Pravāh

# INDUS: Nowcasting for Renewables over the Indian Subcontinent

**Karan Jakhar**[1], **Aman Gupta**[2], **Helgi Hilmarsson**[1] **and Dhruv Suri**[1]
[1]*Pravāh,* [2]*Research Scientist, Stanford University*

**The energy sector needs real-time prediction of solar and wind power generation on horizons of hours, and hence of the near-surface weather that drives it. The standard sources of such guidance are global numerical weather prediction (NWP), a physics-based simulation of the atmosphere run at major forecast centres, and more recently its AI-based counterparts (AIWPs). Both are accurate but issue new forecasts only a few times per day, leaving the latest atmospheric observations unused between issues.** ***Indus-Now*** **fills this gap with** ***nowcasting*****: short-range forecasts for the Indian subcontinent that are refreshed every hour as new observations arrive. A single AI-driven model fuses geostationary satellite imagery, surface station observations and an operational NWP forecast to produce hourly forecasts out to 48 h ahead. Over 2025, a full evaluation year held out from training, Indus-Now improves on the leading operational forecast systems for the variables that drive solar and wind generation: global horizontal irradiance (GHI), 10 m and 100 m wind speed, along with 2 m temperature.**

## Executive summary

- **The gap in current practice.** Indian utilities and generators schedule and settle renewable generation in 15-minute blocks, and revise those schedules through the operating day. The weather guidance behind the decisions comes from global numerical systems that issue forecasts a few times daily on coarse grids. Satellite scans and station reports arriving between issue times are therefore unavailable to the operator at the moment the next decision is made.
- **What Indus-Now provides.** A single deep-learning model fuses geostationary satellite imagery, surface station observations and an operational numerical forecast, is re-initialised every hour, and produces hourly gridded forecasts to 48 h: GHI at ~5 km, 2 m temperature and 10 m wind at ~10 km, and 100 m hub-height wind at ~25 km. All variables are fine-tuned to generate point forecasts corresponding to a particular location.
- **Accuracy against operational baselines.** Over the whole of 2025, Indus-Now records lower error than the operational systems in production at ECMWF and NOAA – IFS-HRES, AIFS and GFS – across the full 48 h horizon for each of the four variables that drive solar and wind output (Figure 3, Figure 4).
- **Performance at Indian generation sites.** At India's largest commissioned solar parks and at wind clusters in Gujarat, Indus-Now follows the observed diurnal cycle of temperature, irradiance and hub-height wind more closely than the operational baseline, and reduces the over-prediction of mid-day irradiance and 100 m wind peaks visible in IFS-HRES (Figure 5, Figure 6).
- **Commercial consequence for generators.** Indian regulation prices forecast error directly. From April 2026 the revenue-neutral deviation band narrows from ±10% to ±5% for solar and hybrid plants, and from ±15% to ±10% for wind. A Grid-India simulation of sixteen operating projects indicates revenue losses of 3.5–11.1% for solar, 2.4–11.8% for hybrids and up to 48% for wind under the narrower bands. Because schedules may be revised up to sixteen times a day, forecast accuracy is realised through intraday revision, and the available accuracy at each revision sets the achievable reduction in settled deviation.
- **Consequence for system operation.** The balancing requirement is growing. The summer evening net-load ramp increased from 35.7 GW in May 2023 to 73.7 GW in May 2026, and about 2.1 TWh of renewable generation, approximately Rs. 629 crore in foregone revenue, was curtailed in FY2025–26. More accurate nowcasts reduce the reserve volume that must be procured, recover generation that would otherwise be spilled, and supply load dispatch centres with the physical fields – irradiance and hub-height wind – that their telemetry does not currently carry.

India is deploying solar and wind capacity at a pace that makes accurate, frequently updated forecasting of surface conditions a first-order operational concern. Photovoltaic output tracks the solar irradiance reaching the ground, while wind generation depends on wind speed at turbine hub height (the height of the rotor, around 100 m above ground); both must be anticipated hours ahead, and revised as conditions evolve, to schedule dispatch, manage reserves and trade in short-term markets. Forecast errors also carry a direct cost: under India's deviation settlement mechanism (DSM), generators pay penalties when actual output strays from their submitted schedule beyond a tolerance band [1, 2]. Global NWP systems supply the baseline guidance, but their few-times-daily updates and global grids fall short of the hourly cadence and fine spatial detail that grid and asset operators need over the subcontinent. The recent generation of data-driven weather models [3, 4, 5] has shown that machine learning can match or exceed physics-based forecasts at a fraction of the computational cost, and deep-learning nowcasting systems such as the MetNet family [6, 7, 8], DGMR [9], NowcastNet [10] and StormCast [11] have brought the same gains to short-range, observation-driven prediction; Indus-Now applies this approach to the renewables-focused nowcasting problem.

