# Climate Wins Weather Analysis

Predicting Weather Conditions and Climate Change With Unsupervised Machine Learning Algorithms

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# Introduction and Background

In recent years weather event data has suggested that weather has grown more erratic and harder to predict across the globe, as well as the severity of extreme weather. This could pose a serious risks to human safety and infrastructure. I

In response to these challenges, ClimateWins is looking toward machine learning models to pursue several key objectives.

1. Detect weather patterns in Europe that deviate from historical regional norms
2. Assess whether these atypical patterns are becoming more frequent
3. Model potential future climate conditions over the next 20 to 50 years based on current trends
4. Identify what he safest regions in Europe will be over the next 25 to 50 years

# Proposed Thought Experiments

These thought experiments outline three conceptual uses of machine learning, the practicality of which will be further explored, including the type of algorithm that would be most appropriate and the insights they would hypothetically generate.

**1. Predictive Climate Mapping Using Time Series Forecasting**

**Thought Experiment:**
What if we could “fast-forward” Europe’s climate trajectory over the next 50 years? By training models on historical temperature, precipitation, and storm frequency data, we could generate projections of likely climate outcomes in different regions of Europe.

**2. Climate Resilience Classification**

**Thought Experiment:**
What if we could train a model to score and rank regions by their projected climate resilience? By integrating environmental data (e.g., projected rainfall, temperature extremes, sea-level rise) with socio-economic and infrastructural data, we could classify regions into tiers of livability and safety.

**2. Regional Risk Profiling Using Anomaly Detection**

**Thought Experiment:**
Imagine we could create a baseline “climate fingerprint” for each European region based on past weather data—then use anomaly detection to flag events or patterns that deviate significantly. Which areas are experiencing a rising frequency of anomalies, and how might that trend progress?

# Machine Learning Models

**1. Long Short-Term Memory (LSTM):**

LSTM can be used for time series forecasting, utilizing historical data, and leading to the creation of a comprehensive predictive climatological map of Europe.

**2. Random Forest Classifier:**

A random forest model can process a great deal of continuous and categorical data—utilizing not only weather observations but also data on different and more varied regional traits, like capacity for infrastructure to endure. This , along with the random forest's feature of importance ranking, would allow for a kind of "resilience ranking" for different cities or regions, providing further insights on where to focus adaptive efforts.

**3. One-Class Support Vector Machine (STM):**

A STM model would be able to identify rare or unusual weather patterns without necessarily needing explicitly labeled data. Tracking this over time, an STM would allow for evaluation of which European regions are experiencing the most variance in climatological stability and even at what pace are they becoming less stable.

# Necessary Additional Data

## LSTM Model—

- **Historical climate data**: Temperature (daily/monthly average highs/lows), precipitation, wind speeds, humidity, etc. over the past 50–100 years.
- **Extreme weather event logs**: Frequency, intensity, and type (e.g., floods, droughts, heatwaves).
- **Temporal granularity**: Data must be timestamped (daily/monthly/yearly) to capture seasonality and long-term trends.
- **Geospatial data**: Latitude, longitude, elevation for each weather observation point.

## Random Forest Model—

- **Current and historical weather data**: Temperature, precipitation, humidity, drought frequency, etc.
- **Infrastructure resilience**: Examples include availability and quality of roads, healthcare services and emergency services, macro-architectural details, etc.
- **Socio-economic data**: Population density, income levels, housing types, insurance coverage.
- **Environmental vulnerability indicators**: Flood zones, wildfire risk, sea-level rise exposure.
- **Optional:** Migration patterns, energy grid, agricultural trends

## STM —

- **Baseline weather norms**: Multi-decade rolling averages for variables like temperature, rainfall, storm frequency, etc., for each region.
- **Recent weather data**: The same metrics collected in the past 5–10 years to detect deviations.
- **Extreme weather events dataset**: Spatial and temporal data on events outside historical bounds.
- **Topography & geography**: Land use, elevation, proximity to coastlines or flood plains.

