Predicting and Understanding Drought

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To use **ECMWF/Copernicus open datasets** to evaluate machine learning (ML) techniques to **better predict one specific kind of an extreme weather event**, e.g. drought or hurricanes; provide templates for future ML work

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Project Overview

Robust, useful pipeline

Predictive System for Agricultural Drought

Interpretable Machine Learning

Communicate Results

Robust, useful pipeline

Export / download → Engineering → Model Training → Analysis

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Predictive System

Agricultural Drought

Target: Vegetation Health Index (VHI) at end of Season

Inputs: Meteorology (Temp, Precip), Hydrology (Soil Moisture), Climate Vars (Nino3.4), Static Variables (Orography)

Challenges: Encoding spatial-temporal information, how to utilise climate variables, masking, Vegetation health observed from satellites?

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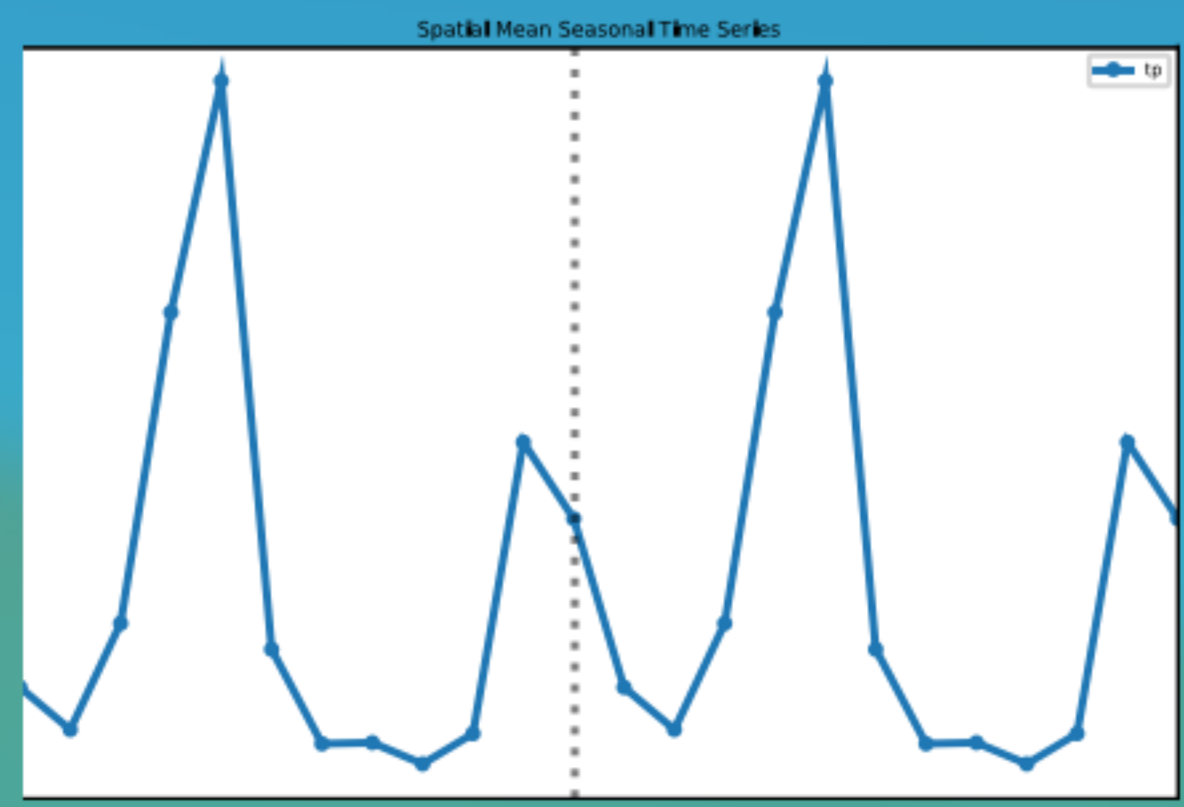
Predictive System



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Predictive System

Decision Trees

Gradient Boosted Trees: XGBoost
Random Forest: Scikit-learn

Neural Networks

RNNs: PyTorch
Linear Models: PyTorch
Segmentation Models: PyTorch

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Predictive System

Aim 1: Forecast

From preceding conditions can we forecast a value ahead of time? This requires us to learn the relationship between the previous conditions and the current conditions.

