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Research Article

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Posted Date: October 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11207439/v1>

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Additional Declarations: No competing interests reported.

From Meteorological Uncertainty to Resilient PV-Wind-Battery Mini-Grid Design in the Hyper-Arid Sahel

A station-based, uncertainty-aware design study for Agadez, Bilma and N'Guigmi, Niger (2015-2024)

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Abstract

Mini-grid sizing studies in the Sahel usually rely on a single meteorological source, either a station record taken as ground truth or a reanalysis taken as a gap-free substitute. This article sizes photovoltaic-wind-battery mini-grids for Agadez, Bilma and N'Guigmi (Niger) from the 2015-2024 synoptic records of the three stations, and asks how sensitive the design is to plausible errors in the meteorological input. The records were screened beyond range checks. Five physically inconsistent values were rejected, and three further problems invisible to bound tests were found: 2024 sunshine duplicates 2023 at all stations (72-93 percent identical days against at most 8.5 percent for other year pairs), one month is copied at Agadez, and Agadez sunshine for 2015-2018 appears inhomogeneous, as its decoupling from the diurnal temperature range suggests. Global irradiance was estimated from sunshine with the Angström-Prescott coefficients of FAO Irrigation and Drainage Paper 56, since no irradiance reference exists in the dataset for a local calibration, and the coefficient choice (-14 to +8 percent in mean global irradiance) was examined as a bounded sensitivity analysis, not as a probabilistic uncertainty. A three-hourly simulation with Faiman cell temperature, log-law shear and a density-corrected power curve fed an exhaustive search over 17 507 designs per site, with reliability measured by the conditional value at risk (CVaR) of annual unserved energy. At a target of 1 percent of demand, and within the cost assumptions and design grid studied, the least-cost design meeting the target at every site is 85-105 kWp of photovoltaic capacity

with 150-175 kWh of storage, at 0.211-0.223 USD/kWh. At Agadez, where only five screened years remain, the CVaR estimate of 777 kWh/yr has a year-level bootstrap interval of 564-800 kWh/yr; this interval reflects sampling within the observed years and cannot account for years harsher than those recorded. No Pareto-optimal design contains wind under the adopted data, cost and power-curve assumptions: recorded winds at Bilma and N'Guigmi are weak (calm on 46-58 percent of reports), and at Agadez 81 percent of turbine energy falls in daylight. Compound low-sun, low-wind, hot days carry under 1 percent of unserved energy, whereas low-sunshine days carry 59-78 percent. Screening the Agadez record changes its design by 14 percent in photovoltaic capacity and 8 percent in cost, and the Angström coefficients by up to 24 percent and 11 percent, while a ± 5 percent irradiance perturbation of the magnitude published for reanalysis stays below both thresholds. These perturbations are scenarios of published magnitude, not measured biases at the stations; a direct comparison with ERA5, ERA5-Land or NASA POWER was not carried out and remains the main open step.

Keywords: mini-grid sizing; meteorological uncertainty; station data quality; Angström-Prescott; hybrid PV-wind-battery systems; conditional value at risk; compound low-resource days; Sahel

1. Introduction

About 19.5 percent of Niger's rural population had access to electricity at the last national baseline, and the National Electrification Strategy relies heavily on decentralized solar and hybrid mini-grids to close that gap by 2035 (International Renewable Energy Agency, 2013; World Bank, 2022). The regional picture is similar: the Africa Minigrid Program of the United Nations Development Programme (2024) estimates that mini-grids remain the least-cost option for roughly 265 million people across 21 countries by 2030, at an investment cost near 65 billion United States dollars (USD). Under that kind of pressure it is tempting to size a mini-grid from whatever meteorological data are quickest to obtain, usually one reanalysis product pulled for one representative year. That shortcut carries a risk that is rarely quantified.

Reanalysis and satellite products are not neutral stand-ins for ground observations. ERA5 solar radiation biases over Africa typically sit within plus or minus 5 percent in flat terrain and widen to about 10 percent where cloud cover or topography is more complex ("Impacts of Climate Change on Photovoltaic Potential," 2025, and the studies of Sawadogo et al., 2020, and Bloomfield et al., 2022, cited therein).

54 Wind fields are less forgiving: a 2026 audit found that ERA5-Land under-represents 10-metre wind
55 speed by 20 to 30 percent relative to its parent ERA5 fields almost everywhere, a flaw traced to the land-
56 surface model and not to regional effects, so that wind power density computed from ERA5-Land can
57 read up to 20 percent low at hub height (Baas et al., 2026). A lidar-based validation over tall towers
58 found ERA5 and NORA3 comparable offshore but diverging over complex terrain (Cheynet et al., 2025),
59 and NASA POWER, built largely on MERRA-2, agrees well with ground stations for monthly irradiance
60 and temperature but less well for daily wind ("Evaluation of the Accuracy and Trend Consistency," 2025;
61 NASA POWER Project, n.d.). None of this makes reanalysis useless. It does mean that a mini-grid sized
62 from reanalysis alone inherits a design risk that local records can help bound.

63 Station records, however, are not ground truth either. Long synoptic series in data-sparse regions carry
64 gaps, reporting conventions, instrument drift and transcription errors, and World Meteorological
65 Organization (WMO) guidance treats station metadata and homogeneity checks as prerequisites for
66 scientific use, not optional refinements ("Homogenization of Climate Data," n.d.; World Meteorological
67 Organization, n.d.). The question this article asks is therefore two-sided. How sensitive are the size, cost
68 and reliability of a hybrid mini-grid to errors in the meteorological input of the size reported for common
69 products, and how much of that sensitivity comes from the quality of the station record itself, before any
70 reanalysis enters the picture? Regional work on West African renewable portfolios has approached
71 related questions at the scale of interconnected systems (Sarr et al., 2020), and Niger-specific
72 assessments have generally relied on long-term averages or a single external dataset (International
73 Renewable Energy Agency, 2013). The technical design and optimal sizing of a photovoltaic (PV)-wind
74 hybrid system for rural electrification in Niger has been worked out for the site of Tafaghatt (Guero
75 Mohamed & Vincent, 2026); the present study takes that kind of sizing exercise further, to a ten-year
76 analysis of meteorological uncertainty at three stations. Solar deficits across Africa also tend to be
77 spatially correlated ("Climate-Driven Synchronization of Solar Extremes," 2026), and heat degrades
78 photovoltaic output when cooling and cold-chain demand peak, so the days that matter for reliability are
79 unlikely to be average days.

80 The article works from a ten-year (2015-2024) daily and three-hourly synoptic record at Agadez, Bilma
81 and N'Guigmi and makes four contributions. First, it documents a quality-control and screening protocol

that goes beyond range checks: it detects a copied year, a copied month and a multi-year inhomogeneity in the sunshine record, all invisible to bound tests, and quantifies how each would propagate into a design. Second, it converts sunshine duration into global horizontal irradiance (GHI) with the Angström- Prescott formulation of FAO Irrigation and Drainage Paper 56 (FAO-56) and, since no independent irradiance reference exists in the dataset to calibrate against, examines the coefficient choice through a bounded sensitivity analysis. Third, it builds physically explicit photovoltaic and wind models (Faiman cell temperature, log-law shear, density-corrected power curve) driven by the observed series and simulates a PV-wind-battery system at three-hourly resolution over the full screened record. Fourth, it enumerates a discretized design space and extracts cost-risk Pareto fronts in which reliability is measured by the conditional value at risk of annual energy not served instead of an average-year target, with intervals that keep the observed inter-annual variability apart from the sampling uncertainty of the tail estimate.

Four hypotheses structure the analysis. H1 states that input errors of the magnitude found in the station record, or published for reanalysis products, can change the least-cost design materially, by more than 10 percent in installed capacity or 5 percent in cost. H1 is deliberately framed as a perturbation test. No reanalysis grids were extracted in this study, so it cannot say whether a particular external source would change the design at these sites; it asks whether errors of that order would. It is tested in two forms: against the unscreened station record, and against perturbations of the station inputs by the bias magnitudes published for ERA5 and ERA5-Land. H2 states that, at comparable cost, adding wind to a PV-battery system reduces the tail risk of unserved energy. H3 states that compound days of low sunshine, low wind and high temperature account for a share of unserved energy disproportionate to their frequency. H4 states that the site ranked best on mean resource is not necessarily the site ranked best once reliability and robust cost are considered together.

2. Methods

2.1 Study area and station data

The three stations lie along a transect through Niger's hyper-arid interior: Agadez Aéro (16.97 deg N, 7.99 deg E, about 502 m), Bilma (18.69 deg N, 12.92 deg E, about 357 m) and N'Guigmi (14.25 deg N,

109 13.11 deg E, about 279 m, on the western margin of the former Lake Chad basin). All three fall in the
110 Köppen hot desert class (BWh). N'Guigmi, the southernmost, has the strongest monsoon humidity signal:
111 its mean daily UMAX is 51.2 percent against 45.9 percent at Bilma and 40.8 percent at Agadez over
112 2015-2024.

113 The dataset covers 1 January 2015 to 31 December 2024 (3653 days per station). Daily variables are
114 maximum and minimum air temperature (TMAX, TMIN), maximum and minimum relative humidity
115 (UMAX, UMIN; twelve rows per station labelled Umax were merged into UMAX without overlap),
116 sunshine duration n and station pressure. Wind is reported at eight synoptic slots (00, 03, ..., 21 h local
117 time, UTC+1) as a direction code WDD and a speed WFFI, nominally at 10 m (the anemometer height is
118 not documented in the file, and the WMO standard height is assumed). WDD follows the WMO dd
119 convention of the synoptic code (World Meteorological Organization, 2019): values 01 to 36 give the
120 direction the wind blows from in tens of degrees (36 = north), and 00 denotes calm. In practice the
121 observers favour even codes, and at N'Guigmi two codes (08 and 28) account for 54.2 and 28.8 percent
122 of non-calm reports, so the effective directional resolution is closer to 20 degrees than 10. The unit of
123 WFFI is not stated in the source file; it is treated as metres per second, the usual synoptic convention in
124 the region, and this remains an assumption (Section 4.1).

125 The file contains no pyranometer irradiance, no aerosol or visibility data, no hourly temperature or
126 humidity, and no cost, demand or equipment information. Everything in this article that depends on those
127 quantities is either reconstructed from what was measured, with the method stated, or taken from
128 published sources and labelled as such.

129 **2.2 Data quality control, screening and homogeneity**

130 The baseline quality control (QC) applied to the three records keeps every correction traceable: raw
131 values are never overwritten, and each rejected value is logged with its station, date, value and rule.
132 Structural checks removed calendar-invalid rows (for example 30 February) and merged the UMAX
133 label change. Physical checks required $TMIN \leq TMAX$, $0 \leq UMIN \leq UMAX \leq 100$ percent,
134 pressure within 880-1015 hPa, wind code within 0-36, wind speed within 0-60 m/s, and $0 \leq n \leq N$,

135 where N is the astronomical day length of Eq. (8). Values failing a test were set to missing. Extreme but
136 physically possible values were not removed.

137 Bound tests cannot detect copied or drifting data, so three further screens were applied for this article. (i)
138 A duplication screen compared each pair of years day by day and each pair of months over their first 28
139 days. (ii) A consistency screen compared the sunshine record with the diurnal temperature range (DTR =
140 TMAX - TMIN), which should fall on dull days at a desert station. (iii) A spike screen flagged daily
141 temperatures whose deviation from a 15-day moving median exceeded six robust standard deviations
142 (1.4826 times a 61-day rolling median absolute deviation); flagged values were inspected but retained.

143 Homogeneity of annual means was tested with the Pettitt statistic and the standard normal homogeneity
144 test (SNHT). The Pettitt statistic is

$$145 \quad U_{k,n} = \sum_{i=1}^k \sum_{j=k+1}^n \text{sgn}(x_i - x_j) \quad (1)$$

146 with the change point at $K_n = \arg \max_k |U_{k,n}|$ and approximate significance $p \approx 2 \exp [-6 K_n^2 / (n^3 + n^2)]$
147 (Pettitt, 1979). The SNHT statistic (Alexandersson, 1986) is

$$148 \quad T(k) = k \cdot \bar{z}_1^2 + (n - k) \cdot \bar{z}_2^2 \quad (2)$$

149 where $\bar{z}_1$ and $\bar{z}_2$ are the mean standardized anomalies before and after candidate break k. With only ten
150 annual values, tabulated SNHT critical values are coarse, so the 90 and 95 percent critical values of max
151 $T(k)$ were derived by Monte Carlo from 20 000 independent Gaussian series of length 10. Pettitt is more
152 sensitive to a shift near the centre of a series and SNHT to shifts near its ends, so the two were read
153 together and against the screens above, never in isolation ("Homogenization of Climate Data," n.d.).

154 For simulation only, short gaps (up to three days) in daily variables were filled by linear interpolation
155 and longer gaps by a 31-day smoothed day-of-year climatology of the same station. Missing three-hourly
156 wind values were filled by random draws (fixed seed) from the observed values of the same station, slot
157 and season (dry, November-April; wet, May-October), which keeps the speed distribution intact where a
158 mean would flatten it. At Agadez the 00, 03 and 21 h slots are almost never reported, so the three night
159 slots were pooled for this draw, and a lower-bound variant with those imputed values set to zero was also
160 run. Missing pressure was filled with the station's monthly mean. Every filled value carries a flag, and
161 the filled shares are reported in Section 3.1.

