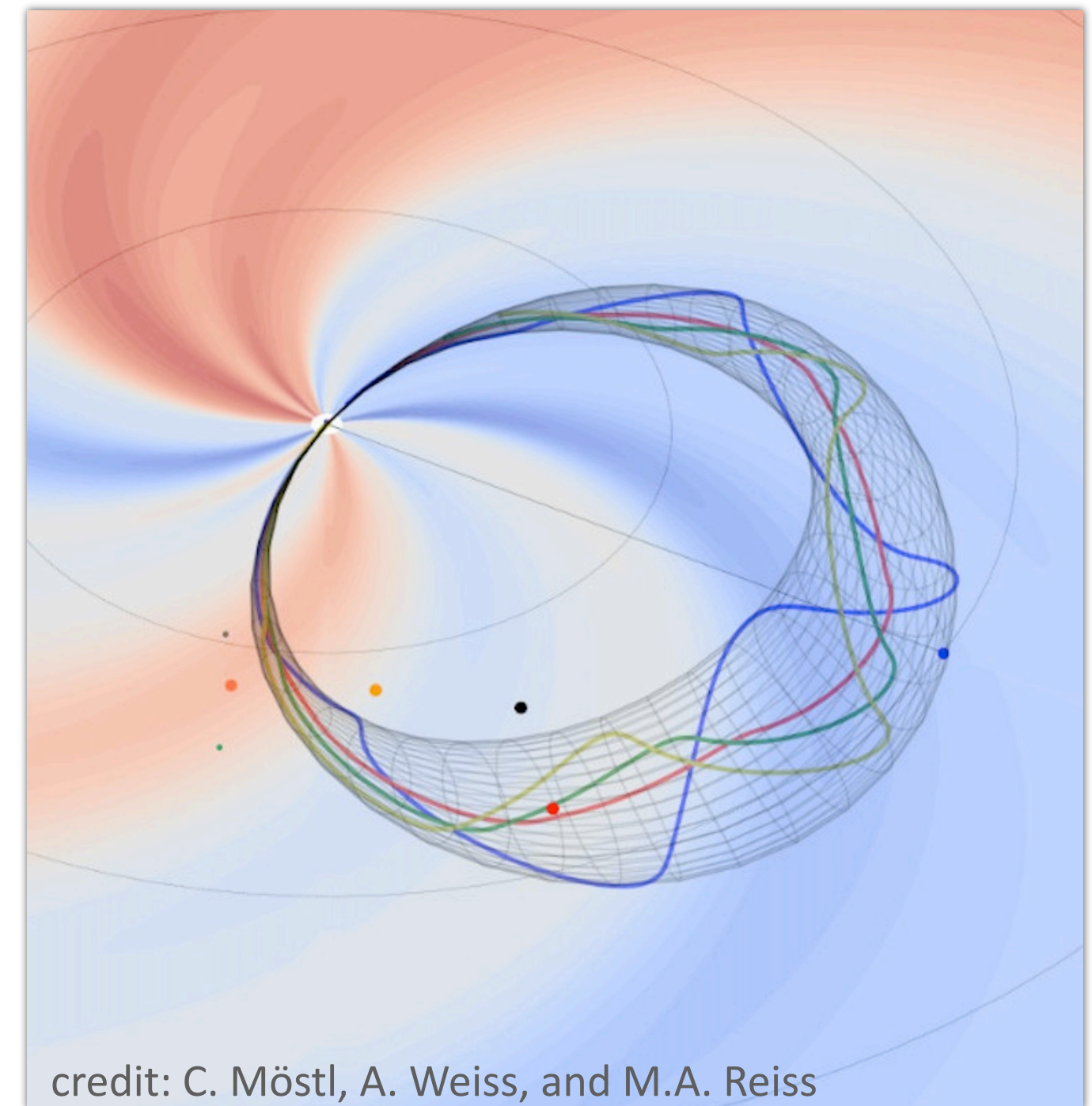
**Ute Amerstorfer**  
IWF Graz

**Tanja Amerstorfer**  
IWF Graz

**Andreas Weiss**  
IWF Graz

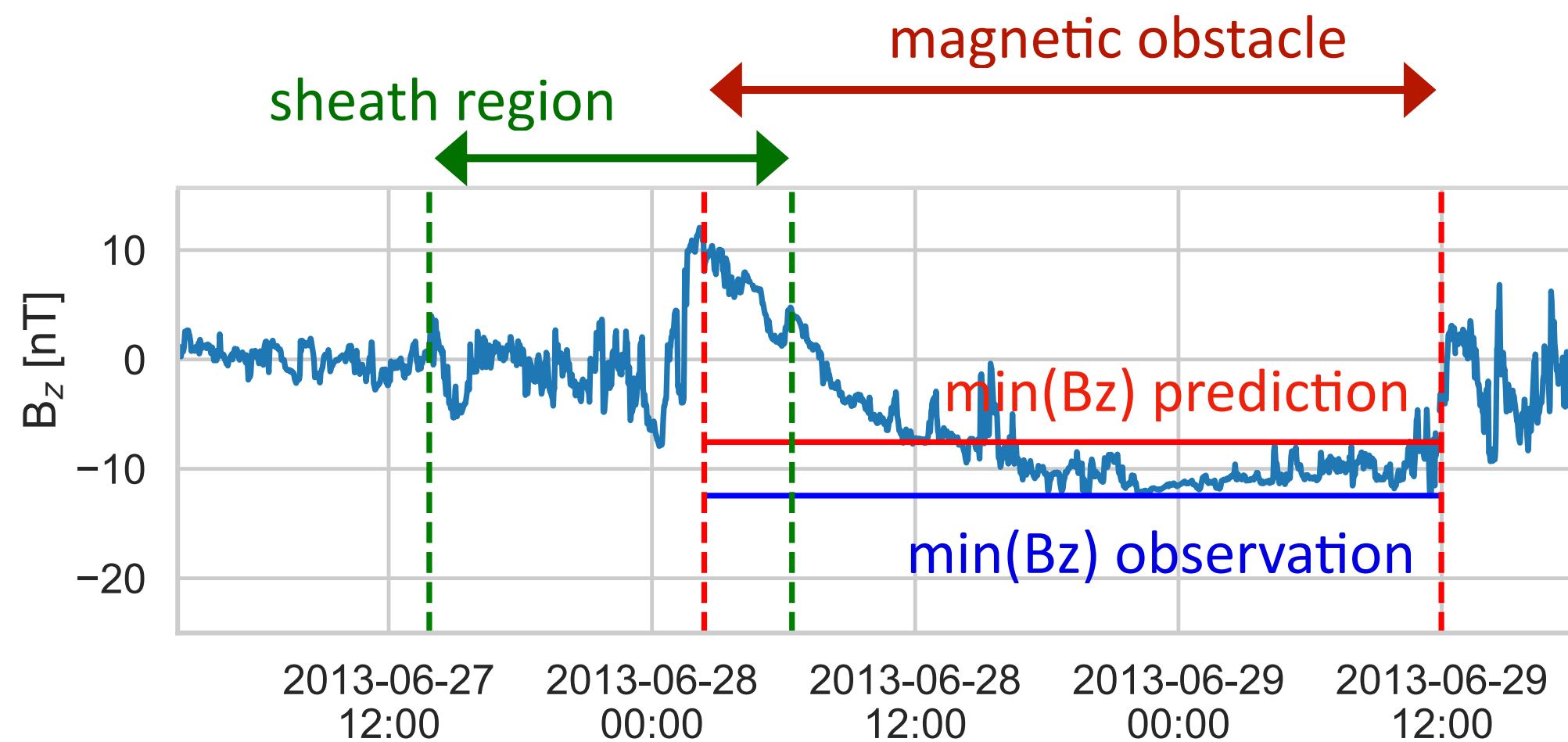
**Jürgen Hinterreiter**  
IWF Graz

**Andreas Windisch**  
Know-Center GmbH



# We study if upstream in situ measurements are useful for predicting estimates of the $B_z$ component in ICMEs before they arrive at Earth