## The Indus-Now system

Indus-Now is a deep-learning model that refines an operational NWP forecast using live observations (Figure 1). It ingests numerical forecasts together with geostationary satellite imagery (Meteosat-IODC SEVIRI) and surface station data. Gridded forecasts are produced hourly out to 48 h, each variable at its native resolution: global horizontal irradiance (GHI) at 0.05° (~5 km), 2 m temperature and 10 m wind at 0.1° (~10 km), and 100 m hub-height wind at 0.25° (~25 km). The model takes the most recent observations as input, and is re-initialised every hour as new satellite and station data arrive. Figure 2 shows the four forecast fields from a single Indus-Now run during the south-west monsoon: cloud-shaded, low-irradiance, over the peninsula, in contrast to the hot and clear north-west.

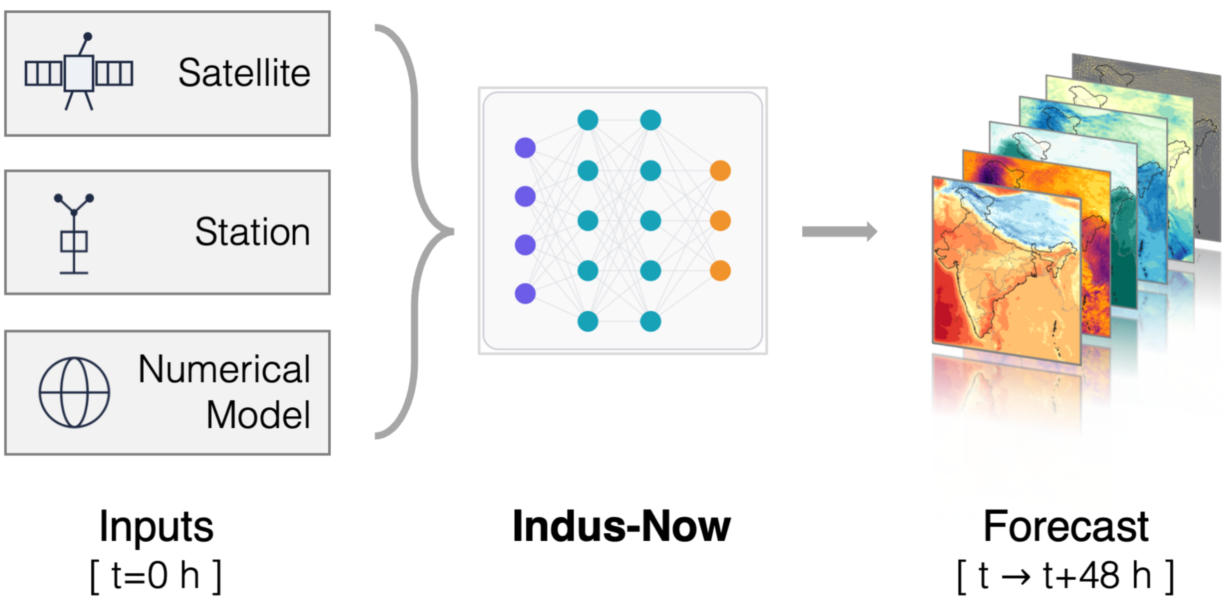


Figure 1 | **Indus-Now forecasting framework.** Satellite, station and numerical-model inputs up to the most recent observation time ($t = 0$ h) are combined by Indus-Now to produce hourly forecasts out to 48 h ahead ($t \rightarrow t + 48$ h) over the Indian subcontinent.

## Forecast performance

We evaluate Indus-Now over the full 2025 test year, which is entirely excluded from the model's training data, against three leading operational forecast systems and a climatological reference, all described below. Error is