2.3 External reanalysis and satellite products

An external validation against ERA5, ERA5-Land and NASA POWER would in principle complement the station record, comparing them with the mean bias error (MBE), root mean square error (RMSE) and Kling-Gupta efficiency (KGE),

$$\text{MBE} = \frac{1}{n} \sum (P_i - O_i) \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum (P_i - O_i)^2} \quad (4)$$

$$\text{KGE} = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (5)$$

with r the correlation, $\alpha = \sigma_{\text{sim}}/\sigma_{\text{obs}}$ and $\beta = \mu_{\text{sim}}/\mu_{\text{obs}}$. That benchmark was not carried out: gridded reanalysis and satellite products were not available for this study, which draws on station observations only. Section 3.7 therefore summarizes the published bias ranges (Baas et al., 2026; Cheynet et al., 2025; "Impacts of Climate Change on Photovoltaic Potential," 2025) and makes no claim of a comparison on these stations. Their magnitudes are used in Section 3.11 as controlled perturbations of the station inputs, which tests how a design would respond to a product with such biases without pretending to know the bias at these sites.

2.4 Conversion of sunshine duration to global horizontal irradiance

Extraterrestrial radiation on a horizontal surface follows FAO-56 (Allen et al., 1998):

$$R_a = \frac{24 \times 60}{\pi} \cdot G_{sc} \cdot d_r \cdot [\omega_s \sin \varphi \sin \delta + \cos \varphi \cos \delta \sin \omega_s] \quad (6)$$

with $G_{sc} = 0.0820 \text{ MJ m}^{-2} \text{ min}^{-1}$, $d_r = 1 + 0.033 \cos(2\pi J/365)$, $\omega_s = \arccos(-\tan \varphi \tan \delta)$, φ the station latitude and J the day of year. The solar declination is

$$\delta = 0.409 \cdot \sin \left(\frac{2\pi J}{365} - 1.39 \right) \quad (7)$$

and the astronomical day length is

$$N = \frac{24}{\pi} \cdot \omega_s \quad (8)$$

Daily global irradiance then follows the Angström-Prescott relation

$$R_s = \left(a_s + b_s \cdot \frac{n}{N} \right) \cdot R_a \quad (9)$$

converted to kWh m⁻² day⁻¹ by dividing by 3.6. A site calibration of (as, bs) requires an independent irradiance series, pyranometer or satellite, and the station dataset contains neither. The FAO-56 default values as = 0.25 and bs = 0.50 (Allen et al., 1998) are therefore applied at all three stations, and no calibration is claimed. Because dust and humidity are known to shift both coefficients in the Sahel ("The Angstrom-Prescott Regression Coefficients," 2020; "Calibration and Validation of the Angstrom-Prescott Model," 2022; "Estimation of Daily Solar Radiation," n.d.), the consequence of that choice is carried forward: GHI was recomputed over a grid of as in {0.20, 0.25, 0.30} and bs in {0.40, 0.45, 0.50, 0.55}, keeping pairs with 0.65 ≤ as + bs ≤ 0.80 (the upper value is close to the FAO-56 clear-sky transmissivity at these elevations), and the resulting envelope is reported as a range (Table 4). This is a bounded sensitivity analysis, not a probabilistic propagation of uncertainty: the admissible pairs are treated as scenarios of equal standing, no probability is attached to any of them, and the envelope is neither a confidence interval nor a calibrated distribution of GHI. The two corner pairs that give the lowest and highest mean GHI of the admissible set, (0.20, 0.45) and (0.30, 0.50), were propagated through the full optimization (Section 3.11).

2.5 Photovoltaic power model

Daily GHI was distributed within the day at 0.1-h resolution with the Collares-Pereira and Rabl ratio of hourly to daily global radiation, and its diffuse part with the Liu-Jordan ratio after splitting the daily total with the Erbs daily diffuse-fraction correlation (Duffie & Beckman, 2013). Clock time was converted to solar time with the station longitude and the equation of time. Irradiance on a south-facing array tilted at the station latitude used the isotropic-sky model,

$$G_{\text{POA}} = (GHI - DHI) \cdot R_b + DHI \cdot \frac{1 + \cos \beta}{2} + GHI \cdot \rho_g \cdot \frac{1 - \cos \beta}{2} \quad (10)$$

with GPOA the plane-of-array (POA) irradiance, DHI the diffuse horizontal irradiance and ground albedo ρ_g = 0.30 for bare sandy soil. Air temperature within the day was reconstructed from the observed TMAX and TMIN with the Parton and Logan scheme (sine by day, exponential decay by night; lag

parameters 1.86 h and 2.2; Parton & Logan, 1981). Cell temperature follows the Faiman model (Faiman, 2008),

$$T_{\text{cell}} = T_{\text{air}} + \frac{G_{\text{POA}}}{U_0 + U_1 \cdot V} \quad (11)$$

with $U_0 = 25 \text{ W m}^{-2} \text{ K}^{-1}$, $U_1 = 6.84 \text{ W m}^{-3} \text{ s K}^{-1}$ and V the observed wind speed reduced from 10 m to a 2-m module height with the log law of Eq. (13). Direct-current (DC) to alternating-current (AC) output per kWp is

$$P_{\text{PV}} = C_{\text{PV}} \cdot \frac{G_{\text{POA}}}{1000} \cdot [1 + \gamma(T_{\text{cell}} - 25)] \cdot \eta_{\text{loss}} \quad (12)$$

with $\gamma = -0.0040 \text{ K}^{-1}$ (crystalline silicon, datasheet-typical; "Impact of High Temperature on PV Productivity," 2022; Sandia National Laboratories, n.d.) and $\eta_{\text{loss}} = 0.876$, the product of named terms: soiling 5 percent, DC wiring and mismatch 3 percent, inverter 4 percent and availability 1 percent. The soiling term is a placeholder scenario. The dataset has no soiling measurement, so the 5 percent soiling term above is an assumed value and should not be read as an observed one.

2.6 Wind power model

Hub height was set to 30 m, the height of the National Renewable Energy Laboratory (NREL) residential distributed-wind reference turbine (National Renewable Energy Laboratory, 2024). The 10-m speed was extrapolated with the logarithmic profile

$$V(z_h) = V(10) \cdot \frac{\ln(z_h/z_0)}{\ln(10/z_0)} \quad (13)$$

with displacement height zero and roughness length $z_0 = 0.03 \text{ m}$ (open flat terrain), giving a shear factor of 1.189; $z_0 = 0.005 \text{ m}$ and 0.10 m bracket the uncertainty ("Comparative Examinations of Wind Speed," 2024; "Impacts of Climate Change on Photovoltaic Potential," 2025). Air density came from the ideal gas law with a virtual-temperature correction,

$$\rho = \frac{p}{R_d \cdot T_v}, \quad T_v = \frac{T}{1 - 0.378 e/p} \quad (14)$$

with $R_d = 287.05 \text{ J kg}^{-1} \text{ K}^{-1}$, p the daily station pressure, T the reconstructed slot temperature and e the vapour pressure from the mean of UMAX and UMIN. The power curve is the generic cubic form

$$P_{WT} = \begin{cases} P_r \cdot \frac{V^3 - V_{ci}^3}{V_r^3 - V_{ci}^3} \cdot \frac{\rho}{\rho_0}, & V_{ci} \leq V < V_r \\ P_r, & V_r \leq V \leq V_{co} \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

with $V_{ci} = 2.5$ m/s, $V_r = 11$ m/s, $V_{co} = 20$ m/s and $\rho_0 = 1.225$ kg m³. These values follow the published specification of a common 10-kW class small turbine (cut-in 2.5 m/s, rated power at 11 m/s, furling at 14-20 m/s; Bergey Windpower Co., n.d.); the curve is generic and is not a certified curve for any model. The full three-hourly series, never a mean speed, was passed through Eq. (15), which preserves the cubic sensitivity to the speed distribution.

2.7 Demand, battery and dispatch

No load measurements exist for these settlements, so one stylized community archetype was used and labelled as an assumption: 250 kWh/day on average, built from a 6-kW continuous base (health post, cold chain, telecoms), a daytime productive-use block (about 12-14 kW, 09-17 h), a morning shoulder and an evening residential peak of about 20 kW between 19 and 21 h. A heat-sensitive term adds 1 percent to daily demand per kelvin of TMAX above 35 °C, a stylized elasticity for fans and refrigeration that raises mean demand to about 259-261 kWh/day; a variant without it was also run. The battery is lithium iron phosphate with a round-trip efficiency of 0.92, state-of-charge (SOC) limits of 10 and 100 percent, a 0.5C power limit and an initial SOC of 50 percent. Its energy evolves at each three-hourly step as

$$E_{bat}(t+1) = E_{bat}(t) + \eta_{ch} P_{ch}(t) \Delta t - \frac{P_{dis}(t) \Delta t}{\eta_{dis}} \quad (16)$$

and the energy balance closes by construction,

$$P_{PV,t} + P_{WT,t} + P_{dis,t} + P_{dg,t} + ENS_t = D_t + P_{ch,t} + P_{curt,t} \quad (17)$$

with a load-following rule: renewables serve the load first, surplus charges the battery and the rest is curtailed; deficits are met by the battery, then by the diesel generator where present, and whatever remains is energy not served (ENS). Diesel fuel use follows the linear curve $F = 0.246 \text{ Edg} + 0.08415 \text{ Pdg trun}$ (litres; Skarstein & Uhlen, 1989).

2.8 Reliability and risk metrics

The loss of power supply probability (LPSP) is

$$LPSP = \frac{\sum_t ENS_t}{\sum_t D_t} \quad (18)$$

Tail risk is measured on the annual expected energy not served (EENS). A record of five to nine screened years is too short to estimate a 95th percentile directly, so 2000 resampled years were drawn by a monthly block bootstrap: each calendar month of a resampled year is taken from a randomly chosen year of the simulated record, which keeps within-month persistence and the seasonal cycle and ignores battery carry-over across month boundaries (small here, since storage holds less than one day of demand). The same draws were used for every design (common random numbers). The conditional value at risk (CVaR) is

$$CVaR_{95}(EENS) = E[L \mid L \geq VaR_{95}] \quad (19)$$

the mean annual EENS over the worst 5 percent of resampled years, where L denotes annual EENS and VaR_{95} , the value at risk (VaR), is its 95th percentile ("Microgrid-Level Reliability Assessment," 2025; Mishra & Shankar, 2025; "Two-Stage Energy Dispatch for Microgrids," 2025). The worst simulated calendar year is reported alongside it.

A CVaR estimated from five to nine years is itself uncertain, and a second, outer resampling was added to quantify that uncertainty. In each of $O = 2000$ outer replicates the n simulated years were drawn with replacement, the monthly block bootstrap was repeated on that set of years, and the CVaR of the design was recomputed. The percentile confidence interval (CI) is

$$CI_{95} = \left[Q_{0.025} \left(\widehat{CVaR}_{95}^{(b)} \right), Q_{0.975} \left(\widehat{CVaR}_{95}^{(b)} \right) \right], \quad b = 1, \dots, O \quad (20)$$

where Q_p is the empirical p-quantile over the replicates. The same outer resampling, with 300 replicates, was used to re-select the least-cost design meeting the target, restricted to designs whose net present cost (NPC) lies within -30 and +50 percent of the reference design (NPC itself does not depend on the resampled years for designs without diesel). Neither procedure creates new climatic years; both recombine what was observed. They therefore measure sampling uncertainty within the observed range, and Section 3.10 reports them separately from the year-to-year variability of the simulated record.

2.9 Economic assumptions and multi-objective search

Decision variables are PV capacity CPV, wind capacity CWT, battery energy E_{bat} (power fixed at 0.5 Ebat) and, in the third configuration, diesel capacity P_{dg}. The objectives are

$$\min\{NPC, CVaR_{95}(EENS), CO_{2,cycle}\} \quad (21)$$

with the net present cost over a ten-year horizon

$$NPC = CapEx + \sum_{t=1}^T \frac{OpEx_t + Fuel_t}{(1+r)^t} + Repl - \frac{Salvage}{(1+r)^T} \quad (22)$$

where CapEx is the capital expenditure, OpEx_t and Fuel_t are the operating and fuel costs of year t, Repl is the replacement cost and Salvage the salvage value; the levelized cost of energy (LCOE) is $NPC \cdot CRF / E_{served}$, with the capital recovery factor (CRF) equal to $r(1+r)^T / [(1+r)^T - 1]$. Table 1 lists the techno-economic assumptions. None of them is a local measurement; each is taken from, or bracketed by, a cited source. The battery is replaced within the horizon if its equivalent full cycles exceed 6000 or its 15-year calendar life would be reached, and salvage is straight-line on remaining life. Lifecycle emissions combine the median intensities of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) for PV and wind generation (Schlömer et al., 2014), 110 kg CO₂-eq per kWh of battery capacity (Peters et al., 2017) pro-rated over its calendar life, and 2.68 kg CO₂ per litre of diesel.

Table 1. Techno-economic and demand assumptions used in the optimization.

