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DAILY AND MONTHLY WIND-SOLAR COMPLEMENTARITY ACROSS NIGER'S SAHARA-TO-SAHEL GRADIENT: HOW MUCH OF THE RAW SIGNAL SURVIVES DESEASONALIZATION?

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ABSTRACT

Negative wind-solar correlations are often cited as evidence that hybrid systems can deliver steadier supply, yet a long daily series contains fewer independent observations than its nominal length suggests, because both resources share an annual cycle and successive days are serially dependent. This study quantifies how much daily complementarity survives once these effects are controlled, using nine years (2015-2023) of synoptic wind and sunshine-duration records from Bilma, Agadez Aéro and N'Guigmi, three Nigerien stations spanning the Sahara-to-Sahel transition. Daily wind-energy proxies were built from a zero-inflated wind-speed mixture and a generic turbine power curve, and daily global irradiance was estimated with the Ångström-Prescott model. Spearman correlations were computed on raw series, deseasonalized anomalies and harmonic day-of-year residuals, with 95% confidence intervals from a month-year block bootstrap, and a stability coefficient was computed for monthly hybrid mixes. Raw correlations were weakly negative and significant at all stations ($r = -0.094$ to -0.152 , $p < 0.001$). After deseasonalization, the signal was no longer robust at Agadez ($r = -0.036$, interval including zero), became weak and borderline at Bilma and remained robust only at N'Guigmi ($r = -0.12$ to -0.13 , interval excluding zero). The variance-minimising monthly mix was solar-dominated, with wind weights of 14-40% and stability coefficients of 0.83-0.95; this stability arose mainly from the low month-to-month variability of solar resource rather than from anti-phase behaviour. Daily wind-solar complementarity in this region is real but modest and station-specific, and pooled daily correlations uncorrected for seasonality and serial dependence overstate it.

Keywords: Wind-solar complementarity; Deseasonalization; Block bootstrap; Stability coefficient; Hybrid renewable systems; Sahel

1 INTRODUCTION

Hybrid wind-solar systems are frequently motivated by the intuition that the two resources complement each other temporally, with periods of low solar output tending to coincide with periods of stronger wind and vice versa, which, if true, would let a hybrid plant deliver steadier output than either resource alone and reduce the storage or backup capacity needed to firm it, an appealing prospect for a country such as Niger whose national resource statistics point to substantial potential in both wind and solar [1]. Continental-scale modelling work on West Africa has found real, policy-relevant synergies of this kind at the scale of national or regional power systems, generally using monthly or coarser-resolution reanalysis-driven resource estimates [2,3]; comparable correlation-based complementarity assessments at national scale have also been carried out elsewhere, for instance in Sweden and in Italy [4,5]. At station level in Niger, a ten-year principal component analysis of the N'Guigmi record related wind speed to temperature, humidity, pressure and insolation and identified temperature and humidity as its main covariates, but did not quantify a direct wind-sunshine relationship [6]. Whether a similar signal is detectable, and how strong it genuinely is, in a decade of station-level daily observations is a separate and much harder question, because a long daily series is not the same thing, statistically, as a correspondingly large sample of independent observations: wind and solar resource both follow the same annual cycle at a given location, and successive days inherit a great deal of their meteorological state from the days immediately before them. A correlation computed across thousands of daily values that are not independent can report an extremely small p-value, and often a misleadingly large one in magnitude if read uncritically as very strong evidence, largely because standard correlation tests assume independent observations and the nominal sample size, not the effective one, drives the test statistic [7].

This paper asks a direct question of three Nigerien station records spanning the Sahara-to-Sahel transition (Bilma, Agadez Aéro and N'Guigmi), using synoptic wind observations at up to eight standard hours per day and daily sunshine-duration records for 2015-2023: how much of the apparent daily wind-solar complementarity survives once the shared annual cycle is removed and the remaining day-to-day dependence is accounted for honestly? We build wind-energy and solar-irradiance proxies for this purpose directly from the raw synoptic archive, with the full construction of each proxy given below rather than treated as a black-box input, because a complementarity analysis that silently inherits an unexamined upstream choice, such as how wind calm periods are handled or which coefficients a sunshine-based irradiance model uses, can propagate that choice invisibly into its conclusions. Setting out both proxies in full, from first principles, is accordingly a central methodological commitment of this paper, not a formality.

Three methodological commitments follow from that question. First, we test the raw correlation against a sequence of increasingly conservative alternatives: deseasonalized anomalies, a harmonic day-of-year regression, and block-bootstrap confidence intervals that resample whole calendar blocks rather than individual days, and we report all of them side by side rather than selecting whichever result is most favourable to a complementarity narrative. Second, rather than only defining a stability coefficient for a hybrid mix, we compute it explicitly, at a resolution and with a definition we state precisely, and we show what actually drives it. Third, where a sub-daily complementarity claim rests on an arbitrary fixed solar profile, we replace that profile with one derived from each day's and each station's true solar geometry, and we are explicit about what that still does, and does not, demonstrate about real intra-day energy complementarity.

