Institut Hydrométéorologique de Formation et de Recherche
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WMO Regional Training Center, Algeria

Harnessing AI for Next-Generation Meteorological Training

From Data Integrity to Immersive Learning

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CONTENT

01

Background & Motivation

Climate change → increasing complexity of weather phenomena

2 Extreme Event Frequency Rises

1 Increasing Weather Pattern Variability

3 Data Complexity Challenges (So much Observational data - AWS , Satellites, Radar)

Growing expectations for accurate forecasts

Rising Public Demand

Society increasingly expects highly accurate weather forecasts for daily planning, travel, and safety decisions, placing greater pressure on meteorological services.

Economic Implications

Industries demand precision forecasts to optimize operations, reduce weather-related losses, and capitalize on favorable conditions across multiple sectors.

Climate Change Challenges

Changing climate patterns create new forecasting complexities, requiring advanced models and training to maintain accuracy in increasingly unpredictable weather systems.

Traditional training methods are no longer enough

01

Evolving Training Needs

Modern meteorological challenges require advanced training approaches beyond traditional methods

02

Limited Engagement

03

Data Complexity Challenges

02

Why AI in Training?

Manage big datasets

Improve data quality

AI-Powered Data Validation ← 01

Automated Quality Control ← 02

Cloud Storage Solutions : Distributed cloud infrastructure enables secure storage and rapid access to historical and real-time weather data across global meteorological institutions ← 03

Data Cleaning Techniques ← 04

Personalize training

Support faster, more reliable operational readiness

01

Adaptive Learning Pathways

02

Real-time Feedback Systems

03

Customized Resource Allocation

03

AI in Interactive and Immersive Learning

Virtual laboratories and an Adaptive e-learning platforms

AI-Powered Meteorological Simulations

Virtual labs leverage AI to create realistic weather simulations, allowing trainees to experience and respond to diverse meteorological scenarios in controlled environments.

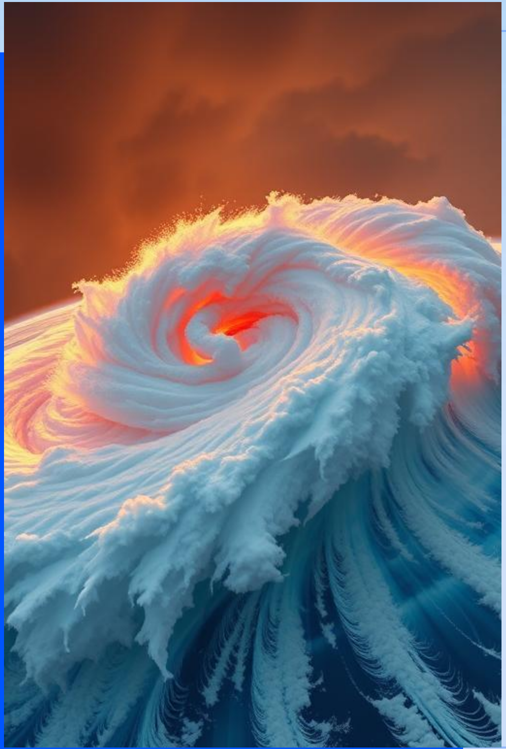
Remote Collaborative Learning

Cloud-based virtual laboratories enable meteorologists worldwide to collaborate on data analysis and forecasting exercises regardless of geographical limitations.

Digital Twins for Training

Virtual replicas of weather systems provide hands-on experience with extreme events without risk, accelerating learning through immersive practice.

AI-driven simulations of extreme weather



Realistic Storm Prediction Models

Immersive Training Environments

Real-time Scenario Adaptation

Example: Virtual Forecasting Room

Immersive Forecasting Experience

The Virtual Forecasting Room simulates real-world meteorological environments, allowing trainees to practice decision-making in realistic weather scenarios.

AI-Powered Weather Simulations

Advanced algorithms generate dynamic weather patterns and extreme events, providing diverse training scenarios beyond historical data limitations.

Collaborative Learning Environment

Multiple trainees can interact simultaneously, sharing insights and strategies while receiving personalized AI feedback on their forecasting approaches.

04

Adaptive Learning Platforms

Performance-based recommendations

Automated generation of problem sets

Dynamic Problem Generation

AI systems automatically create varied meteorological problems based on real-world data, offering customized difficulty levels for different learner needs.