Goal: Predictive Accuracy

Challenge: Are we reproducing / competing with physically based models?

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Predictive System

Aim 2: Identify Correlations

Can we use the high dimensional fields (SST, SLP) to identify connections between remote regions in space and time.

Goal: Identify climate drivers of variability from data

Challenge: Crazy high dimensions (atmospheric levels [z], geographic regions [x,y], lagged in time, multiple variables - 5D space)

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Predictive System

Aim 1: Forecast

Operationalise

$$f(X_{train}) =$$

$$f(X_{SEAS5}) =$$

where

precip temp soil M

$X =$

t-1
t-2
...
t-n

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Predictive System

Aim 2: Identify Correlations

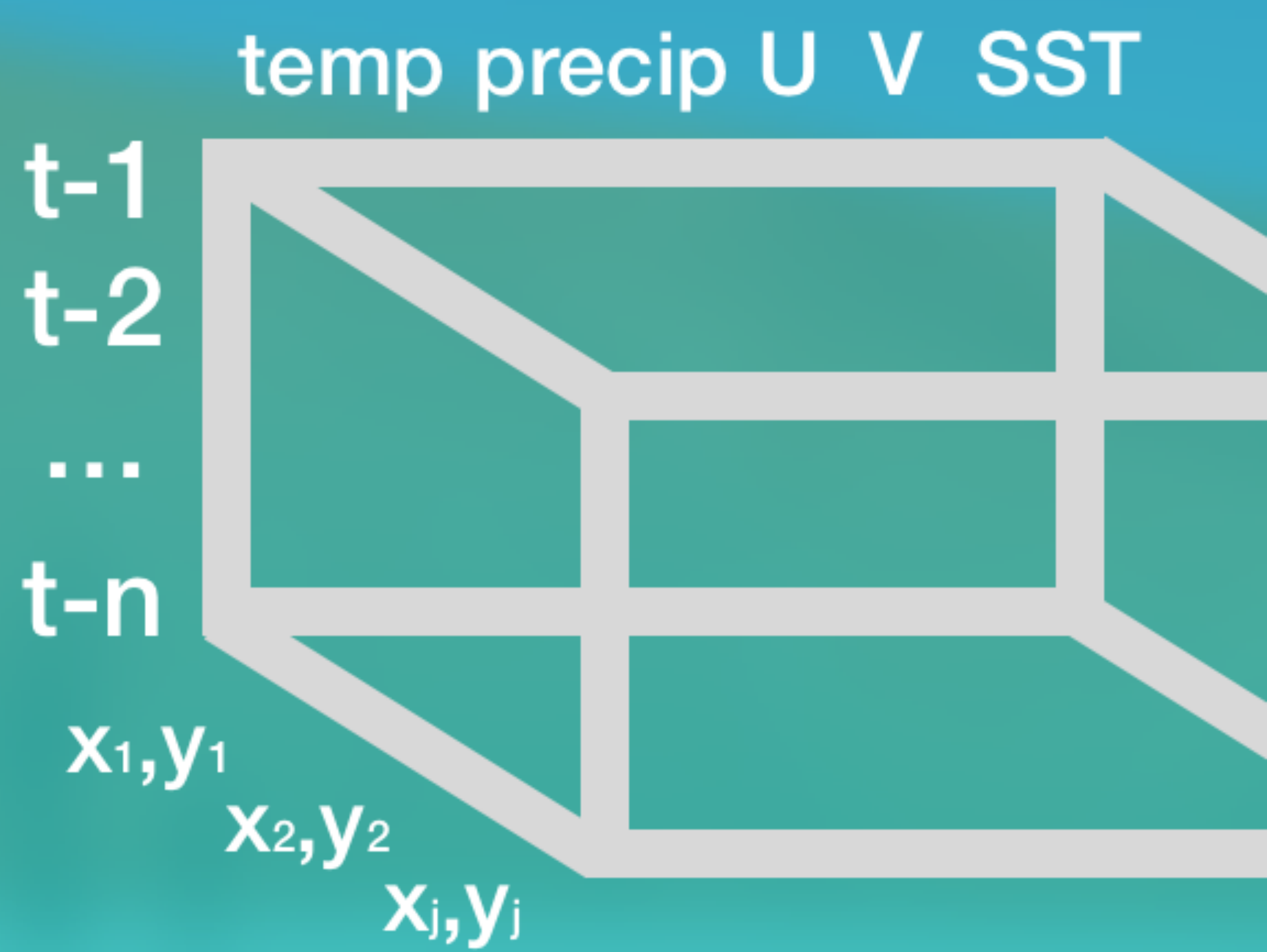
Operationalise

$$f\,(\,X_{train}\,) =$$

$$f\,(\,X_{now}\,) =$$

where

$X =$



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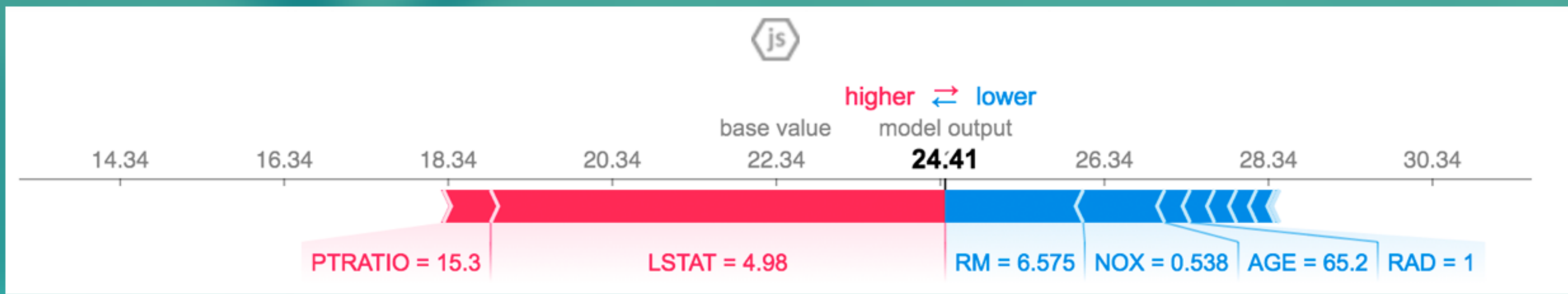
Interpret Models

SHAP Values

A method for assigning payouts to players (features) depending on their contribution to the total payout (predictive accuracy).

$$\text{importance of } j = f\ (\text{with } j) - f\ (\text{without } j)$$

Visualisations:



sum of all SHAP values = difference of prediction - base
(24.41 - 22.34)

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Interpret Models

Where do we find 'predictive skill' (geographically)?

How do we compare with physically-based forecasts?

Which of our features give us the best improvement in skill?

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Experiments

- choice of thresholds
- choice of definition
- choice of variable

Drought metrics vs. Drought impacts

Identify Teleconnections in SST/SLP data

Does soil moisture offer predictability for rainfall?

Can we quantify the human element in drought risk?

Combine ML Vegtation with SEAS5 Precipitation

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Communicate Results

Flexible Pipeline

An experimental pipeline for easily exchanging models, definitions and input features.

Extensible: Python classes and funtions

Well Documented: Example notebooks, test suite

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Communicate Results

Blog Posts

Blog posts throughout the process outlining our thinking and our implementations.