2 MATERIALS AND METHODS

2.1 Study area and data

We use a 2015-2024 archive of synoptic wind speed, reported as integer values in m s^{-1} at the standard hours 00, 03, 06, 09, 12, 15, 18 and 21 UTC, and of daily sunshine duration, from three stations of the national synoptic network (Table 1), provided by the Direction de la Météorologie Nationale du Niger (DMN). The sunshine records for 2024 duplicate those of 2023 at all three stations (72%, 88% and 93% of daily values identical at Agadez Aéro, Bilma and N'Guigmi, against 1-8% for any other pair of consecutive years), as also reported in [8], and the September 2022 sunshine record at Agadez Aéro repeats that of June 2022. Both were discarded, so every paired wind-solar analysis in this paper covers the nine years 2015-2023; the wind records show no comparable duplication. Wind coverage is uneven across hours: at Agadez Aéro the archive contains almost only the five daytime hours 06-18 UTC (5.1 observations per day on average), against 7.2 at Bilma, where most 00 UTC records are missing, and 7.9 at N'Guigmi. Because calm conditions are more frequent at night, this difference affects the daily wind proxy, so all correlations were also recomputed using only the five hours common to the three stations (06, 09, 12, 15 and 18 UTC); this check is reported in Section 3.1. Within 2015-2023, sunshine duration is missing for seven months at Agadez Aéro (mostly in 2016-2017), two at Bilma and four at N'Guigmi, and four station-months recorded twice in the Agadez sunshine sheet were deduplicated. This paper's focus is the relationship between the two resources rather than either resource's record quality considered on its own, so we do not reproduce a full station-by-station data-quality audit here; we summarise the quality-control points that

bear directly on the complementarity analysis as they arise in Sections 2.2-2.3 and in Section 3.8, and we give, self-containedly, every formula this paper uses below.

Table 1: Station locations

Station	Latitude	Longitude	Elevation (m)	Climatic zone
Bilma	18.69°N	12.92°E	357	Hyper-arid Sahara
Agadez Aéro	16.97°N	7.98°E	502	Sahara-Sahel transition
N'Guigmi	14.25°N	13.12°E	286	Sahel / Lake Chad basin

2.2 A self-contained daily wind-energy proxy

A synoptic wind-speed record of this kind contains a substantial fraction of records coded as exactly zero, following the WMO convention of pairing a zero speed with a zero (calm) direction code [9,10]. Discarding these, or filling them with a reconstructed positive value, both distort the energy content of the record in opposite directions. We instead build a daily wind-energy proxy as an explicit zero-inflated mixture, in the spirit of the zero-inflated count models used elsewhere in applied statistics for a response variable with an excess of exact zeros [11]: for each station-day, we compute the fraction of that day's available synoptic observations recording exactly zero speed ($p_{0,\text{day}}$), and we compute the mean cubed wind speed, and the mean generic-turbine power fraction, among that day's strictly positive-speed observations only. The day's energy-relevant proxy is then each of those conditional means scaled by $(1 - p_{0,\text{day}})$:

$$\langle v^3 \rangle_{\text{day}} = (1 - p_{0,\text{day}}) \text{mean}(v^3 | v > 0, \text{that day}) \quad (1)$$

Algebraically, Eq. 1 equals the mean of v^3 over all of the day's observations, zeros included; the mixture form is kept because it makes the contribution of calm records explicit. Days with fewer than three valid wind observations are discarded. We use two alternative versions of this proxy throughout: the cubed-speed proxy above, which is physically motivated by the fact that available wind power scales with v^3 , and a turbine-power proxy that replaces the bare cube with the fractional output of a generic three-bladed turbine power curve (cut-in 2.5 m/s, rated 9 m/s, cut-out 25 m/s, cubic ramp in between) [12,13], again averaged over the day's positive-speed observations and scaled by $(1 - p_{0,\text{day}})$. The cubed-speed proxy ignores cut-in, rated and cut-out behaviour entirely and will overstate the energy contribution of both very low and very high wind speeds relative to a real turbine; we report both versions in Section 3.1 specifically so that the correlation results can be checked for sensitivity to this choice.

