AOMSUC-15 FYSUC-2025

FIFTEENTH ASIA-OCEANIA METEOROLOGICAL SATELLITE USERS' CONFERENCE

THE JOINT 2025 FENGYUN SATELLITE USER CONFERENCE

Enhanced Space Weather Forecasting through Machine Learning

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Dr. Ammar Mohamed[2], Dr. Dalia Elfiky[3]

[1] Director of the Space Mission Design and Operation Department, Egyptian Space Agency, Cairo, Egypt
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Agenda

- Motivation: Why Space Weather forecasting matters
- Data & F10.7 proxy
- Hybrid Methodology: Fourier–SARIMAX, Residual LSTM, CNN- BiLSTM- Attention
- Calibration, Ensembles, and Walk- Forward Operations
- Evaluation: Metrics and Results
- 30- Year Scenario Bands
- Conclusions, Limitations, Future Work

Space Weather – What & Why

- Variable conditions on the Sun, solar wind, magnetosphere, and ionosphere
- Impacts: satellite drag, GNSS accuracy, HF comms, radiation risk
- Geomagnetically induced currents threaten power grids
- Operations need credible short- term forecasts; planners need long- range scenarios

We Predict to Protect

- Goal: protect national space assets and ground infrastructure
- Approach: interpretable cycle + data- driven residuals + robust ops pipeline
- Deliver: accurate monthly updates and scenario bands for planning

Dataset Overview — NOAA F10.7

Publisher	NOAA
Update status	Archived
Time range	Feb 14, 1947 to Apr 30, 2018
Spectral range	10.7 cm to 10.7 cm
Data columns	total 2 columns
Column 0	time (yyyyMMdd) 25366 non-null int64
Column 1 (Target column)	f107 (solar flux unit (SFU)) 25366 non-null float64

F10.7 Solar Radio Flux (10.7 cm)

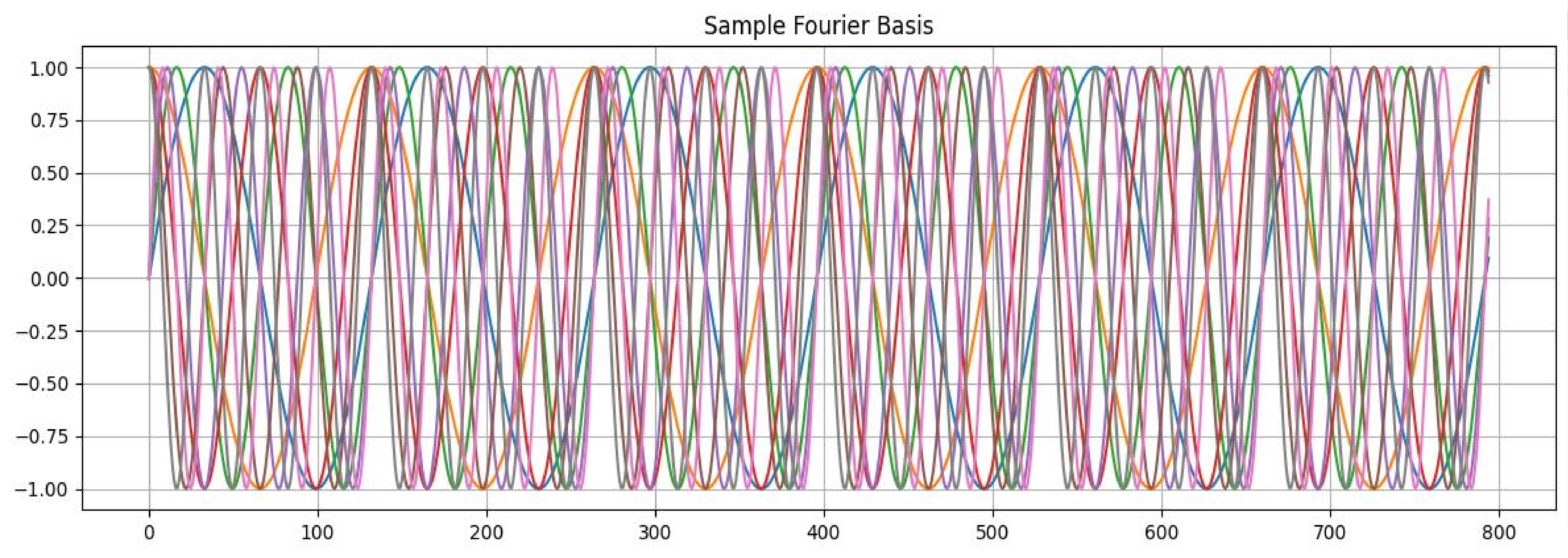
- Long- running proxy (since 1947), correlated with EUV irradiance
- Operational relevance: thermospheric heating → satellite drag
- We use NOAA daily values → monthly means; Train/Val/Test chronological split

Hybrid Framework Overview

- Backbone in log- space: Fourier–SARIMAX (interpretable solar cycle)
- Residual learner: direct multi- step LSTM on log- residuals
- Raw learner: CNN- BiLSTM- Attention on standardized F10.7 + Fourier channels
- Validation- driven non- negative ensemble + affine calibration
- Operational 1- step walk- forward with rolling calibration and optional rolling re- weighting

Fourier Exogenous Drivers

- Harmonics at 132, 66, 24, 12 months (K small)