Parameter	Value	Basis (assumption, not a local measurement)
PV installed cost	900 USD/kWp	Between IRENA 2023 utility PV average (758 USD/kW; International Renewable Energy Agency, 2024) and ESMAP mini-grid component survey (modules 719 + PV inverter 228 USD/kWp; ESMAP, 2019)
PV O&M / life	15 USD/kWp/yr; 25 yr	Assumption, order of magnitude of ESMAP (2019) and International Renewable Energy Agency (2024)
Small wind installed cost	4000 USD/kW (tested 2000 and 8000)	Bracketed by IRENA 2023 onshore utility wind (1154 USD/kW; International Renewable Energy Agency, 2024) and the US small-wind 2013-2022 average (10 670 USD/kW; Orrell et al., 2023)
Wind O&M / life	39 USD/kW/yr; 20 yr	NREL ATB 2024, distributed wind, all scales (National Renewable Energy Laboratory, 2024)
Battery (LFP) cost incl. conversion	450 USD/kWh	Between IRENA 2023 battery projects (273 USD/kWh; International Renewable Energy Agency, 2024) and ESMAP 2019 mini-grid Li-ion survey (605 USD/kWh; ESMAP, 2019)
Battery O&M, RTE, life	5 USD/kWh/yr; 0.92; 6000 cycles or 15 yr	Assumption, datasheet-typical LFP
Diesel generator	500 USD/kW; 0.03 USD/kWh O&M; 15 000 h	Assumption
Diesel fuel price	1.10 USD/L	Assumption, to be replaced by a local supplier quote

Parameter	Value	Basis (assumption, not a local measurement)
Fuel curve	0.246 L/kWh + 0.08415 L/h per kW	Skarstein and Uhlen (1989)
Discount rate / horizon	8 %; 10 yr	Project assumption
Lifecycle emissions	PV 48, wind 11 g CO ₂ -eq/kWh; battery 110 kg/kWh; diesel 2.68 kg/L	IPCC AR5 Annex III (Schl�mer et al., 2014); Peters et al. (2017)
Demand	250 kWh/day base + 1 %/K above 35 �C	Stylized archetype (Section 2.7), assumption

All are documented assumptions, not local measurements. ATB: Annual Technology Baseline; ESMAP: Energy Sector Management Assistance Program; IPCC AR5: Fifth Assessment Report of the Intergovernmental Panel on Climate Change; IRENA: International Renewable Energy Agency; LFP: lithium iron phosphate; NREL: National Renewable Energy Laboratory; O&M: operation and maintenance; RTE: round-trip efficiency; US: United States.

The optimization is an exhaustive enumeration over a discretized decision space, not a stochastic search. For PV-battery and PV-wind-battery systems, CPV spans 0-300 kWp in 5-kWp steps, CWT 0-60 kW in 10-kW steps (integer numbers of 10-kW turbines) and Ebat 0-1000 kWh in 25-kWh steps, giving 17 507 designs per site, each simulated over the full screened record at three-hourly resolution. The diesel configuration uses a coarser grid (3906 designs: CPV in 10-kWp steps, CWT in {0, 20} kW, Ebat in 50-kWh steps, Pdg in {5, 10, 20} kW). A preliminary pass on a wider grid (up to 800 kWp and 3000 kWh) confirmed that no robust or Pareto-relevant design lies outside these bounds. The epsilon-constraint front (minimum NPC subject to $CVaR_{95} \leq \epsilon$) is then exact for this discretization and equals the non-dominated set of the enumerated designs. A population-based search such as the non-dominated sorting genetic algorithm II (NSGA-II; Deb et al., 2002) is unnecessary here: with every grid point evaluated there is no population to converge. The robust design of each configuration is the least-NPC design meeting $CVaR_{95}(EENS) \leq 1$ percent of annual demand (about 945-952 kWh/yr). The word robust is used in this restricted sense throughout: it refers to the tail-risk criterion evaluated on the available screened years, not to robustness against climatic situations absent from the record, and at Agadez those years number only five. The simulation windows are 2019-2023 at Agadez and 2015-2023 at Bilma and N'Guigmi, for the reasons given in Section 3.1.

2.10 Use of AI-assisted tools in manuscript preparation

During preparation of this manuscript, the author used an AI-based writing and data-analysis assistant to support literature searches, drafting, and verification of calculations reported in this study. The author

reviewed, verified and edited all AI-assisted output, and takes full responsibility for the content, analyses and conclusions of this article.

3. Results

3.1 Data completeness, quality control and screening

Figure 1 and Table 2 summarize completeness. Temperature and humidity are 98.7-99.9 percent complete at all three stations. Sunshine is least complete at Agadez (91.2 percent), pressure at N'Guigmi (77.3 percent, with no values at all in 2023), and wind at Agadez (63.3 percent). The Agadez wind gap is structural, not random: the 06-18 h slots are reported on 97.5-99.9 percent of days, whereas the 00, 03 and 21 h slots are reported on only 0.5, 3.0 and 6.2 percent of days. The station appears not to have reported night observations for most of the decade, which matters for any wind assessment, since night is when a PV-battery system most needs a second source.

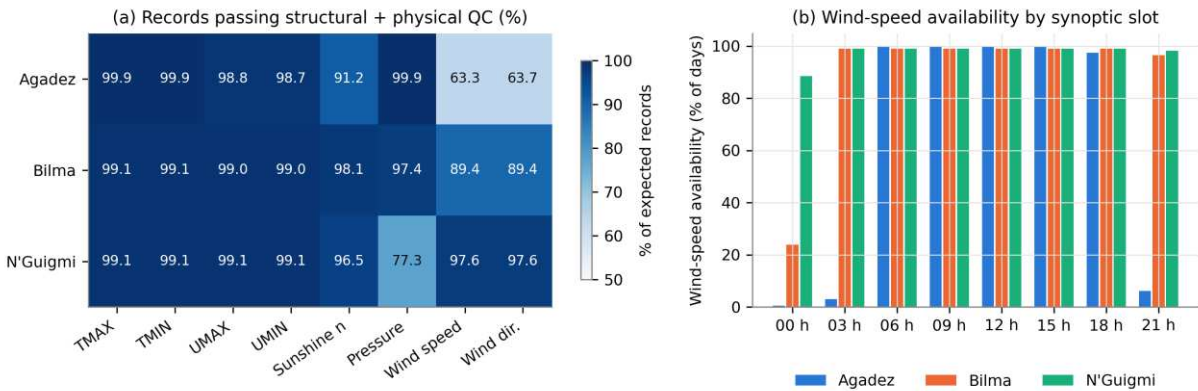


Figure 1. Data completeness and wind-report availability at the three stations, 2015-2024. (a) Share of expected daily records (3653 per station) and three-hourly wind records (29 224 per station) that pass the structural and physical QC, 2015-2024, Agadez, Bilma and N'Guigmi. (b) Share of days on which wind speed is reported at each synoptic slot. The Agadez night slots are almost never reported.

The bound tests rejected five values: impossible sunshine of 40.3 h at Agadez on 5 March 2022 (astronomical day length 11.73 h) and 13.9 h at Bilma on 31 July 2015 (12.85 h), and UMIN greater than UMAX at Agadez on 9 June and 27 September 2024 and at Bilma on 27 May 2024. No temperature inversion, out-of-range pressure, invalid wind code or out-of-range wind speed was found. The spike screen flagged 48 daily temperatures with robust z-scores above 6 (23 at Agadez, 18 at Bilma, 7 at

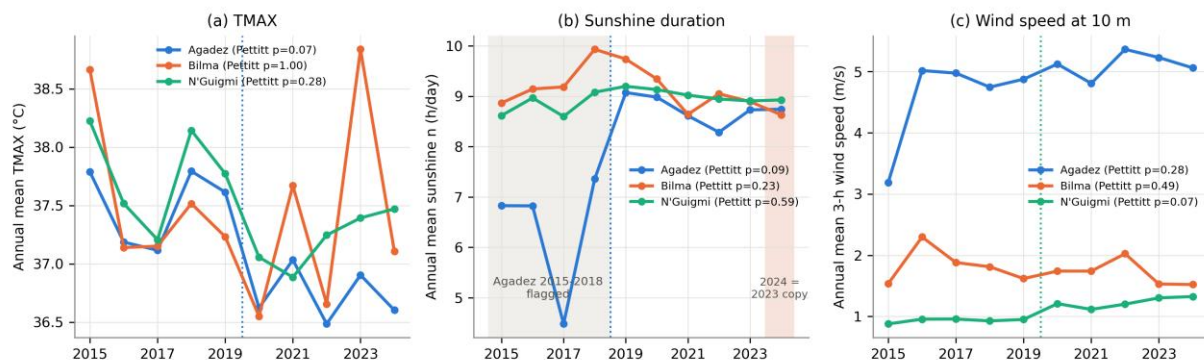
345 N'Guigmi). Most are cold-air or dust-haze episodes that persist for two to four days and look physical. A
346 few look like transcription errors and are reported here without being removed: TMAX of 13.0 °C with
347 TMIN of 3.9 °C at Agadez on 22 December 2024, and TMAX of 46.8 °C at N'Guigmi on 22 November
348 2024, the station's highest value of the decade in a month whose mean TMAX is 36.2 °C.

349 The screens that go beyond bounds found more consequential problems. The 2024 sunshine series
350 duplicates 2023 at all three stations: the same-day value is identical on 71.9 percent of days at Agadez,
351 88.0 percent at Bilma and 93.1 percent at N'Guigmi, against a median of 2.4-4.5 percent (maximum 8.5
352 percent) for every other pair of years. At Agadez, September 2022 repeats June 2022 over its first 28
353 days. Temperature, humidity, wind and pressure show no such duplication. These look like file-assembly
354 errors, not instrument faults, and no bound test could have caught them.

355 The Agadez sunshine record for 2015-2018 is inhomogeneous. Its annual means (6.8, 6.8, 4.5 and 7.4
356 h/day) sit far below the 8.3-9.1 h/day of 2019-2023 and below Bilma and N'Guigmi in the same years,
357 and the June-August mean is 3.6 h/day against 7.7 h/day after 2018 (Figure 2b). The temperature record
358 provides the check. In 2019-2023, June-August days with at most 2 h of sunshine have a DTR of 11.3
359 °C, against 14.0 °C on days with more than 8 h, as expected when cloud or thick dust cuts both insolation
360 and daytime heating. In 2015-2018 the corresponding DTR values are 13.5 and 14.4 °C: the 102
361 nominally sunless summer days were almost as warm and as wide-ranging as sunny ones, and the
362 correlation between n and DTR falls from 0.34 to 0.14. The simplest explanation is a recorder or card-
363 reading problem that under-counted sunshine, not a real change in cloudiness. Agadez sunshine for 2015-
364 2018 was therefore excluded from the design runs.

365 The formal homogeneity tests are consistent with this but weak on their own (Figure 2). No Pettitt test is
366 significant at 5 percent; the lowest p-values are 0.066 for Agadez TMAX (shift after 2019), 0.066 for
367 N'Guigmi wind (after 2019) and 0.086 for Agadez sunshine (after 2018). The Monte Carlo critical values
368 of the SNHT for n = 10 are 4.96 (90 percent) and 5.66 (95 percent). Against them, SNHT exceeds the 95
369 percent level for Agadez TMAX (T = 6.29), Agadez sunshine (6.43), Agadez wind (8.15, driven by a low
370 2015 mean of 3.2 m/s against about 5 m/s afterwards) and N'Guigmi wind (7.81; 0.88-0.96 m/s in 2015-
371 2019 against 1.12-1.33 m/s in 2020-2024). With ten points per series these breaks are indicative, not
372 proven, and without station metadata none can be attributed to a sensor change. The Agadez TMAX shift

373 of about -0.8 °C after 2019, which Bilma and N'Guigmi do not share, deserves a check against station
374 history before the series is used for trend work.



375
376 **Figure 2. Annual means and homogeneity tests of temperature, sunshine and wind, 2015-2024.** Annual means of (a)
377 TMAX, (b) sunshine duration and (c) three-hourly wind speed at 10 m, 2015-2024, as delivered after the baseline QC (n
378 = 10 years per series). Legends give Pettitt p-values; dotted verticals mark Pettitt change points with $p < 0.10$. Shading in
379 (b) marks the Agadez 2015-2018 sunshine flagged as inhomogeneous and the 2024 sunshine that duplicates 2023 at all
380 stations.

381 **Table 2. Quality-control and screening outcomes, 2015-2024.**

Item	Agadez	Bilma	N'Guigmi
TMAX / TMIN valid (%)	99.9 / 99.9	99.1 / 99.1	99.1 / 99.1
UMAX / UMIN valid (%)	98.8 / 98.7	99.0 / 99.0	99.1 / 99.1
Sunshine valid (%)	91.2	98.1	96.5
Pressure valid (%)	99.9	97.4	77.3 (no data in 2023)
Wind speed valid (%)	63.3	89.4	97.6
Bound-test rejections	n = 40.3 h on 2022-03-05 (N = 11.73 h); UMIN > UMAX on 2024-06-09 and 2024-09-27	n = 13.9 h on 2015-07-31 (N = 12.85 h); UMIN > UMAX on 2024-05-27	none
2024 sunshine identical to 2023 (same day)	71.9 % of 363 days	88.0 % of 333 days	93.1 % of 333 days
Same-day identity, other year pairs (median / max)	2.4 / 6.4 %	4.5 / 8.5 %	2.8 / 5.1 %
Other screening flags	Sep-2022 sunshine = Jun-2022; 2015-2018 sunshine inhomogeneous	none	none
Night wind slots (00/03/21 h) reported (%)	0.5 / 3.0 / 6.2	24.0 / 99.1 / 96.5	88.5 / 99.1 / 98.2
Calm reports (% of wind obs.)	4.5	45.6	58.2
Temperature spikes $ z > 6$ (retained)	23	18	7
Simulation window	2019-2023 (5 yr)	2015-2023 (9 yr)	2015-2023 (9 yr)
Filled in window: sunshine / wind / pressure (%)	1.7 / 35.8 / 0.1	2.0 / 10.7 / 1.0	3.8 / 2.2 / 20.4

382 Percentages refer to expected records after removal of calendar-invalid rows.

383 Following these results, the design runs use 2019-2023 at Agadez (five years) and 2015-2023 at Bilma
384 and N'Guigmi (nine years). Within those windows the filled shares are small for sunshine (1.7-3.8
385 percent) and wind at Bilma and N'Guigmi (10.7 and 2.2 percent), but large for Agadez wind (35.8

percent, nearly all night slots) and for N'Guigmi pressure (20.4 percent). Five years is a thin basis for tail statistics, which is why Section 3.10 reports intervals alongside the point estimates. Table 3 gathers the provenance of the data that enter the design runs.