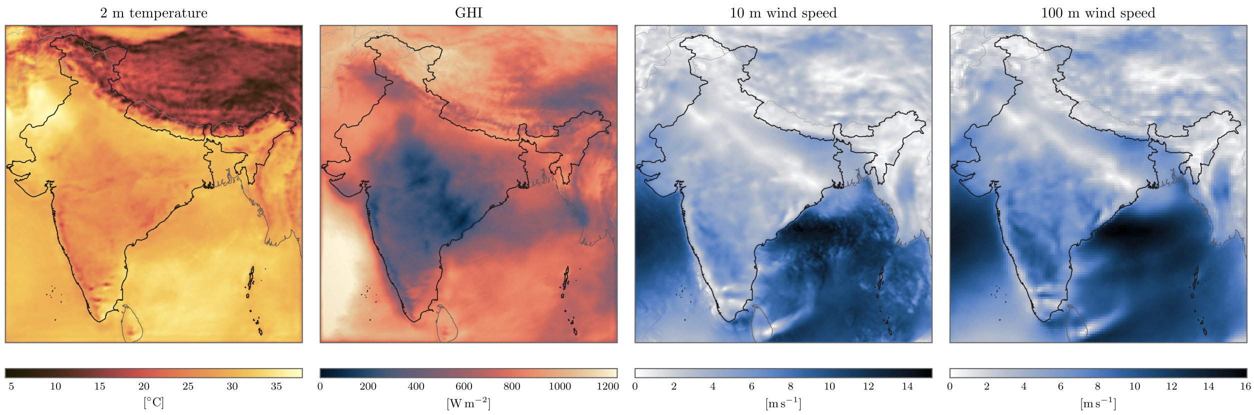


Figure 2 | **Example Indus-Now forecast fields.** A single Indus-Now forecast over the Indian subcontinent, initialised at 08:30 IST (03:00 UTC) on 1 July 2025 and shown at a lead time of three hours, valid at 11:30 IST (06:00 UTC): 2 m temperature, global horizontal irradiance (GHI), and 10 m and 100 m wind speed. The snapshot captures the south-west monsoon: cloud-shaded, low-irradiance, cooler conditions over the peninsula, contrasting with hot, clear skies in the north-west.

measured as root-mean-square error (RMSE) as a function of *lead time* (how far ahead of its start a forecast applies), with each grid cell weighted by the cosine of its latitude so that cells count in proportion to their true surface area, following the WeatherBench 2 convention [12].

Figure 3 shows RMSE as a function of lead time for each variable, and Figure 4 summarises the corresponding skill relative to IFS-HRES. Across the renewables-relevant variables (2 m temperature, 10 m and 100 m wind speed, and global horizontal irradiance), Indus-Now matches or improves on the operational baselines throughout the 48 h horizon. Models are scored on their native grids, and a finer grid resolves sharper local extremes and therefore tends to incur a higher RMSE, so Indus-Now versus IFS-HRES, both on the finer grid, is the strictly like-for-like comparison.

**Baseline forecast systems.** *IFS-HRES* is the high-resolution deterministic configuration of the ECMWF Integrated Forecasting System (0.1°, ∼10 km, hourly output) [13]. *AIFS* is ECMWF's data-driven (machine-learning) forecasting system (0.25°, ∼25 km, 6-hourly) [5]. *GFS* is the NOAA/NCEP Global Forecast System (0.25°, ∼25 km, 6-hourly) [14]. The climatological reference predicts, for each calendar day and hour, the historical average for that day and hour computed from ERA5 reanalysis data (described below); it uses no information about current conditions, so it marks the error level any useful forecast should beat.

**Verification data.** The "truth" against which the RMSE is computed comes from independent sources, principally *reanalysis*: a best-estimate reconstruction of past weather on a regular grid, produced by blending historical observations with a physics model. We use ERA5 [15], the ECMWF fifth-generation global reanalysis, for 100 m wind; its higher-resolution land counterpart ERA5-Land [16] for 2 m temperature and 10 m wind; and the satellite-derived Meteosat down-welling surface shortwave flux for GHI [17]. Models are scored at their native resolution and output cadence; to put all systems on an equal footing, GHI is evaluated as a common 6-hour mean at 0.25°.

## Forecast at major solar and wind sites

The aggregate metrics above describe average skill; their operational value is easiest to see in individual forecasts at real power plants. Figure 5 and Figure 6 show 48 h forecast profiles (each a single forecast issued at one initialisation time and followed over its full horizon) at some of India's largest commissioned solar and wind installations, comparing Indus-Now against the operational IFS-HRES baseline. In these examples Indus-Now tracks the observed diurnal cycle of temperature, irradiance and hub-height wind far more closely than IFS-HRES, most visibly damping the baseline's over-prediction of the mid-day irradiance and 100 m wind peaks.