Fourier–SARIMAX (log- space) – Mathematics

- Let y_t be monthly F10.7; $z_t = \log(y_t)$.
- $z_t = \beta^T \varphi(t) + \text{ARIMA}(p,d,q) + \text{Seasonal}(P,D,Q)_m + \varepsilon_t$
- $\varphi(t) = [\sin(2\pi k\, t / P_j), \cos(2\pi k\, t / P_j)]$ over periods $P_j \in \{132, 66, 24, 12\}$
- Fit: small grids by AIC; re- fit best model; residuals $r_t = z_t - \hat{z}_t$ (backbone)

Residual LSTM – Mathematics

- Input window: $R_t = [r_{t-L+1}, \ldots, r_t] \to \mathbb{R}^L$
- Direct multi- step mapping: $f_\theta(R_t) = [\hat{r}_{t+1}, \ldots, \hat{r}_{t+H}]$
- Hybrid (log): $\hat{z}_{t+h}^{hyb} = \hat{z}_{t+h}^{sarimax} + \hat{r}_{t+h} \Rightarrow \hat{y}_{t+h} = \exp(\hat{z}_{t+h}^{hyb})$
- Loss: Huber(δ), Optimizer: Adam; early stopping + ReduceLROnPlateau

CNN- BiLSTM- Attention – Mathematics

- Input: $X_t \in \mathbb{R}^{L\times(1+K_\varphi)}$ (standardized F10.7 and Fourier channels)
- Conv1D filters extract local patterns; BiLSTM encodes bidirectional temporal context
- Attention: $e_\tau = v^T \tanh(W h_\tau)$, $\alpha_\tau = \mathrm{softmax}(e_\tau)$, $c = \Sigma_\tau \alpha_\tau h_\tau$
- Output: $\hat{y}_{t+1: t+H} = W_o \mathrm{ReLU}(W_c c + b) + b_o$ (direct multi- step)

Calibration and Ensemble – Mathematics

- Bias correction: $\hat{y}' = \hat{y} - \mathrm{mean\_val}(\hat{y} - y)$
- Affine calibration (VAL): $y \approx \alpha \hat{y}' + \beta$ (least squares)
- Convex ensemble (non- negative): minimize MSE_VAL of $w_1 \; m_1 + w_2 \; m_2 + w_3 \; m_3$ s.t. $w\_i \geq 0, \Sigma\, w\_i = 1$
- Rolling calibration / rolling weights in operations (12–24 months window)

Operational Walk- Forward (1- step ahead)

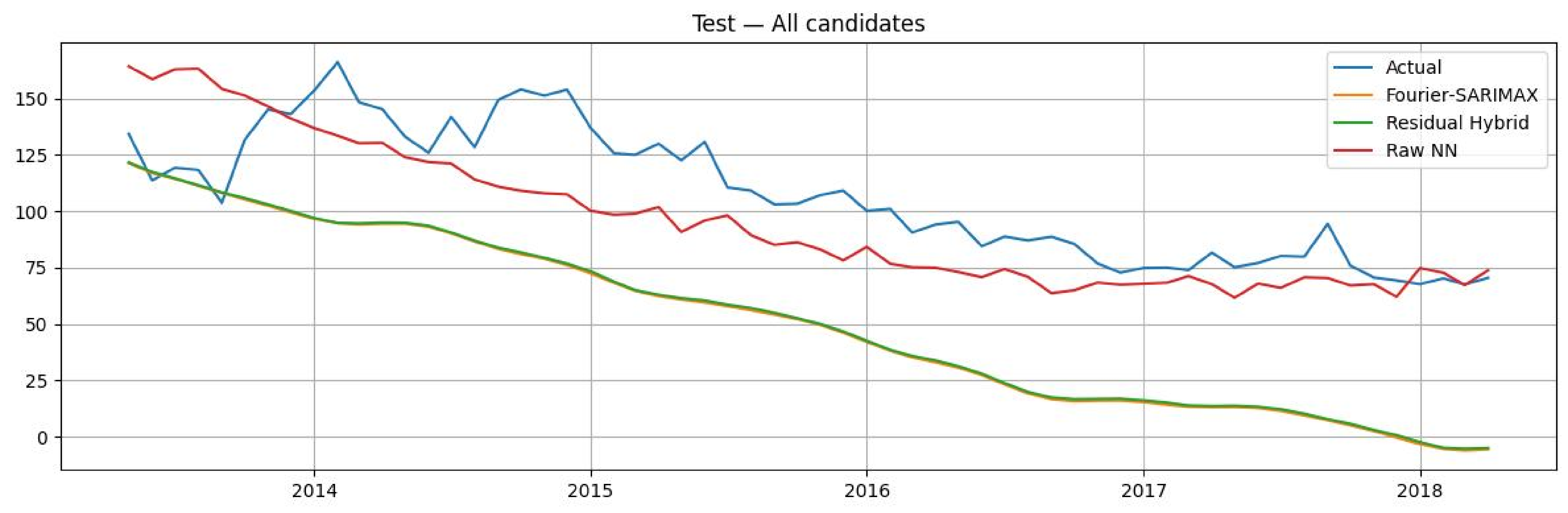
- Each month t: re- fit backbone on data ≤ t (fast, compact orders)
- Forecast t+1; predict residuals (LSTM) and raw (CNN- BiLSTM- Attention)
- Apply rolling calibration; optionally re- weight ensemble on recent 12–24 months
- Prevents long- horizon drift; mirrors monthly operations