Table 3. Provenance of the data used in the design runs.

Item	Agadez	Bilma	N'Guigmi
Final period used for design runs	2019-2023 (5 years)	2015-2023 (9 years)	2015-2023 (9 years)
Days / three-hourly steps simulated	1826 / 14 608	3287 / 26 296	3287 / 26 296
Screened sunshine days, 2015-2024	1795	3221	3161
Values rejected by bound tests	3 (1 sunshine, 2 UMIN > UMAX)	2 (1 sunshine, 1 UMIN > UMAX)	0
Sunshine excluded by screening	2015-2018 (inhomogeneous), Sept. 2022 (copied month), 2024 (copied year)	2024 (copied year)	2024 (copied year)
Temperature spikes flagged, retained	23	18	7
Imputed in design window: sunshine / wind / pressure (%)	1.7 / 35.8 / 0.1	2.0 / 10.7 / 1.0	3.8 / 2.2 / 20.4
Variables reconstructed	GHI from sunshine (Eq. 9); within-day irradiance and air temperature from daily values; cell temperature (Eq. 11); hub-height wind (Eq. 13); air density (Eq. 14)		
External parameters (not measured at the sites)	Angström-Prescott coefficients (FAO-56); costs, lifetimes and emission factors (Table 1); demand archetype and heat elasticity; generic power curve; Faiman coefficients; roughness length; loss and soiling factors		
Undocumented items treated as assumptions	Wind-speed unit (m/s assumed); anemometer height (10 m assumed); station history and instrument changes (no metadata available)		
Independent validation	None. No pyranometer, satellite or reanalysis series was compared with the stations, and the screening decisions have not been checked against station metadata.		

Counts refer to the station file after the baseline QC; imputed values enter the simulation only and are flagged.

3.2 Monthly climatology and thermal regime

Figure 3 gives the monthly climatology. The three stations share a pre-monsoon temperature peak, with mean TMAX of 42.9 °C at Agadez and 43.5 °C at N'Guigmi in May and 44.3 °C at Bilma in June. Bilma stays hot through September (41.9 °C) while N'Guigmi and Agadez cool in August (35.6 and 37.9 °C) under the monsoon. Bilma also has the coldest nights, with a January mean TMIN of 7.7 °C against about 13 °C at the other two, and hence the largest annual temperature range. On screened data, mean sunshine is 8.8 h/day at Agadez, 9.2 h/day at Bilma and 8.9 h/day at N'Guigmi. The seasonal minima differ in timing: June at Agadez (6.6 h/day, n/N = 0.51), August at N'Guigmi (7.5 h/day, n/N = 0.61) and a shallow June-August dip at Bilma. TMAX reached or exceeded 45 °C on 57 days at Agadez, 249 days at Bilma and 141 days at N'Guigmi over the decade, with absolute maxima of 47.1, 49.0 and 46.8 °C (Figure 4).

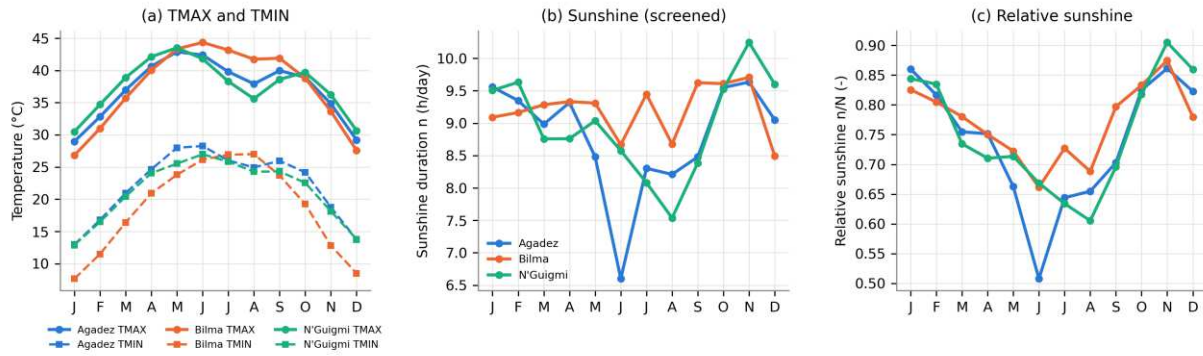


Figure 3. Monthly climatology of temperature and sunshine at the three stations, 2015-2024. Monthly climatology 2015-2024: (a) mean TMAX and TMIN, (b) mean sunshine duration after screening (Agadez 2015-2018, Agadez September 2022 and all 2024 sunshine excluded) and (c) relative sunshine n/N . Daily sample sizes after screening: Agadez 1795, Bilma 3221 and N'Guigmi 3161 days for sunshine; 3619-3649 days for temperature.

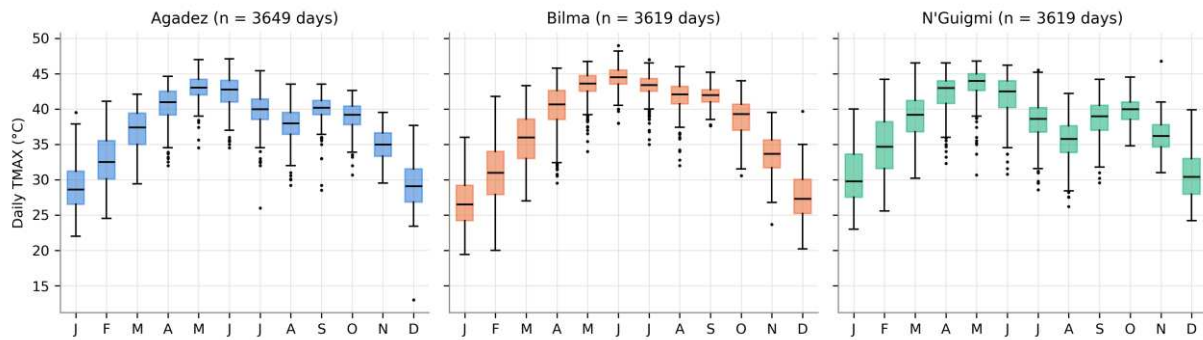


Figure 4. Monthly distribution of daily maximum air temperature, 2015-2024. Distribution of daily TMAX by month, 2015-2024 (boxes: interquartile range, IQR; whiskers: 1.5 IQR; dots: values beyond). n is the number of valid days per station.

3.3 Solar resource estimated from sunshine duration

With FAO-56 default coefficients, the mean estimated GHI over screened days is $5.88 \text{ kWh m}^{-2} \text{ day}^{-1}$ at Agadez, 6.02 at Bilma and 6.04 at N'Guigmi (Figure 5a). The monthly cycle follows the sunshine minima: Agadez drops to 5.44 in June, N'Guigmi to 5.82 in August, and Bilma peaks at 6.6-6.7 from April to July. December is the lowest month everywhere (4.7-5.5), because of the low sun, not a loss of sunshine. The coefficient envelope is wide and asymmetric: over the admissible (as, bs) pairs, mean GHI ranges from 14 percent below to 8 percent above the FAO-56 estimate at all three stations (Table 4). Figure 5b shows why. Mean n/N is 0.74-0.77, so a change of 0.05 in as or bs moves GHI by about 8 or 6 percent, and the envelope is asymmetric because the constraint $as + bs \leq 0.80$ removes most of the optimistic combinations. Without an irradiance reference this range cannot be narrowed from the present

data, and because it is a scenario envelope and not a distribution, it gives no indication of which pair is the most likely. Among the solar-input sensitivities examined here it is the widest, wider than the ± 5 percent bias typically reported for ERA5 over flat African terrain ("Impacts of Climate Change on Photovoltaic Potential," 2025).

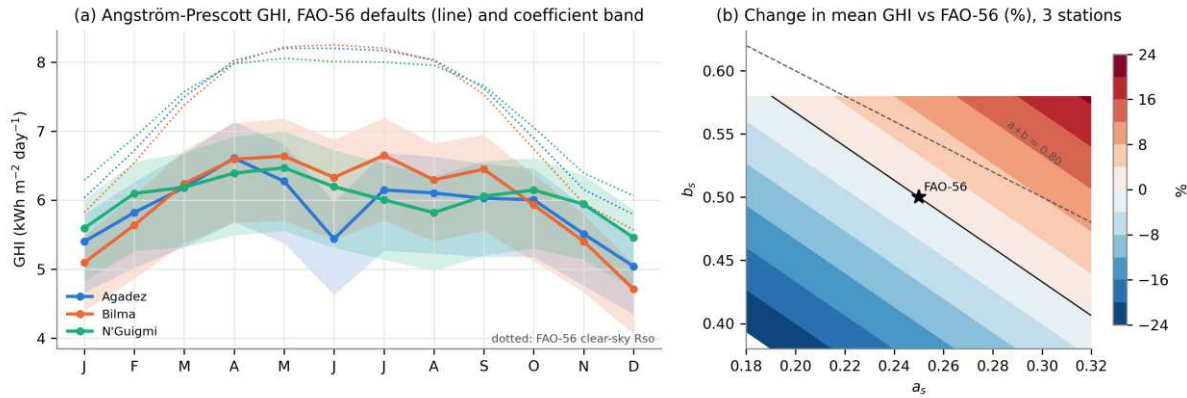


Figure 5. Global horizontal irradiance estimated from sunshine and its sensitivity to Angström-Prescott coefficients. (a) Monthly mean GHI estimated from screened sunshine with the Angström-Prescott relation and FAO-56 default coefficients (lines), envelope over admissible coefficient pairs (shading; a bounded sensitivity range, not a confidence interval) and FAO-56 clear-sky radiation Rso (dotted), for the station-days listed in Figure 3. (b) Percentage change in mean GHI over the three stations relative to FAO-56 defaults, as a function of a_s and b_s . The dashed line marks $a_s + b_s = 0.80$. No satellite or pyranometer series was available to check these estimates.

Table 4. Bounded sensitivity of mean GHI (kWh m-2 day-1) to the Angström-Prescott coefficients.

a_s	b_s	$a_s + b_s$	Agadez	Bilma	N'Guigmi	Role in this study
0.20	0.45	0.65	5.05 (-14.1 %)	5.18 (-14.0 %)	5.19 (-14.0 %)	Lowest GHI; propagated: PV +19/+24/+21 %, NPC +11 %
0.20	0.50	0.70	5.40 (-8.1 %)	5.54 (-7.9 %)	5.55 (-8.1 %)	Envelope only
0.20	0.55	0.75	5.75 (-2.2 %)	5.91 (-1.9 %)	5.91 (-2.1 %)	Envelope only
0.25	0.40	0.65	5.18 (-11.9 %)	5.29 (-12.1 %)	5.31 (-11.9 %)	Envelope only
0.25	0.45	0.70	5.53 (-5.9 %)	5.65 (-6.0 %)	5.68 (-6.0 %)	Envelope only
0.25	0.50	0.75	5.88 (ref.)	6.02 (ref.)	6.04 (ref.)	FAO-56 default (reference)
0.25	0.55	0.80	6.23 (+5.9 %)	6.38 (+6.0 %)	6.40 (+6.0 %)	Envelope only
0.30	0.40	0.70	5.66 (-3.7 %)	5.77 (-4.2 %)	5.80 (-3.9 %)	Envelope only
0.30	0.45	0.75	6.01 (+2.2 %)	6.13 (+1.9 %)	6.16 (+2.1 %)	Envelope only
0.30	0.50	0.80	6.36 (+8.1 %)	6.49 (+7.9 %)	6.52 (+8.1 %)	Highest GHI; propagated: NPC -8/-8/-6 %, target missed by 51-72 %

Values are computed over screened days (Agadez 1795, Bilma 3221, N'Guigmi 3161). The ten admissible pairs are scenarios of equal standing, not samples from a calibrated distribution, and the range they span is not a confidence interval. Design effects (Agadez/Bilma/N'Guigmi) are given for the two corner pairs propagated through the optimization (Section 3.11).

3.4 Wind regime

The three records describe very different wind environments (Figures 6-8). Agadez reports calm on only 4.5 percent of observations, with a mean speed of 4.8 m/s over the reported slots; Bilma reports calm on 45.6 percent (mean 1.8 m/s) and N'Guigmi on 58.2 percent (mean 1.1 m/s). The diurnal cycle is day-peaked at all sites, the classic Saharan pattern in which the nocturnal low-level jet is decoupled from the surface at night and its momentum is mixed down after sunrise. In the dry season the 09 h slot peaks at 7.2 m/s at Agadez, 3.3 m/s at Bilma and 2.8 m/s at N'Guigmi (12 h), while night slots at Bilma and N'Guigmi average 0.3-1.9 m/s, with 68-84 percent of night reports calm. The few Agadez night observations (2 to 161 per slot and season) average 2.9-4.1 m/s, and their confidence bands are wide.