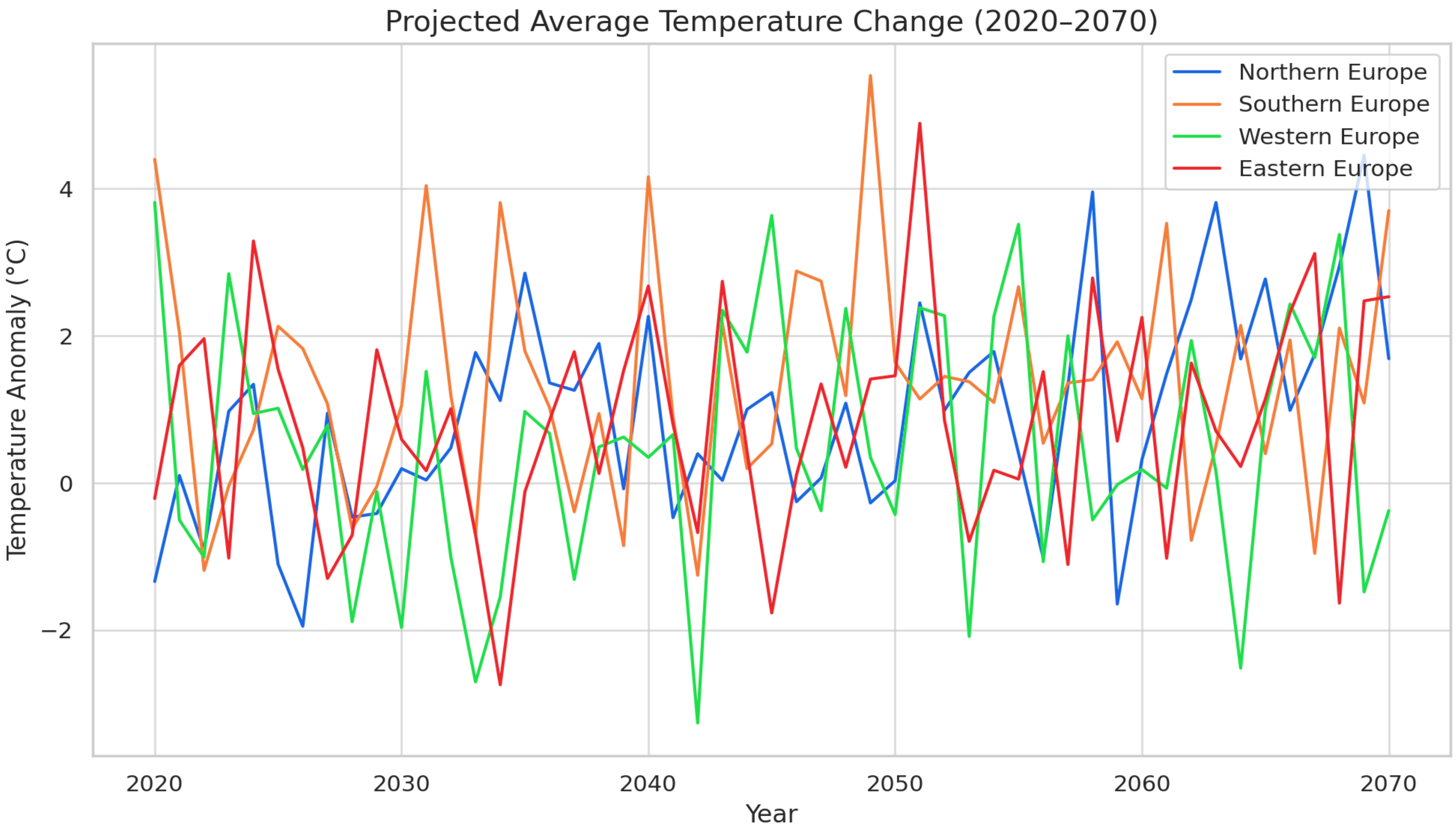
# #1: Predictive Climate Mapping Using LSTM to Forecasting Time Series

- **Hypothesis:**
  If recent trends in temperature and precipitation continue, certain regions in Europe will experience significantly greater climate instability over the next 20–50 years.
- **Objective:**
  To forecast future climate variables (e.g., temperature, precipitation) at a regional level in Europe to identify where climate conditions will become more extreme or variable.