2.3 A self-contained daily solar-irradiance proxy

For each station and day of year, we compute solar declination, the sunset hour angle, and extraterrestrial radiation R_a from standard solar-geometry formulae [14,15], and estimate daily global irradiance from the day's recorded sunshine duration n and the astronomically possible day length N via the Ångström-Prescott model with generic literature coefficients:

$$R_{s,\text{day}} = R_{a,\text{day}} \left(0.25 + 0.50 \frac{n_{\text{day}}}{N_{\text{day}}} \right) \quad (2)$$

This is a standard formulation of the Ångström-Prescott model, using generic literature coefficients since no local pyranometer record exists to calibrate them for these three stations; we compute it here from each station's own coordinates and its own daily solar geometry. A quality-control pass over the sunshine-duration record identifies six days across the three stations where recorded sunshine duration n exceeds the astronomically possible day length N , a physical impossibility. One of these, at Agadez Aéro on 5 March 2022, records 40.3 hours of sunshine against a possible maximum of 11.7 hours; a duplicate record of the same month in the archive gives 10.3 hours for that day, which confirms a transcription error. We exclude this day and treat it as missing. The remaining five exceed N by at most 1.1 hours, consistent with ordinary rounding tolerance, and we retain them with n/N capped at 1.0, a physically necessary constraint rather than a judgement call specific to this analysis.

2.4 A seven-layer correlation framework

For each station, we merge the daily wind-energy proxy and the daily solar-irradiance estimate on calendar date, retaining only days with both quantities present (2,938 to 3,222 days per station, depending on data completeness), and compute Spearman's rank correlation (our primary statistic throughout, since neither proxy is expected to be normally distributed) at seven levels of correction, moving from least to most conservative:

The raw correlation uses the full daily series exactly as built in Sections 2.2 and 2.3, with no correction for shared seasonality. The deseasonalized-anomaly correlation subtracts each station's own monthly climatological mean from each day's wind and solar values separately before correlating the resulting anomalies, removing the shared annual cycle by construction. The day-of-year-controlled correlation instead regresses each series on a two-harmonic (annual and semi-annual) Fourier expansion of day-of-year and correlates the residuals, a smoother and less step-wise alternative to the monthly-anomaly approach that should give a similar answer if the anomaly approach is not an artefact of the specific monthly binning chosen. The seasonal correlation computes the raw correlation separately within each of the four meteorological seasons (DJF, MAM, JJA, SON), asking whether any apparent annual-scale complementarity is in fact concentrated in one part of the year rather than present uniformly. The inter-annual correlation computes the raw correlation separately within each of the ten calendar years, asking the same question across years rather than seasons. Finally, the block-bootstrap confidence interval resamples, with replacement, whole month-year blocks (so an entire calendar month's worth of paired daily observations moves together), refits the Spearman correlation on 500 resampled datasets, and reports the 2.5th and 97.5th percentiles as a 95% interval that respects at least month-scale serial dependence in both series [16,17,18]; this bootstrap is applied to both the raw and the deseasonalized-anomaly correlation, so that the confidence interval itself can be compared across correction levels.

2.5 A stability coefficient, computed rather than merely defined

We assess a hypothetical wind-solar hybrid mix at monthly resolution, to keep synoptic-scale noise from dominating the variance calculation. Let X_m and S_m be the monthly means of the wind proxy and of R_s over the calendar months of 2015-2023 with at least 15 valid paired days (96 to 106 months per station), each divided by its own station maximum. For a wind weight w between 0 and 1, the hybrid series is

$$H_m(w) = wX_m + (1 - w)S_m \quad (3)$$

The stability coefficient is then defined as

$$C_{\text{stab}} = 1 - \frac{CV_{\text{hybrid}}}{CV_{\text{ref}}} \quad (4)$$

where CV_{hybrid} is the coefficient of variation (standard deviation divided by mean) of $H_m(w)$, and CV_{ref} is the coefficient of variation of whichever single normalised resource (wind or solar alone) is more variable at that station (wind, at all three stations in this dataset, as Section 3.4 shows). A C_{stab} of zero means the hybrid mix is exactly as variable as the more variable single resource; a C_{stab} approaching one means the hybrid mix is almost perfectly stable by comparison. We report C_{stab} across the full range of mixing weights w , together with the weight that minimises the variance of $H_m(w)$, which has the closed form

$$w^* = \frac{\sigma_S^2 - \sigma_{XS}}{\sigma_X^2 + \sigma_S^2 - 2\sigma_{XS}} \quad (5)$$

where σ_X^2 and σ_S^2 are the variances of X_m and S_m , σ_{XS} is their covariance, and w^* is truncated to the interval [0,1]. This weight minimises variance, not the coefficient of variation, so it need not coincide with the weight that maximises C_{stab} . We report the full curve rather than a single number for an arbitrary 50/50 mix.