## Overview - Predictive $B_z$ Tool



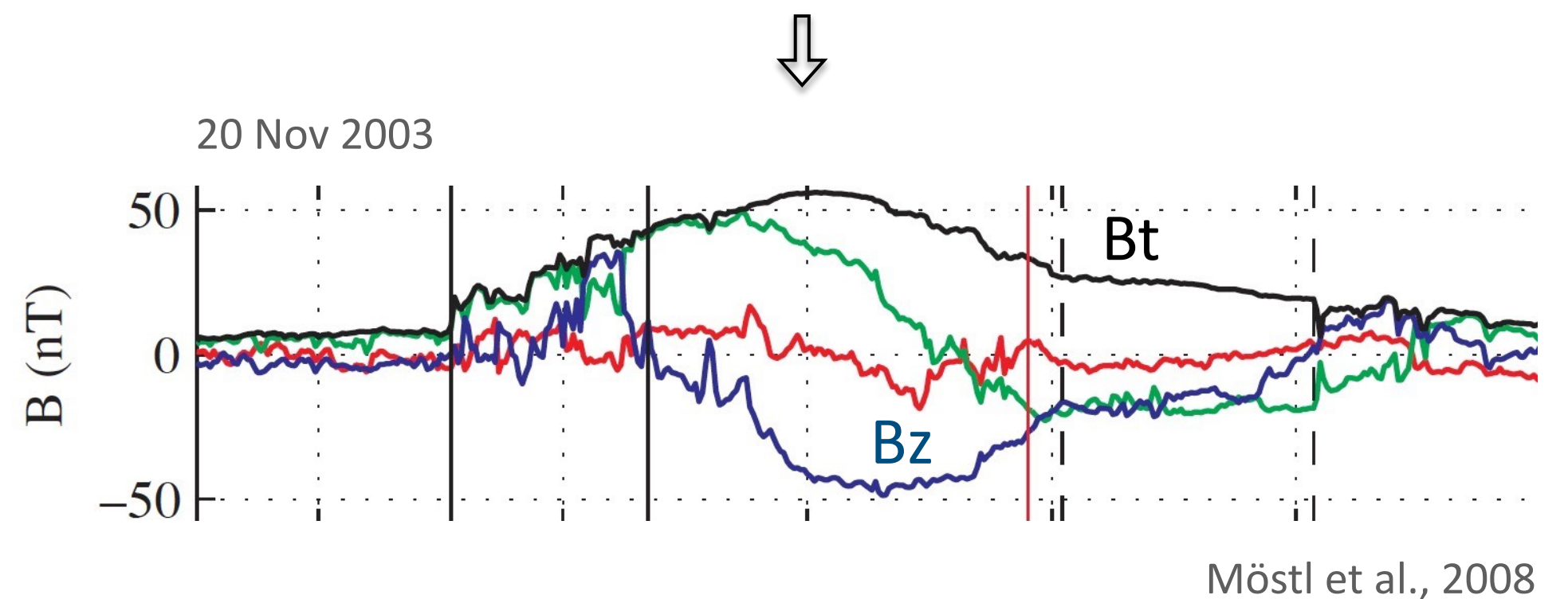
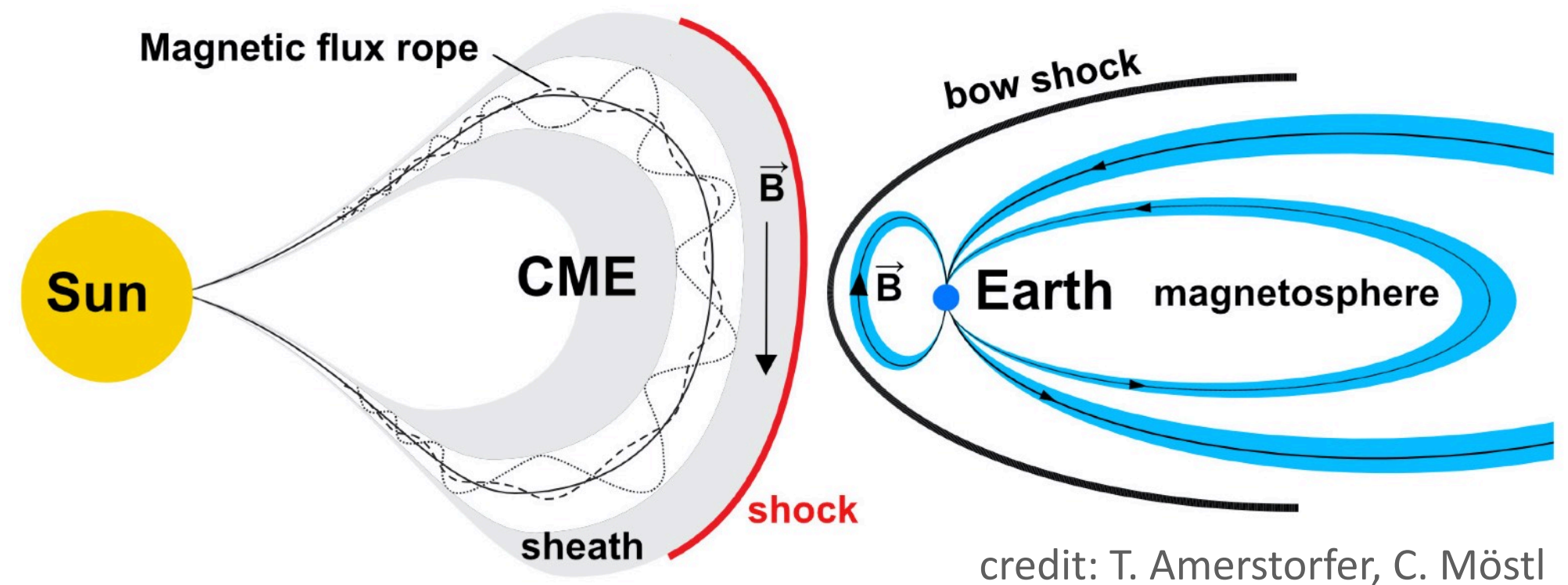
Reiss et al., 2021b