**Processes:**

- **Data preprocessing**: Collect and clean historical weather data (temperature, precipitation, etc.) over the last 50–100 years.
- **Feature engineering**: Normalize variables, handle missing data, and encode time components (year, seasonality).
- **Modeling**:
  - Use **LSTM networks** for prediction of non-linear, and seasonal data sequences.
  - Project conditions over 20–50 years, using both current data and historical patterns.

**Hypothetical Results Interpretation:**
Regions showing strong upward trends in average temperature, increased precipitation variability, or persistent seasonal shifts may be flagged as high-risk zones. Results would provide map-based visualizations of projected climate zones, helping inform relocation or adaptation strategies.



Projected Average Temperature Change (2020–2070)
Northern Europe
Southern Europe
Western Europe
Eastern Europe
Temperature Anomaly (°C)
4
2
0
−2
2020
2030
2040
2050
2060
2070
Year

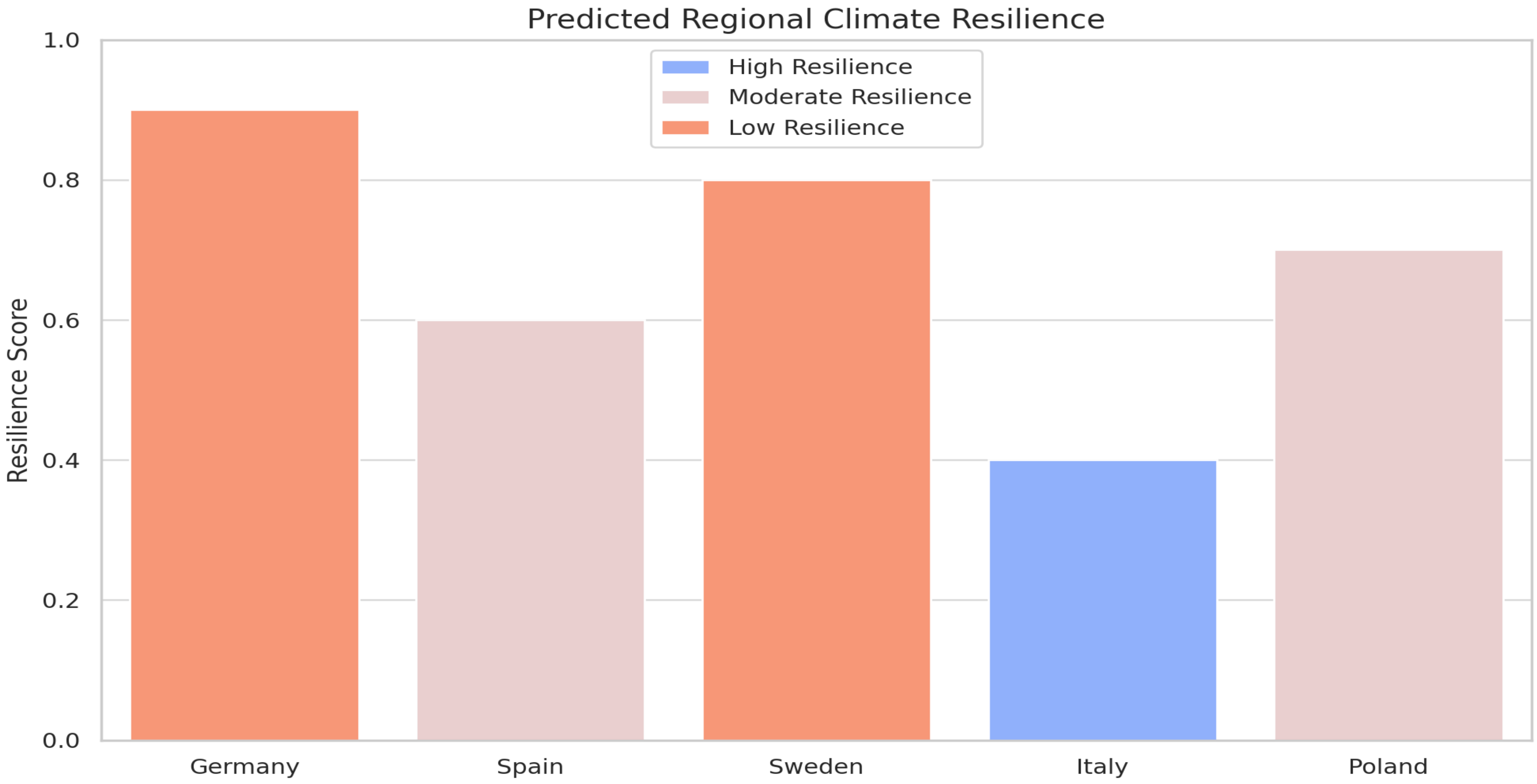
# #2: Climate Resilience Classification with Random Forest Classifier