2.6 A geometry-based sub-daily solar profile

To compare wind and solar at sub-daily (synoptic-hour) resolution, a fixed 06:00-18:00 sinusoidal solar profile applied uniformly to every station, season and day is a convenient but physically arbitrary simplification: it ignores the real seasonal variation in day length, sunrise and sunset timing, and solar elevation at each latitude. We replace it with a clear-sky geometric weight based on each day's actual solar zenith angle,

$$g(h) = \max(0, \sin \varphi \sin \delta + \cos \varphi \cos \delta \cos[15^\circ(h - 12)]) \quad (6)$$

evaluated at each station's latitude φ , each day's declination δ , and each of the eight synoptic hours h (UTC, used here as a local-solar-time approximation that ignores longitude and the equation of time, a simplification we flag explicitly rather than silently). This profile correctly produces zero weight before sunrise and after sunset, a day length that lengthens and shortens with season and latitude, and a smooth noon peak, all properties the fixed sinusoid lacked, but it remains a clear-sky geometric idealisation: it does not incorporate cloud cover, dust loading, or any measured sub-daily irradiance, none of which this archive records. We present the resulting profiles in Section 3.5 explicitly as a property of this geometric model, not as a measured or demonstrated energy-system result.

2.7 Software and reproducibility

All proxy construction, correlation, bootstrap and C_{stab} calculations were implemented independently for this paper in Python 3.13 using pandas [19], NumPy [20], and SciPy [21] (Spearman and Pearson correlation, numerical integration for the turbine power curve), with Matplotlib [22] for plotting. The block-bootstrap random seed (7) is fixed for exact reproducibility of the intervals reported in Section 3.1.

3 RESULTS AND DISCUSSION

3.1 How much of the raw correlation survives correction

Table 2: Spearman correlation between the daily wind-energy proxy and the daily solar-irradiance estimate, by correction level. “Raw” uses the v^3 proxy of Eq. 1 unless stated; the turbine-power-proxy column substitutes the generic turbine-curve version. 95% CI columns are 500-replicate block bootstrap resampling whole month-year blocks.

Station	n (days)	Raw r	Raw r, turbine proxy	Anomaly r	Day-of-year r	95% CI, raw	95% CI, anomaly
Agadez Aéro	2,938	-0.107***	-0.106***	-0.036*	-0.034 (ns)	[-0.181, -0.038]	[-0.099, 0.020]
Bilma	3,222	-0.094***	-0.101***	-0.066***	-0.052**	[-0.148, -0.042]	[-0.123, -0.002]
N'Guigmi	3,161	-0.152***	-0.149***	-0.131***	-0.118***	[-0.208, -0.102]	[-0.190, -0.067]

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ns = not significant at $p < 0.05$. Paired days 2015-2023.

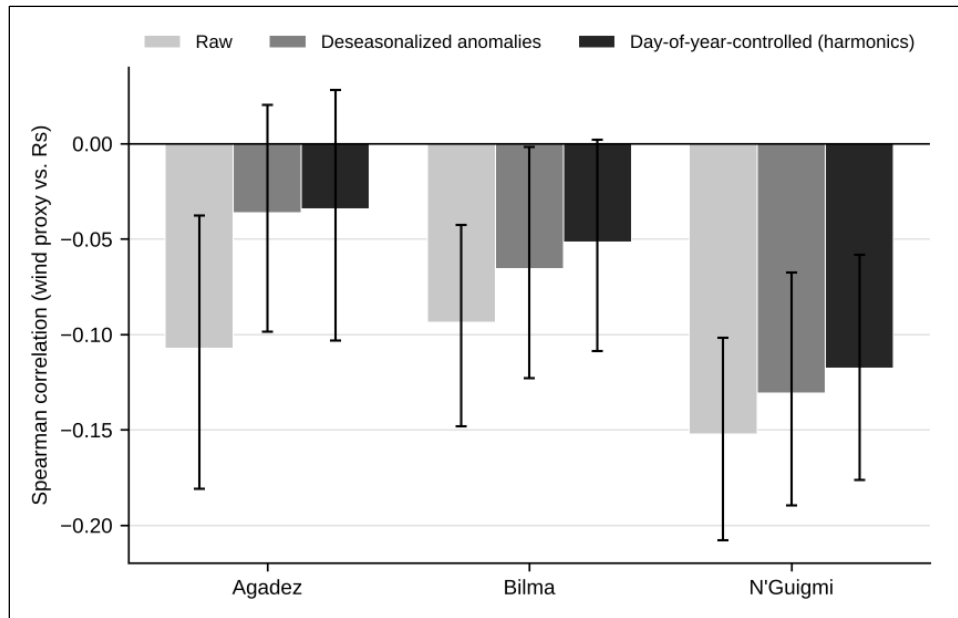


Figure 1: Raw, deseasonalized-anomaly and day-of-year-controlled Spearman correlation between the wind proxy and R_s , by station, with 95% block-bootstrap intervals (500 resamples of whole month-year blocks) on all three estimates.