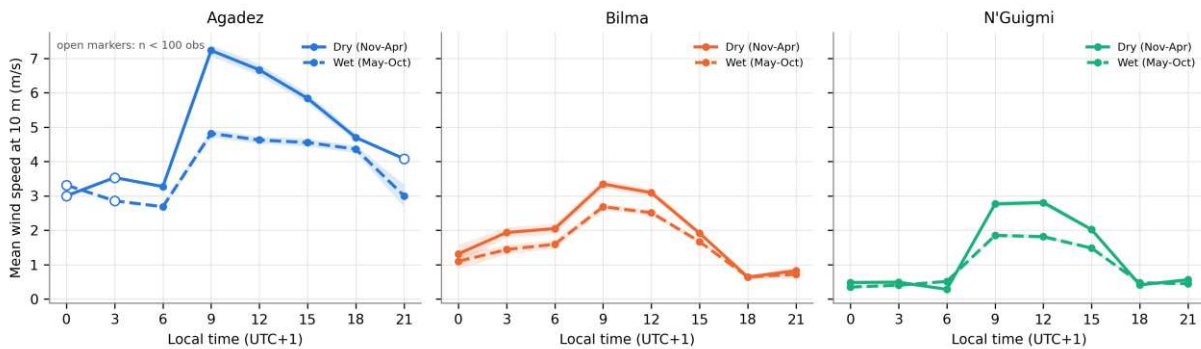


Figure 6. Diurnal cycle of 10-m wind speed by season. Mean 10-m wind speed by synoptic slot, dry season (November-April, solid) and wet season (May-October, dashed), 2015-2024, with 95 percent confidence bands where a slot has at least 100 observations. Open markers: fewer than 100 observations (Agadez 00, 03 and 21 h).

Directions confirm the seasonal regimes (Figure 7). In the dry season, winds come overwhelmingly from the east to east-north-east Harmattan sector at all three sites, with circular mean directions of 100, 88 and 73 degrees and resultant lengths of 0.71, 0.63 and 0.93. In the wet season the pattern breaks down at Agadez (resultant length 0.05) and reverses at N'Guigmi to a westerly monsoon flow (mean 278 degrees). The N'Guigmi reports concentrate on two codes, which accounts for its very peaked rose.

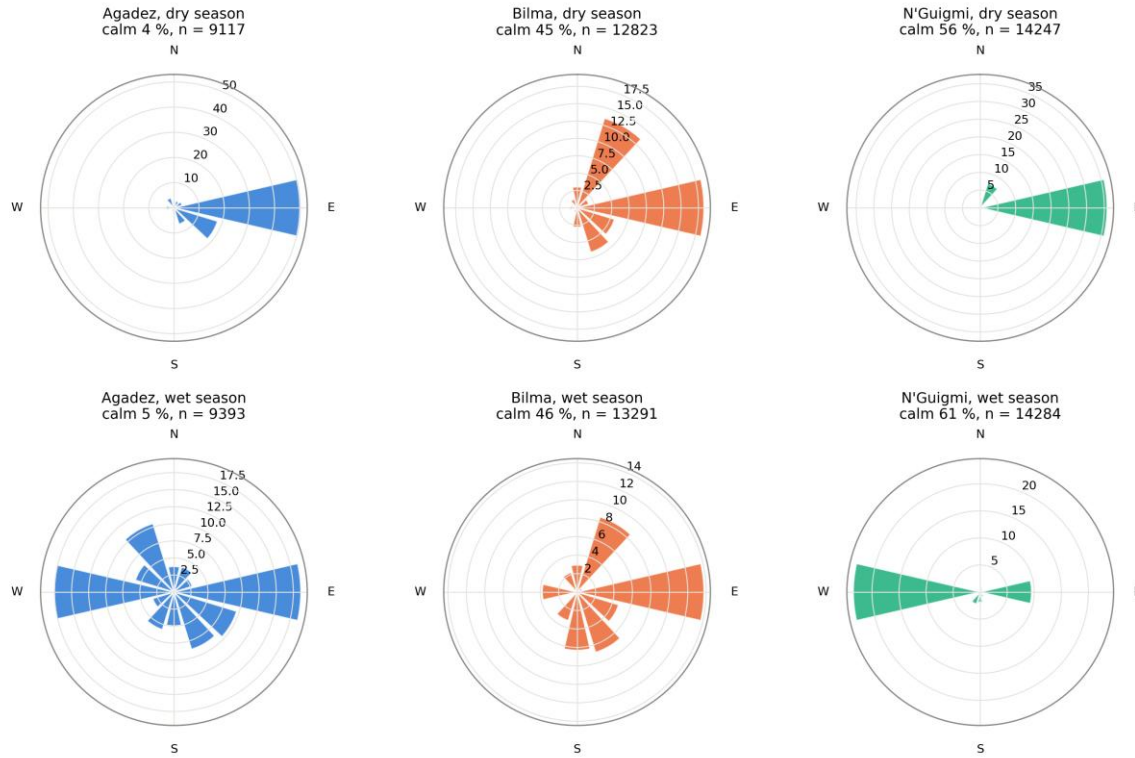


Figure 7. Seasonal wind roses at the three stations, 2015-2024. Seasonal wind roses from WMO dd codes in 30-degree sectors (percentage of all observations in the season, calms counted in the denominator), 2015-2024. Titles give the calm frequency and the number of observations n.

At 30 m, the log-law extrapolation (factor 1.189) gives mean speeds of 5.8, 2.1 and 1.3 m/s and wind power densities of 250, 68 and 16 W m⁻². Fitted to non-calm hub-height speeds, the Weibull parameters are $k = 1.88$ and $c = 6.82$ m/s at Agadez, 1.42 and 4.30 m/s at Bilma, and 2.03 and 3.47 m/s at N'Guigmi (Figure 8a); the fits are approximate because speeds are reported as integers. Only 25 percent of Bilma observations and 14 percent of N'Guigmi observations reach the 2.5 m/s cut-in speed at hub height, against 78 percent at Agadez. Figure 8b places these means on the power curve.

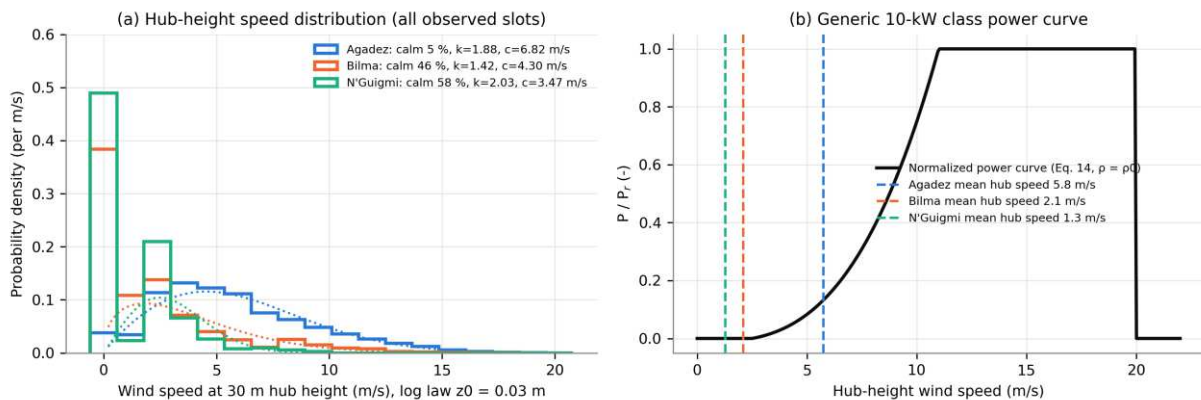


Figure 8. Hub-height wind speed distributions and position on the generic power curve. (a) Distribution of hub-height (30 m) wind speed from all reported slots, 2015-2024 ($n = 18\,511$, $26\,114$ and $28\,531$ observations), with calm fraction and Weibull fits to non-calm values (dotted). Bins are aligned on the extrapolated integer speeds. (b) Normalized generic power curve of Eq. (15) with the mean hub-height speed of each station.

These station speeds are low. A 58 percent calm frequency and a 1.1 m/s mean at N'Guigmi are hard to reconcile with an exposed anemometer in open, flat terrain crossed by the Harmattan. Sheltering by buildings or vegetation, a stalled cup anemometer, a reporting convention that codes light air as calm, or a unit other than m/s could each contribute; the file cannot separate them. Taken at face value, the station record leaves little room for wind at Bilma and N'Guigmi under the assumptions used here; it does not establish that the local wind resource is poor. Whether a reanalysis would agree is precisely what the missing benchmark would show, and in this case the station, not the reanalysis, may be the more suspect source.

3.5 Cell temperature and thermal derating

The Faiman model driven by observed temperature and wind gives a mean daily maximum cell temperature of 55.2 °C at Agadez, 63.5 °C at Bilma and 64.7 °C at N'Guigmi, with 95th percentiles of 69.6, 76.6 and 78.9 °C (Figure 9). The daily maximum reached 70 °C on 4.5 percent of valid days at Agadez, 24.2 percent at Bilma and 29.5 percent at N'Guigmi. The temperature term of Eq. (12) removes 9.2, 11.6 and 12.2 percent of annual DC energy, and 12-14 percent in May-September at Bilma and N'Guigmi. Agadez runs coolest despite similar air temperatures because its daytime wind is two to three times stronger, and convective cooling in Eq. (11) scales with wind speed. The thermal loss is therefore partly a wind-record effect as well: if the low Bilma and N'Guigmi speeds are instrumental artefacts, their derating is overestimated.

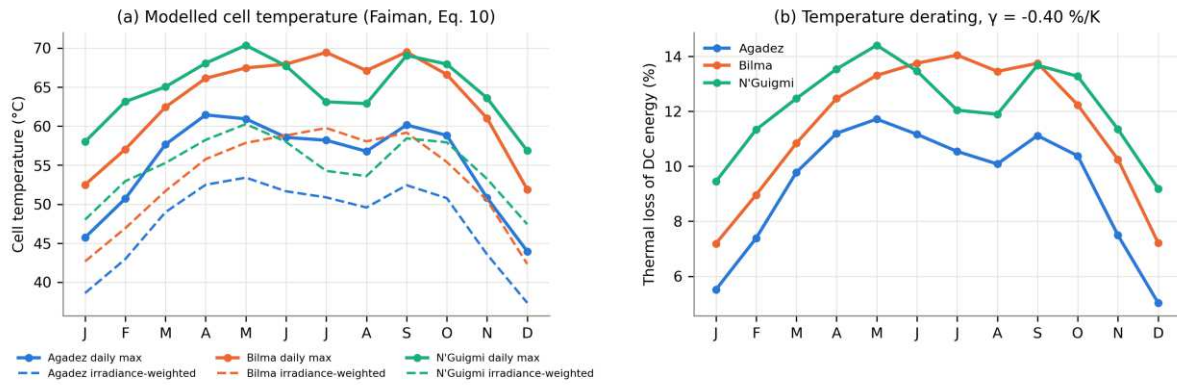


Figure 9. Monthly cell temperature and thermal derating of photovoltaic output. (a) Monthly mean of daily maximum and irradiance-weighted cell temperature from Eq. (11), and (b) monthly thermal loss of DC energy relative to a 25 °C cell, for days with screened sunshine and at least one wind report (Agadez 1795, Bilma 3221 and N'Guigmi 3161 days).

3.6 Inter-station and interannual resource

Once derating and the transposition to a latitude tilt are included, annual PV specific yield is 1745-1803 kWh/kWp at Agadez (2019-2023), 1707-1840 kWh/kWp at Bilma and 1699-1774 kWh/kWp at N'Guigmi (Figure 10a). Year-to-year spread is small, about ± 4 percent. The generic turbine's capacity factor is 16-20 percent at Agadez from 2016 onward (10.5 percent in 2015, the year flagged by SNHT), 4-10 percent at Bilma and 0.6-2.6 percent at N'Guigmi (Figure 10b). The ranking reverses between the two resources: N'Guigmi has the highest mean GHI but the lowest PV yield, because of stronger derating and a smaller tilt gain at its lower latitude, and Agadez has by far the best wind but the lowest mean GHI.

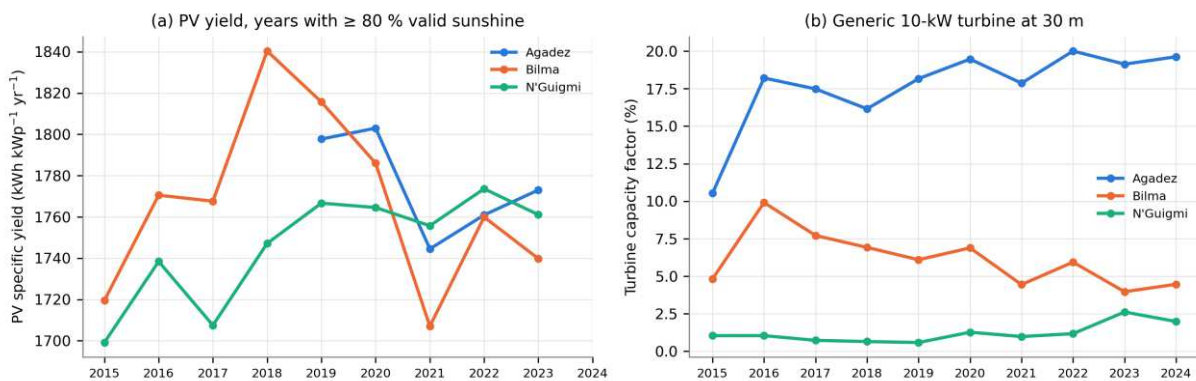


Figure 10. Annual photovoltaic specific yield and wind capacity factor. (a) Annual PV specific yield (latitude tilt, losses of Section 2.5) for years with at least 80 percent screened sunshine days; (b) annual capacity factor of the generic 10-kW turbine at 30 m. Agadez sunshine years 2015-2018 are omitted in (a).