More polished blog posts to follow towards the end of the ESoWC Project

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Communicate Results

Academic Papers

- Overview of the pipeline and functionality (JOSS, GMD).
- Overview of predictive accuracy and the algorithmic approach.
- Overview of scientific insights (e.g. SSTs in Western Pacific Warm Pool)

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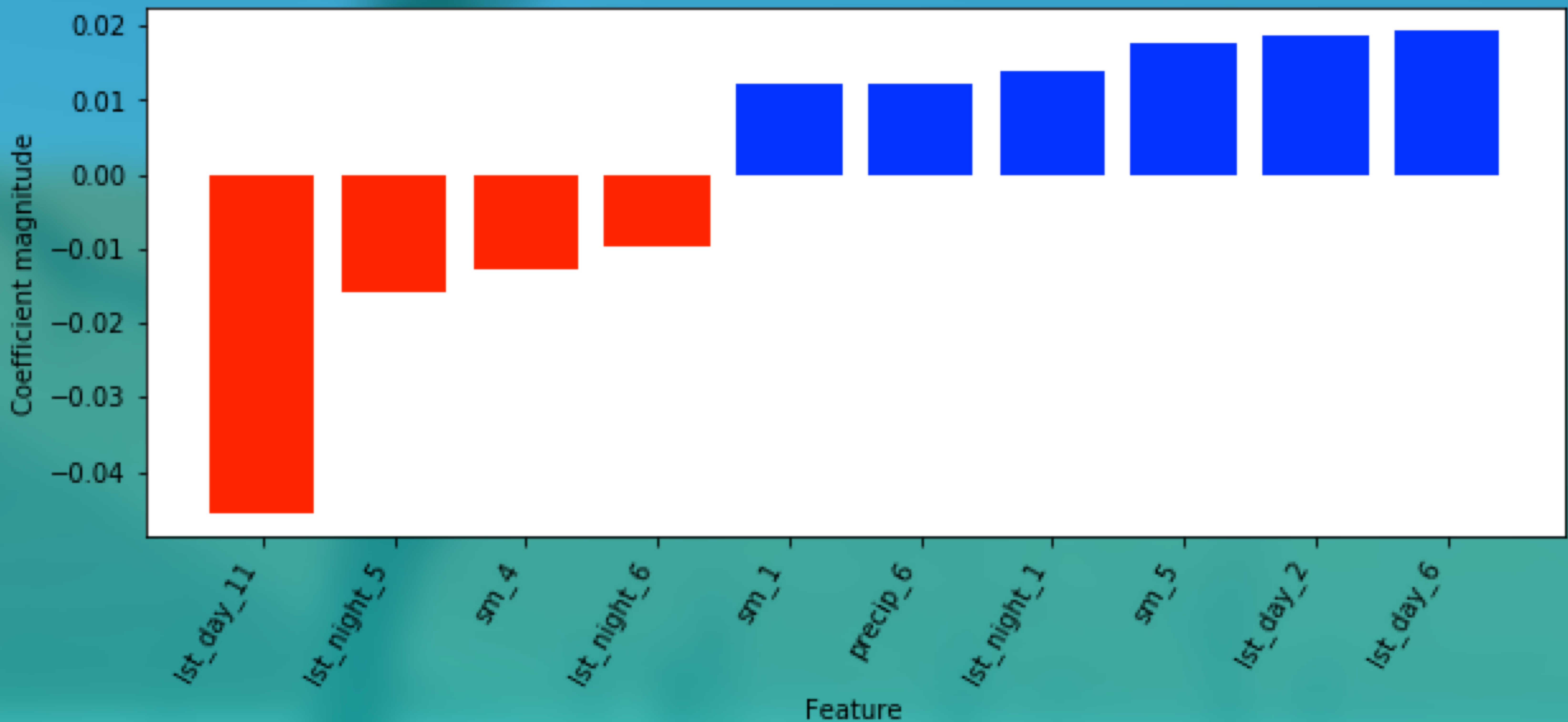
(VERY) initial results