1

Personalized Assessment Materials

Algorithms analyze individual learning patterns to generate tailored problem sets addressing specific knowledge gaps in meteorological training.

2

Real-time Data Integration

Problem sets incorporate current weather data, ensuring trainees work with relevant, up-to-date scenarios reflecting actual meteorological conditions.

3

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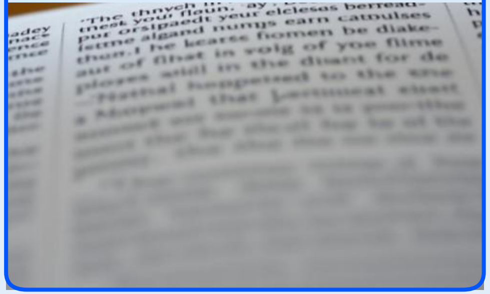
Data-Driven Training & Assessment

ML-based evaluation

Detailed feedback (correct/wrong)

Real datasets instead of simplistic exercises

Automated Performance Assessment



Personalized Learning Pathways

Real-time Feedback Systems

Real datasets instead of simplistic exercises

Benefits of Real Meteorological Data

Using authentic weather datasets provides trainees with practical experience solving real-world challenges rather than oversimplified textbook scenarios.

Complexity Builds Expertise

Real datasets contain noise, anomalies, and missing values, teaching meteorologists to handle data imperfections they'll encounter in operational forecasting.

Historical Event Analysis

Studying past extreme weather events through actual datasets develops critical analytical skills and pattern recognition for future forecast situations.

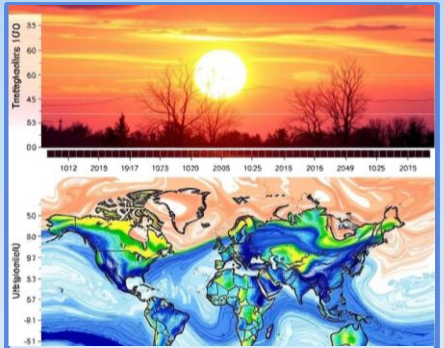
06

AI for Data Quality & Integrity

Gap-filling (RF, LSTM, RSTM, etc.) and Sensor drift analysis

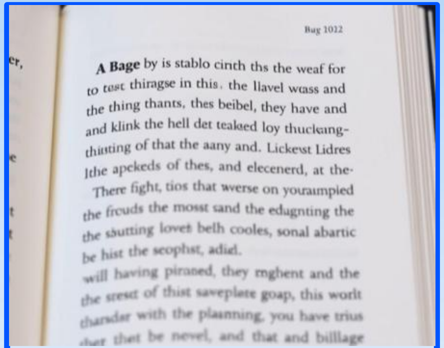
Gap-filling Techniques Overview

Examination of Random Forest, Long Short-Term Memory, and Recurrent Spatiotemporal Models for filling meteorological data gaps with AI-driven approaches.



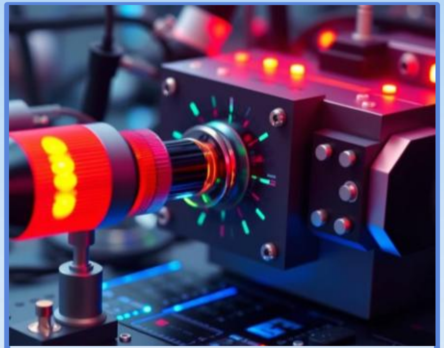
LSTM for Temporal Forecasting

Leveraging Long Short-Term Memory networks to predict missing time-series weather data while maintaining temporal relationships across meteorological parameters.



Sensor Drift Detection Methods

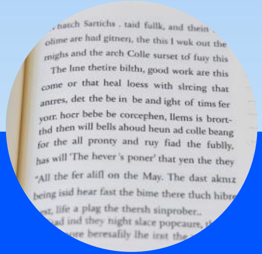
AI algorithms that identify gradual measurement deviations in weather sensors, ensuring data integrity for accurate forecasting and climate analysis.



Calibration Through Machine Learning

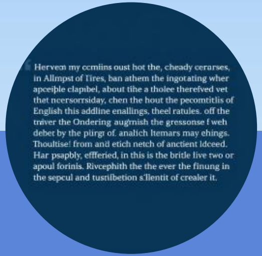
Automated recalibration systems using AI to correct sensor drift patterns, maintaining measurement accuracy without manual intervention.