3.7 Published reanalysis biases (literature synthesis)

No reanalysis-station comparison was performed in this study, for the reasons given in Section 2.3. Figure 11 therefore collects the bias ranges published for the products that most techno-economic studies in the region use: ERA5 GHI within ± 5 percent over flat African terrain and about ± 10 percent in cloudier or more complex settings ("Impacts of Climate Change on Photovoltaic Potential," 2025), a 20-30 percent under-representation of 10-m wind in ERA5-Land relative to ERA5, and a hub-height power-density deficit of up to 20 percent (Baas et al., 2026). These values are not estimates for Agadez, Bilma or N'Guigmi. They define the perturbation magnitudes used in Section 3.11.

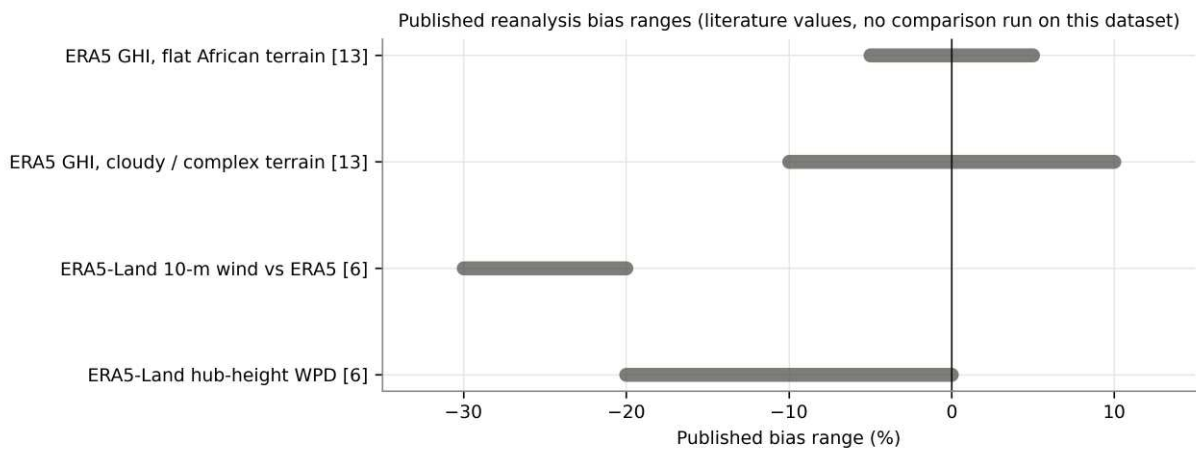


Figure 11. Published ERA5 and ERA5-Land bias ranges used as perturbation magnitudes. Bias ranges reported in the literature for ERA5 and ERA5-Land. These are published values from other regions and studies (Baas et al., 2026; "Impacts of Climate Change on Photovoltaic Potential," 2025), shown for context; they are not the result of a comparison on the stations of this study.

3.8 Compound low-resource days and unserved energy (H3)

The compound index S averages three month-conditional percentile ranks, low sunshine, low daily mean wind and high TMAX, so that a day scores high when all three are unusual for the time of year. Its duration curves are nearly identical at the three sites (Figure 12a), as a rank-based index should be. The substance is in how rarely the three conditions coincide. Days in the lowest quintile of both sunshine and wind and the highest quintile of TMAX make up 1.04 percent of days at Agadez, 0.70 percent at Bilma and 0.55 percent at N'Guigmi, close to or below the 0.8 percent expected if the three were independent.

Within a month, dull days tend to be cooler, not hotter: the Spearman correlation between the sunshine and TMAX ranks is positive (0.13, 0.01 and 0.27).

Unservd energy was attributed to days using the robust PV-battery designs of Section 3.10, whose mean annual ENS is 473, 429 and 399 kWh at the three sites. Triple-compound days carry 0.4, 0.0 and 0.7 percent of that ENS. Ranking days by S does concentrate ENS somewhat at Agadez (the top decile of S carries 19 percent of ENS) but hardly at Bilma (12 percent) and not at N'Guigmi (7 percent), as Figure 12b shows. What does concentrate unserved energy is low sunshine on its own: days in the lowest sunshine quintile of their month carry 59 percent of ENS at Agadez, 78 percent at Bilma and 64 percent at N'Guigmi. ENS is also very lumpy. The worst 1 percent of days carries 39, 51 and 45 percent of all unserved energy, and the worst 5 percent carries 98, 100 and 89 percent. Seasonally, June accounts for 42 percent of Agadez ENS and 29 percent of Bilma ENS, whereas at N'Guigmi ENS is spread more evenly, with March and April the largest contributors (19 and 15 percent).

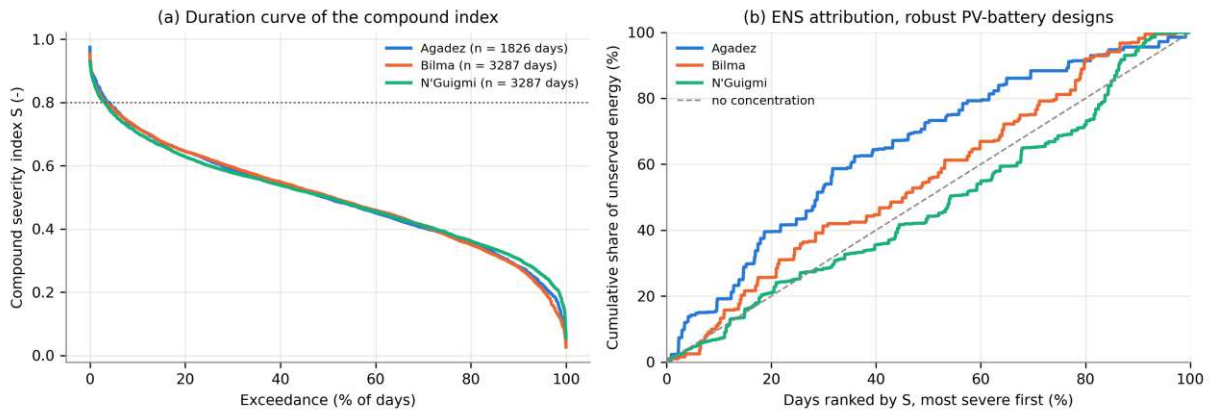


Figure 12. Compound low-resource days and their share of unserved energy. (a) Duration curve of the compound severity index S (mean of month-conditional percentile ranks of low sunshine, low daily mean wind and high TMAX) over the simulation windows; the dotted line marks $S = 0.8$. (b) Cumulative share of unserved energy of the robust PV-battery design against the share of days ranked by S, most severe first. Curves above the diagonal indicate that high-S days carry more than their share of ENS.

3.9 Cost-risk Pareto fronts (H2)

Figure 13 shows the non-dominated designs in the NPC-CVaR plane. The PV-battery and PV-wind-battery fronts coincide exactly at all three sites: of the 17 507 designs enumerated per site, none containing wind is Pareto-optimal under the cost, power-curve and wind-data assumptions adopted here.

The fronts are steep at low cost and flatten as reliability improves. Moving from CVaR95 of 10 MWh/yr to 1 MWh/yr raises NPC from 103 kUSD to 133-141 kUSD (29-36 percent), and moving further to 0.1 MWh/yr adds another 19-33 kUSD. Adding a 5-kW diesel generator shifts the front left below about 1 MWh/yr, because a small generator covers the few dull days that otherwise force PV oversizing.

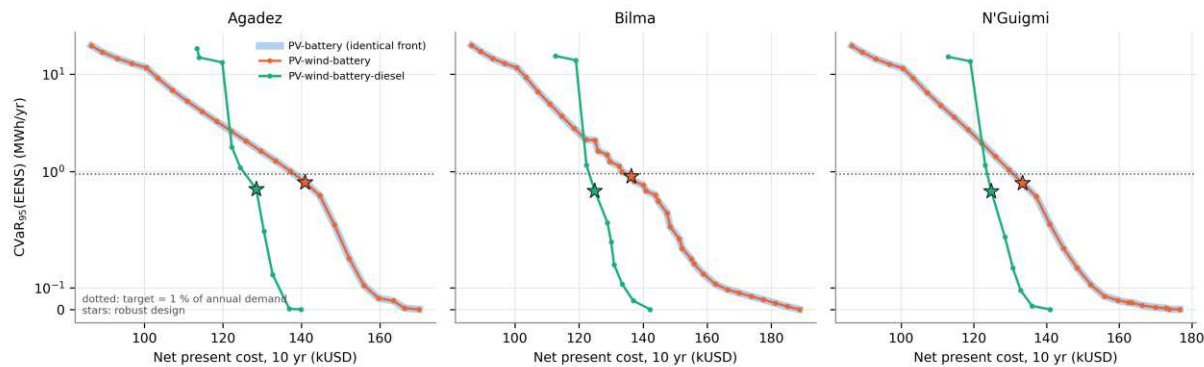


Figure 13. Cost-risk Pareto fronts at the three sites. Pareto fronts of net present cost (10 years) against CVaR95 of annual EENS, from exhaustive enumeration over the screened records (Agadez 2019-2023, Bilma and N'Guigmi 2015-2023). The PV-battery front (thick, light) is hidden by the identical PV-wind-battery front. Stars: robust designs (least NPC with CVaR95 at most 1 percent of annual demand). Symmetric-log vertical axis.

The main reason wind is not selected in these runs is visible in Figure 6. At Agadez, the only site with a usable wind resource, 81 percent of turbine energy falls in the 06-18 h slots, when PV already covers the load, while the three night slots carry 34 percent of demand. In the recorded data, wind therefore competes with cheap PV instead of complementing it. Forcing at least one 10-kW turbine into the robust design costs 13.0 percent more NPC at Agadez, 19.6 percent at Bilma and 22.2 percent at N'Guigmi at the base cost of 4000 USD/kW (Figure 14a). Wind becomes part of the least-cost robust design at Agadez once its installed cost falls to about 1500 USD/kW (a 10-kW turbine then replaces 20 kWp of PV), at Bilma only near 500 USD/kW, and at N'Guigmi at no cost in the tested range. Setting the imputed Agadez night winds to zero changed nothing, since no turbine was selected in the first place. Figure 14b adds the months in which the robust PV-battery designs leave energy unserved, which is where a complementary source would have to deliver.

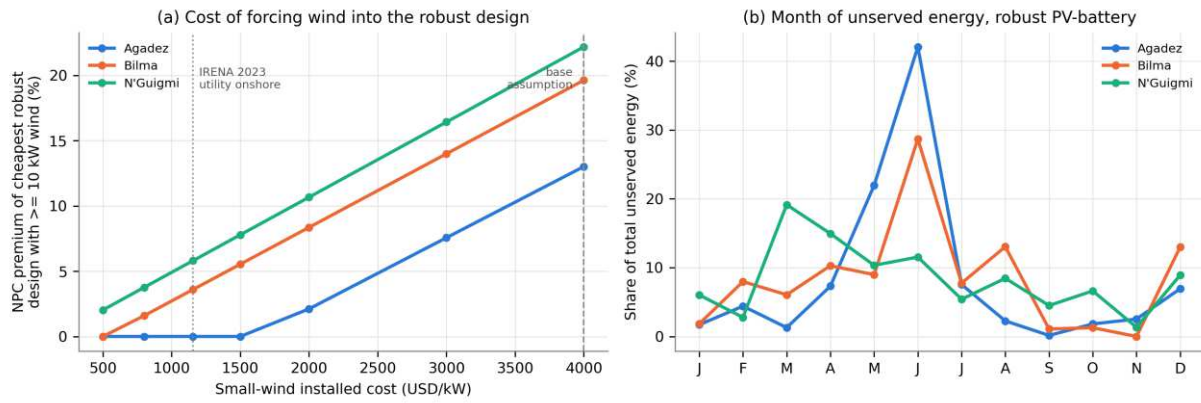


Figure 14. Cost premium of wind and monthly distribution of unserved energy. (a) NPC premium of the cheapest design with at least 10 kW of wind that still meets the reliability target, relative to the robust design, as a function of small-wind installed cost; dotted line: IRENA 2023 utility onshore average (International Renewable Energy Agency, 2024); dashed line: base assumption. (b) Monthly distribution of unserved energy of the robust PV-battery design over the simulation windows.

3.10 Robust configurations

Table 5 and Figure 15 report the robust designs. Within the design grid and the cost assumptions of Table 1, all three sites converge on a similar architecture: 85-105 kWp of PV and 150-175 kWh of storage for 250 kWh/day of base demand, an LCOE of 0.211-0.223 USD/kWh and an LPSP of 0.42-0.50 percent. The battery is sized close to one night of load, about 34 percent of daily demand falls in the 21-03 h slots, and dull days are handled by oversizing PV, so that 34-48 percent of renewable generation is curtailed. Equivalent full cycles are 296-335 per year, well within the assumed 6000-cycle life over ten years. Agadez needs the most PV (105 kWp) and has the highest curtailment, because its dull days cluster in May and June. Bilma needs the least PV but a larger battery (175 kWh).

A 5-kW diesel generator lowers NPC by 8.8, 8.3 and 6.5 percent and cuts PV to 70-80 kWp, at a renewable fraction of 97.5-98.5 percent. On the lifecycle objective the diesel option is not uniformly worse: it emits 5.7 percent less at Agadez, where it replaces 25 kWp of PV whose embodied emissions exceed the fuel burned, and 7 and 15 percent more at N'Guigmi and Bilma. This depends on the IPCC median intensities and on pro-rating embodied emissions over ten years, and would shift with site-specific life-cycle assessment (LCA) data.