## Content

1. Why does accurate  $B_z$  prediction in ICMEs matter?
2. What's the research question and how does the predictive tool work?
3. What are the results?
4. What are the lessons learned and future objectives?

# Why does accurate $B_z$ prediction in ICMEs matter?

- Energy input into the Earth's magnetosphere is largely determined by the  $B_z$  component of the IMF
- The  **$B_z$  problem** refers to the lack of  $B_z$  forecasting capabilities
- The  **$B_z$  problem** is most challenging during ICMEs when accurate  $B_z$  predictions are needed most
- Progress is hindered by observational limitations (Vourlidas et al. 2019)
- Without a definitive physical solution, it is worthwhile to study predictive tools (Chen et al., 1996, 1997; Riley et al., 2017; Owens et al., 2017; Salman et al., 2018)





# What's the research question and how does the predictive tool work?

## Research Question

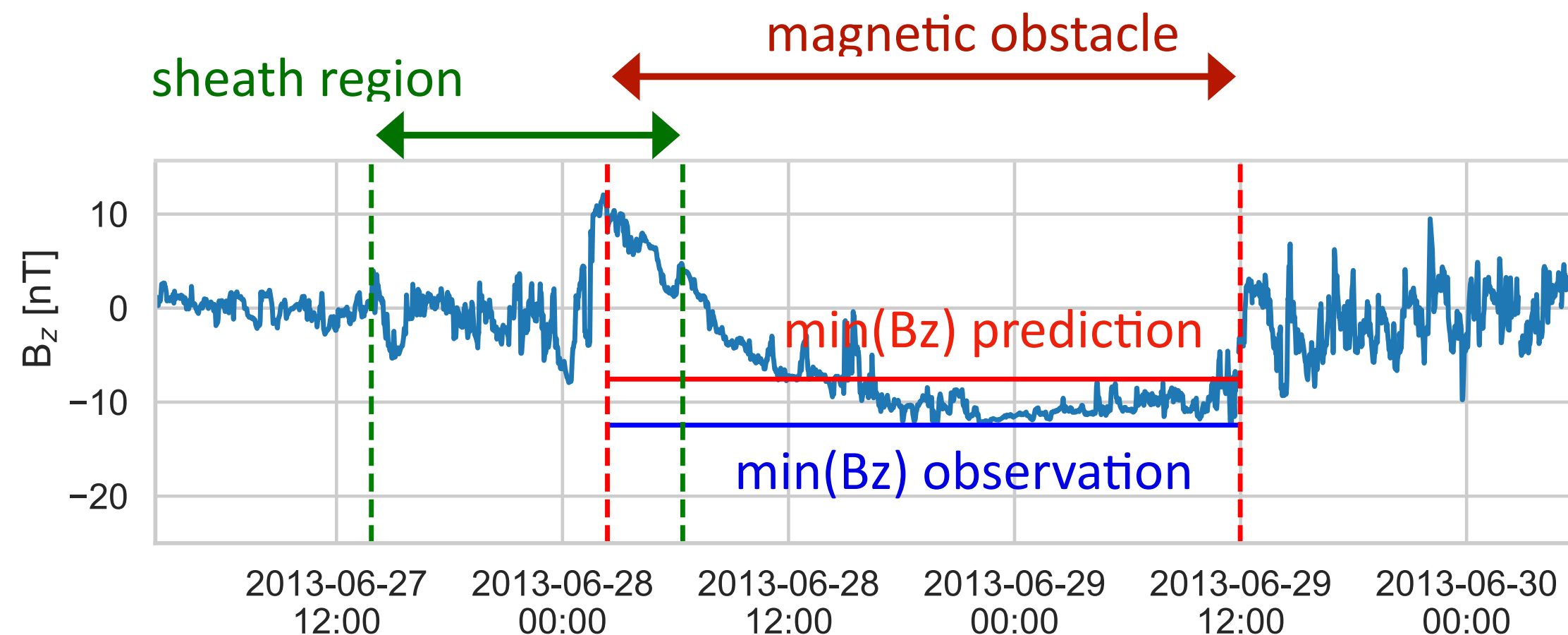
- We study if upstream in situ measurements of the sheath region and the first few hours of the magnetic obstacle are sufficient to predict estimates of the  $B_z$  component in ICMEs

