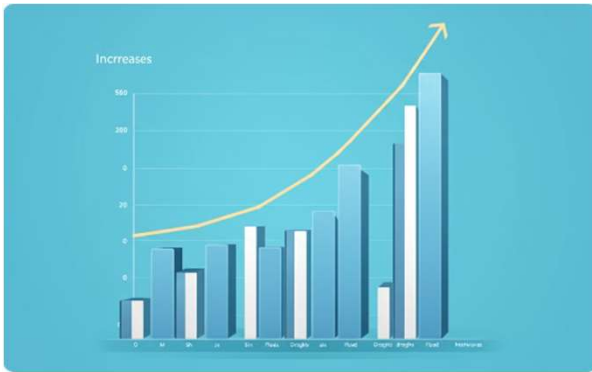# Climate Wins – Predicting Climate Change with Machine Learning

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02/11/2024

# Introduction



### Increasingly Unpredictable Weather

The issue of climate change has been vocal over the years yielding transformation through science and with the integration of machine learning (ML).

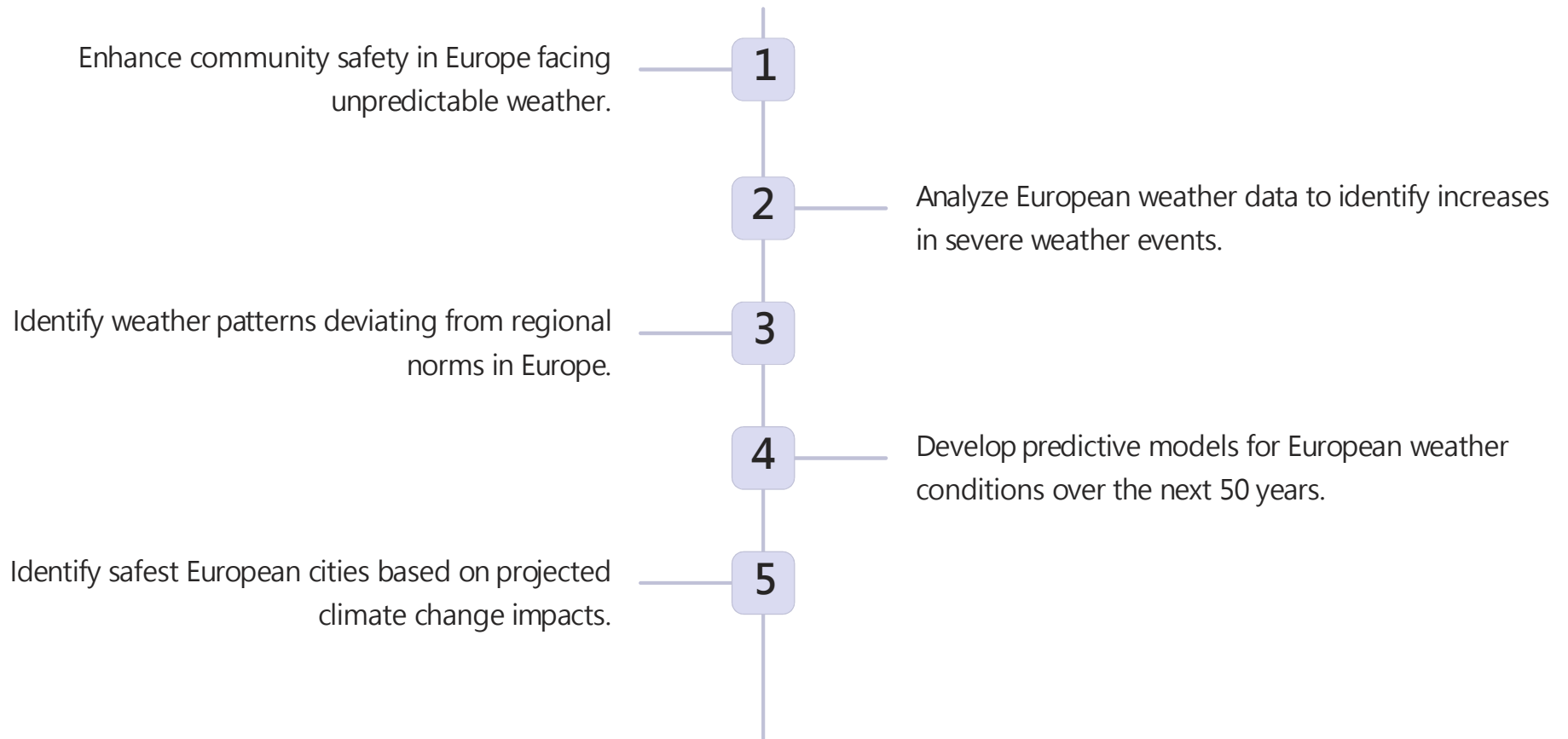

### Endangered Communities

A rise in severe weather events has put many communities' safety in jeopardy.