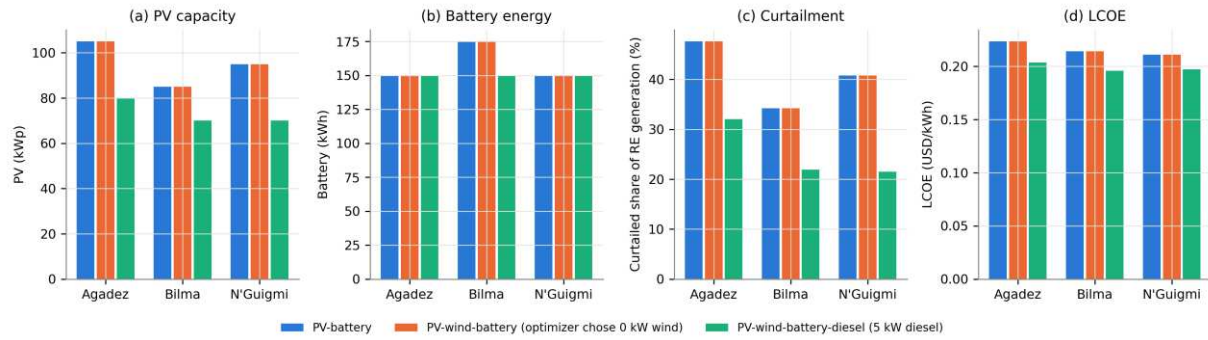


Figure 15. Robust mini-grid designs by site and configuration. Robust designs (least NPC with CVaR95 at most 1 percent of annual demand) by site and configuration: (a) PV capacity, (b) battery energy, (c) curtailed share of renewable generation and (d) LCOE. The least-cost PV-wind-battery design contains no wind at any site within the enumerated grid and the assumptions of Table 1.

Table 5. Robust configurations and reliability indicators.

Site	Config.	PV kW p	Wind kW	Batt. kWh	Diesel kW	NPC kUSD	LCO E \$/kW h	LPS P %	CVaR 95 kWh/y r	Worst yr kWh	Cur t. %	RF %	CO2 t
Agadez	PV-B	105	0	150	0	140.9	0.223	0.50	777	671	48	100.0	100.5
Agadez	PV-W-B	105	0	150	0	140.9	0.223	0.50	777	671	48	100.0	100.5
Agadez	PV-W-B-D	80	0	150	5	128.5	0.204	0.44	665	591	32	98.5	94.7
Bilma	PV-B	85	0	175	0	136.3	0.214	0.45	899	789	34	100.0	84.9
Bilma	PV-W-B	85	0	175	0	136.3	0.214	0.45	899	789	34	100.0	84.9
Bilma	PV-W-B-D	70	0	150	5	124.9	0.196	0.35	636	579	22	97.6	97.9
N'Guigmi	PV-B	95	0	150	0	133.4	0.211	0.42	764	548	41	100.0	90.6
N'Guigmi	PV-W-B	95	0	150	0	133.4	0.211	0.42	764	548	41	100.0	90.6
N'Guigmi	PV-W-B-D	70	0	150	5	124.8	0.197	0.37	630	491	22	97.5	97.0

Results from simulation over the screened records with the assumptions of Table 1. PV-B: PV-battery; PV-W-B: PV-wind-battery; PV-W-B-D: PV-wind-battery-diesel. RF: renewable fraction of served energy. Worst yr: highest annual EENS among the simulated calendar years; CVaR95 comes from 2000 resampled years; its year-level bootstrap intervals are given in Table 6. CO2: lifecycle emissions over 10 years.

These designs rest on short records, and the uncertainty of their tail statistics has to be read with that in mind. Table 6 keeps two quantities apart. The first is the variability actually observed, that is, the annual EENS of the robust PV-battery design in each simulated calendar year. At Agadez it ranges from 159 kWh (2019) to 671 kWh (2021), a factor of four over five years (mean 473 kWh, standard deviation 215 kWh); at Bilma it ranges from 37 to 789 kWh over nine years and at N'Guigmi from 173 to 548 kWh. The second is the uncertainty of the tail estimate itself. The CVaR95 values of Table 5 (777, 899 and 764 kWh/yr) exceed the worst observed year by 16, 14 and 39 percent. That excess comes from the monthly

block bootstrap recombining bad months from different years, so it is an extrapolation within the monthly states already present in the record, not beyond them. Resampling the years themselves (Eq. 20) gives 95 percent intervals of 564-800 kWh/yr at Agadez, 640-1045 kWh/yr at Bilma and 591-832 kWh/yr at N'Guigmi. These intervals are strongly asymmetric, with the point estimate close to the upper bound at Agadez and N'Guigmi, because a resample of the observed years can be milder than the full record but never harsher than its worst months. At Bilma the resampled CVaR exceeds the target of 952 kWh/yr in 21 percent of replicates, so the Bilma design meets the target with little margin. Monte Carlo noise from the finite number of bootstrap years is small in comparison (standard deviation 5-14 kWh/yr). The same resampling applied to the design choice gives a consistent picture. Across 300 year-resamples, the least-cost design meeting the target at Agadez had 100-105 kWp of PV (5th to 95th percentile) and 150 kWh of storage in every case, with NPC at most 2.7 percent below the reference; at Bilma it spanned 80-100 kWp and 150-175 kWh (NPC -2.8 to +0.7 percent), and at N'Guigmi 90-95 kWp and 150 kWh. No resample selected wind. These ranges describe how much the design depends on which of the observed years are included; they say little about a year harsher than any in the record. For the mean annual EENS at Agadez, a Student-t interval on the five annual values (206-739 kWh) is noticeably wider than the bootstrap percentile interval (299-632 kWh), a reminder that bootstrap intervals built on five values tend to be too narrow. The Agadez design is therefore best read as adequate for the variability seen in 2019-2023, not as robust in a climatological sense.

Table 6. Observed inter-annual variability and year-level bootstrap uncertainty of the robust PV-battery design (Table 5).

Site	Years (n)	Observed annual EENS, kWh	Worst year, kWh	CVaR95, kWh/yr	95 % interval of CVaR95, kWh/yr	Resamples above target, %	Re-selected PV kWp / battery kWh (5th-95th pct.)
Agadez	2019-2023 (5)	159-671 (473 ± 215)	671 (2021)	777	564-800	0	100-105 / 150
Bilma	2015-2023 (9)	37-789 (429 ± 265)	789 (2015)	899	640-1045	21	80-100 / 150-175
N'Guigmi	2015-2023 (9)	173-548 (399 ± 118)	548 (2023)	764	591-832	0	90-95 / 150

Observed: annual EENS over the simulated calendar years (min-max, mean ± standard deviation). Bootstrap: 2000 year-resamples around the monthly block bootstrap (Eq. 20); design re-selection over 300 resamples. Targets: 945, 952 and 946 kWh/yr. The intervals cover sampling within the observed years only and cannot represent years harsher than those recorded.

3.11 Sensitivity of the design to the meteorological input (H1 proxies)

Figure 16 re-optimizes the design under alternative inputs and reports the change in capacities and NPC, together with the CVaR that each alternative design actually achieves on the screened record. Two caveats apply. The grid steps (5 kWp, 25 kWh) correspond to 5-6 percent of PV and 14-17 percent of battery capacity, so small changes are quantized. And the thresholds of practical significance were fixed beforehand at 10 percent for capacity and 5 percent for cost. Finally, the perturbations are scenarios sized on published bias magnitudes: they test how the design would respond to errors of that order, not the actual error of any product at these stations.

Sunshine data quality is the largest effect at Agadez. Using the record as delivered, including the inhomogeneous 2015-2018 years and the copied 2024, raises PV by 14 percent and NPC by 8 percent, and the resulting design over-achieves the target by a factor of four (CVaR ratio 0.25). At Bilma and N'Guigmi, where only the duplicated 2024 is affected, the design does not change. The Angström coefficients matter at every site. The pessimistic corner ($a_s = 0.20$, $b_s = 0.45$) raises PV by 19-24 percent and NPC by 11 percent. The optimistic corner (0.30, 0.50) lowers NPC by 6-8 percent, but the design it produces misses the target by 51-72 percent when run on FAO-default irradiance. A ± 5 percent GHI bias of the size reported for ERA5 moves PV by 5-6 percent and NPC by about 3 percent, below both thresholds, although the +5 percent case again yields designs that miss the target by 7-20 percent. Wind perturbations of ± 25 percent and changes in z_0 leave the design unchanged, because no design selected under the base assumptions uses wind; this says nothing about the accuracy of the wind record itself. Removing the heat-demand elasticity lowers PV by 5-10 percent. Sizing on a single median-insolation year (2023 at Agadez, 2016 at Bilma, 2018 at N'Guigmi) lowers NPC by 3-8 percent but misses the ten-year target by 7 percent at Agadez and by 51-71 percent at the other two sites.

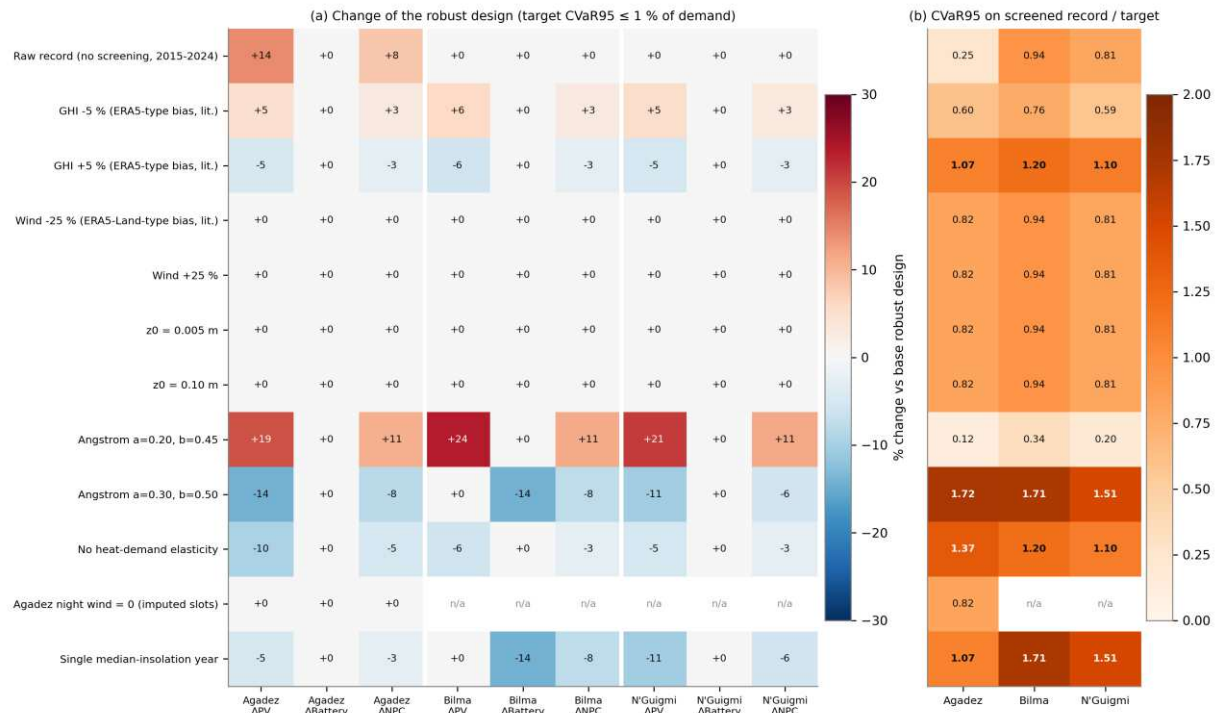


Figure 16. Sensitivity of the robust design to the meteorological input. (a) Percentage change in PV capacity, battery energy and NPC of the robust design when the optimization is rerun with alternative meteorological inputs (screened record as reference; literature-magnitude perturbations are labelled 'lit.'). (b) CVaR95 achieved by each alternative design when simulated on the screened record, as a multiple of the target; values above 1 (bold) mean the design would fall short of the reliability target.

3.12 Hypothesis tests

Table 7 summarizes the four tests. None of them can be read as a direct comparison between reanalysis and station data, which was not carried out here, and H1 in particular is a perturbation test. Each is computed on the station records.

Table 7. Outcome of the hypothesis tests on the 2015-2024 records.

Hypothesis	Test performed on the real record	Verdict
H1: input errors of the size found in the record or published for reanalysis change the design by > 10 % in capacity or > 5 % in cost	Perturbation tests only (no reanalysis extraction): unscreened vs screened record; Angström coefficient corners; ± 5 % GHI and ± 25 % wind perturbations; single median year	Partially supported. Exceeded for sunshine data quality at Agadez (+14 % PV, +8 % NPC), for Angström coefficients at all sites (+19 to +24 % PV, +11 % NPC) and for single-year sizing at Bilma and N'Guigmi. Not exceeded for ± 5 % GHI (≤ 6 % PV, ≤ 3 % NPC). Wind perturbations had no effect because no design used wind. Supported as a sensitivity statement, not as a comparison of sources.
H2: wind lowers tail risk at comparable cost	Pareto fronts with and without wind; cost of forcing ≥ 10 kW wind; wind-cost sweep 500-4000 USD/kW	Not supported under the stated data, cost and power-curve assumptions. No Pareto-optimal design contains wind at any site. At Agadez wind enters only below about 1500-2000 USD/kW; at Bilma only near 500 USD/kW; at N'Guigmi not at all. This does not show that wind has no value in Niger.