## Proposed Tool

- To do so, we develop a predictive  $B_z$  tool based on machine learning that is trained and tested on 348 ICMEs from Wind, STEREO-A, and STEREO-B measurements (2007 to 2021)

## Tool Components

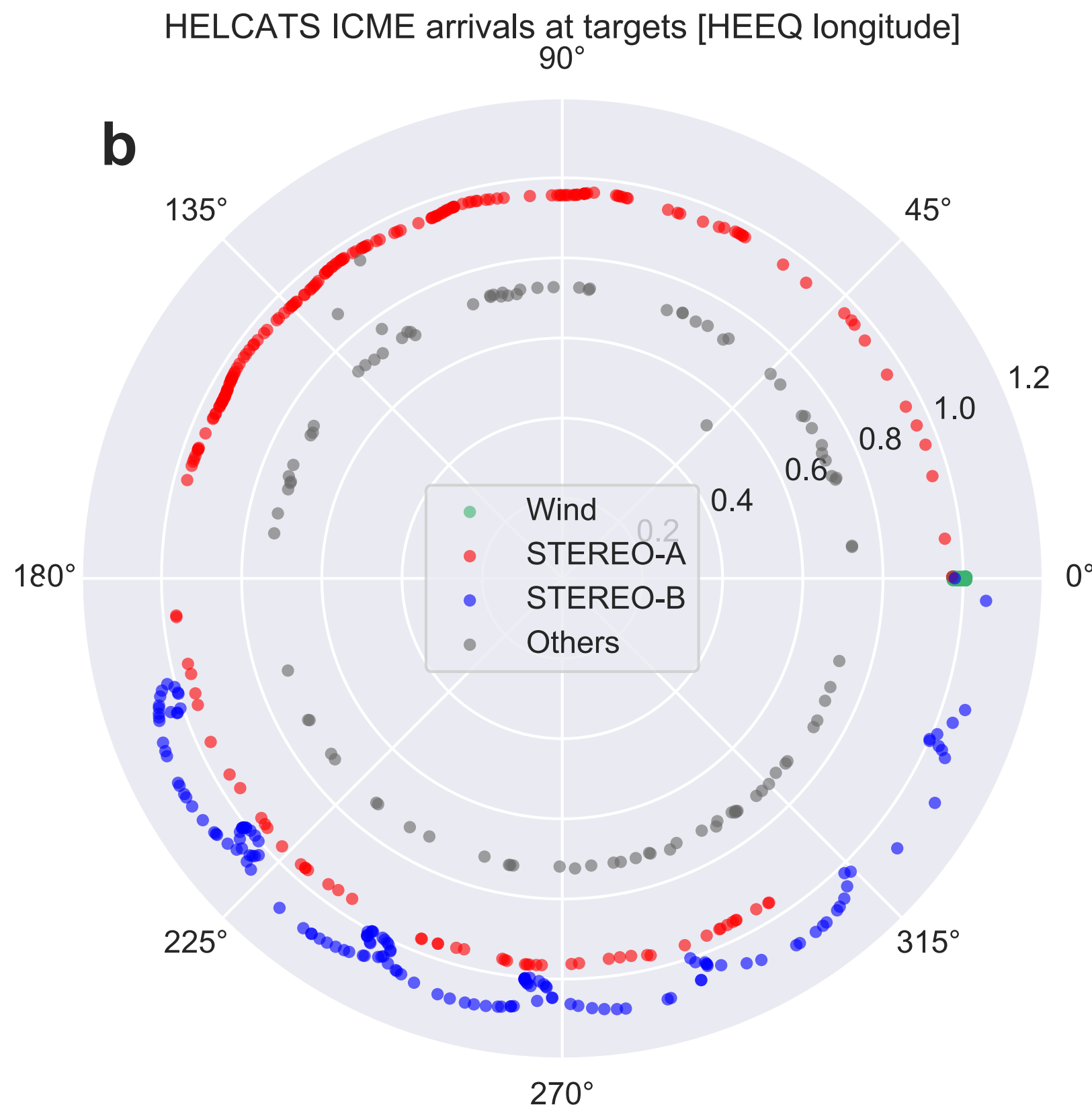
1. Data Input
2. Feature Extraction
3. Machine Learning