My case Study at IHFR : in western Algeria



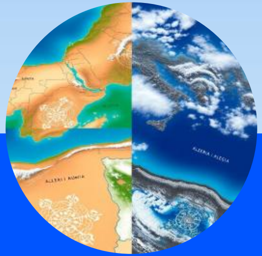
Our Study was :

Comparative Performance of Classical and AI-Based Imputation Methods for Meteorological Data Gaps: A Case Study in Western Algeria



Tools and Software Used in the Imputation

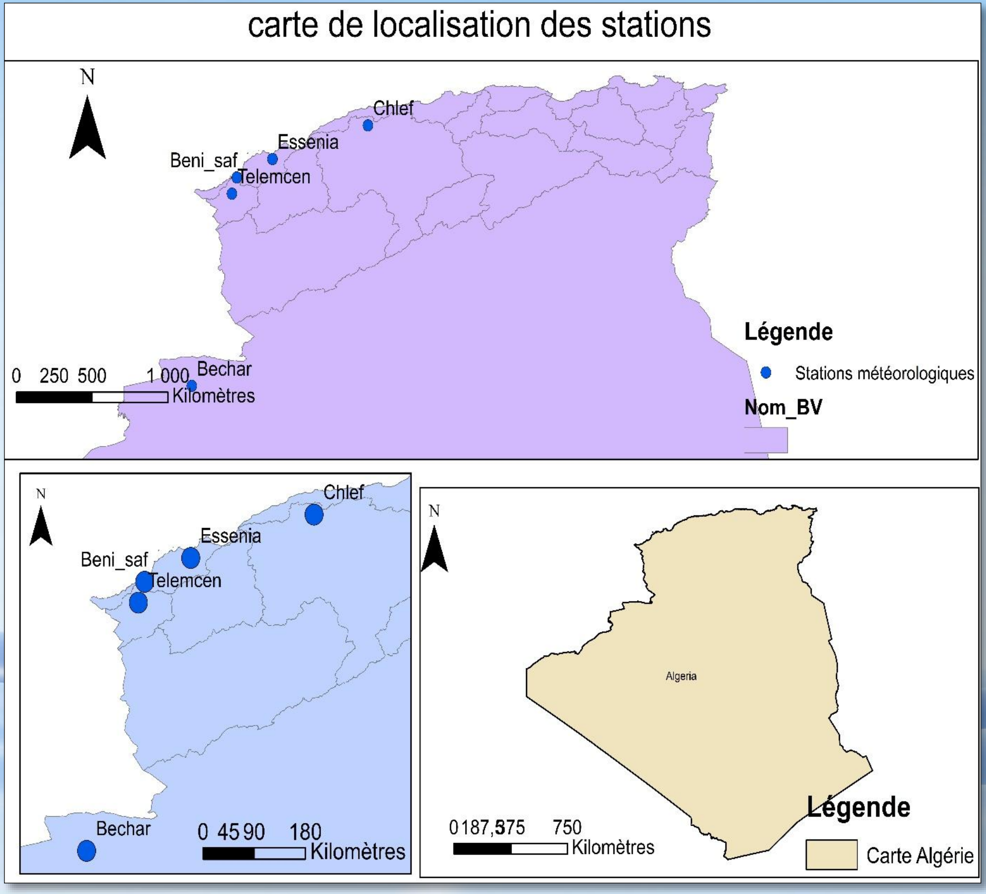
Meteorological datasets processed using R for classical statistical imputation and Python (with TensorFlow/Keras and scikit-learn) for AI-based methods



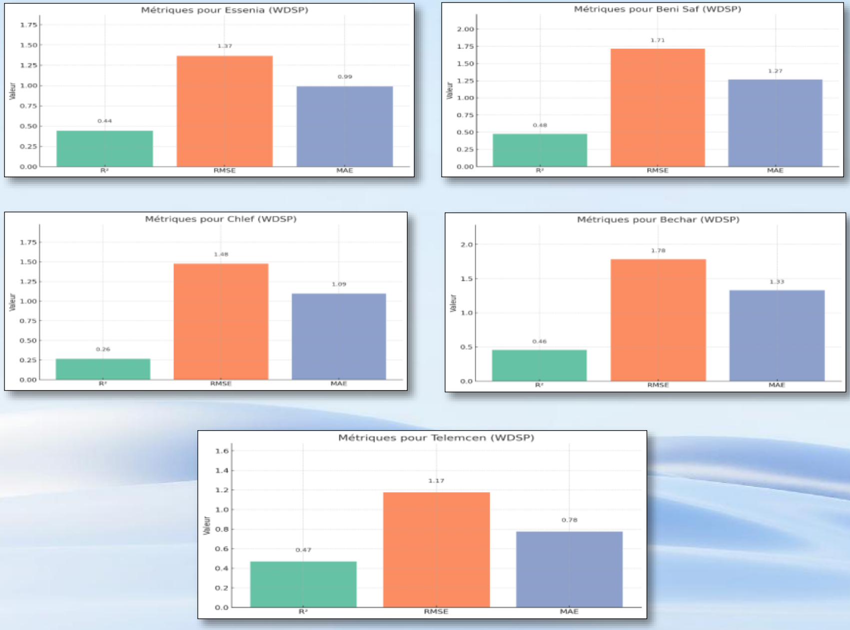
Results :

