NAO prediction

Machine Learning with TensorFlow Project by:
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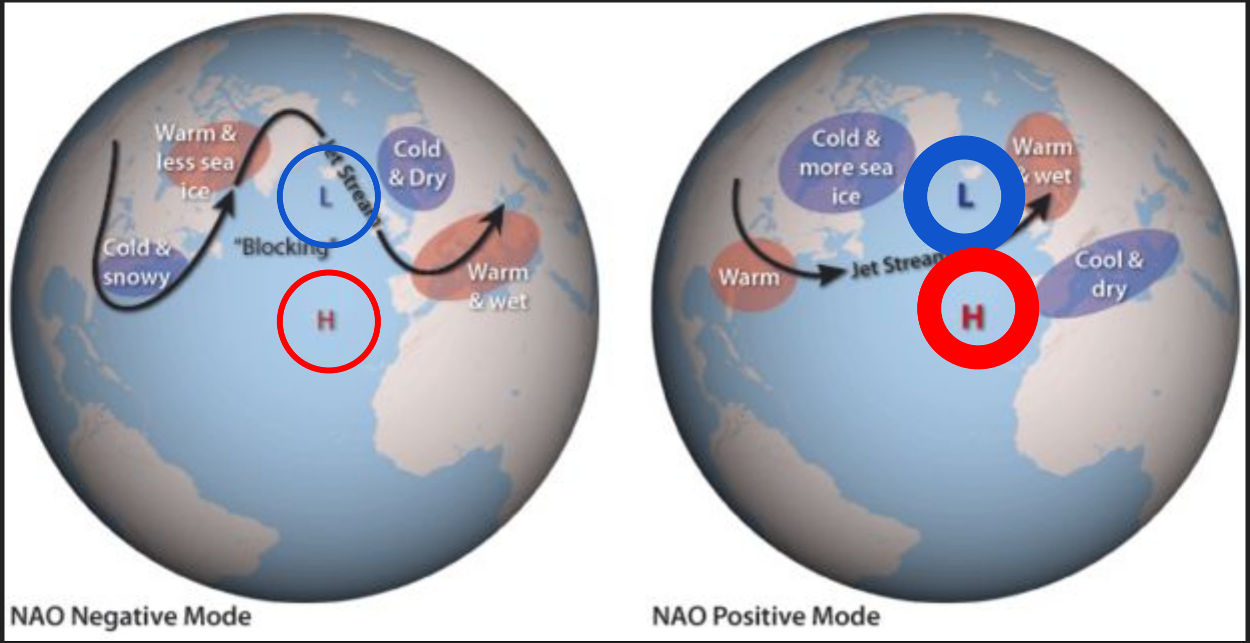
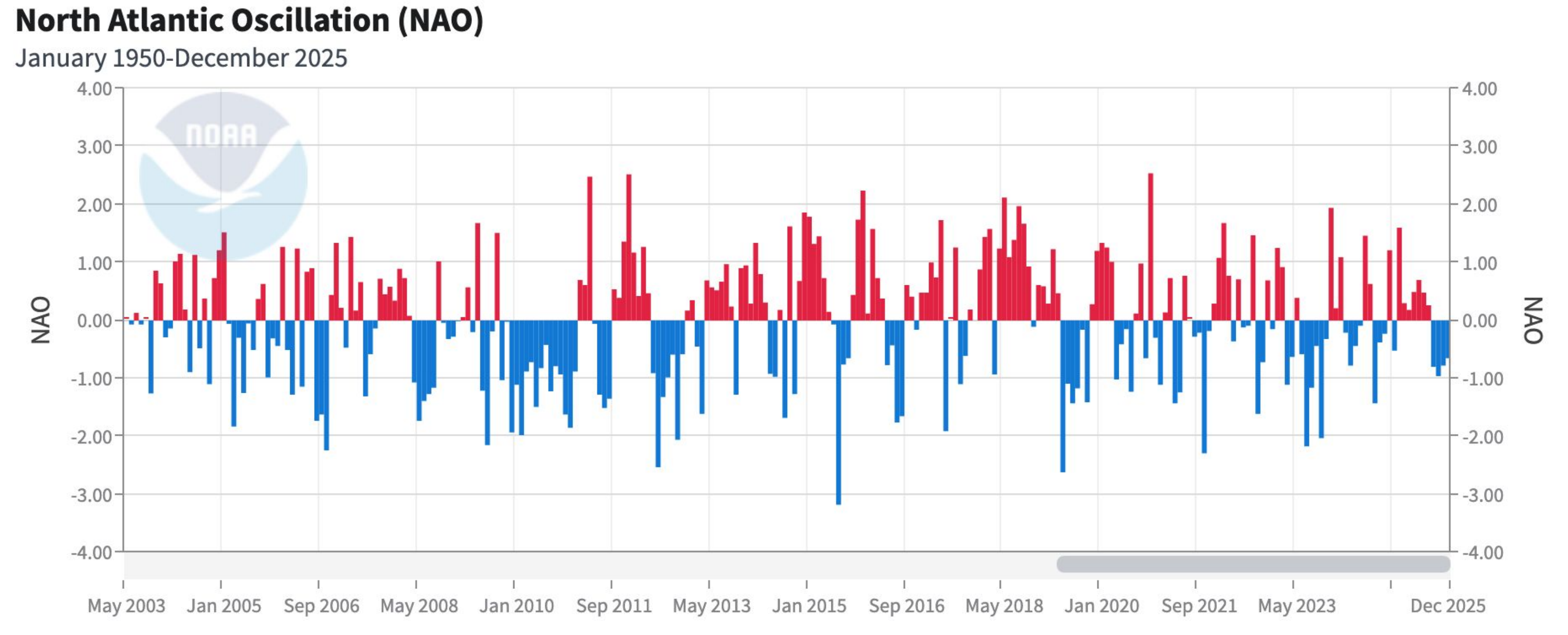
Introduction: Who is NAO? Paula

