Hybrid AI–Physics Calibration of a 1D Fog Model: Improving Near-Surface and Visibility Forecasts at a Moroccan Airport

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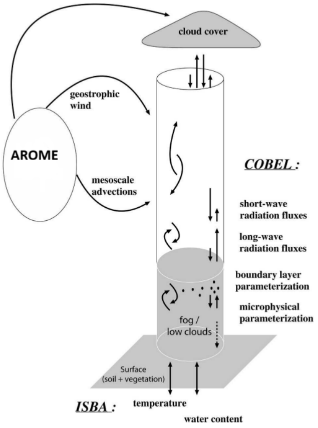
7 May 2026

EGU26-5760

Outline

Introduction and Research Problem

- Fog at Casablanca–Nouasseur Airport is a major challenge for aviation safety *(Bari and El Khlifi, 2015)*.
- **COBEL–ISBA 1D model** *(Bergot and Guedalia, 1994)*:
  - Designed for fog and boundary-layer processes;
  - Sensitive to initial conditions and forcing errors *(Bari, 2019)*.
- Persistent **systematic biases** motivate post-processing strategies (Mayer,2023).



AROME forcing and COBEL–ISBA framework

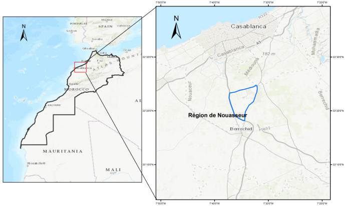
Objective, Data and Experimental Period

Objective:

- Develop a **hybrid AI–physics calibration framework**.
    - Correct COBEL–ISBA outputs while preserving physics;
    - Machine learning as post-processing;
    - Benchmark vs Bias Correction (BC) and Quantile Mapping (QM).

Data and Experimental Period:

- Period: **winter seasons 2015–2016 and 2016–2017**.
- Variables: T_{2m}, RH_{2m}, U_{10m}, V_{10m}, and *Visibility*.
- Forecast range: **0–12 h lead time**; runs: **0–23 UTC**.
- Data split:
    - Training: 80%;
    - Testing: 20% using temporal holdout.



Study site: ***Nouasseur Airport (Morocco)*** *(GMMN, WMO ID 60156)*

Handling Imbalance and Training Protocol

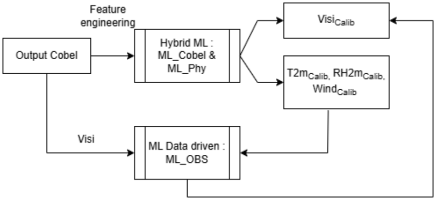
- Visibility was discretized into **five classes**.
- Resampling strategies:
  - ORIG: natural distribution;
  - RUS: random undersampling;
  - SMOTE: synthetic oversampling.

Method	n_{total}	c_1 < 1000	c_2 1000–3000	c_3 3000–5000	c_4 5000–8000	c_5 8000–10000
ORIG	35 935	701	594	1 410	3 485	29 745
SMOTE	148 725	29 745	29 745	29 745	29 745	29 745
RUS	2 970	594	594	594	594	594

- Machine learning models:
  - Random Forest (RF) *(Breiman, 2001)* ;
  - XGBoost (XGB) *(Chen and Guestrin, 2016)*.

Methodology: Hybrid ML Strategies

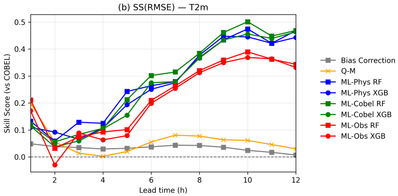
- **ML-COBEL:** Direct learning $\widehat{X}_{\text{Calib}} = f_\theta(\mathbf{p}_{\text{COBEL}})$
- **ML-Phys:** Residual learning $e = X_{\text{OBS}} - X_{\text{COBEL}}$
  $\widehat{X}_{\text{Calib}} = X_{\text{COBEL}} + f_\theta(\mathbf{p}_{\text{COBEL}})$
- **ML-OBS:** Observation-driven
  $\widehat{X}_{\text{Calib}} = f_\theta([\mathbf{p}_{\text{OBS}}, X_{\text{COBEL}}])$
- **ML-OBS-Calib:** Pre-calibrated
  $\widehat{\text{Vis}}_{\text{Calib}} = f_\theta([\mathbf{p}_{\text{Calib}}, \text{Vis}_{\text{COBEL}}])$

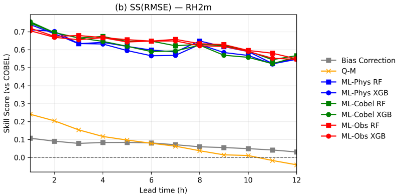


Hybrid AI–physics calibration workflow

Results: Lead-Time Evolution

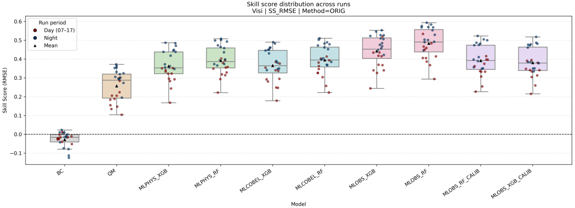
- Strong RH2m skill: **SS** ≈ **0.70–0.78** (H1–H3), stable ≈ **0.55** (H12)
- T2m skill increases with lead time, outperforming ML-OBS after H4 **SS** ≈ **0.40–0.57**
- Wind: **SS** ≈ **0.15–0.53**, recovering up to **70%** of ML-OBS skill
- Visibility: robust **SS** ≈ **0.34–0.40**, **66%** of theoretical upper bound.
- **Impact of resampling:** RUS best for fog **(SS** ≈ **0.5–0.7)**, SMOTE optimal for intermediate regimes **(SS** ≈ **0.55)**, ORIG dominates high visibility **(SS** ≈ **0.5)**
- Classical methods **(BC, QM)** show limited performance

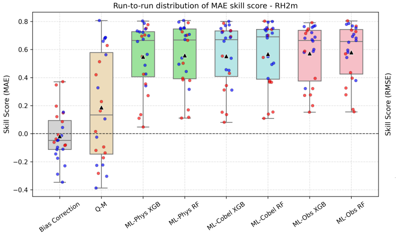




Results: Diurnal Variability

- RH2m: **SS ≈ 0.55–0.60 (≈60%** error reduction)
- T2m: moderate gains (**SS ≈ 0.24–0.33**), hybrid > ML-OBS
- Strong nocturnal improvement (stable boundary layer)
- Wind: **SS ≈ 0.18–0.40**, up to **90%** of ML-OBS skill
- Visibility: **SS ≈ 0.23–0.39**, best performance at night
- Classical methods show weak or degrading performance





Conclusions and Perspectives

Conclusions:

- Hybrid calibration significantly improves COBEL–ISBA outputs and outperforms classical post-processing methods.
- Without resampling, machine learning tends to ignore critical events to minimize global error.

Perspectives:

- Development of probabilistic forecasting based on hybrid ML.
- Extend the analysis to **RVR data**, given uncertainties in SYNOP visibility observations.
- Explore PINNs to combine data-driven accuracy with physical consistency in ML-based forecasting.

"AI doesn't replace physics—it makes it more accurate for decision-makers."

Thank you for your attention

References

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