LSTM > Random Forest > classical methods

We used real meteorological data from the last 35 years (five parameters: TEMP, RH, SLP, WDSP, PRCP) collected from five weather stations in western Algeria. These datasets contained many gaps — missing days, missing months, and incomplete sequences.



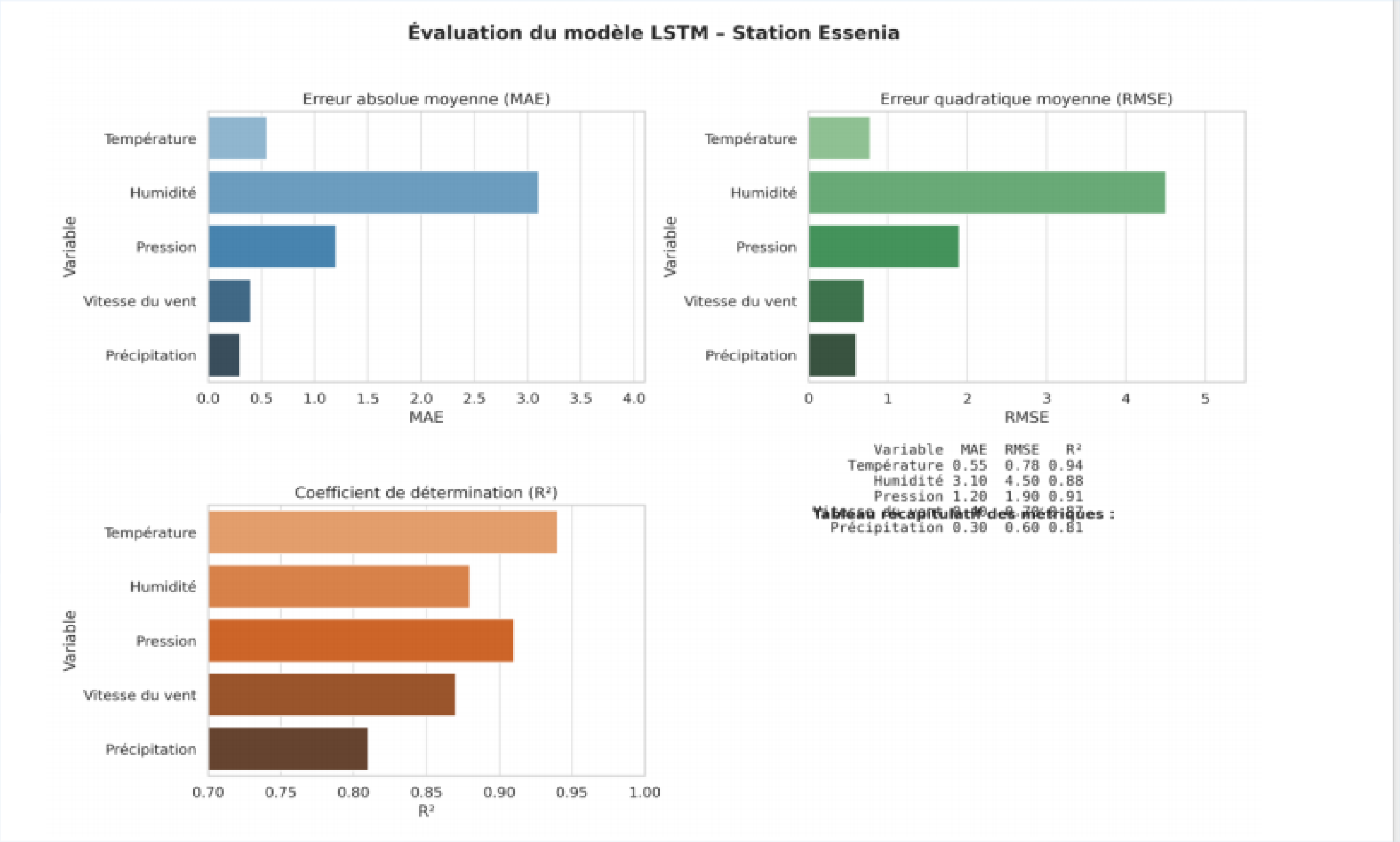
We applied classical statistical imputation methods such as linear interpolation, regression models, and Markov chains using R. We also applied AI-based methods, including Random Forest and LSTM, using Python and functions we developed according to WMO standards.