North **A**tlantic **O**scillation



negative Phase
→ cold winter for Kiel

Introduction: NAO Index Paula



Literature Survey 1

Foundation and Predictability of the Atlantic Sector

Based on Source 1: A Review of Predictability Studies (JCLI)

- **Objective & Methodology**
  - Comprehensive assessment of North Atlantic climate and **NAO predictability** over decadal timescales.
  - Comparison of observational data, statistical models, and decadal hindcast experiments.
- **Key Findings**
  - **Limited Predictability:** Skill exists but is heavily modulated by **Ocean-Atmosphere coupling** and Sea Surface Temperature (SST) anomalies.
  - **Seasonal Variance:** Winter NAO exhibits the highest potential for prediction skill.
  - **Challenges:** High levels of internal atmospheric noise and model bias remain significant barriers to short-term transition accuracy.
- **Strategic Relevance to Our Project**
  - **Baseline Expectations:** Provides a benchmark for what is "predictable" versus "noise."
  - **Feature Selection:** Validates the use of SST and ocean circulation as critical predictors for machine learning inputs.

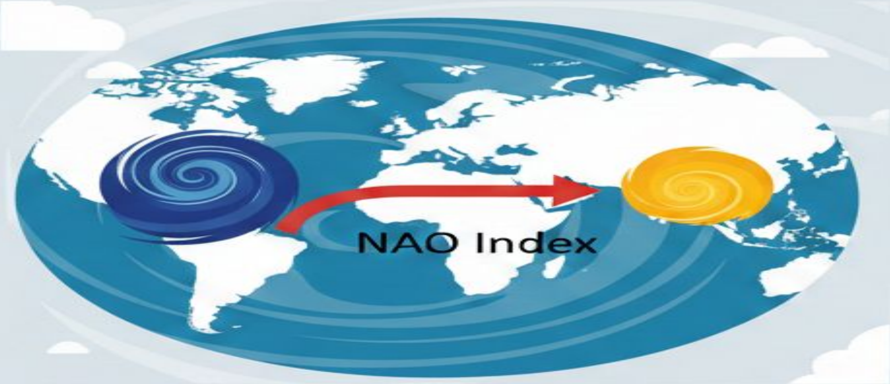
Literature Survey 2

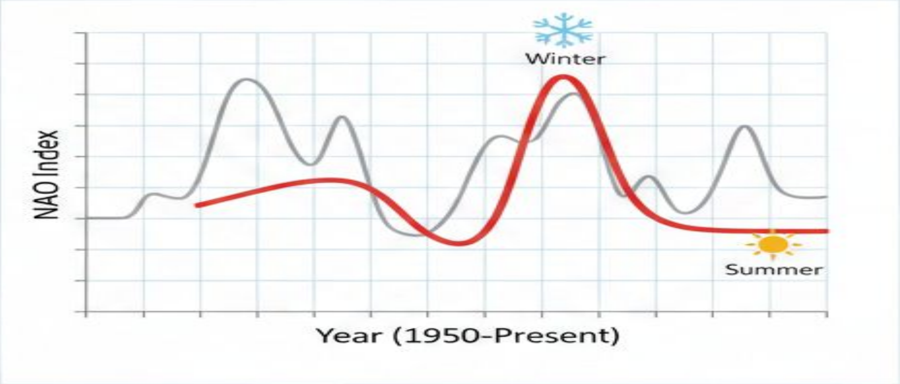
Deep Learning & Causal Discovery in NAO Forecasting

Based on Source 2: Multivariate Air–Sea Coupled Model (Atmosphere, 2023)

