

## Introduction

When Europeans experience a heavy temperature drop in winter, chances are that a Sudden Stratospheric Warming (SSW) has happened. This phenomenon is characterized by a strong temperature increase in the stratosphere, possibly up to 50°C within a few days. Being able to predict these events can help meteorologists improve weather forecasting.

In this work, we aim to classify and predict SSWs. To the best of our knowledge, this is the first successful attempt for the prediction of this phenomenon using machine learning approaches. Although SSWs can be identified after they happened, *climate scientists still don't agree on a uniform definition*. In fact, there have been multiple efforts to find optimal definitions of SSWs [1, 2]. Despite their importance to climate research and meteorology, only few researchers have tried to classify them using supervised [3, 4] or unsupervised [5] learning approaches. Following a systematic approach, we are able to achieve almost perfect classification accuracy for past events and decent results in the prediction of SSWs.

## Experimental Setup

### Input Data and Pre-Processing

- Raw input: simulated data (2959 years) [7], real data (58 years) [8]
- Over 9TB of raw data
- Pre-processed input: time series (210 days x 3 variables)
- Labels for the three most widely used definitions: CP07, U&T and U65 [1,2]

### Tasks

1. **Classification:** Given time series data for the entire winter, determine whether an SSW happened or not (binary classification)
2. **Prediction:** Given time series data for some days in a winter, predict whether an SSW will happen in one of the next week(s)

### Evaluation Methodology

- Simulated data: 5-fold cross-validation
- Real data: Training on full simulation dataset and testing on full real dataset