Input variables (linear model)



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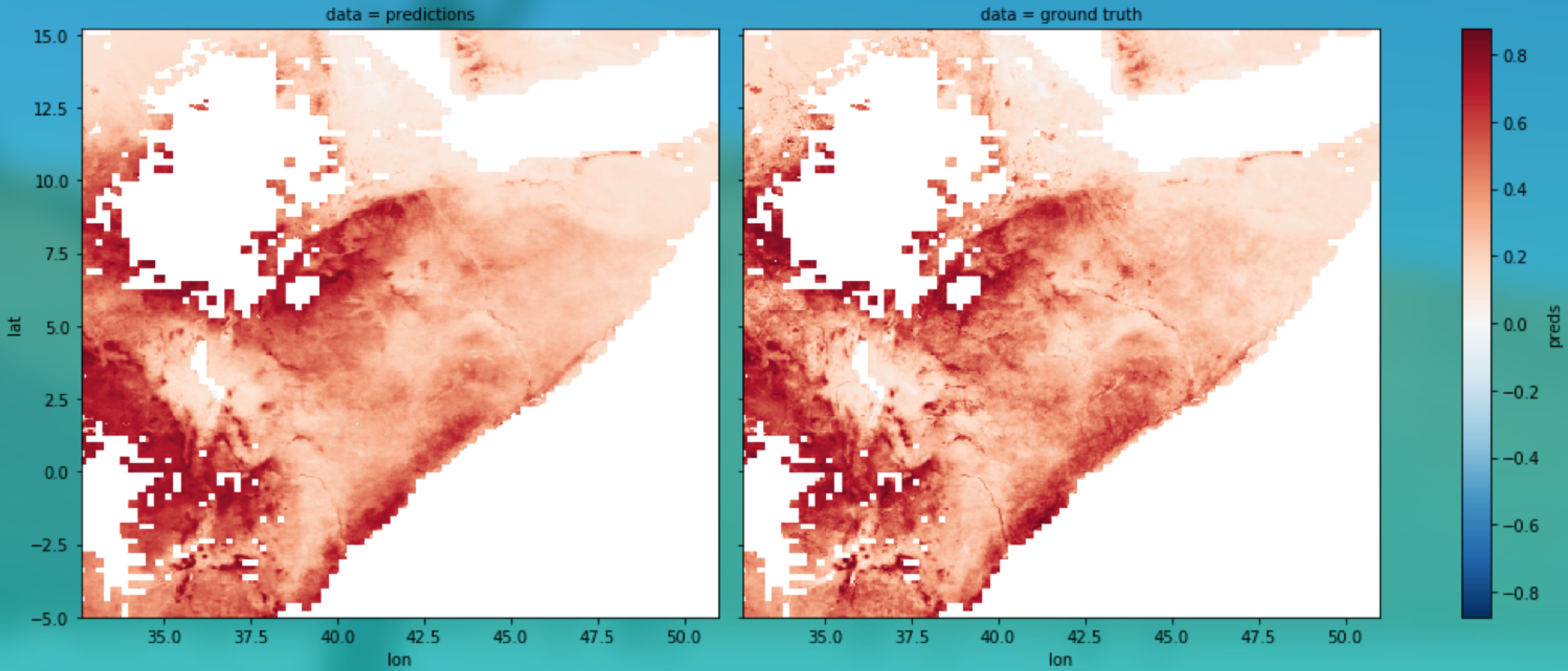
(VERY) initial results