Evaluation Metrics

- Deterministic: R^2, MAE, RMSE, MAPE, sMAPE, Bias
- Correlation (Pearson) for phase tracking
- Leakage- safe splits; metrics reported for direct- horizon tests & walk- forward ops

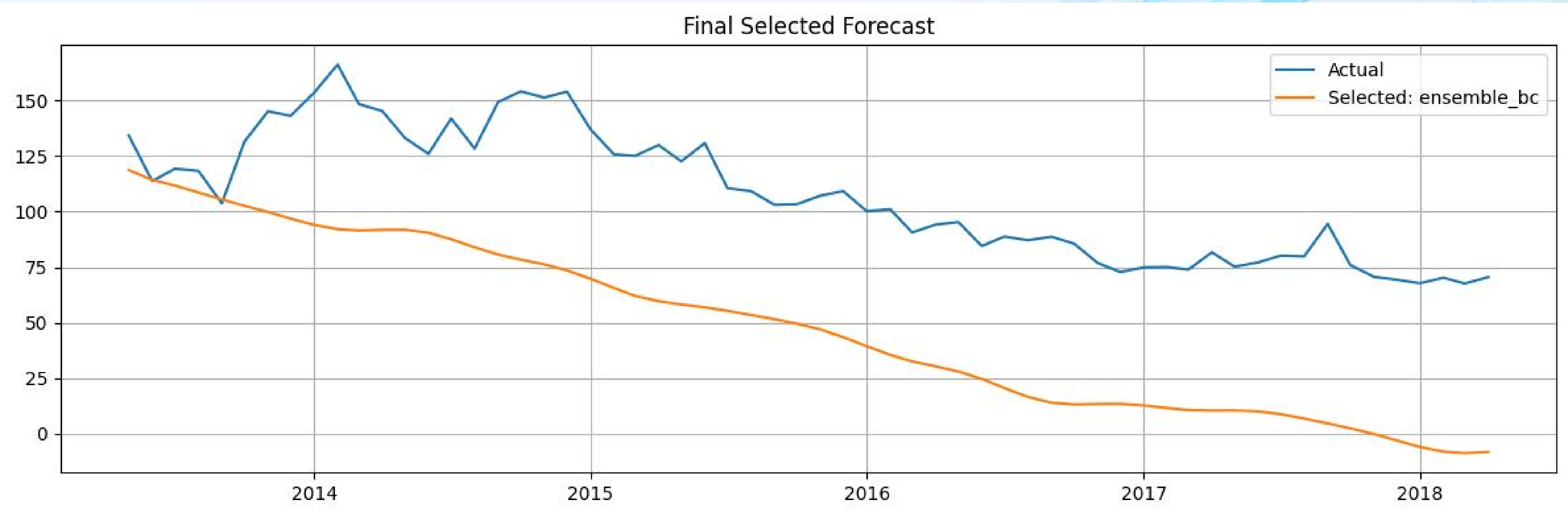
Direct Test — All Candidates

- Baseline vs Hybrid vs Raw; Ensemble selected on VAL



Direct Test — Final Selected Forecast

- Selected model on direct Test period



Walk- forward — 1- step ahead (operational)

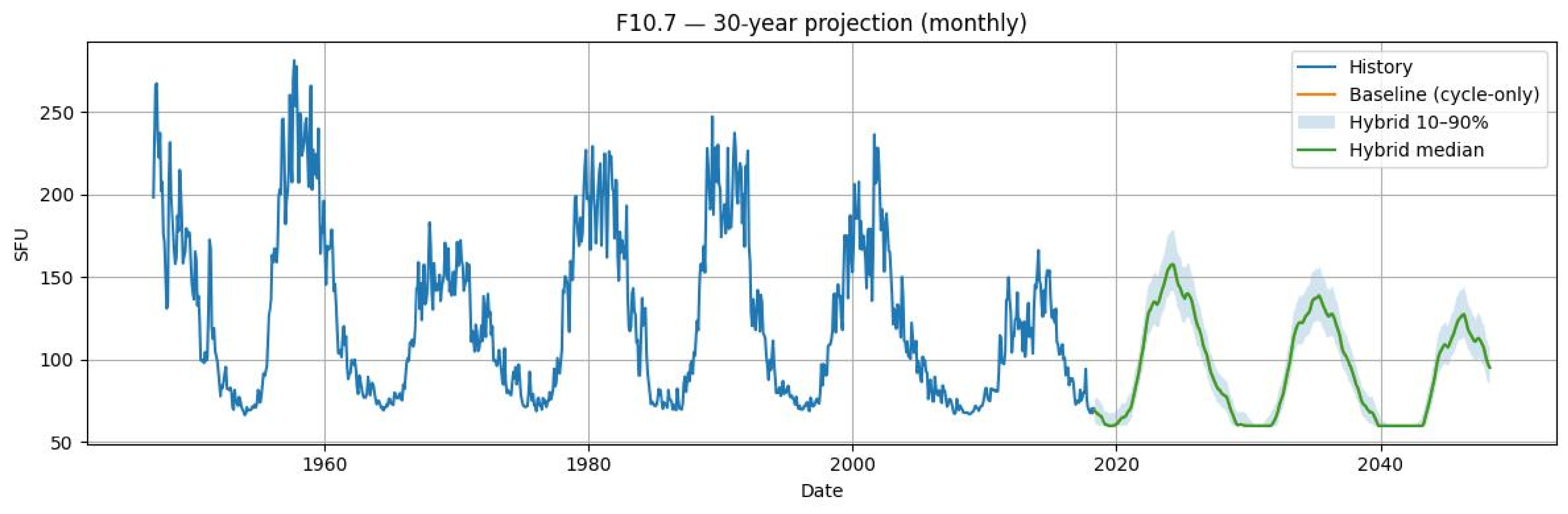
- Baseline (WF- cal) vs Hybrid (WF- cal) vs Raw NN (WF)