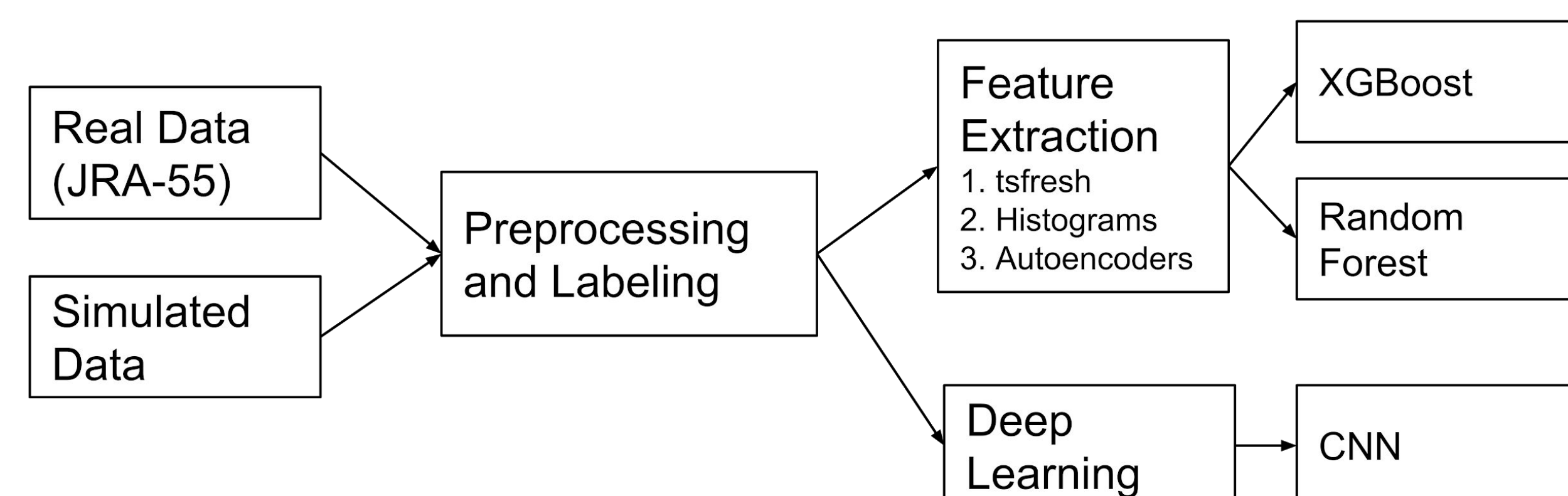


Fig 1. Overview of the project pipeline

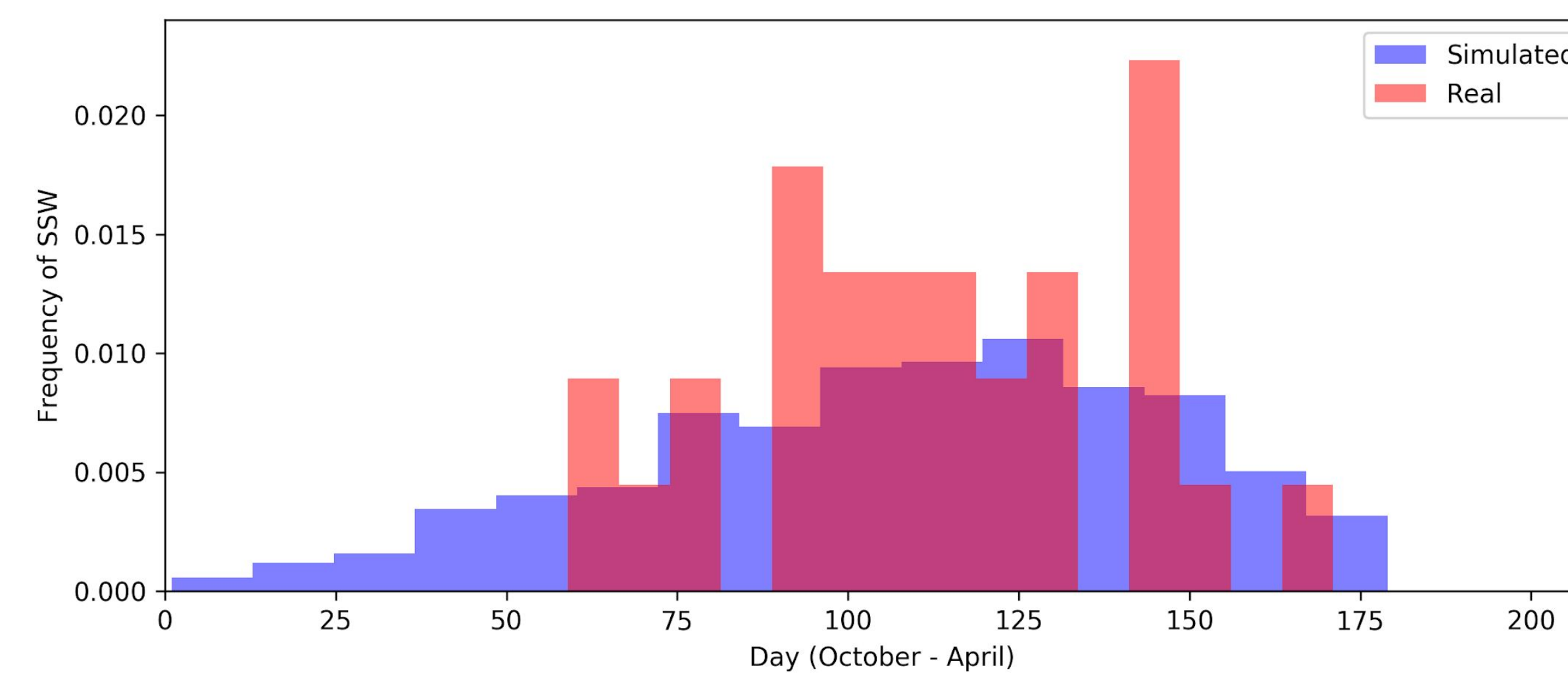


Fig. 2. Distribution of SSWs for real and simulated data