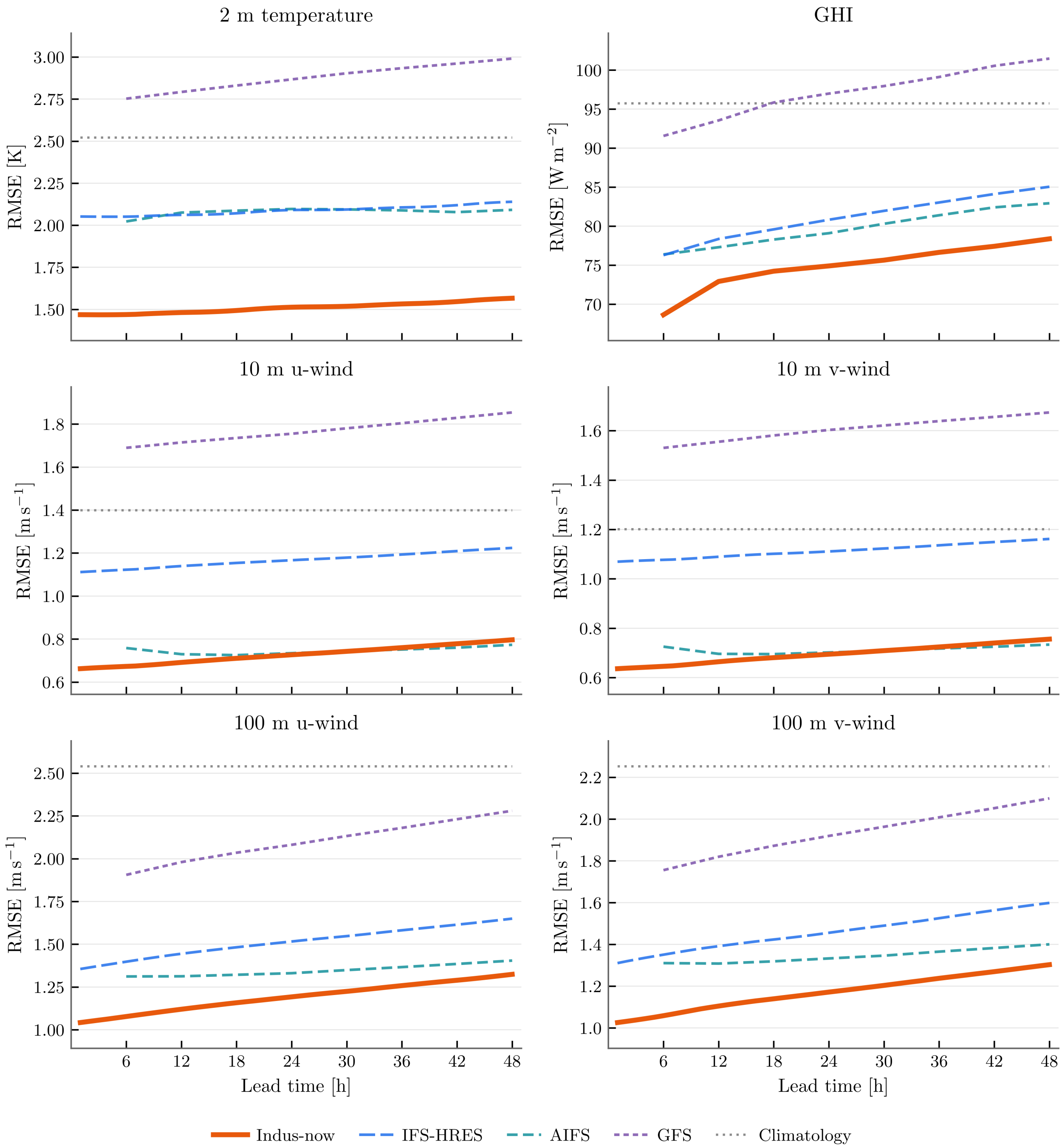


Figure 3 | **Root-mean-square error as a function of forecast lead time.** Cos-latitude-weighted RMSE over the Indian subcontinent for 2025, for 2 m temperature, global horizontal irradiance (GHI), and the eastward ($u$) and northward ($v$) components of the 10 m and 100 m wind. Indus-Now (solid) is compared with the leading operational forecasts ECMWF IFS-HRES, ECMWF AIFS and NOAA GFS (dashed) and a climatology baseline (dotted); lower is better. Forecasts are verified against ERA5-Land reanalysis (2 m temperature, 10 m wind), ERA5 reanalysis (100 m wind) and satellite-derived Meteosat irradiance (GHI). Indus-Now and IFS-HRES are evaluated at hourly output on the verification grids (0.1° for 2 m temperature and 10 m wind, 0.25° for 100 m wind); AIFS and GFS at their native 0.25°, 6-hourly output. GHI is evaluated as a common 6-hour mean at 0.25° for all models.

