Interim Report
Weather Conditions and Climate Change with ClimateWins

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Executive Summary

Goal: Classify daily conditions as “pleasant” or “unpleasant” per station to support planning & early warning workflows.

88 %
KNN average accuracy across stations(baseline)

Station variability
Accuracy differs by location - monitor per-station

Recommendation
Scaled ANN for highest accuracy; KNN as a strong baseline

What we build

- Data prep + scaling (StandardScaler)
- Optimization demo: gradient descent convergence.
- Supervised learning: KNN, Decision Tree, ANN
- Evaluation: train/test accuracy + station confusion matrices

Objective & Research Hypothesis

Objective: Use machine learning to help ClimateWins understand and anticipate weather patterns linked to climate change.

Hypotheses

- H1: Station temperature patterns can predict whether a day is “pleasant” vs “unpleasant”.
- H2: Scaling input features improves ANN performance compared to unscaled data.
- H3: Some algorithms handle class imbalance better when “unpleasant” days are rare.

Data: Source, Scope and Labels

Where the data comes from

- European Climate Assessment & Dataset
- Daily station observations across Europe
- Used 18 stations (late 1800s - 2022)

What we modeled

- Inputs: station features (e.g. mean temperature)
- Target: “pleasant” vs “unpleasant” label per station
- Split: consistent train/test sets for fair comparisons

Common issues to expect

- Measurement changes over decades
- Missing days/uneven station coverage
- Class imbalance (more of one label)
- Non-stationarity: climate change shifts patters

Bias, Ethics, and Data Accuracy

Bias risks

- Geographic bias: stations are European - weaker generalization elsewhere
- Coverage bias: some stations have cleaner/denser records
- Label bias: “pleasnat” thresholds are human-chosen
- Rare extremens: fewer examples - higher uncertainty

Accuracy (baseline)

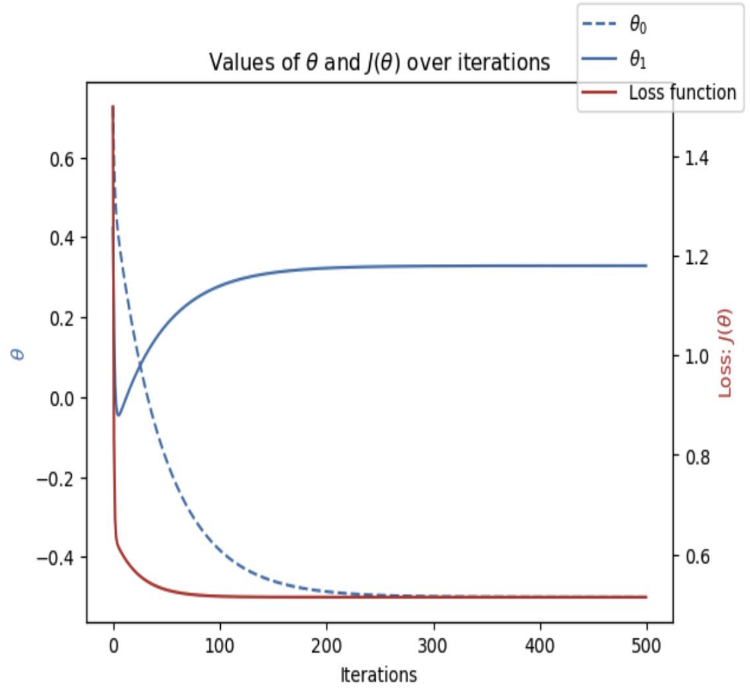
KNN station accuracy

Average - 88% (range = 83% - 100%)

100% can indicate class imbalance (interpret carefully)

Data Optimization: Gradient Descent (Convergence)

- Gradient descent updates parameters to reduce loss.
- Tuned learning rate (step size) + iterations until loss stabilized.
- Scaling features improved stability and convergence.
- Scaling the data helped gradient descent converge more smoothly and consistently.