- **The Approach: NAO-MCD Model**
  - **Feature Engineering:** Uses data-driven **causal discovery** to select statistically significant predictors (ENSO, Sea Ice, 500hPa Geopotential Height, Wind).
  - **Architecture:** A hybrid deep learning structure:
    - **ConvLSTM:** Encodes spatiotemporal features.
    - **GCN (Graph Convolutional Network):** Models air-sea coupling.
    - **Symmetrical Decoder:** Predicts Sea Level Pressure (SLP) to derive the NAO index.
- **Performance Outcomes**
  - **Superiority:** Outperformed traditional numerical models at **2- to 6-month lead times**.
  - **Stability:** Confirmed that winter forecasting is significantly more robust than other seasons.
- **Direct Application to Our Project**
  - **Model Design:** Suggests that adding a **spatial component** (using ConvLSTM or GCN) may yield better results than 1D time-series data alone.
  - **Refinement:** We should consider focusing on winter-specific models to maximize initial success.

Data Charatersitics





Source: NOOA Daily Records (1950—Present)

Procprecisszing: 30-day rolling mean for “monthly” trends.

Target: NAO Index (Nmlized Pressure Diff)

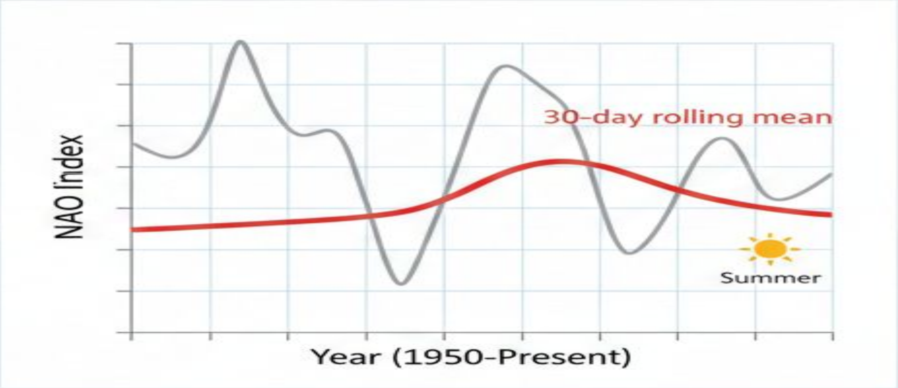
Distribution: Near-Normal (fμ=0.0.5), Range: Range: −1.55 to 1.71.

Features:

Season Flag: Winter-Apr / Summer / May-Oct.