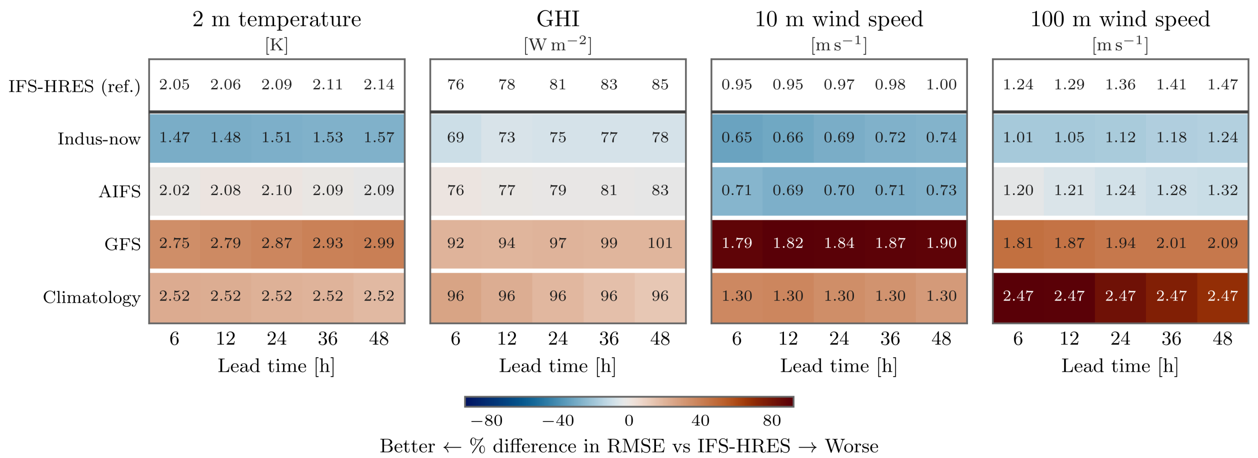


Figure 4 | **Skill scorecard against ECMWF IFS-HRES.** Cell values give the cos-latitude-weighted RMSE of each model (rows) at lead times of 6–48 h (columns), for 2 m temperature, GHI, and 10 m and 100 m wind speed, over the Indian subcontinent for 2025. Cell colour encodes the percentage change in RMSE relative to IFS-HRES (blue: lower error than IFS-HRES; red: higher); the IFS-HRES reference row is shown in white. Verification sources and resolution conventions follow Figure 3.

## Consequences and value proposition

The skill differences reported above have operational and financial consequences because Indian regulation prices renewable forecast error directly, and settles it in 15-minute blocks.

**How forecast error is priced.** A renewable generator submits a day-ahead schedule of expected injection in 15-minute blocks, and is settled block by block on the difference between the schedule and the energy actually injected. Under the deviation settlement mechanism (DSM), deviations that fall inside a tolerance band are revenue-neutral; beyond the band the generator pays a deviation charge or forgoes payment for the energy. The charge rate follows short-term market prices and ancillary-service costs, subject to a ceiling of Rs. 12/kWh under the current central regulations. Schedules are not fixed once submitted: a generator may revise them during the operating day, up to sixteen times, roughly one revision per 1.5-hour slot. Each revision is an opportunity to reduce the deviation that is ultimately settled, and each revision is limited by the most recent forecast available to the generator.

**Tolerance bands from April 2026.** Table 1 summarises the deviation bands under the central framework. From 1 April 2026 the revenue-neutral band narrows for both technologies, and the denominator against which percentage deviation is measured shifts progressively from available capacity to scheduled generation. A simulation of sixteen operating projects over 41 weeks, conducted by Grid-India, indicates revenue losses of 3.5–11.1% for solar, 2.4–11.8% for hybrid plants and up to 48% for wind under the narrower bands, with generators falling inside the permissible band in 45–58% of blocks for solar and 32–73% for wind under present practice. Around half of all settled blocks therefore fall outside the band before the narrower limits take effect. Implementation is phased and, at the time of writing, subject to litigation, so the trajectory may change.

Present-day charges are smaller. Developers report DSM charges of order 10–12 paise/kWh for solar and 20–25 paise/kWh for wind, amounting in typical cases to 0.3–0.5% of generation revenue and rising to 5–10% for plants that forecast poorly. Several states cap the exposure: Karnataka and Tamil Nadu both limit annual renewable deviation charges to three paise per unit of annual generation. Others, Gujarat among them, apply bands narrower than the central ones and compute deviation against available capacity. Requirements vary across states, and the narrowest band in force sets the accuracy a generator must reach to remain revenue-neutral across a distributed portfolio.

**Renewable plant operators.** Hourly guidance on GHI and hub-height wind enters an operator's decisions in four places. First, scheduling: a schedule that requires less correction attracts fewer deviation charges, and the saving grows as the bands narrow. Second, market participation: the real-time market clears in 15-minute