## Classifying SSWs

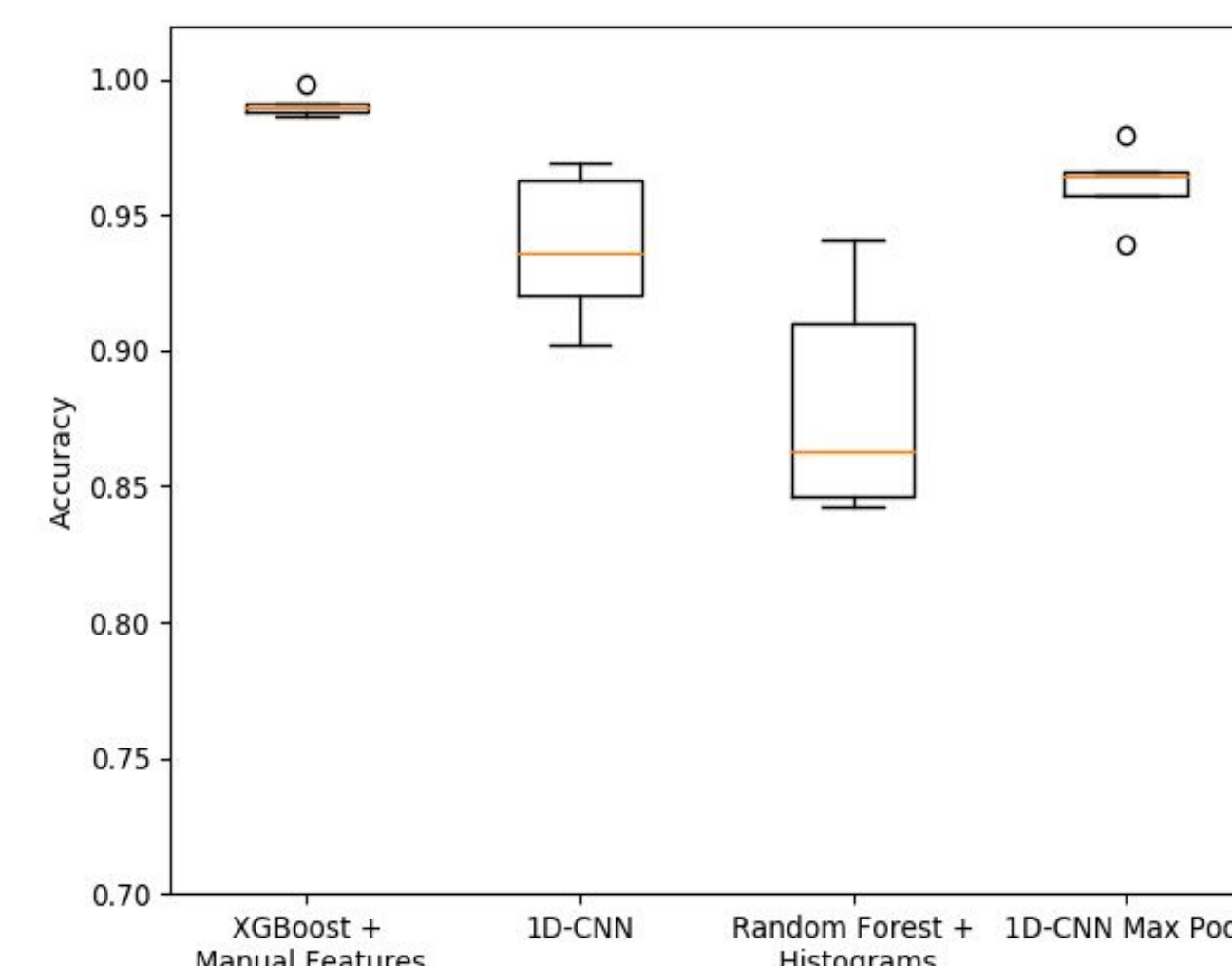


Fig. 3. Classification accuracy on the simulated data using various classifiers