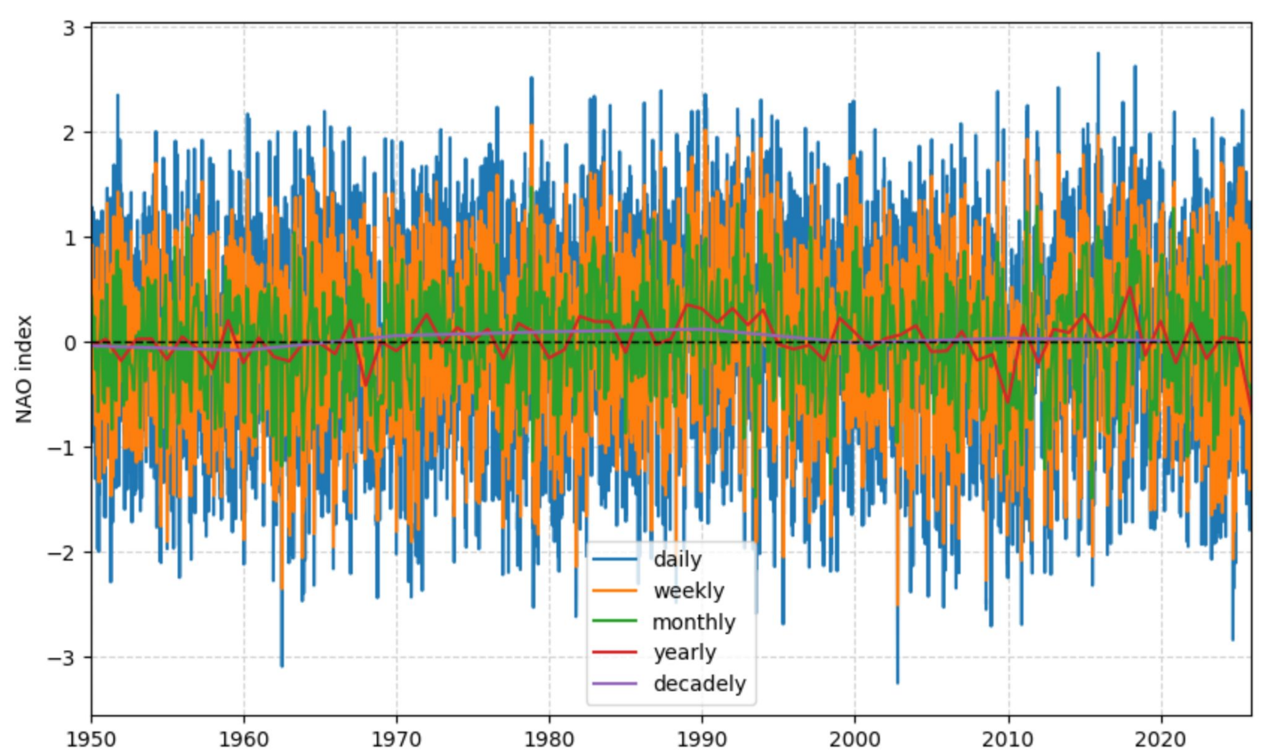
Temporal: Month & Decade

Future: SST, ENSO, AMV (Coupled Deep Learning)



Data characteristics

daily > 27700 values → decided to take less noisy monthly values, 75 years x 356 days