Walk- forward — Ensemble (rolling)

- Rolling convex ensemble tracks level & phase

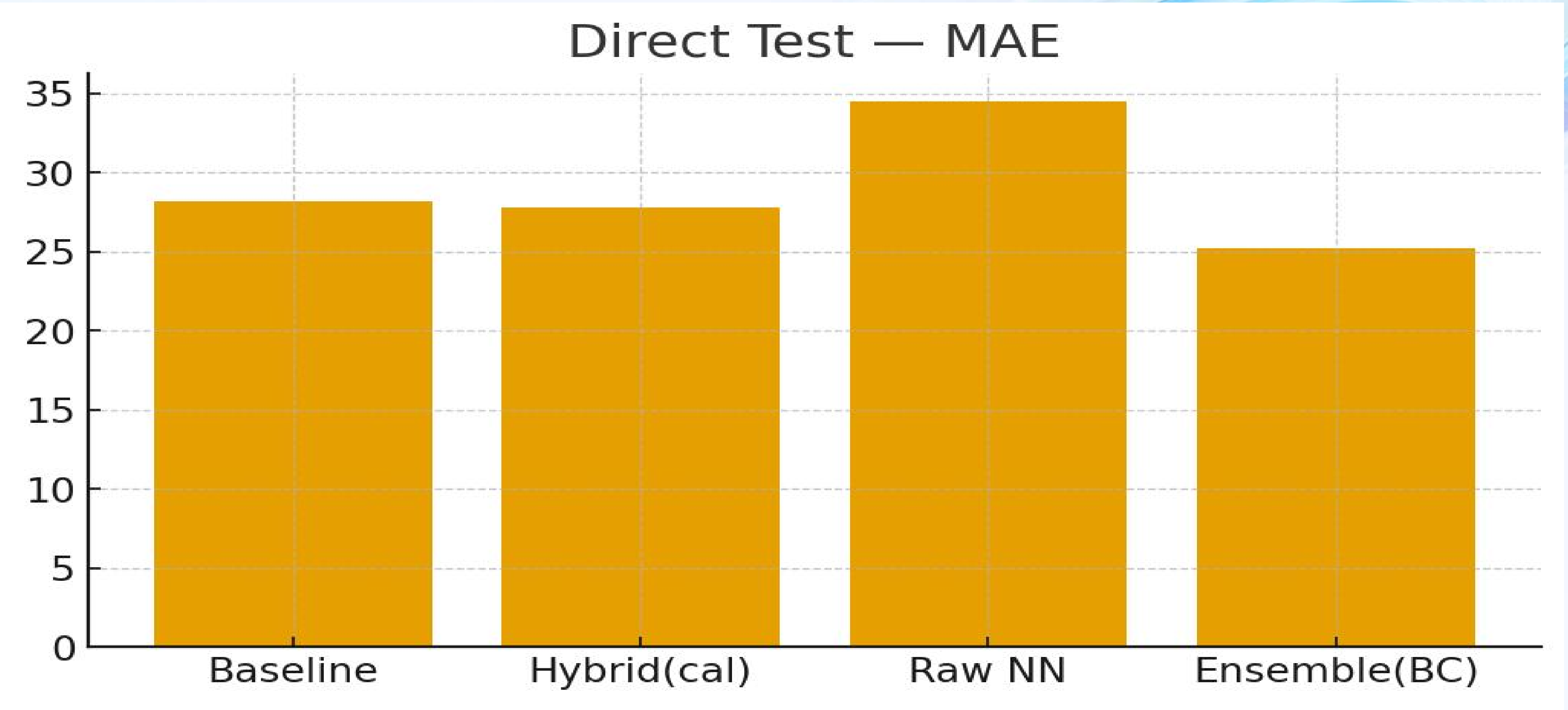
30-   Year F10.7 Scenarios