The raw, pooled correlation is negative and conventionally “highly significant” ($p < 0.001$) at all three stations (Table 2, Figure 1), and this is the result that a less cautious reading of this kind of record would report as evidence of robust complementarity. It survives, essentially unchanged in sign and magnitude, when the v^3 proxy is replaced by the turbine-power proxy, which at least rules out the possibility that the raw result is an artefact of the specific wind-energy proxy chosen. It does not, however, survive deseasonalization uniformly. At Agadez, the anomaly correlation falls to -0.036 ($p = 0.0499$, at the conventional threshold) and the day-of-year-controlled value to -0.034 ($p = 0.063$), and the 95% block-bootstrap interval of the anomaly correlation includes zero: most of the raw correlation at this station is attributable to the fact that wind and solar resource both follow a broadly similar annual cycle (both tend to be higher in the dry season), not to a robust day-to-day anti-phase relationship. At Bilma, both deseasonalized correlations remain

nominally significant (-0.066 , $p < 0.001$, and -0.052 , $p = 0.003$), but they are small and their bootstrap intervals sit at the edge of zero ($[-0.123, -0.002]$ for the anomaly correlation and $[-0.109, 0.002]$ for the day-of-year-controlled one): we read this as a weak, borderline signal that the raw correlation overstates. At N'Guigmi, by contrast, the anomaly correlation remains materially negative (-0.12 to -0.13 depending on method) and its 95% bootstrap interval excludes zero by a clear margin: this is the one station, of the three, where this analysis finds robust evidence of a day-to-day relationship between wind and solar resource beyond what shared seasonality alone would produce.

Two checks support this reading. Restricting the daily wind proxy to the five hours common to the three stations (06–18 UTC) leaves the picture unchanged: the anomaly correlation becomes -0.033 at Agadez (95% CI $[-0.097, 0.024]$), -0.053 at Bilma ($[-0.109, 0.003]$) and -0.111 at N'Guigmi ($[-0.173, -0.050]$). Excluding the possibly inhomogeneous 2015–2018 Agadez sunshine record (Section 3.8) strengthens the raw Agadez correlation to -0.237 but leaves the anomaly correlation weak (-0.059 , 95% CI $[-0.116, 0.004]$), so the conclusion for that station does not depend on those years.

3.2 Seasonal structure of the correlation

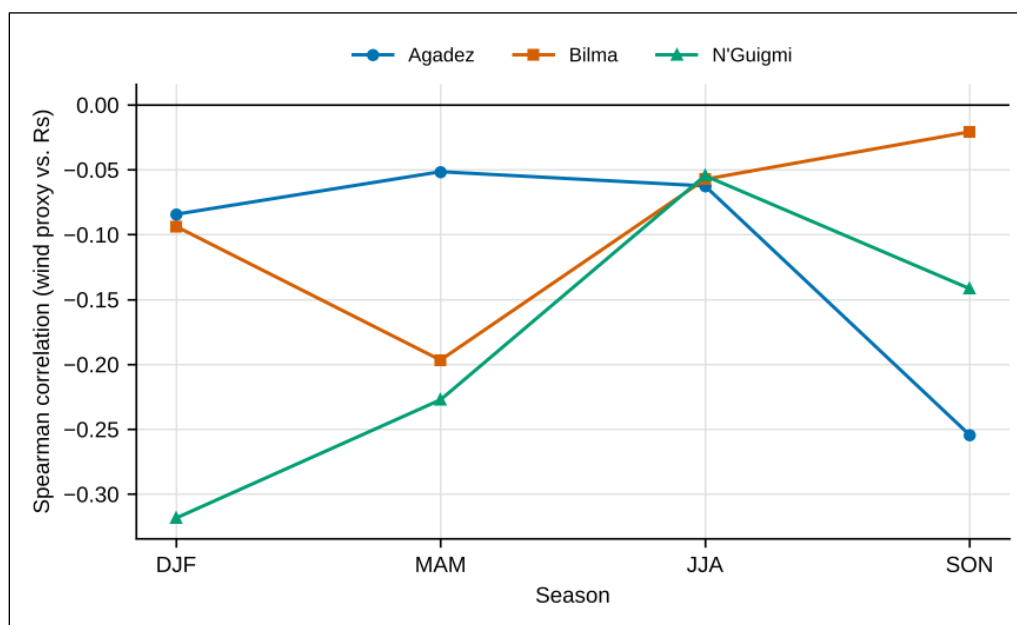


Figure 2: Raw Spearman correlation computed separately within each meteorological season, by station.

The within-season breakdown (Figure 2) reinforces the station-dependence of Section 3.1 rather than contradicting it. At Agadez, the correlation is weak and not clearly distinguishable from zero in three of four seasons, with a markedly stronger negative value in SON ($r = -0.254$) that likely reflects the sharp autumn transition out of the monsoon rather than a feature present year-round. At Bilma, only MAM shows a materially negative within-season correlation ($r = -0.197$); the other three seasons are weak or, in SON, essentially zero. At N'Guigmi, DJF and MAM both show the strongest within-season signal ($r = -0.319$ and -0.227 respectively), while JJA is weak, suggesting that even this station's more robust overall anomaly correlation is not uniformly distributed across the year.