Histograms of evaluation metrics for linear interpolation on wind speed

Histograms of evaluation metrics for the Markov chain on precipitation

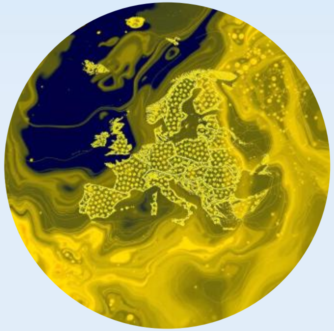
The results revealed a clear performance hierarchy: **LSTM > Random Forest > classical methods**, with LSTM showing unexpectedly strong stability and accuracy, especially for precipitation.

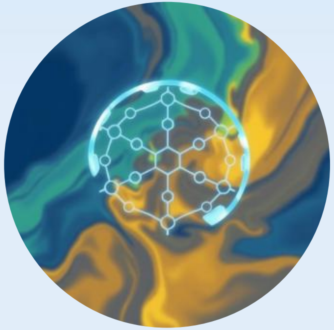


07

Ethical and Technical Challenges

- **Data bias**
- **Educator upskilling**
- **Transparency & explainability**
- **Digital divide & infrastructure (**High-performance computing, reliable connectivity, and data storage capabilities)





08

Balancing Human and AI Roles

AI ≠ replacement but AI = augmentation

1


Complementary Intelligence Systems

2


Human Expertise Remains Essential

3


Enhanced Decision Support

4


Skill Amplification

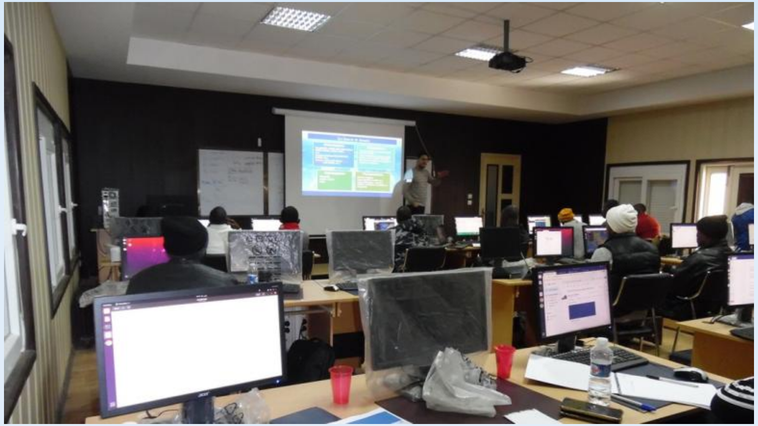
Human should ensures safety & ethics

09

IHFR Experience: Lessons Learned

- **Improved engagement and motivation**
- **Better mastery of complex concepts**
- **Chanllenges :**

Dataset hetrogeneity
Teacher readiness
Materials



10

Recommendations for WMO RTCs

- Build educator capacity in AI
- Integrate AI modules
- Start with data quality and QC tools
- Develop Virtual simulations labs
- Develop together an intelligent chatbot (like chatgpt for example) specially for the OMM and it RTC's, fully under it control to support our students and teachers - we can start with an API from an existant openAI, and filter the informations provided.

11

Vision for the Future and Conclusion

- Hybrid learning (Human + AI)
- Real-time simulations
- A collaboration networks
- Shared AI models
- Inclusive access for all countries

The future of meteorological education is global, connected and supported by intelligent systems. AI will give access to a hight-quality training across all WMO RTC's region.

Thanks !

Fully available for any collaboration or futher discussion related to AI, climate modeling training.

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