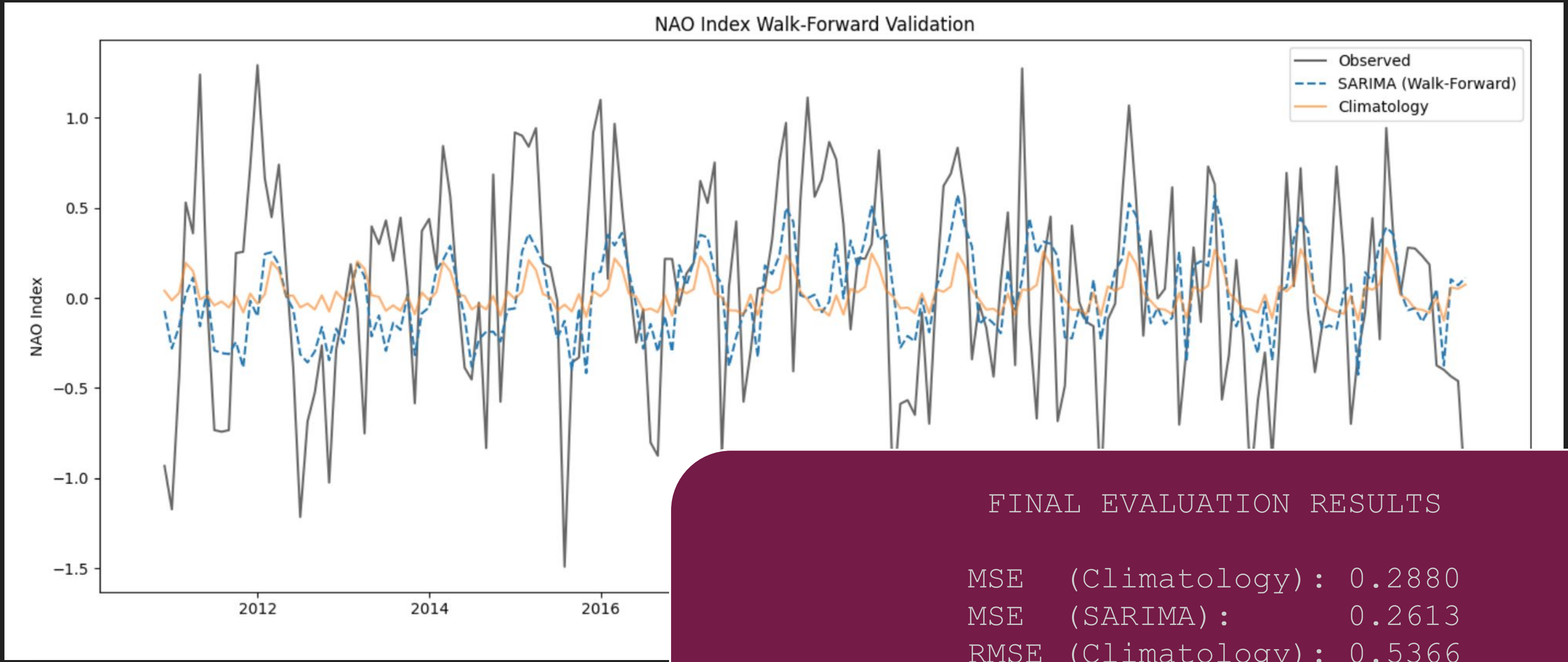


Features:

month
season
year
decade

previous winter
autom- min, max, std, mean
10yr freq, 20yr freq

Baseline Model




```
FINAL EVALUATION RESULTS

MSE   (Climatology): 0.2880
MSE   (SARIMA):      0.2613
RMSE  (Climatology): 0.5366
RMSE  (SARIMA):      0.5112
ACC   (Climatology): 0.3895
ACC   (SARIMA):      0.4334
```