# To develop the predictive tool we use the Helio4Cast ICME catalog

## Key Points

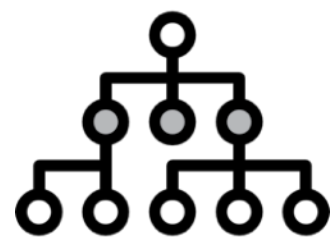
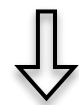
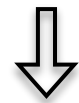
- ICME catalog includes events observed from 2007 to 2021
- Lists physical properties from WIND, STEREO-A, and STEREO-B measured close to 1 AU
- Living ICME catalog consists of manually added events (Möstl et al., 2020)
- From this ICME catalog, we select **348 ICMEs** with a clear magnetic obstacle signature
- Catalog open-access at <https://helioforecast.space/icmecat>



# How does the predictive tool work?

## Input:

42 features  
and 2 targets



## Output:

min(Bz)  
max(Bt)

### 1. Data Input (Features and Targets)

Study physical properties of 348 ICMEs from the ICME catalog including magnetic field data, plasma density and temperature

### 2. Feature Extraction

For 7 different physical properties, we compute 6 statistical measures, which results in 42 features

### 3. Machine Learning Algorithms

Use Linear regressor (LR), random forest regressor (RFR), and gradient boosting regressor (GBR) from the Python package Scikit-Learn