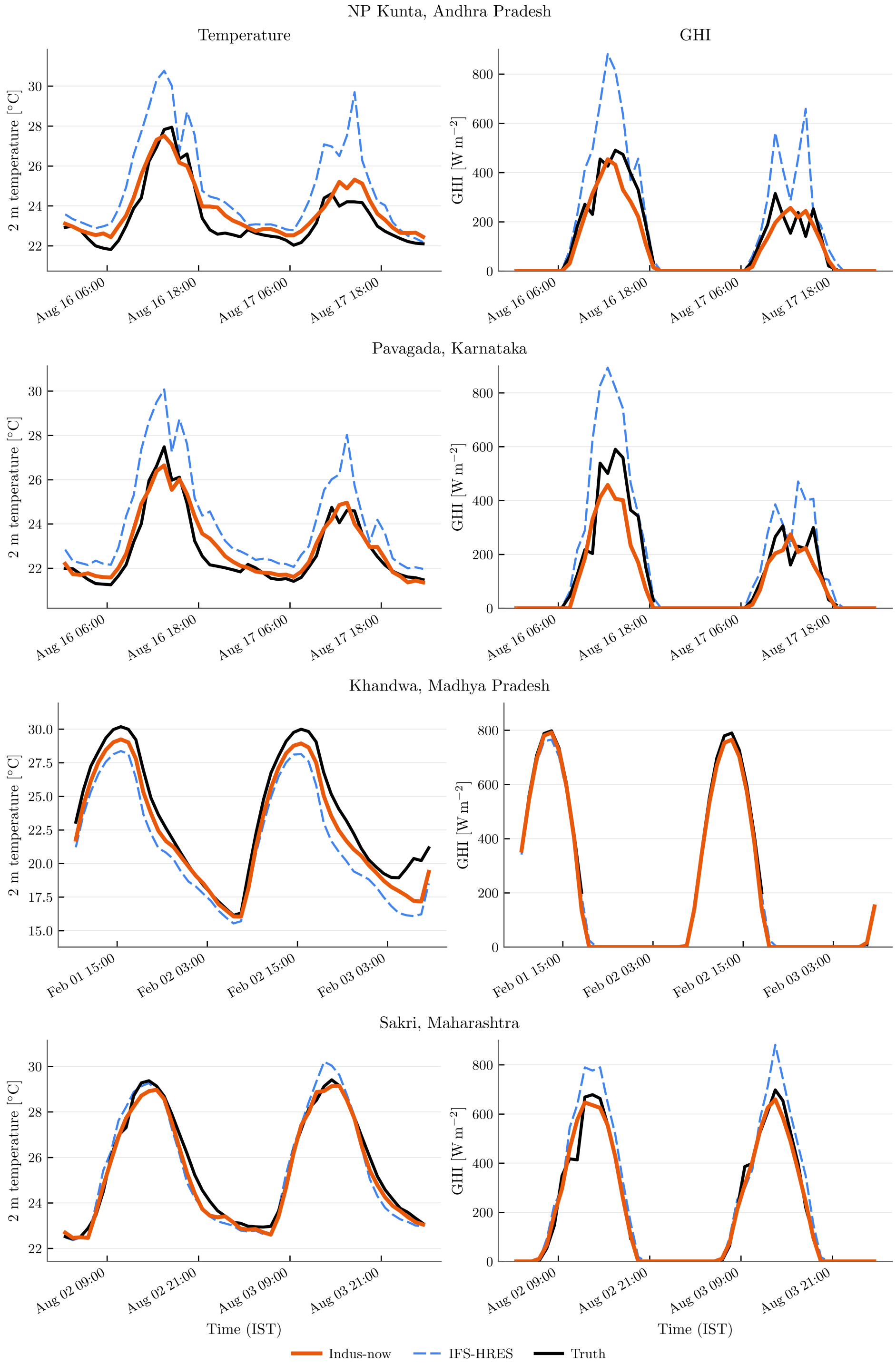


Figure 5 | **Example 48-hour forecast profiles at major Indian solar power sites: 2 m temperature and GHI.** Single-initialisation forecasts of 2 m temperature (left) and global horizontal irradiance (GHI, right) from Indus-Now (orange, solid) and ECMWF IFS-HRES (blue, dashed), each verified against ERA5-Land reanalysis (black, "Truth"). Each row is one of India's largest operational solar sites: *NP Kunta Ananthapuramu Ultra Mega Solar Park, Andhra Pradesh* (~0.50 GW commissioned); *Pavagada Ultra Mega Solar Park, Karnataka* (~2.3 GW across 71 projects, among the world's largest solar parks); *Khandwa, Madhya Pradesh* (~0.37 GW); and *Sakri, Dhule, Maharashtra* (~0.38 GW). Commissioned capacities are aggregated over each site's nearby area. Each panel is a single real forecast; the x-axis is time in IST (UTC+5:30). Indus-Now stays nearer the truth throughout, notably damping the IFS-HRES over-prediction of the mid-day temperature and irradiance peaks on cloudy days.