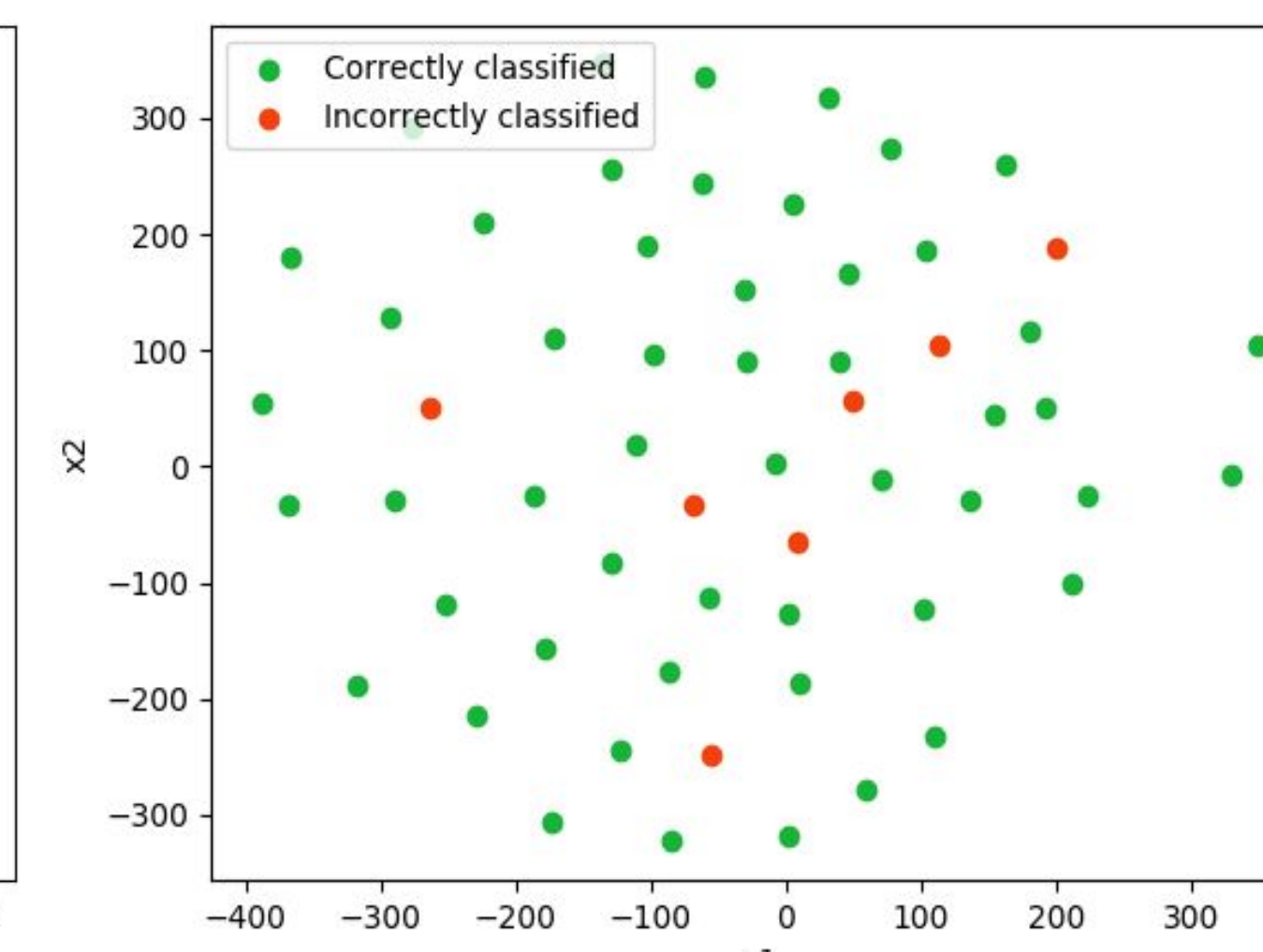


Fig. 4. 2-dimensional T-SNE embeddings of the real data, classified using the XGBoost classifier and manual features