Predictions vs. Truth



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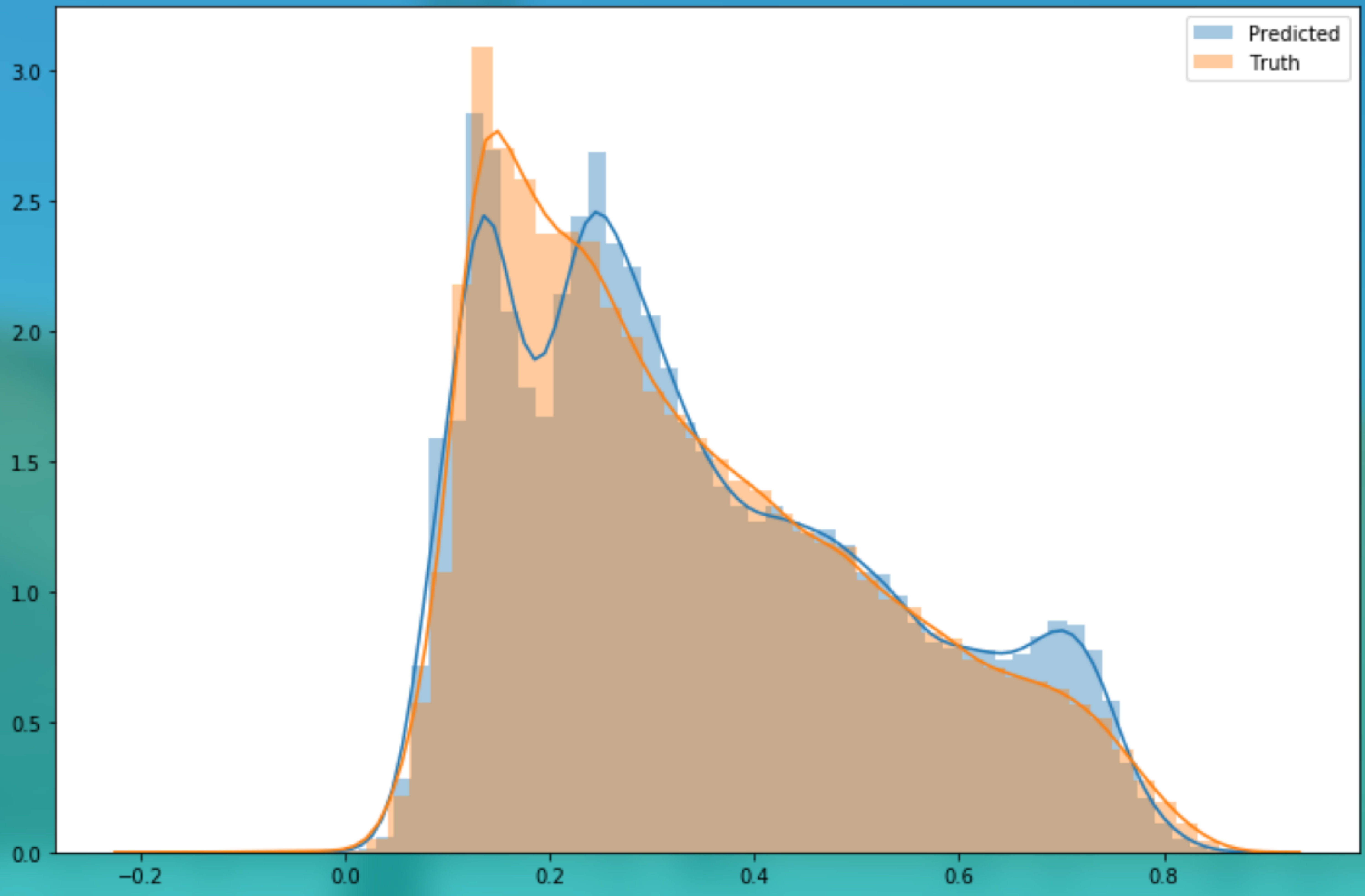
(VERY) initial results