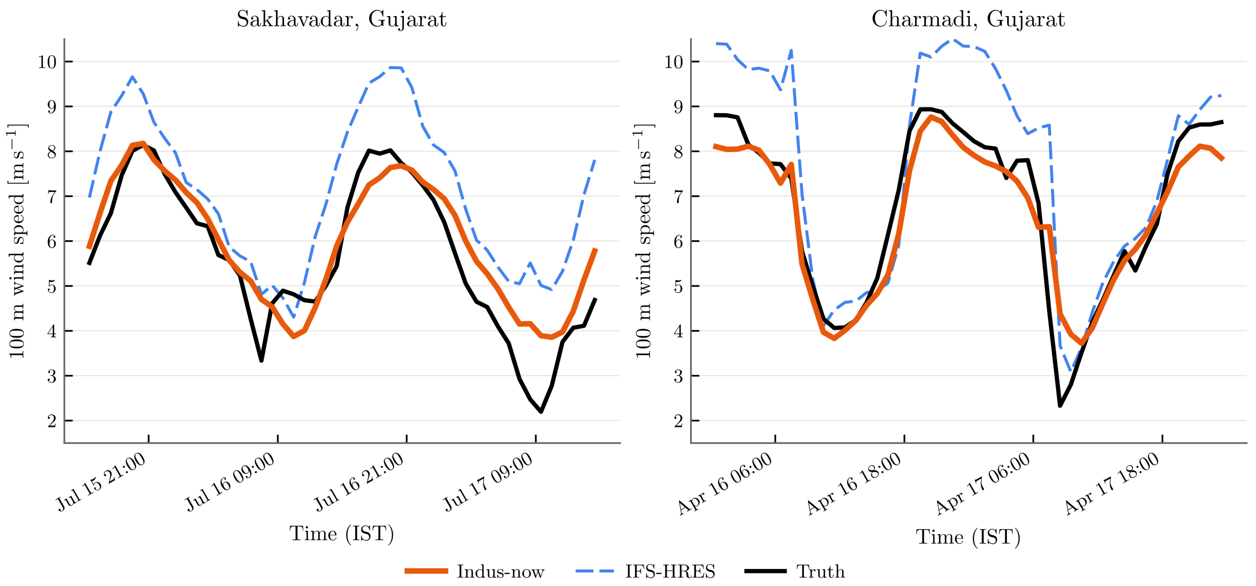


Figure 6 | **Example 48-hour forecast profiles of 100 m wind speed at Indian wind sites.** Single-initialisation 100 m wind-speed forecasts (speed = $\sqrt{u^2 + v^2}$) from Indus-Now (orange, solid) and ECMWF IFS-HRES (blue, dashed), each verified against ERA5 reanalysis (black, "Truth"), at two commissioned wind clusters in *Gujarat*: *Sakhavadar, Bhavnagar* (~0.26 GW) and *Charmadi, Amreli* (~0.13 GW), with capacity aggregated over each cluster's nearby area. Each panel is a single real forecast; the x-axis is valid time in IST (UTC+5:30). Indus-Now stays close to the observed wind speed and its diurnal variation, whereas IFS-HRES over-predicts the 100 m wind throughout these forecasts.

Table 1 | **Revenue-neutral deviation bands under the central DSM framework.** Deviations within the band attract no charge; beyond it the generator pays a deviation charge or forgoes payment. Bands narrow from 1 April 2026, with the deviation denominator shifting from available capacity toward scheduled generation on a phased trajectory.

| | Solar & wind–solar hybrid | Wind |
|---|---|---|
| Current band | ±10% | ±15% |
| Band from 1 April 2026 | ±5% | ±10% |
| Deviation charge ceiling: Rs. 12/kWh | | |
| State annual caps (Karnataka, Tamil Nadu): 3 paise per unit of annual generation | | |

blocks through the operating day, so a generator that anticipates a shortfall can cover it before the shortfall is settled as a deviation. Third, storage dispatch: hybrid and firm-and-dispatchable renewable (FDRE) contracts penalise shortfalls against a monthly demand-fulfilment ratio at up to 1.5 times the PPA tariff, and meeting the ratio requires forecasts of the resource and of the battery state of charge together. Fourth, plant operations: module cleaning, tracker and inverter management, and maintenance windows are scheduled against expected irradiance and wind over the following one to two days.

**Grid operators and load dispatch centres.** India's eleven renewable energy management centres (REMCs), dedicated in 2020, forecast and monitor the renewable fleet for the national, regional and state load dispatch centres. The telemetry reaching them is largely restricted to AC power output, with limited access to the physical drivers of that output: irradiance, module temperature and wind speed. Gridded hourly forecasts of those fields supply the missing inputs. The balancing task has also grown. The summer evening net-load ramp (the rate at which demand net of renewable generation rises as solar output falls) increased from 35.7 GW in May 2023 to 73.7 GW in May 2026, and the morning ramp-down from roughly 18 GW to 53 GW. Operating reserves are conventionally sized on a high percentile of net-load forecast error, typically the 95th, so a reduction in that error reduces the volume of reserve that must be procured.

## References


[1] Indradip Mitra, Detlev Heinemann, Aravindakshan Ramanan, Mandeep Kaur, Sunil Kumar Sharma, Sujit Kumar Tripathy, and Arindam Roy. Short-term PV power forecasting in India: recent developments and policy analysis. *International Journal of Energy and Environmental Engineering*, 13:515–540, 2022.