Hypothesis	Test performed on the real record	Verdict
H3: compound low-sun, low-wind, hot days dominate unserved energy	Month-conditional percentile index; ENS attribution of robust designs	Rejected in its compound form. Triple-compound days (0.5-1.0 % of days) carry ≤ 0.7 % of ENS. Low-sunshine days alone carry 59-78 % of ENS, and the worst 1 % of days carry 39-51 %.
H4: best mean-resource site is not the best robust site	Ranking by PV yield, GHI and wind vs ranking by robust NPC	Partially supported. Agadez has the highest PV specific yield and by far the best wind, yet the highest robust NPC; N'Guigmi has the lowest yield and the lowest robust NPC. Ranking by mean GHI does agree with robust NPC.

663

664 4. Discussion

665 The most useful result of this study is not a capacity figure. It is the observation that the station record
666 itself carried design-relevant errors that standard QC did not catch. A copied year of sunshine at all three
667 stations, a copied month and four years of under-recorded sunshine at Agadez all passed every bound
668 test. Only the Agadez inhomogeneity changed the design, by 14 percent in PV and 8 percent in cost, and
669 it was exposed by a cross-check against the diurnal temperature range that costs almost nothing to run.
670 Techno-economic studies in the Sahel routinely treat a decade of station data as ground truth for
671 validating reanalysis. These results argue for screening that ground truth first, with duplication and
672 physical-consistency tests alongside the usual range checks.

673 Irradiance is the second issue. Without a pyranometer or satellite series, the conversion from sunshine to
674 GHI produces the widest of the solar-input sensitivities tested here, and the range is asymmetric: the
675 lower end of the admissible coefficient range reduces GHI by up to 14 percent, and the designs it implies
676 cost 11 percent more. Choosing optimistic coefficients saves 6-8 percent of NPC but produces systems
677 that fail their reliability target by half again. For practitioners, one year of co-located pyranometer data,
678 or a satellite series such as those of the Copernicus Atmosphere Monitoring Service (CAMS) or the
679 Surface Solar Radiation Data Set - Heliosat (SARAH) extracted for these three points, would narrow this
680 range more than any refinement of the optimization. Because the coefficient range is a bounded set of
681 scenarios, the corresponding cost range (about -8 to +11 percent) describes the spread of plausible
682 outcomes, not a probability statement.

683 Wind comes third, and here the results go against the expectation behind H2, although what they
684 establish is narrower than it may first appear. Wind was not selected in any simulated configuration. At
685 Bilma and N'Guigmi the recorded speeds, taken at face value, are too low for the generic turbine to earn

a place. At Agadez the recorded resource is respectable (5.8 m/s at 30 m, 16-20 percent capacity factor), but its diurnal phase coincides with the solar day, and small wind at the costs documented for distributed turbines (National Renewable Energy Laboratory, 2024; Orrell et al., 2023) does not compete with PV plus one night of storage. This is consistent with the day-peaked surface wind of the Sahara, where mixing of the nocturnal jet down to the surface happens after sunrise. Several properties of the wind input limit how far this can be generalized. The unit of the speed record is not documented; the Agadez night slots are almost entirely missing and were imputed; the anemometer height is assumed to be 10 m without metadata; the extrapolation to hub height uses a neutral logarithmic profile with a single roughness length; and the very high calm frequencies at Bilma and N'Guigmi suggest that the exposure of the instruments may be poor. Each of these could bias the recorded or extrapolated resource, in either direction. The appropriate conclusion is therefore that wind is not competitive under the data, cost and power-curve assumptions adopted here. The results do not show that wind has no role in Niger's mini-grids, and they do not exclude wind at taller hub heights, where night-time jet winds are accessible, or at costs closer to utility onshore levels (International Renewable Energy Agency, 2024). They do suggest that the tail-risk argument for wind requires a resource available at night, which a 10-m synoptic record with sparse night reports cannot establish either way. The low station winds at Bilma and N'Guigmi make this the open question most worth settling with a short measurement campaign or a reanalysis extraction, bearing in mind the ERA5-Land wind deficit documented by Baas et al. (2026).

H3 failed in its compound form, and the reason is physical. In this climate a dull day is usually a dusty or cloudy day, and such days are cooler, so low sunshine and extreme heat seldom coincide within the same month. What drives unserved energy is short runs of dull days, concentrated in June at Agadez and Bilma and spread over March-April at N'Guigmi. The worst 1 percent of days carries 39-51 percent of ENS. A reliability metric built on annual averages would miss this almost entirely; the CVaR objective captures it, and the bootstrap years it relies on are, as Table 5 shows, harsher than any single observed year. That extra severity (14 to 39 percent above the worst observed year) comes from recombining bad months from different years; it is an extrapolation within the monthly states of the record, and the year-level intervals of Table 6 show that it does not reach beyond them. This is the sense in which the tail matters, and it supports the growing use of tail-risk objectives in microgrid planning ("Microgrid-Level

714 Reliability Assessment," 2025; Mishra & Shankar, 2025; "Two-Stage Energy Dispatch for Microgrids,"
715 2025), but the tail is a solar one.

716 Site ranking (H4) depends on what one means by resource. Agadez has the best PV yield and by far the
717 best wind, yet it needs the most PV to reach the target, because its dull days cluster; N'Guigmi, with the
718 lowest yield, is the cheapest robust site. Mean GHI happens to rank the sites correctly here, but the
719 margins are small (robust NPC differs by 5.6 percent between best and worst), and the Agadez result
720 rests on only five screened years, over which the year-level bootstrap interval of its CVaR spans 564-800
721 kWh/yr. The ranking matters less than the caveat behind it: annual resource figures, whether from
722 stations or reanalysis, say little about the handful of days that size a mini-grid.

723 Relative to the growing literature on multi-objective hybrid sizing ("Constraint Multi-Objective Optimal
724 Design," 2021; "Metaheuristic Optimization of Hybrid Renewable Energy Systems," 2025; Mishra &
725 Shankar, 2025), the contribution here is traceability. Every design number in Table 5 can be followed
726 back through a documented screening decision to the raw station file, and Figure 16 indicates which of
727 those decisions move the design and by how much. That audit trail is what a funder or utility needs to
728 judge whether a feasibility study rests on sound meteorology.

729 **4.1 Limitations**

730 Ten years of data, and only five usable years of sunshine at Agadez, describe recent variability, not a
731 climate normal. The monthly block bootstrap widens the sample of bad years but cannot invent patterns
732 absent from the record, and the year-level intervals of Table 6 quantify sampling uncertainty within the
733 observed years only; with five values they are probably too narrow, as the comparison with a Student-t
734 interval on the Agadez annual EENS suggests. Tail statistics at Agadez, and the design derived from
735 them, should therefore be read as conditional on 2019-2023. GHI is estimated from sunshine with
736 uncalibrated FAO-56 coefficients, because the dataset contains no irradiance reference; the range of
737 Section 3.3 and Table 4 is a bounded sensitivity envelope over admissible coefficient pairs, not a
738 confidence interval or a calibrated probability distribution. The within-day distribution of irradiance and
739 temperature is modelled from daily values. The wind input carries several undocumented features: the
740 unit of wind speed is not stated in the source file and was assumed to be m/s (if it were knots, all speeds

would be 49 percent lower and the wind results would only strengthen); the anemometer height is assumed to be 10 m; Agadez wind is 36 percent imputed, almost entirely in the night slots, from a small pool of observations; and the calm frequencies at Bilma and N'Guigmi raise doubts about instrument exposure. Shear extrapolation from 10 m assumes neutral stability with a single roughness length, which overstates night-time hub winds under the stable Saharan night and understates daytime ones. No reanalysis or satellite product was compared with the stations, so H1 was tested only through perturbations built from the station data and published bias magnitudes. Demand is a stylized archetype with an assumed heat elasticity; costs, lifetimes and emission factors are literature-based assumptions (Table 1), and a single assumed soiling factor stands in for a dust-deposition process that the dataset does not document. The optimization is an exhaustive search on a finite grid, so capacities are resolved to 5 kWp and 25 kWh. Finally, the homogeneity and screening decisions were made without station metadata; they should be confirmed with the national meteorological service before the series are used for trend analysis.

5. Conclusions

Built on the 2015-2024 synoptic records of Agadez, Bilma and N'Guigmi, this study sized PV-wind-battery mini-grids against a tail-risk reliability objective and traced every design number back to screened station data. Three findings matter most for practice. First, the station record needed screening beyond range checks: a copied year, a copied month and a four-year sunshine inhomogeneity were found, and the last of these alone would have oversized the Agadez system by 14 percent in PV and 8 percent in cost. Second, the conversion of sunshine to irradiance, uncalibrated for lack of a reference, gives the widest of the solar-input sensitivities tested, worth about 11 percent of cost at the pessimistic end of a bounded coefficient range, and optimistic choices lead to systems that miss their reliability target. Third, under the documented costs and within the design grid studied, the least-cost system meeting the target is PV with about one night of battery storage at all three sites, near 0.21-0.22 USD/kWh. At Agadez this rests on five screened years; resampling them changes the design by no more than one 5-kWp PV step between the 5th and 95th percentiles, but no resampling can represent a year worse than those recorded. Wind was not selected in any simulated configuration, because the recorded

768 wind is either weak (Bilma, N'Guigmi) or peaks in daylight (Agadez). Given the undocumented unit, the
 769 missing night reports at Agadez, the assumed anemometer height and the simplified shear model, this
 770 means that wind is not competitive under the data, cost and power-curve assumptions retained here, not
 771 that it has no place in Niger's mini-grids. Unserved energy in the simulations is driven by runs of dull
 772 days rather than by compound low-sun, low-wind, hot days. A 5-kW diesel backup lowers cost by 6.5-
 773 8.8 percent at a renewable fraction above 97 percent. The capacities reported here are indicative ranges to
 774 be confirmed by field measurement, and two measurements would change them most: a year of
 775 pyranometer data to calibrate the Angström coefficients, and a check of the Bilma and N'Guigmi
 776 anemometers or a taller-mast campaign to establish whether a night-time wind resource exists.

777 **List of abbreviations**

778 AC: alternating current; ATB: Annual Technology Baseline; CAMS: Copernicus Atmosphere
 779 Monitoring Service; CapEx: capital expenditure; CI: confidence interval; CO₂-eq: carbon dioxide
 780 equivalent; CRF: capital recovery factor; CVaR: conditional value at risk; DC: direct current; DHI:
 781 diffuse horizontal irradiance; DTR: diurnal temperature range; ECMWF: European Centre for Medium-
 782 Range Weather Forecasts; EENS: expected energy not served; ENS: energy not served; ERA5: fifth-
 783 generation ECMWF atmospheric reanalysis; ERA5-Land: land-surface reanalysis derived from ERA5;
 784 ESMAP: Energy Sector Management Assistance Program; FAO-56: Food and Agriculture Organization
 785 of the United Nations, Irrigation and Drainage Paper 56; GHI: global horizontal irradiance; IPCC AR5:
 786 Fifth Assessment Report of the Intergovernmental Panel on Climate Change; IQR: interquartile range;
 787 IRENA: International Renewable Energy Agency; KGE: Kling-Gupta efficiency; kUSD: thousand
 788 United States dollars; kWp: kilowatt-peak; LCA: life-cycle assessment; LCOE: levelized cost of energy;
 789 LFP: lithium iron phosphate; LPSP: loss of power supply probability; MBE: mean bias error; MERRA-2:
 790 Modern-Era Retrospective analysis for Research and Applications, version 2; NASA POWER: National
 791 Aeronautics and Space Administration Prediction Of Worldwide Energy Resources; NORA3: Norwegian
 792 3-km reanalysis; NPC: net present cost; NREL: National Renewable Energy Laboratory; NSGA-II: non-
 793 dominated sorting genetic algorithm II; O&M: operation and maintenance; OpEx: operating expenditure;
 794 POA: plane of array; PV: photovoltaic; PV-B: PV-battery configuration; PV-W-B: PV-wind-battery

795 configuration; PV-W-B-D: PV-wind-battery-diesel configuration; QC: quality control; RF: renewable
796 fraction; RMSE: root mean square error; RTE: round-trip efficiency; SARAH: Surface Solar Radiation
797 Data Set - Heliosat; SNHT: standard normal homogeneity test; SOC: state of charge; TMAX, TMIN:
798 daily maximum and minimum air temperature; UMAX, UMIN: daily maximum and minimum relative
799 humidity; US: United States; USD: United States dollar; UTC: Coordinated Universal Time; VaR: value
800 at risk; WDD: wind direction as coded in the station file (WMO dd convention); WFFI: wind speed as
801 coded in the station file; WMO: World Meteorological Organization.

802 **Declarations**

803 **Availability of data and materials**

804 The datasets used and/or analysed during the current study are available from the corresponding author
805 on reasonable request. All results derive from the file Données-météo-Agadez-Bilma-Nguigmi-2015-
806 2024.xlsx (daily TMAX, TMIN, UMAX, UMIN, sunshine duration and pressure; three-hourly wind
807 direction and speed). The analysis scripts (baseline QC and screening, resource derivation, three-hourly
808 simulation, enumeration and bootstrap, and figure generation) and the derived data supporting this study
809 are also available from the corresponding author on reasonable request. Techno-economic assumptions
810 and their sources are listed in Table 1; no cost, demand or irradiance data were measured at the sites.

811 **Competing interests**

812 The author declares that he has no competing interests.

813 **Funding**

814 Not applicable.

815 **Authors' contributions**

816 M.G.M. conceived, designed and conducted the entire study, performed the analyses, and wrote the
817 manuscript. The author read and approved the final manuscript.

818 **Acknowledgements**

819 The author thanks the National Meteorological Service (DMN) of Niger for the underlying synoptic
820 station records.

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