Model for NAO Prediction

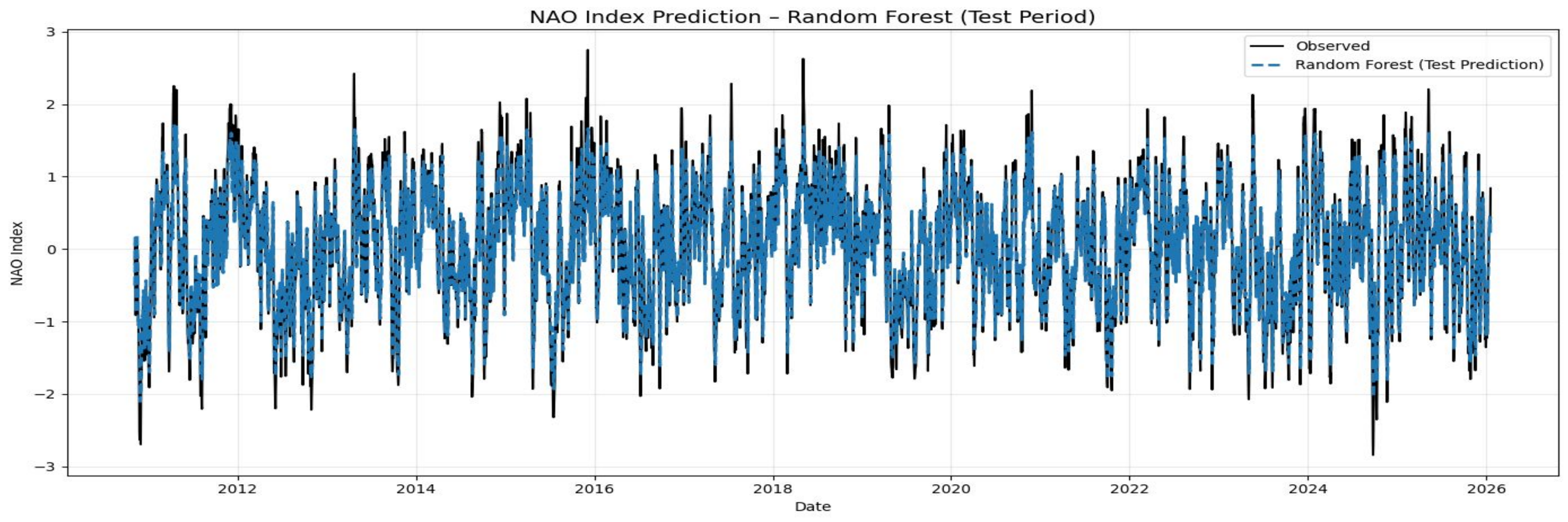
Designed for:
Nonlinear, high-variance time-series with complex interactions

Strengths:
Captures nonlinear dynamics, handles multicollinearity, robust to noise

Limitations:
Lower interpretability than linear models

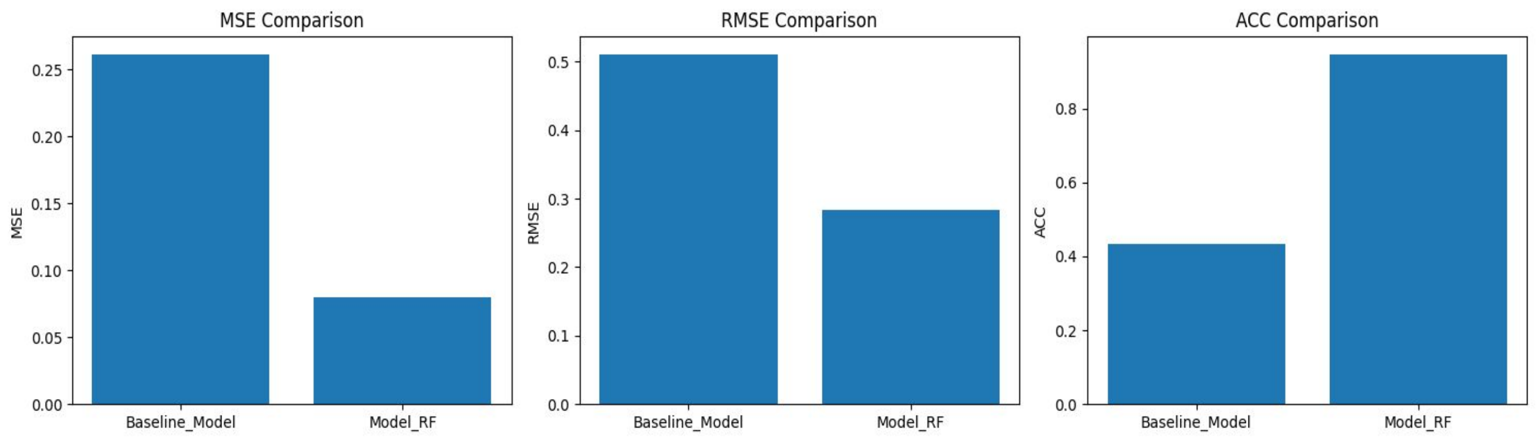
```
n_total = len(df_rf)
n_train = int(0.8 * n_total)

X_train, X_val = X[:n_train], X[n_train:]
y_train, y_val = y[:n_train], y[n_train:]
```