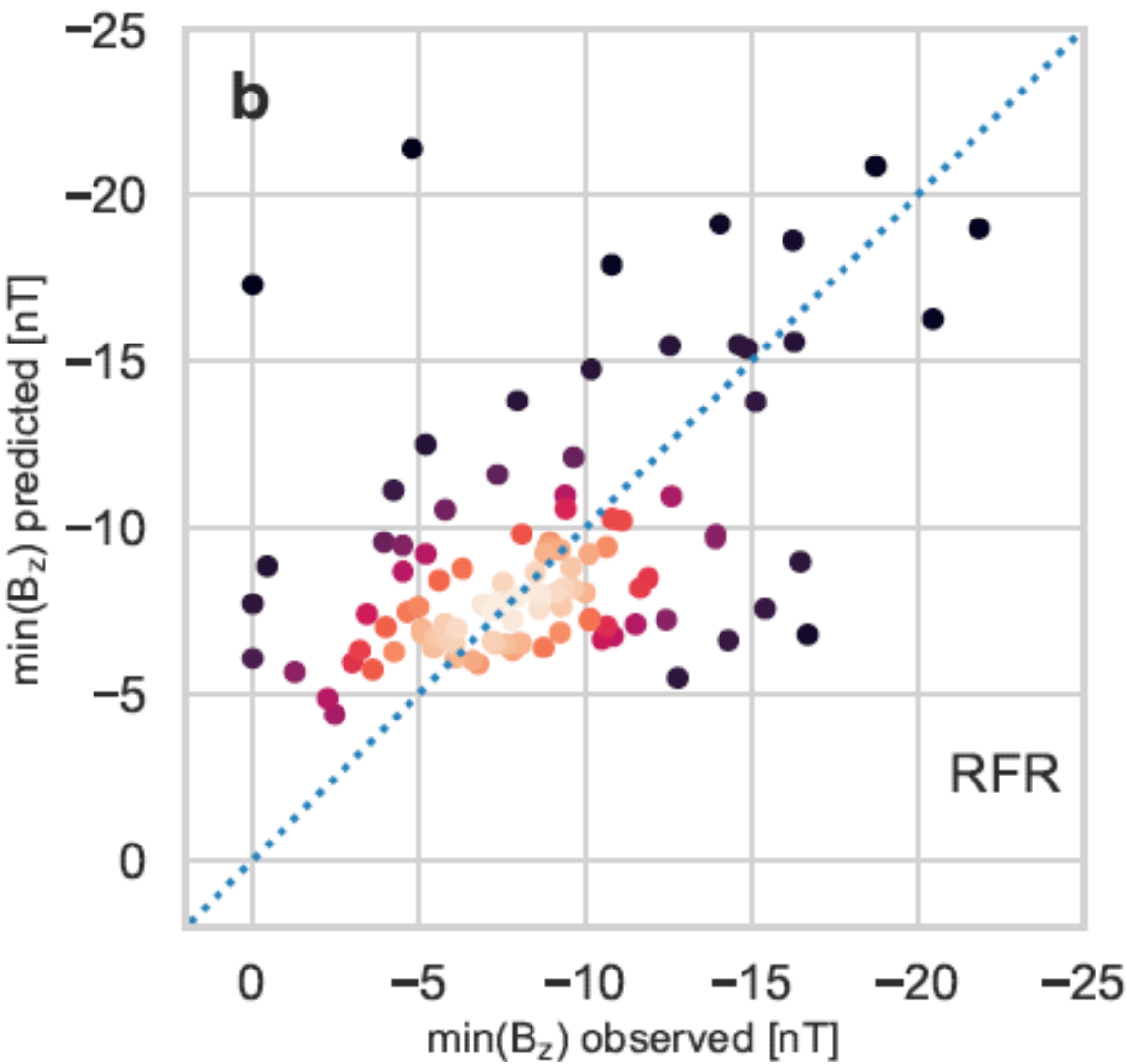
### Training and Testing:

Split the data into 70% training and 30% testing, where the test set is not used in training. During the training, we use a 5-fold cross validation and apply early stopping