### ClimateWins Solution

ClimateWins leverages machine learning to enhance safety, analyze European weather trends, and identify deviations from regional norms.

# ClimateWins' Machine Learning Objectives

**1** — Enhance community safety in Europe facing unpredictable weather.

**2** — Analyze European weather data to identify increases in severe weather events.

**3** — Identify weather patterns deviating from regional norms in Europe.

**4** — Develop predictive models for European weather conditions over the next 50 years.

**5** — Identify safest European cities based on projected climate change impacts.

# Data Requirements Beyond Historical Weather Data

**Satellite and Radar Imagery**

Visual context of changing weather patterns for deep learning models.

**Real-time Weather Station Data**

Immediate model updates for improved forecast accuracy.

**Topographical and Climate Zone Data**

Understanding the impact of geography on regional weather.

# Three Thought Experiments

**1**  **1. Predicting Weather Anomalies**

Ensemble models analyze weather pattern shifts using historical data for improved anomaly prediction accuracy.
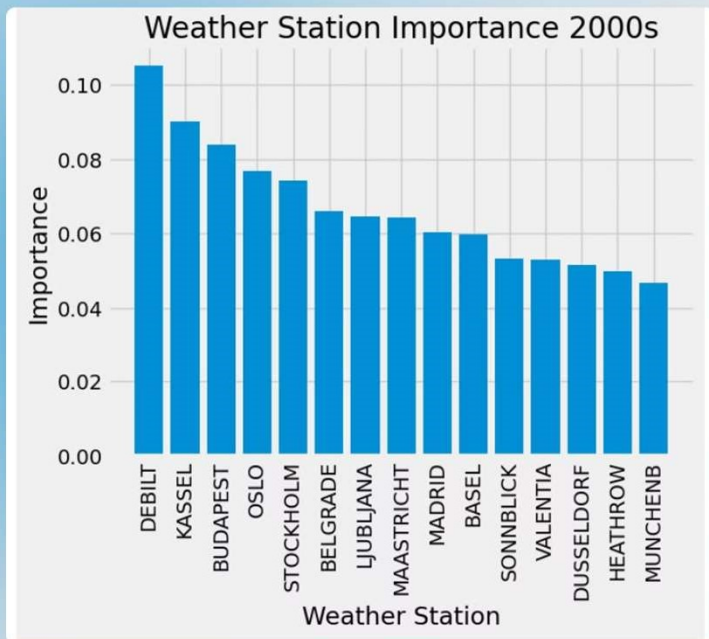
**2**  **2. Deep Learning: CNNs**

CNNs process satellite imagery to detect climate change indicators like deforestation and glacial melt, identifying patterns in large datasets.

**3**  **3. GANs for Weather Projections**

Generative Adversarial Networks (GANs) generate possible future weather scenarios to simulate climate variations.

Weather Station Importance 2000s

# Random Forest Model for all the stations

ClimateWins' Random Forest model analyzed weather data to identify clusters and trends, correlating weather conditions across stations against a "pleasant weather" standard. This revealed weather patterns, parallels, and deviations, providing insights into local weather traits and improving ClimateWins' data analysis.

Weather Station Importance 2000s
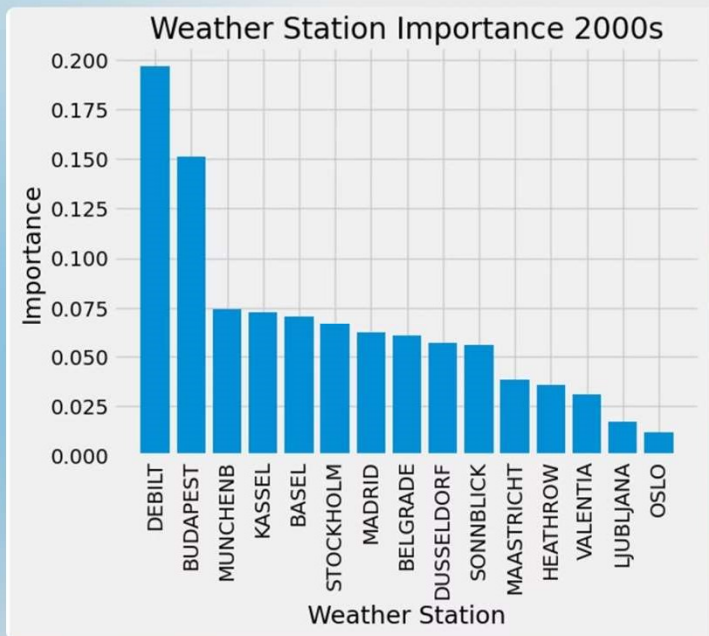
# Optimization Random Forest Model Results

Model accuracy increased 0.67% post-optimization. The simpler, less overfit model generalizes better, prioritizing key features.