3.3 Inter-annual variability

Year-to-year variability in the correlation is substantial at every station (Figure 3; standard deviation across the nine years of 0.16 at Agadez, 0.09 at Bilma and 0.12 at N'Guigmi), and the sign itself reverses in individual years at every station: Agadez in 2015 and 2017; Bilma in 2015 and 2018; N'Guigmi in 2018. The Agadez value for 2017 rests on only seven months of sunshine data. A single pooled multi-year correlation, however small its p-value, is therefore averaging over genuinely different year-to-year relationships rather than describing a stable, repeating annual pattern, which is a further reason to treat the pooled raw statistic in Table 2 with caution independent of the deseasonalization result in Section 3.1.

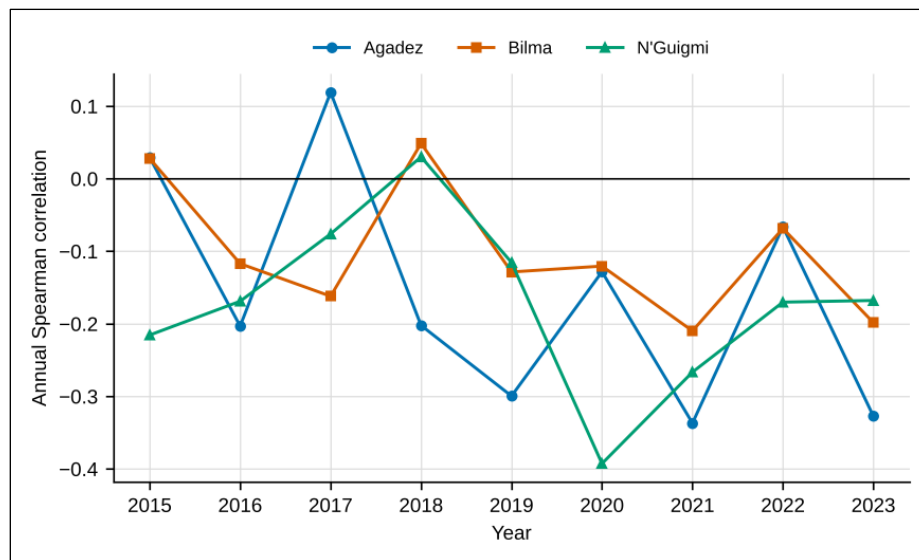


Figure 3: Raw Spearman correlation computed separately within each calendar year, 2015-2023, by station.

3.4 Stability coefficient

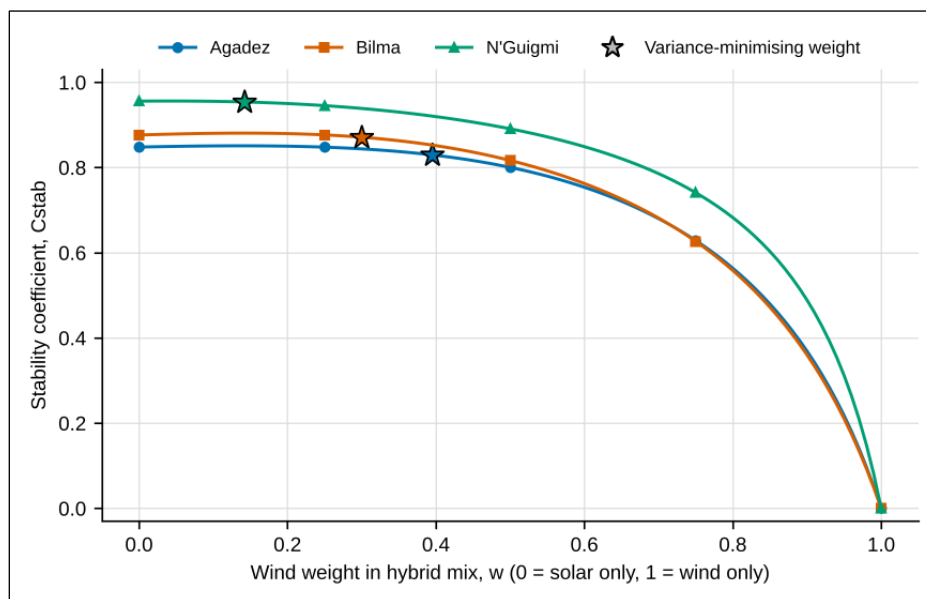


Figure 4: Stability coefficient C_{stab} (Eq. 4) as a function of the wind weight w in a hybrid mix, at monthly resolution. Lines show the continuous curve for w between 0 and 1, markers the five tabulated weights (0, 0.25, 0.5, 0.75, 1), and stars the variance-minimising weight at each station.