- Baseline cycle (mean), Hybrid median, and 10–90% band



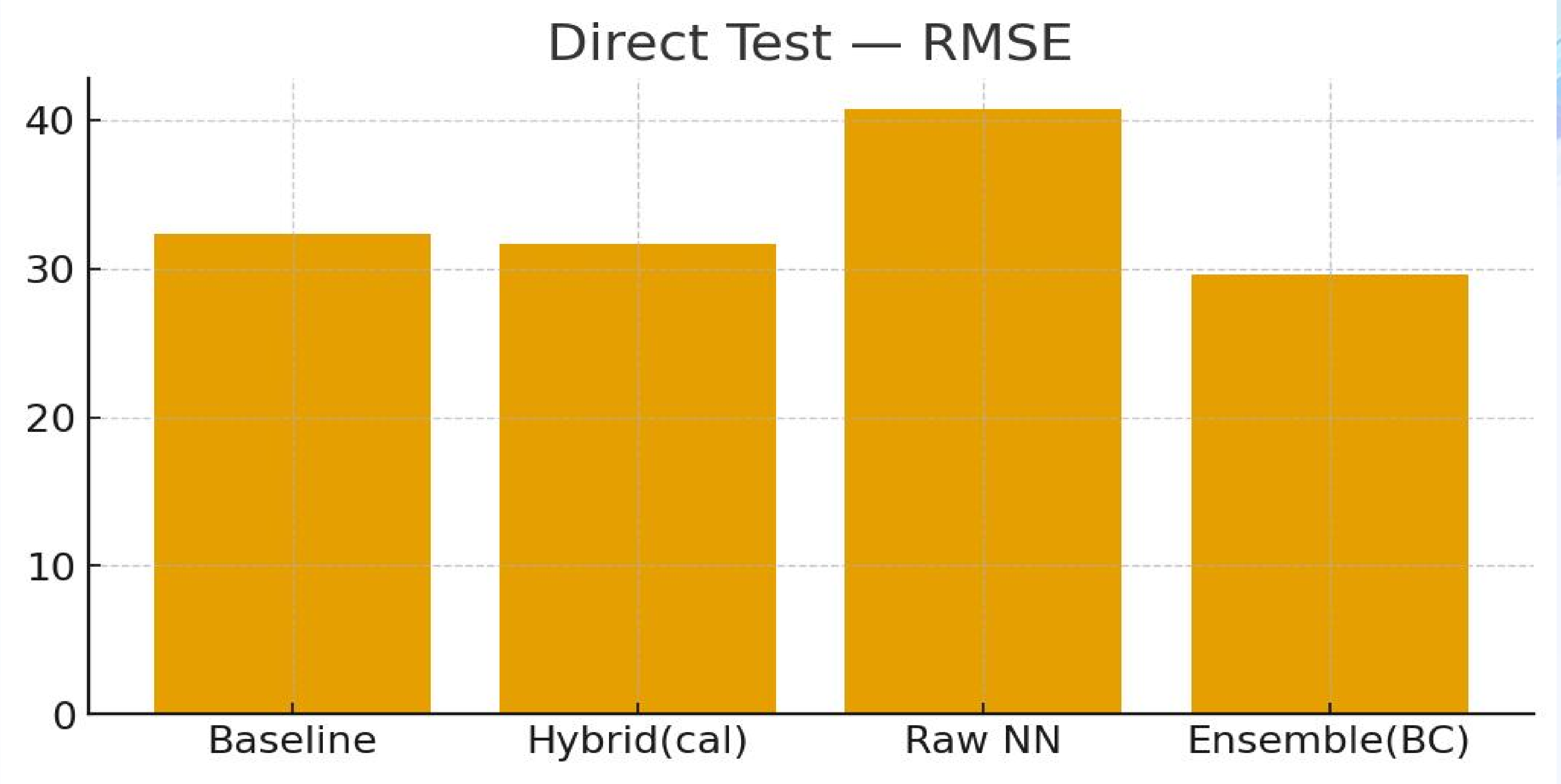
Direct Test — MAE

- MAE by model (direct horizon)