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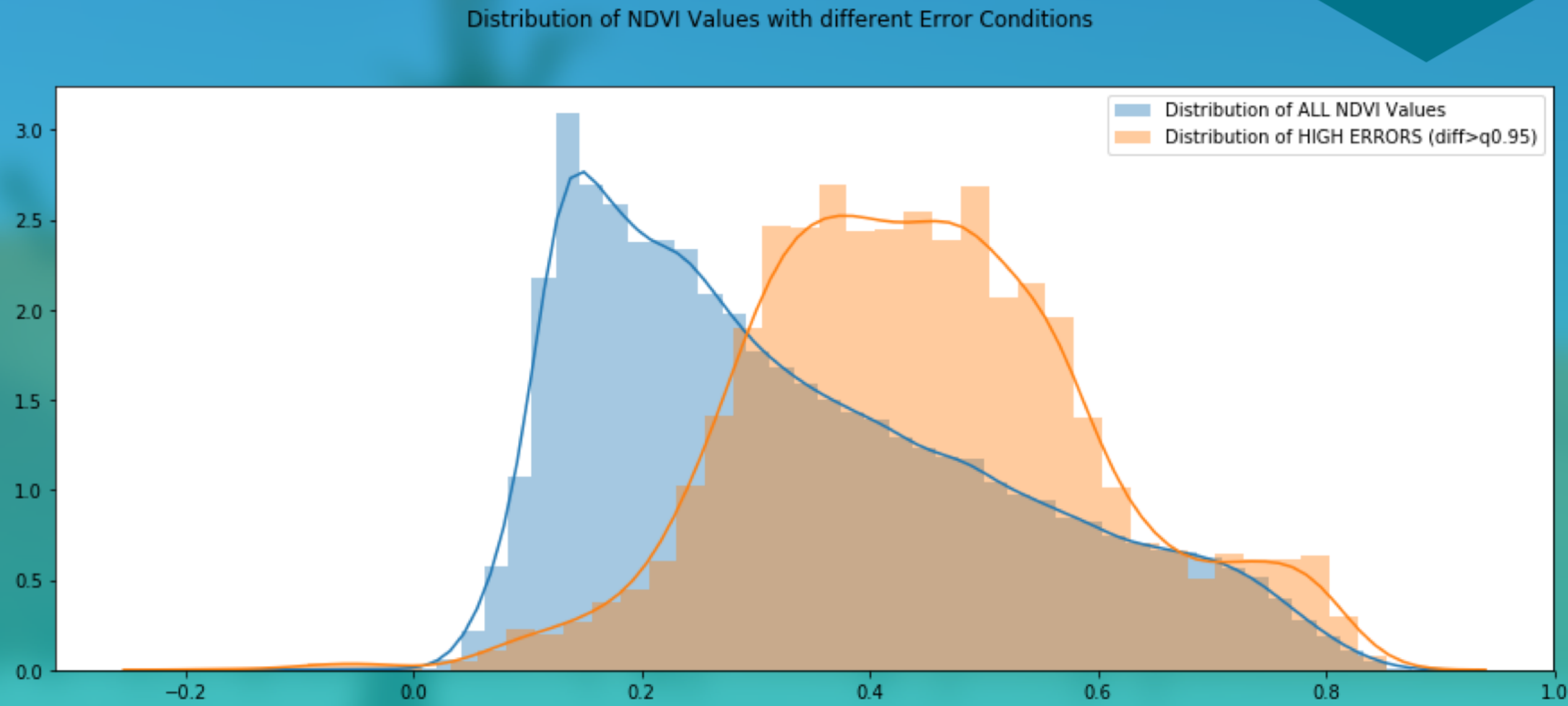
(VERY) initial results



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https://github.com/esowc/ml_drought

@tommylees112

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Appendix

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Predictive System

Hydrological Drought

Target: Soil Moisture Time Series

Inputs: Meteorology (Temp, Precip), Vegetation Health (NDVI, VHI), Climate Vars (Nino3.4), Static Variables (Orography, Soil Type)

Challenges: Encoding spatial-temporal information, how to utilise climate variables, masking, is the data correct?