[2] Raviraj P. Raj and Anupama Kowli. Handling forecast uncertainty and variability in solar generation to mitigate schedule deviation penalties. *Solar Energy*, 271:112401, 2024.

[3] Remi Lam, Alvaro Sanchez-Gonzalez, Matthew Willson, Peter Wirnsberger, Meire Fortunato, Ferran Alet, Suman Ravuri, Timo Ewalds, Zach Eaton-Rosen, Weihua Hu, et al. Learning skillful medium-range global weather forecasting. *Science*, 382(6677):1416–1421, 2023.

[4] Kaifeng Bi, Lingxi Xie, Hengheng Zhang, Xin Chen, Xiaotao Gu, and Qi Tian. Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, 619(7970):533–538, 2023.

[5] Simon Lang, Mihai Alexe, Matthew Chantry, Jesper Dramsch, Florian Pinault, Baudouin Raoult, Mariana C. A. Clare, Christian Lessig, Michael Maier-Gerber, Linus Magnusson, et al. AIFS – ECMWF's data-driven forecasting system. *arXiv preprint arXiv:2406.01465*, 2024.

[6] Casper Kaae Sønderby, Lasse Espeholt, Jonathan Heek, Mostafa Dehghani, Avital Oliver, Tim Salimans, Shreya Agrawal, Jason Hickey, and Nal Kalchbrenner. MetNet: A neural weather model for precipitation forecasting. *arXiv preprint arXiv:2003.12140*, 2020.

[7] Lasse Espeholt, Shreya Agrawal, Casper Sønderby, Manoj Kumar, Jonathan Heek, Carla Bromberg, Cenk Gazen, Rob Carver, Marcin Andrychowicz, Jason Hickey, et al. Deep learning for twelve hour precipitation forecasts. *Nature Communications*, 13:5145, 2022.

[8] Marcin Andrychowicz, Lasse Espeholt, Di Li, Samier Merchant, Alexander Merose, Fred Zyda, Shreya Agrawal, and Nal Kalchbrenner. Deep learning for day forecasts from sparse observations. *arXiv preprint arXiv:2306.06079*, 2023.

[9] Suman Ravuri, Karel Lenc, Matthew Willson, Dmitry Kangin, Remi Lam, Piotr Mirowski, Megan Fitzsimons, Maria Athanassiadou, Sheleem Kashem, Sam Madge, et al. Skilful precipitation nowcasting using deep generative models of radar. *Nature*, 597(7878):672–677, 2021.

[10] Yuchen Zhang, Mingsheng Long, Kaiyuan Chen, Lanxiang Xing, Ronghua Jin, Michael I. Jordan, and Jianmin Wang. Skilful nowcasting of extreme precipitation with NowcastNet. *Nature*, 619(7970):526–532, 2023.

[11] Jaideep Pathak, Yair Cohen, Piyush Garg, Peter Harrington, Noah Brenowitz, Dale Durran, Morteza Mardani, Arash Vahdat, Shaoming Xu, Karthik Kashinath, and Michael Pritchard. Kilometer-scale convection allowing model emulation using generative diffusion modeling. *arXiv preprint arXiv:2408.10958*, 2024.

[12] Stephan Rasp, Stephan Hoyer, Alexander Merose, Ian Langmore, Peter Battaglia, Tyler Russell, Alvaro Sanchez-Gonzalez, Vivian Yang, Rob Carver, Shreya Agrawal, et al. WeatherBench 2: A benchmark for the next generation of data-driven global weather models. *Journal of Advances in Modeling Earth Systems*, 16(6):e2023MS004019, 2024.

[13] ECMWF. IFS Documentation CY48R1. Technical report, European Centre for Medium-Range Weather Forecasts, Reading, UK, 2023.

[14] National Centers for Environmental Prediction. Global Forecast System (GFS). Model documentation, NOAA National Weather Service, 2021.

[15] Hans Hersbach, Bill Bell, Paul Berrisford, Shoji Hirahara, András Horányi, Joaquín Muñoz-Sabater, Julien Nicolas, Carole Peubey, Raluca Radu, Dinand Schepers, et al. The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049, 2020.

[16] Joaquín Muñoz-Sabater, Emanuel Dutra, Anna Agustí-Panareda, Clément Albergel, Gabriele Arduini, Gianpaolo Balsamo, Souhail Boussetta, Margarita Choulga, Shaun Harrigan, Hans Hersbach, et al. ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9):4349–4383, 2021.

[17] Isabel F. Trigo, Carlos C. Dacamara, Pedro Viterbo, Jean-Louis Roujean, Folke Olesen, Carla Barroso, Fernando Camacho-de Coca, Dominique Carrer, Sandra C. Freitas, Javier García-Haro, et al. The Satellite Application Facility for Land Surface Analysis. *International Journal of Remote Sensing*, 32(10):2725–2744, 2011.