- **Hypothesis:**
  Regions with higher infrastructure resilience, stable climate projections, and lower environmental exposure are more likely to remain safely habitable over the next 25–50 years.
- **Objective:**
  Classify European regions by their future climate resilience, helping prioritize safe zones for future planning.

**Processes:**

- **Data collection**: Merge historical and projected climate data with socio-economic, geographic, and infrastructure metrics.
- **Labeling**: Define target labels (e.g., High, Medium, Low resilience) using composite indices or expert labeling.
- **Model training**: Use random forest to train labeled data, adjusting for accuracy.
- **Feature importance**: Analyze which factors (e.g., flood risk, healthcare access, projected temp rise) drive each classification most.

**Hypothetical Results Interpretation:**
The model might classify regions like Southern Germany or Northern Spain as “High Resilience” due to moderate climate changes and strong infrastructure, while coastal or southern Mediterranean regions may be flagged as “Low Resilience.” The model’s feature importance would help policymakers understand what factors most contribute to long-term habitability.


Predicted Regional Climate Resilience
High Resilience
Moderate Resilience
Low Resilience
Resilience Score
1.0
0.8
0.6
0.4
0.2
0.0
Germany
Spain
Sweden
Italy
Poland

# #3. Regional Risk Profiling with Support Vector Machine

- **Hypothesis:**
  Some regions in Europe are experiencing increasingly frequent deviations from their historical weather norms, signaling emerging patterns of future instability.
- **Objective:**
  Identify which European regions are showing a growing trend in climate anomalies (e.g., unseasonal heatwaves, unexpected storms, etc.)