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Predictive System

Meteorological Drought

Target: Standardised Precipitation Index (SPI)

Inputs: Preceding Meteorology (Temp, Precip), Hydrology (Soil Moisture), Climate Vars (Nino3.4), Static Variables (Orography, Soil Type)

Challenges: Encoding spatial-temporal information, how to utilise climate variables, Performance vs. SEAS5

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Predictive System

Hydrological Drought 2

Target: Streamflow

Inputs: Preceding Meteorology (Temp, Precip), Hydrology (Soil Moisture), Climate Vars (Nino3.4), Static Variables (Orography, Soil Type)

Challenges: Encoding spatial-temporal information, how to utilise climate variables, Performance vs. SEAS5

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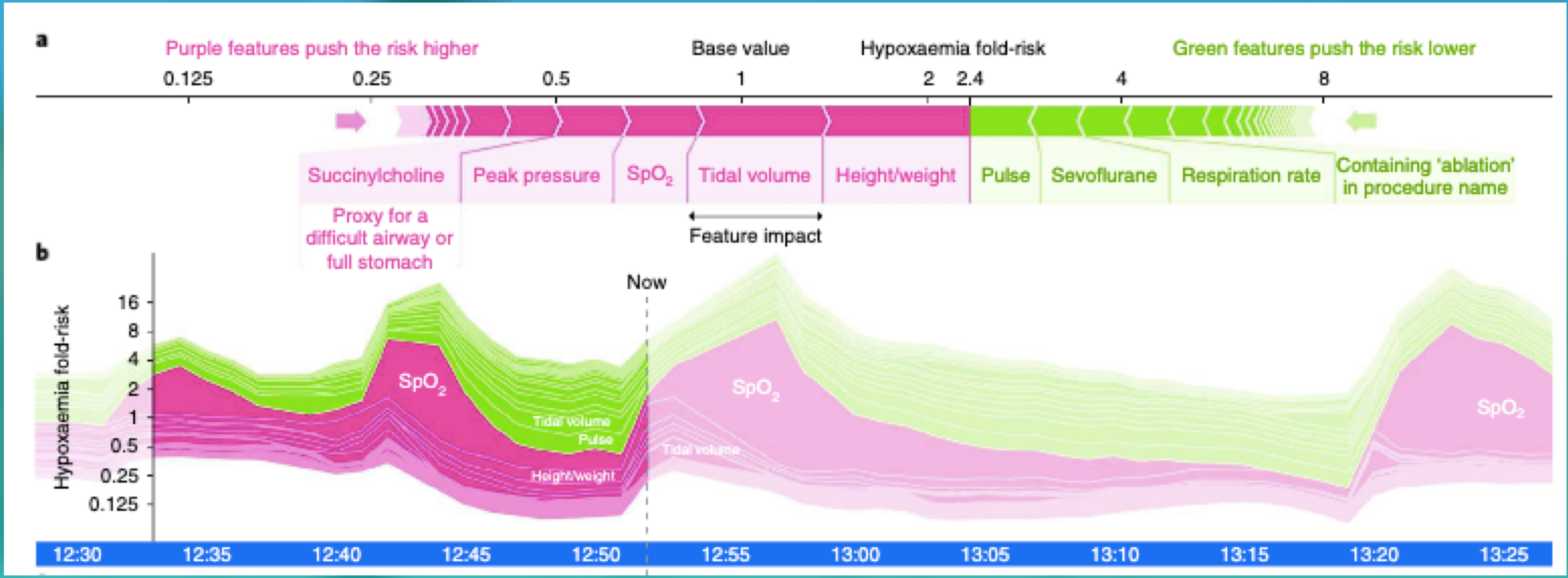
Interpret Models

SHAP Values

Package: SHAP (https://github.com/slundberg/shap)

Interpret Models

SHAP Values



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Interpret Models

SHAP Values

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