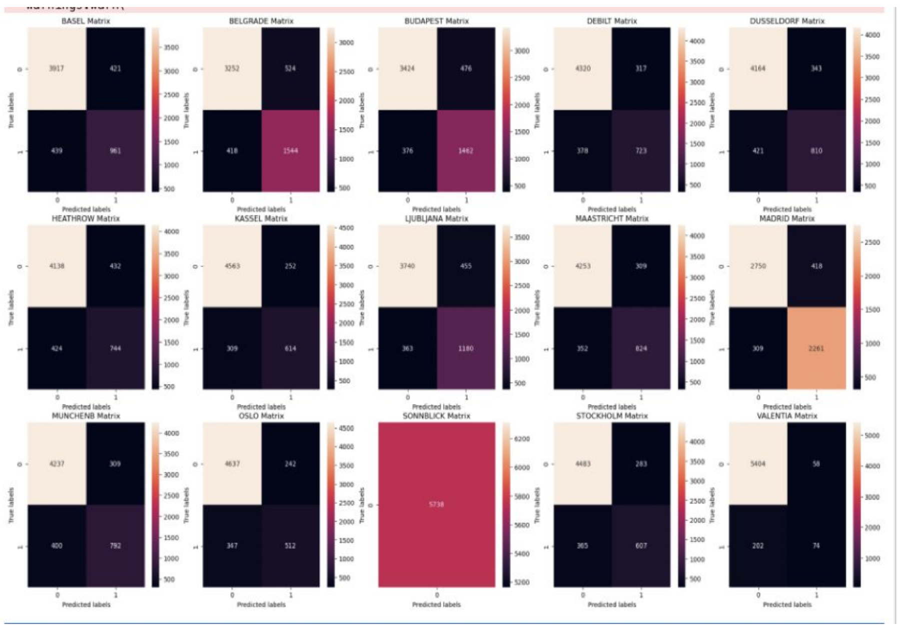
Supervised Learning: Model Comparison

I compared three model families to evaluate accuracy, interpretability and risk.

Model	Strengths	Watch-outs	Best use
KNN	Strong baseline, simple, good average station accuracy (88%).	Sensitive to feature scale, slower with large data.	Quick, reliable baseline and comparison point.
Decision Tree	Interpetable rules, easy to explain to stakeholders.	Can overfit when deep, unstable with small data shifts.	Explainable insights, baseline rules and feature importance.
ANN	Handles complex patterns, often improves with scaling.	Harder to interpret, needs tuning and careful validation.	Higher accuracy when performance is the priority.

Station Diagnostics: Confusion Matrices

I reviewed performance per station to spot uneven accuracy and potential data issues.



What to look for

- Big diagonal = more correct predictions
- Off-diagonal = false positives/negatives
- Station outliers may indicate imbalance or missing data
- Use station-level monitoring in production

Recommendation, Next Steps and Future Analysis

Recommendation:

Use a scaled ANN for highest accuracy, keep KNN as a strong baseline and Decision Trees for explainability.

Next steps:

- Tune hyperparameters (K. tree depth, ANN layers) using cross-validation
- Address class imbalance (class weights/resampling)
- Define alert thresholds with domain experts
- Track station-level performance over time

Future analysis:

- Hold-out recent years to test climate drift (non-stationarity)
- Add more features (wind, precipitation, radiation) for richer signals.
- Forecast extremes (heatwaves, heavy rain) as separate targets
- Build dashboards for decision-maker

Summary

Goal: Predict whether a day is “pleasant” or “unpleasant” using European weather station data.

Data: 18 European stations, late 1800s - 2022 and reviewed bias risks.

Methods: Optimization (gradient descent + scaling) and supervised models (KNN, Decision Tree, ANN).

Results: KNN averaged 88% accuracy across stations, performance varies by station and class imbalance.

Recommendation: Use scaled ANN when accuracy is the priority, keep KNN as a strong baseline.

Next steps: Cross validation, hyperparameters tuning, handle imbalance, and test on new year's/stations to confirm generalization.

Questions

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