# What are the results?

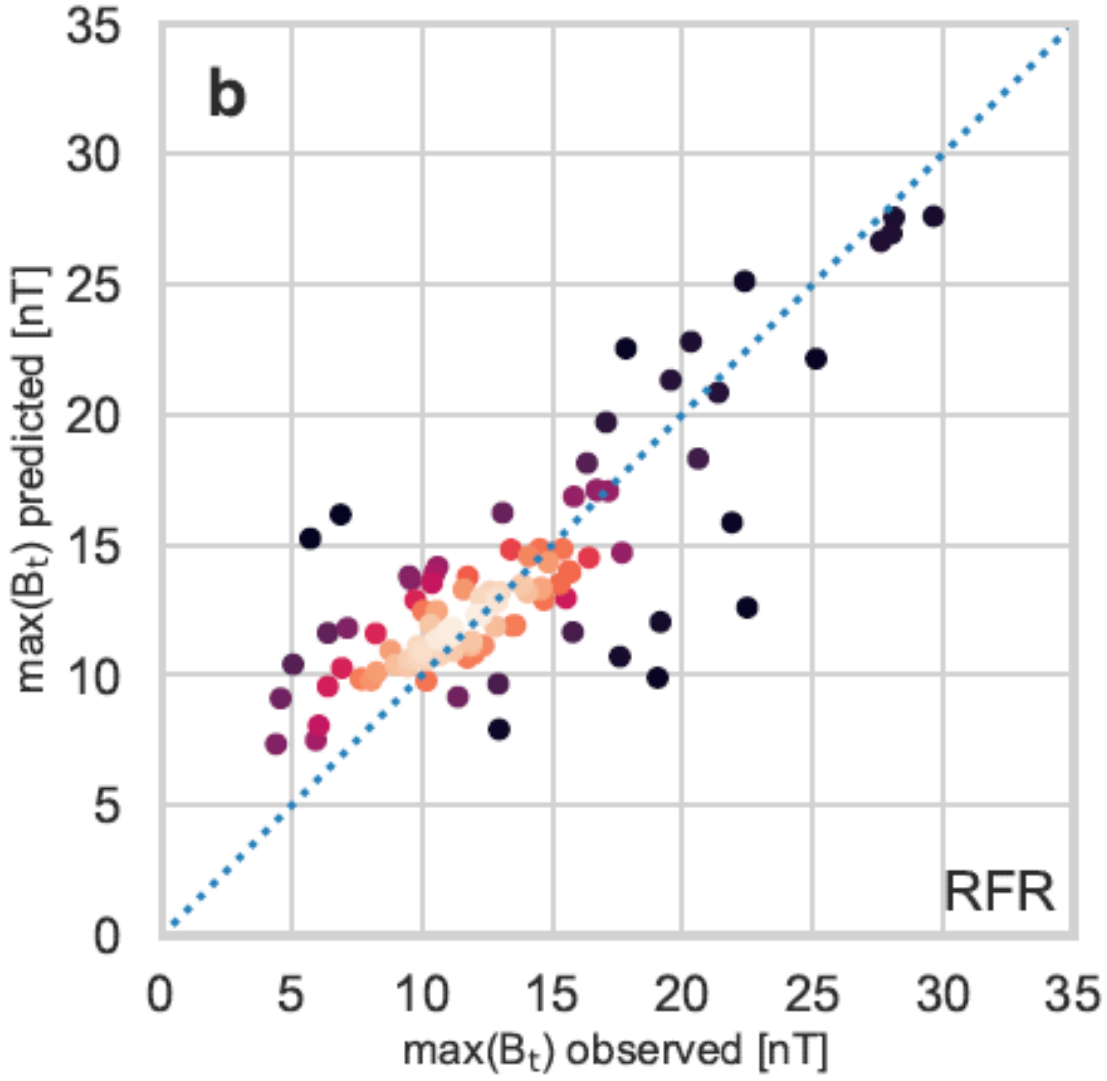
## min(B<sub>z</sub>) - RFR

Sheath region plus 4 hours into MO



## max(B<sub>t</sub>) - RFR

Sheath region plus 4 hours into MO



## Error Measures

min(B <sub>z</sub> )	RMSE [nT]	Corr. Coeff R
GBR	4.77	0.71
RFR	4.73	0.70
LR	11.97	0.32
NN	5.03	

max(B <sub>t</sub> )	RMSE [nT]	Corr. Coeff R
GBR	3.20	0.91
RFR	3.79	0.88
LR	9.48	0.54

Data and figures from Reiss et al., 2021b

# What are the lessons learned?

- $\min(B_z)$  and  $\max(B_t)$  predictions are considerably easier than predicting the  $B_z$  time series
- The question of how well we can extrapolate the predictive  $B_z$  skill to operations remains
- Applying the predictive tool in operations needs an accurate automated ICME detection (e.g., Telloni et al., 2019; Nguyen et al., 2019)
- Combining our predictive tool with an automated ICME detection algorithm introduces new problems we would need to work on

## Future perspectives

- Develop a framework that combines the predictive  $B_z$  tool with automated ICME detection
- Work on new strategies to forecast the temporal evolution of the  $B_z$  component
- Use a semi-empirical flux rope model (Weiss et al., 2021a, 2021b) to fit the rest of the magnetic flux rope from the first few hours of the ICME



# Summary: Machine Learning for predicting the Bz component in ICMs

## Key Points

- Studied the research question if upstream in situ measurements are sufficient for predicting the Bz component in ICMs
- Selected machine learning as tool to answer this question on the example of 348 ICMs.
- Found reasonable results for estimates of the Bz component:  
min(Bz): MAE of 3.12 nT and PCC of 0.71  
max(Bt): MAE of 2.23 nT and PCC of 0.91
- Predictive tool is far from solving the Bz problem but the prototype shows promising first results

## Links

Open Access: [Link](#)

GitHub: <https://github.com/helioforecast>

## Funding

Austrian Science Fund (FWF):  
31659-N27 (PI: Christian Möstl)

## Contact

[martin.reiss@oeaw.ac.at](mailto:martin.reiss@oeaw.ac.at)

[christian.moestl@oeaw.ac.at](mailto:christian.moestl@oeaw.ac.at)