Monthly coefficients of variation are far larger for the normalised wind-energy series than for the normalised solar-irradiance series at every station (wind CV of 0.87, 0.92 and 1.37 at Agadez, Bilma and N'Guigmi respectively, against solar CV of 0.13, 0.11 and 0.06), so wind, not solar, is the reference resource in Eq. 4 throughout. The variance-minimising mix allocates a modest wind share (40% at Agadez, 30% at Bilma, and just 14% at N'Guigmi) and achieves a correspondingly high C_{stab} (0.83, 0.87 and 0.95 respectively). This is a materially different story from the one a negative daily correlation alone would suggest: the stabilising effect of a wind-solar hybrid mix at these stations, at monthly resolution, comes predominantly from solar power's much lower seasonal variability relative to wind, not from a strong anti-phase relationship between the two resources. A 50/50 mix, which an equal-weighting intuition about “complementarity” might suggest, is less stable than the variance-minimising mix at every station (stability coefficients of 0.80, 0.82 and 0.89; Figure 4), and at N'Guigmi, where Section 3.1 found the most genuine evidence of anti-phase daily behaviour, the optimal mix is nonetheless the most solar-dominated of the three stations, a reminder that a statistically detectable negative correlation and an economically meaningful stabilisation effect are related but distinct quantities.

3.5 Sub-daily solar profile

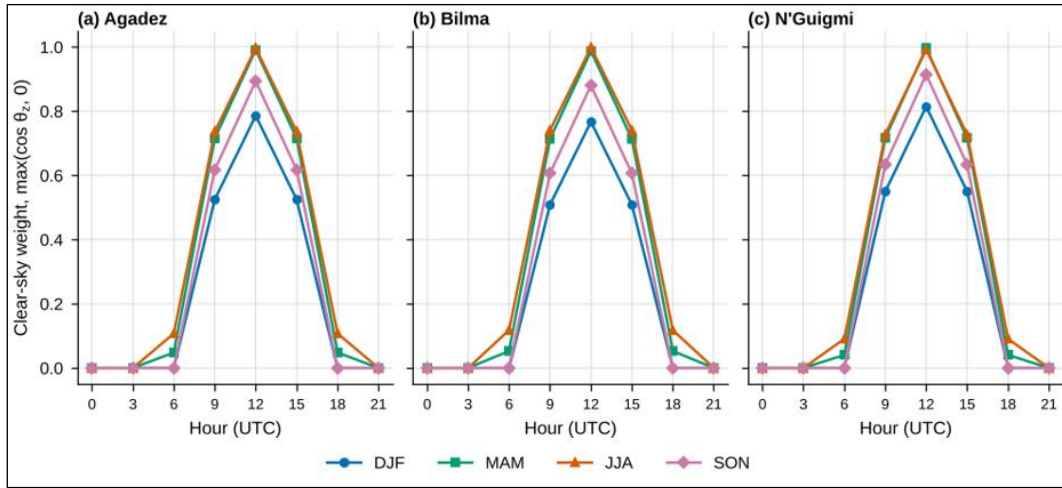


Figure 5: Clear-sky geometric solar weight, $\max(\cos \theta_z, 0)$ (Eq. 6), at each station's eight synoptic hours for one representative day per season (days 15, 105, 195 and 288 of the year), used here in place of a fixed 06:00–18:00 sinusoidal profile.

The geometry-based profile (Figure 5) reproduces the seasonal lengthening and shortening of the sunlit window that a fixed 06:00–18:00 window cannot: at Bilma in December-January-February, for instance, the geometric weight at both 06:00 and 18:00 UTC is essentially zero, reflecting a shorter boreal-winter day, while the same hours carry non-trivial weight in June-July-August. We note, as a limitation rather than a result, that this remains a clear-sky idealisation with no cloud, dust or measured-irradiance input, and that any sub-daily complementarity statement building on it, including the near-total day-night separation it implies at the shortest-day stations in winter, describes a property of the geometric model, not a demonstrated reduction in storage or backup requirement for an actual hybrid system.

3.6 Daily-resolution relationship

Figure 6 shows the full joint distribution of the two daily proxies. At all three stations the cloud of days is diffuse and shows no dominant monotonic structure, which is consistent with the weak rank correlations of Table 2. The Agadez panel also displays a horizontal band of zero-sunshine days whose count (159) is much larger than at Bilma (28) or N'Guigmi (25); this anomaly may be related to the possible inhomogeneity of the Agadez sunshine series discussed in Section 3.8.