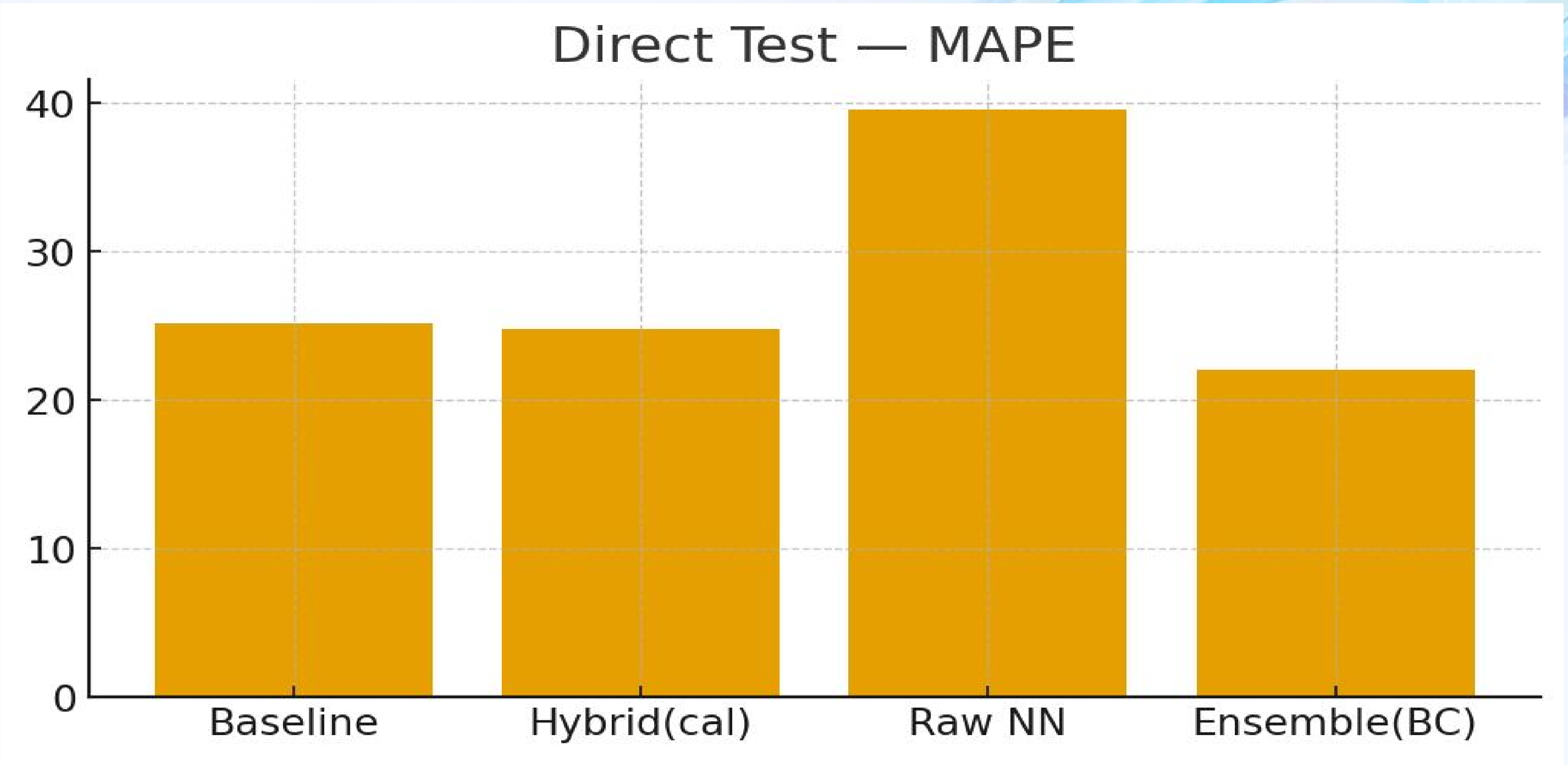
Direct Test — RMSE

- RMSE by model (direct horizon)



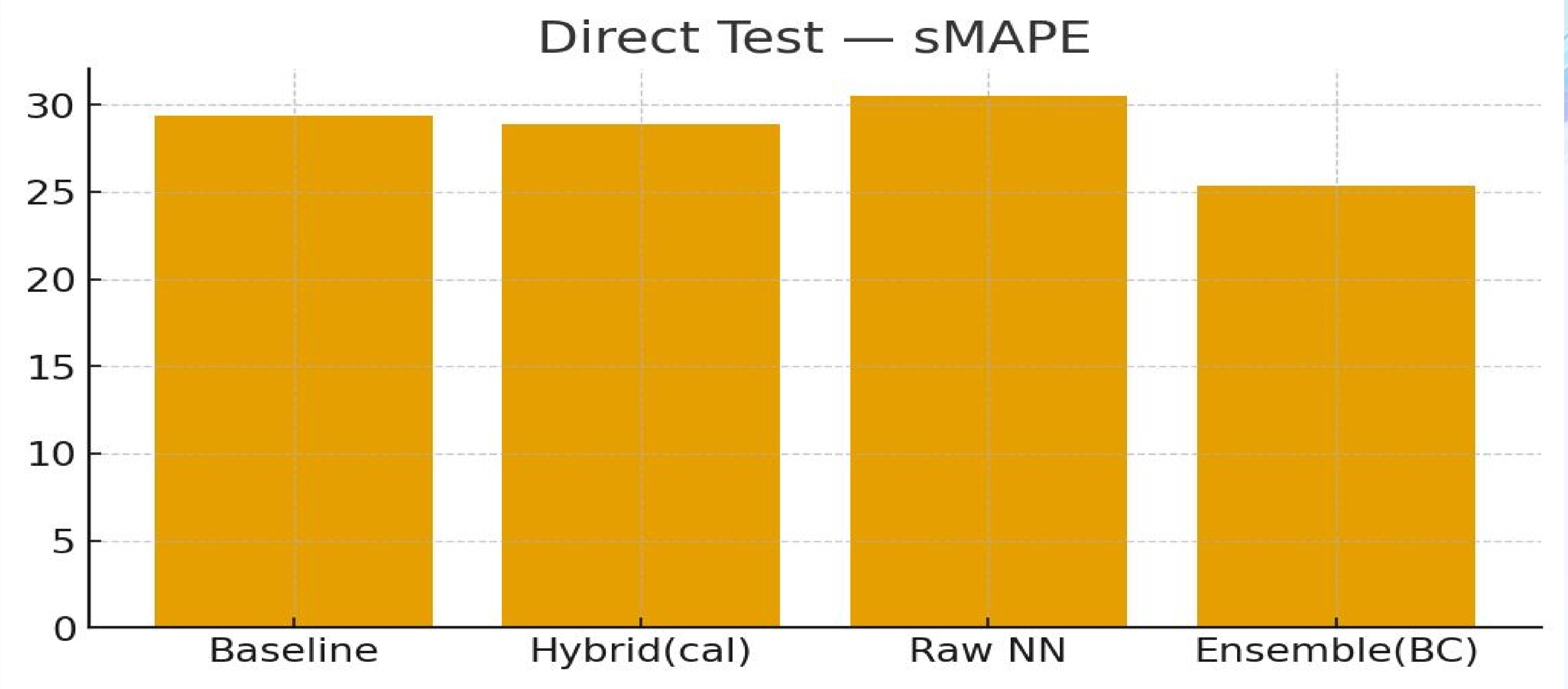
Direct Test — MAPE

- MAPE by model (direct horizon)