Debilt's importance further increased, becoming the most significant station. Budapest rose to second (from third), and Munchenb's importance significantly increased (from last to second). Conversely, Kassel's importance decreased (from second to fourth).
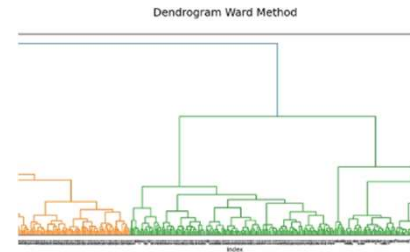
The optimized model reweights station importance, highlighting key stations and downplaying less relevant ones.

# Dendrogram and Clustering Analysis
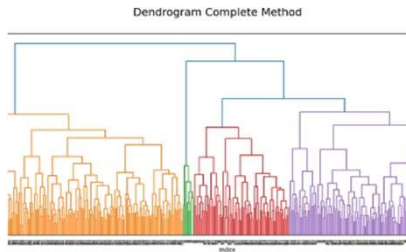


### Complete Method

The Complete Method visually represents data patterns by comparing maximum cluster distances. It produces evenly distributed clusters, offering a balanced view of relationships.

### Ward Method

The Ward Method shows two clusters using a hierarchical technique that minimizes intra-cluster variance.

# GANs for Synthetic Weather Projections

GANs simulate future weather scenarios, revealing potential patterns.

A 10% accuracy gap (after 50 epochs) between training and validation sets, primarily due to misclassifying cloudy conditions as sunny, suggests insufficient training data.
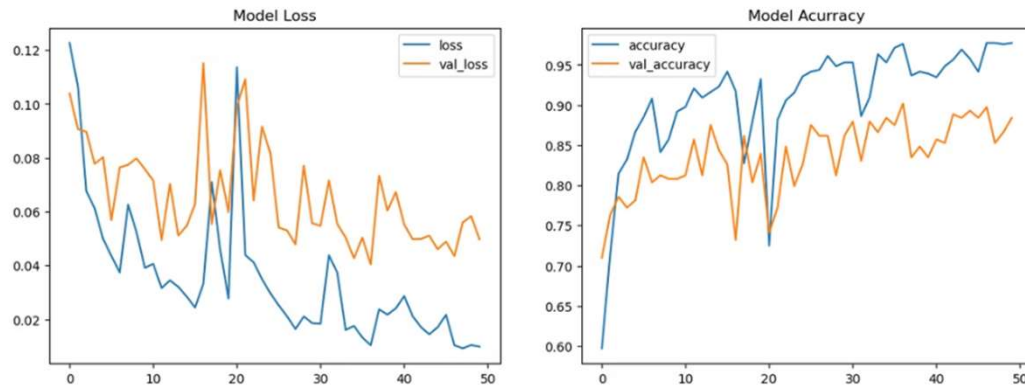




The model reached 97.7% accuracy after 50 epochs.

# Key ML Contributions

**Extreme Weather Events**

ML models predict hurricanes, floods, and droughts, improving disaster preparedness and reducing risks.

**Carbon Footprint Tracking**

Algorithms monitor global emissions, aiding effective policy for climate change mitigation.

**Land and Ocean Dynamics**

ML analyzes ecosystem changes, enhancing conservation efforts for biodiversity protection.

# Challenges in ML for Climate

### Data Limitations

Unequal global data availability and inconsistencies hinder model accuracy and generalizability, leading to biased predictions.

### Model Transparency

Complex ML models lack transparency, raising trust issues and hindering their acceptance.

### Resource Intensity

High computational demands limit the accessibility and sustainability of large-scale models.

# Opportunities and Future Potential

### Hybrid Systems

Combine physics-based models with ML for more accurate climate predictions.

### Policy Integration

Use ML outputs to shape climate policies and improve infrastructure planning.

### Global Collaboration

Shared data and research accelerate climate solutions, fostering innovation.

# Conclusion and Recommendations



## Global Scale Impact

Machine learning offers unprecedented opportunities to enhance climate prediction and mitigation strategies at global scales.

## Key Climate Indicators

The persistent significance of precipitation and maximum temperature indicates their crucial role in forecasting future climate variability. Prioritize temperature alongside precipitation.

## Policy-Making and Understanding

Innovative ML applications enable better understanding, preparation, and policy-making in the fight against climate change.

# Machine Learning Techniques and Summary

### Deep Learning

CNNs analyze satellite imagery for deforestation and glacial melt.

### Time Series Models

RNNs and LSTMs forecast climate trends.

### Unsupervised Learning

Clustering reveals climate anomalies and regional weather patterns.

### Observation

Actionable insights support ClimateWins' adaptation to changing weather.

# Thank you