Results



RANDOM FOREST PERFORMANCE
MSE : 0.0802
RMSE : 0.2831
ACC : 0.9476

Baseline Model vs Model

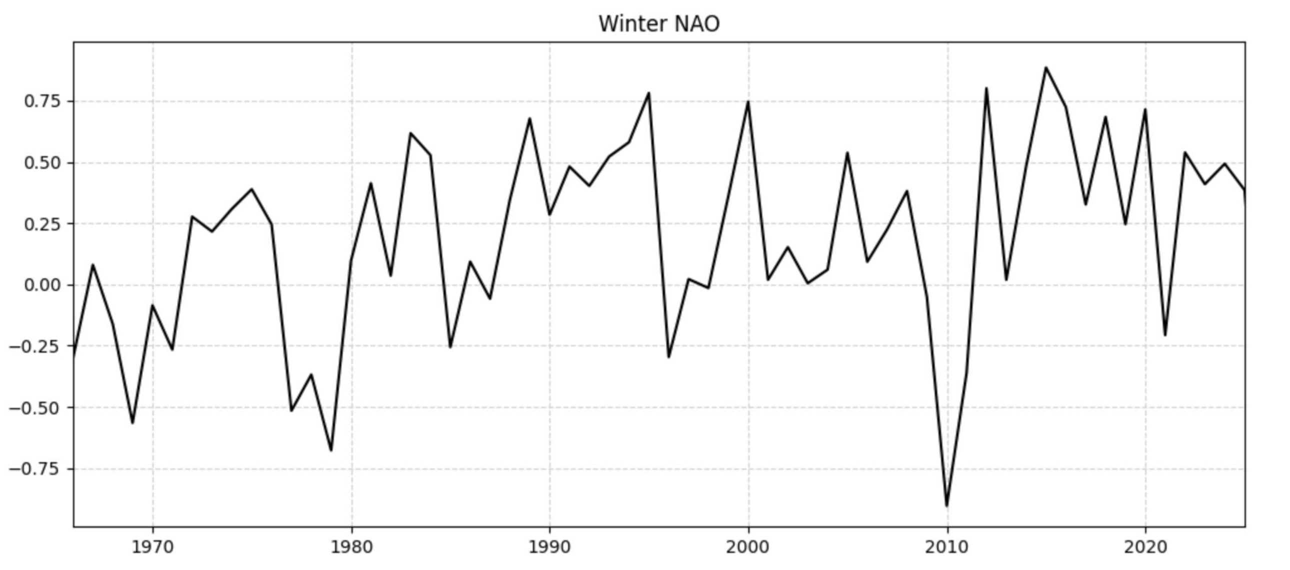


- Random Forest outperforms the baseline across all metrics
- **MSE and RMSE are significantly reduced**
- **ACC improves from ~0.43 to ~0.95**
- Higher ACC indicates better phase and variability capture
- Confirms superiority of nonlinear ML over linear baselines

Only predict winter NAO

Winter Value is what we are interested in in the end.

→ only one value per year → somewhat small dataset, only 75 values



many features:

SON_features:mean,std,min,max

regime_features,

prev_winter,

lowfreq (10yr),

nao_lowfreq_20yr,

neg_extreme,

son_max_persistence,

son_p10

Only predict winter NAO: model description Ridge

Model class: Regularised linear regression (Ridge)