## Predicting SSWs

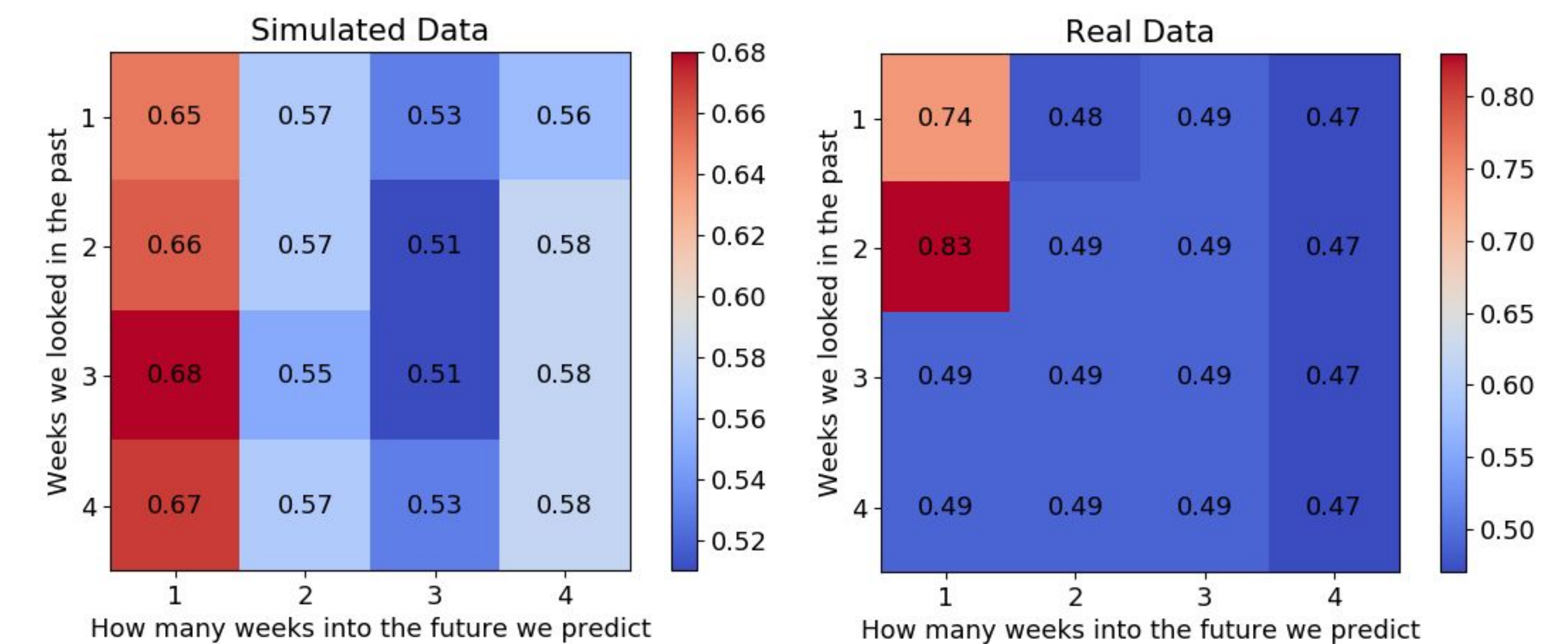


Fig. 5. F1 scores for CP07 in February using the XGBoost classifier with manual features

## Conclusions

- We achieved almost perfect classification results using various definitions and classifiers.
- We showed that it is achievable to predict SSWs within a horizon of one week using machine learning approaches.
- We found deep learning approaches for the prediction task to perform rather poorly.
- Even deterministic dynamical systems cannot predict an SSW for a horizon of more than a few days [6].
- We hope that our approach will make a step towards a better prediction of SSWs over a longer period in the future and support meteorologists in weather forecasting.

## References

1. Butler et al. Optimizing the definition of a sudden stratospheric warming. *Journal of Climate*, 31(6):2337ff. 2018.
2. Butler et al. Defining sudden stratospheric warmings. *Bulletin of the American Meteorological Society*, 96.11 1913ff. 2015.
3. Blume et al. Supervised learning approaches to classify sudden stratospheric warming events. *Journal of the Atmospheric Sciences*, 69(6):1824ff. 2012.
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5. Coughlin et al. A continuum of sudden stratospheric warmings. *Journal of the Atmospheric Sciences*, 66(2):531ff. 2009.
6. Karpechko et al. Predictability of sudden stratospheric warmings in the ecmwf extended-range forecast system. *Monthly Weather Review*, 146(4):1063ff. 2018.
7. Vallis et al. Isca, v1. 0: a framework for the global modelling of the atmospheres of earth and other planets at varying levels of complexity. 2018.
8. Kobayashi et al. *Journal of the Meteorological Society of Japan*. Ser. II, 93(1): 5ff. 2015.

| Definition | Rank | Feature   |
|------------|------|---|
| CP07       | 1    | Location of the first minimum of the wind at 60° latitude |
|            | 2    | Number of x-axis crossings of the wind at 60° latitude    |
|            | 3    | Minimum of the wind at 60° latitude                       |

Table 1. Feature importance ranking for classification by the XGBoost classifier for the CP07 definition