**Processes:**

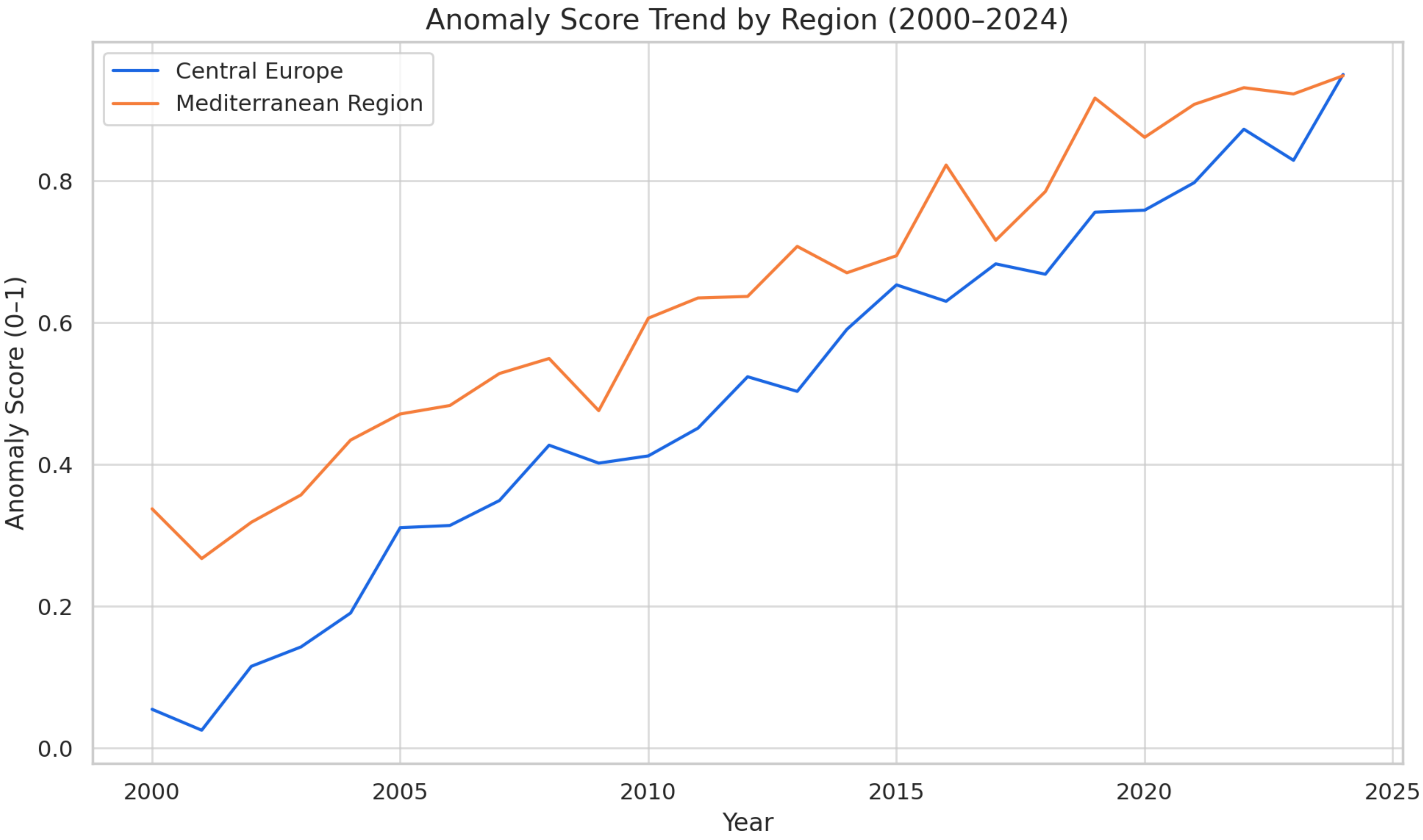
**Baseline**: Compute a "normal" climate profile per region using long-term historical data.

**Anomaly model training**: Train One-Class SVM on normal climate data to learn distribution.

**Detection**: Feed recent weather data (last 5–10 years) through the model.

**Scoring**: Measure deviation from learned baseline with higher scores indicating anomalies.

**Hypothetical Results Interpretation:**
Regions with a high and rising anomaly score over recent years may be entering a state of climate volatility. For instance, Southern France might show increasing anomaly density during traditionally stable months, suggesting a changing climate baseline.


Anomaly Score Trend by Region (2000–2024)
Central Europe
Mediterranean Region
Anomaly Score (0–1)
0.0
0.2
0.4
0.6
0.8
2000
2005
2010
2015
2020
2025
Year

# Next Steps

**1. Data Acquisition & Cleaning**

- Collect long-term historical and recent climate data (temperature, precipitation, extreme events) across European regions.
- Source socio-economic and infrastructure datasets
- Standardize and clean datasets for consistency (handle missing values, normalize formats, etc.)

**2. Exploratory Analysis**

- Identify preliminary regional baselines and outliers.
- Visualize trends, seasonality, and regional weather shifts to inform model design.

**3. Model Development**

- **Predictive Modeling**: Implement LSTM model for time series forecasting of future climate patterns.
- **Anomaly Detection**: Train one-class SVMs on historical norms to detect recent deviations.
- **Resilience Classification**: Use Random Forests to score and rank regional long-term habitable zones

**4. Model Validation & Tuning**

- Evaluate models using accuracy/loss metrics
- Adjust hyperparameters to optimize predictive accuracy and reduce overfitting.

**5. Visualization & Communication**

- Build dashboards and geographic maps to convey insights to decision-makers.
- Use results to highlight at-risk areas and identify safe zones across Europe.

**6. Integration**

- Recommend adaptive planning based on model outcomes ( urban development, migration risk zones, etc.).
- Align findings with EU climate adaptation and sustainability initiatives.

Thank You!

For further questions, please contact me at: robschassler@gmail.com

To view the scripts and datasets used, please visit my github repository for this analysis at:

https://github.com/rschassler/ClimateWins-Machine-Learning