Designed for: Small-sample, noisy, correlated-predictor problems

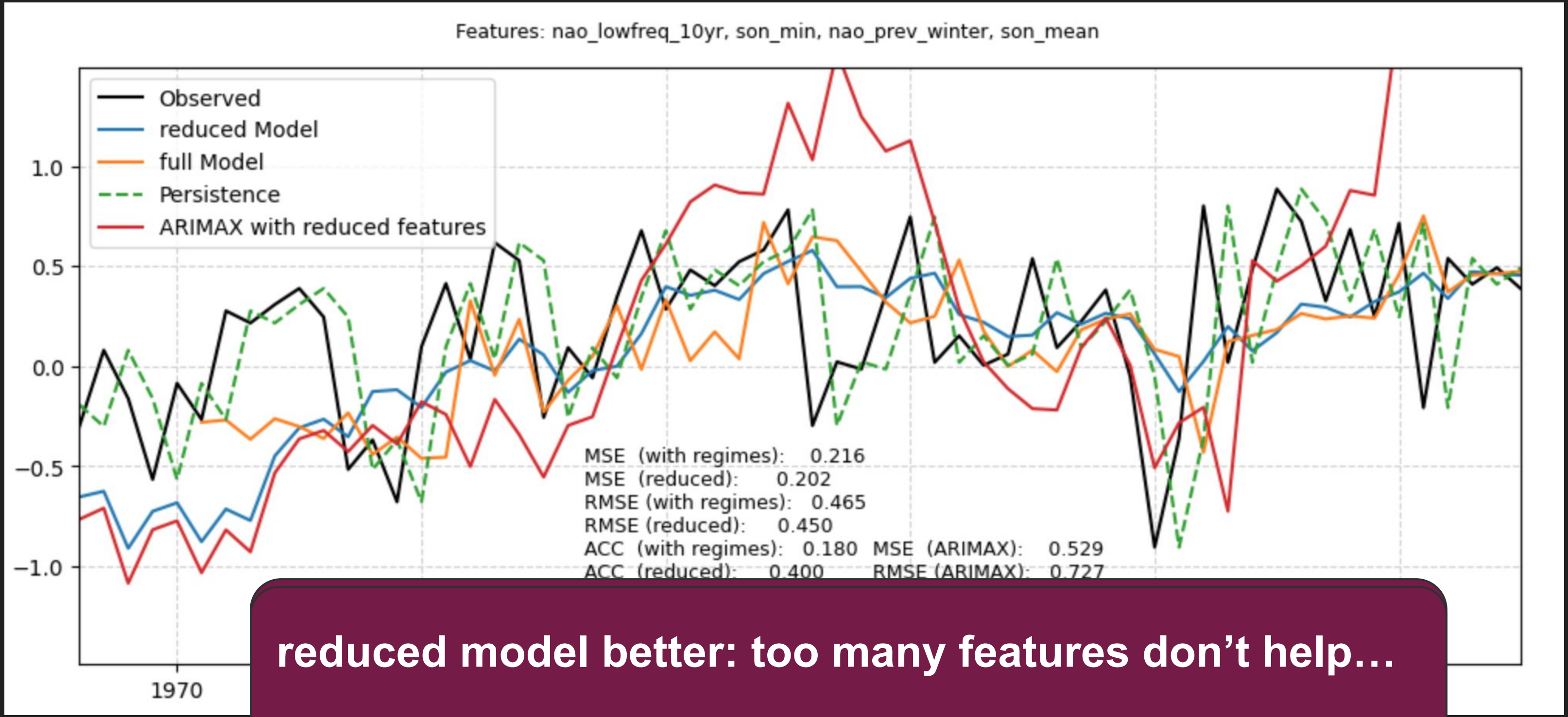
Strengths: Stability, interpretability, robustness

Limitations: Cannot capture nonlinear or state-dependent dynamics

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge

model = Pipeline([
    ("scaler", StandardScaler()),
    ("ridge", Ridge(alpha=1.0))
])
```

```
tscv = TimeSeriesSplit(n_splits=5)
#Split 1: Train: winters 1951–1975, Test:  winters 1976–1982
#Split 2: Train: winters 1951–1982,Test:  winters 1983–1989
#...
```

Only predict winter NAO: ARIMAX



reduced model better: too many features don't help…

Future work

“external” features: include ENSO, ocean features

Summary

prediction of monthly NAO index

Literature: so far not made with a lot of success

Random Forest: very high accuracy and low errors

only winter predict.: take better less but better features
okaish prediction but no real live advantage…