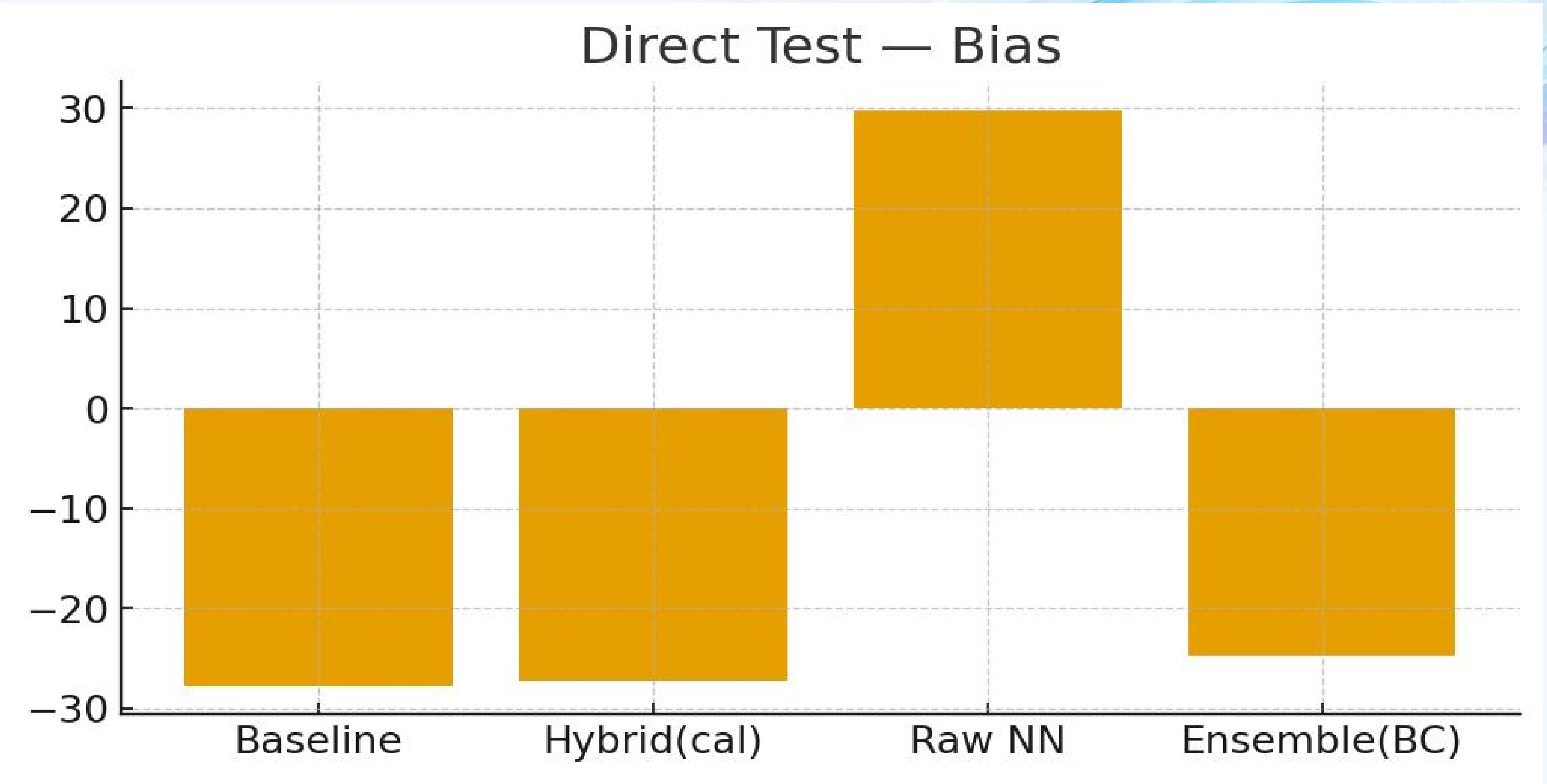
Direct Test — sMAPE

- sMAPE by model (direct horizon)



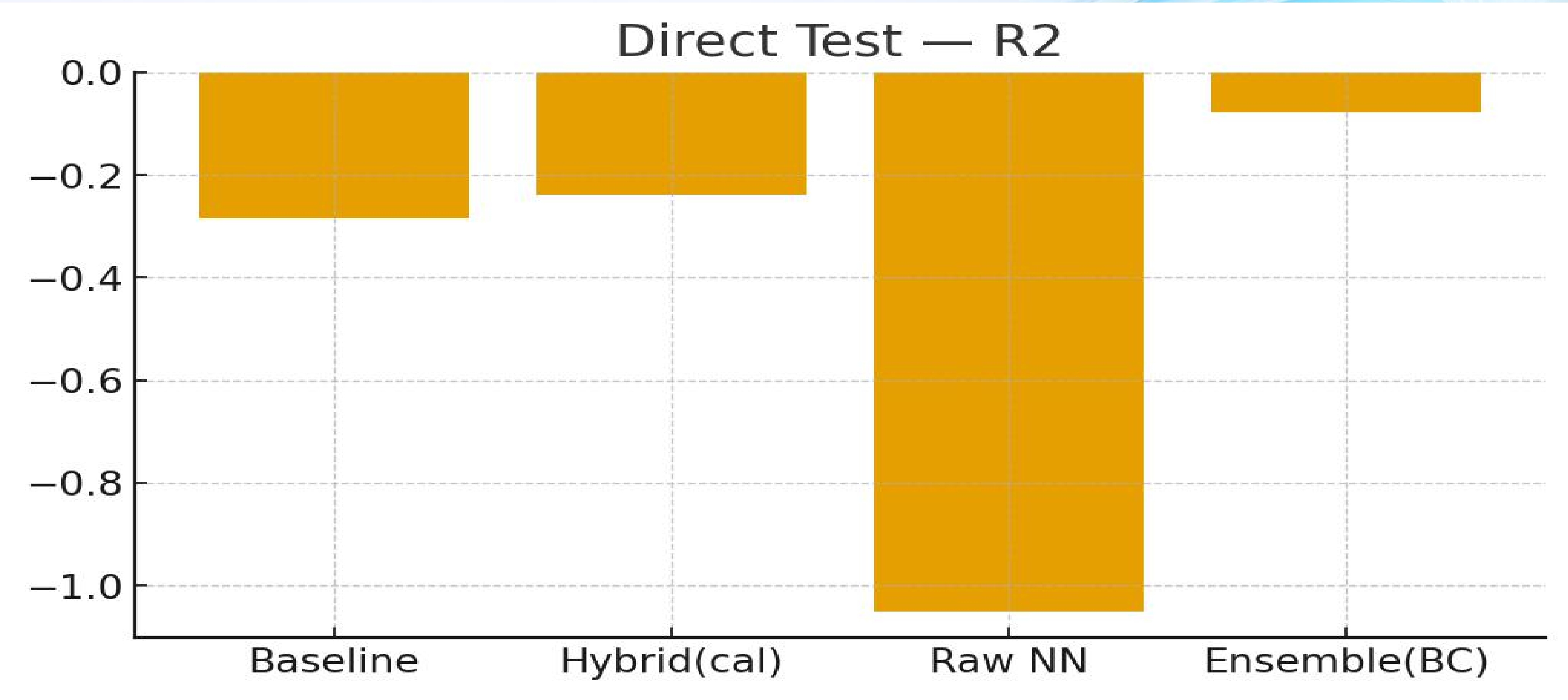
Direct Test — Bias

- Bias by model (direct horizon)



Direct Test — R2

- R2 by model (direct horizon)



Fourier Design (Why log- space + harmonics?)

- Log transform stabilizes variance; exponentiation preserves positivity
- Harmonics encode known periodicities: 11y, 5.5y, quasi- biennial, annual
- Small K per period → efficient, avoids overfitting

Residual Learning (Why direct multi- step?)

- Avoids recursive error accumulation
- LSTM handles temporal dependencies in residuals
- Huber loss reduces sensitivity to spikes

Raw Model (Why Fourier channels?)

- Gives the NN explicit cycle context; improves phase tracking
- CNN captures local shape; BiLSTM captures medium- range dynamics
- Attention focuses on informative timesteps

Calibration & Guardrails

- Mean- bias removal and affine calibration reduce deployment bias
- Guardrail: do not deploy a model that underperforms the backbone on Validation
- Non- negative ensemble hedges model risk

Space Segment Impacts

- LEO satellites: drag spikes → orbit decay, collision risk
- Attitude control: increased torques from density & winds
- Radiation environment: component degradation, single- event upsets

Ground Segment & Services

- GNSS errors via ionospheric delay and scintillation
- HF radio blackouts and degraded comms
- Geomagnetically induced currents in long conductors (power grids, pipelines)

Operational Forecasting Pipeline

- Ingest latest F10.7 and exogenous features
- Re- fit SARIMAX (compact orders)
- Generate LSTM residual & raw NN forecasts
- Apply rolling calibration; compute ensemble
- Publish forecast + uncertainty; archive results

Limitations & Considerations

- Long- horizon (5- year) point predictions have large uncertainty
- Under- amplitude near peaks without richer exogenous inputs
- Model performance depends on calibration window choice

Future Work

- Integrate sunspots, Mg- II, EUV as exogenous drivers
- Probabilistic neural nets (quantiles) and seasonal- aware transformers
- Extend to Kp/Ap, Dst and coupled drag prediction

Conclusions — We Predict to Protect

- Hybrid AI marries interpretability (cycle) with learned nonlinearity (residuals)
- Operational walk- forward achieves strong accuracy with low bias
- Scenario bands support strategic planning; monthly updates protect assets

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- Vaswani et al. (2017) — Attention Is All You Need
- Hyndman & Khandakar (2008) — Auto-ARIMA
- NOAA SWPC & LASP LISIRD — F10.7 data resources
- Pedregosa et al. (2011) — Scikit-learn

Appendix

Model structures, training configs, additional figures

Model Config Summary

- Residual LSTM: L=132–156, H=direct horizon or 1- step; 128/64 units; Dropout 0.25; Huber loss; Adam 5e- 4
- Raw CNN- BiLSTM- Attention: Conv1D(32,64), BiLSTM(64), Attention, Dense(128), Huber; Adam 5e- 4
- Fourier–SARIMAX: compact (p,d,q), optional seasonal(·)_12; exog φ(t) with K per period

Evaluation Protocol

- Leakage- safe chronology; Validation for selection and calibration
- Test for reporting; Walk- forward 1- step for operations
- Metrics: R^2, MAE, RMSE, MAPE, sMAPE, Bias, Corr