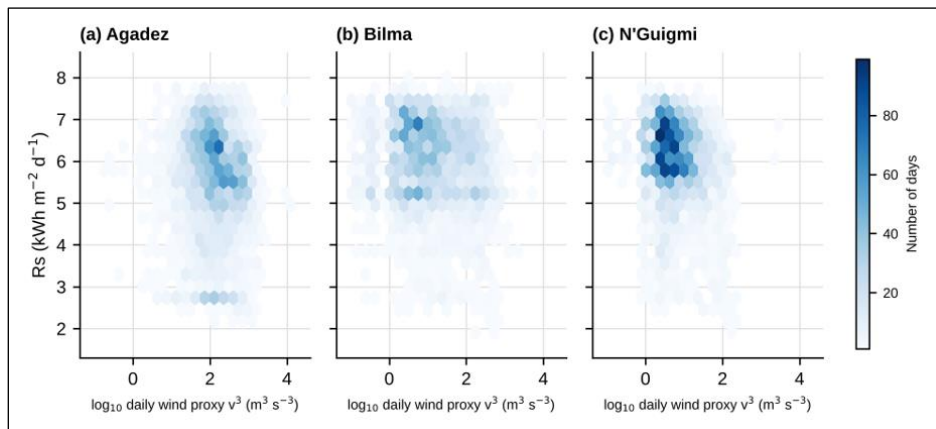


Figure 6: Daily wind-energy proxy v^3 (log scale) against the daily estimate of R_s over 2015–2023. Hexagonal bins are coloured by the number of days, on a scale common to the three panels. The horizontal band near 2.7 $\text{kWh m}^{-2} \text{d}^{-1}$ in the Agadez panel is made of the 159 days with zero recorded sunshine, for which the Ångström-Prescott estimate reduces to $a \cdot R_a$ (28 and 25 such days at Bilma and N'Guigmi). Days with a zero wind proxy (1 at Agadez, 43 at Bilma and 131 at N'Guigmi) cannot be shown on the logarithmic axis.

4 DISCUSSION

The headline figure a less careful version of this analysis would report, a negative, $p < 0.001$ daily correlation at all three stations, is not wrong as a description of the pooled raw sample, but it substantially overstates the evidence for a genuine, exploitable day-to-day complementarity once the shared seasonal cycle and serial dependence that inflate its apparent significance are properly accounted for. At two of the three stations, Agadez and Bilma, most of the raw signal is attributable to shared seasonality rather than to a day-to-day anti-phase relationship, and what remains at Bilma is small and borderline in its bootstrap intervals. Only at N'Guigmi does a materially negative, bootstrap-robust association survive deseasonalization, which we consider the paper's most defensible positive finding. Even there, though, Section 3.4's stability-coefficient analysis shows that the practical stabilising value of a hybrid mix comes mainly from solar's low variability rather than from this anti-phase signal specifically.

A negative correlation, however computed, is also not the same claim as an operational or economic benefit. It says nothing directly about storage sizing, backup capacity, curtailment, unserved energy, or system cost, each of which would require a dispatch simulation against a representative demand profile that this station-level resource analysis does not attempt. We regard the gap between a correlation statistic and a system-level complementarity claim as one of this paper's central points, not a minor caveat: the two are often conflated in the applied literature on renewable complementarity, and our own stability-coefficient result in Section 3.4, where the optimal mix turns out to be solar-dominated at every station including the one with the most robust negative correlation, is a concrete illustration of why that conflation can mislead.

Two mini-grid studies point in a similar direction, although neither tests complementarity directly. A design study for a village in the Maradi region split a daily demand of 160 kWh between 75% PV and 25% wind, a ratio it checked against a HOMER Pro case [23]. A sizing analysis based on the same 2015–2024 records from these three stations found no wind capacity among its Pareto-optimal PV-wind-battery designs, and attributed 59 to 78% of unserved energy to low-sunshine days, against less than 1% for days that combined low sun, low wind and heat [8]. The solar-dominated variance-minimising mixes of Section 3.4, with wind weights of 14% to 40%, are consistent with both results. They are not independent evidence: the second study rests on the same observations, and both address design cost and reliability, not the variability of a normalised resource mix.

A related methodological point concerns normalisation. Min-max normalising each station's wind and solar series to its own 0–1 range before computing a correlation coefficient, as we avoided doing here for the correlation analysis itself (Table 2 uses the proxies in their natural units), does not change a Pearson or Spearman correlation at all, since both are invariant to any monotonic linear rescaling of either variable. Min-max normalisation does not, therefore, deliver the cross-station comparability it is sometimes assumed to provide for a correlation coefficient. It does matter, and matters differently, for a variance-based quantity like C_{stab} , which is why Section 2.5 normalises by each station's own maximum specifically for that calculation and states so explicitly, rather than applying one normalisation convention uniformly across every statistic in the paper regardless of whether it is invariant to it.

4.1 Limitations of the study

- **Shared station-level data-quality risk.** Both the wind and solar proxies used here are built from the same synoptic station network, often from the same calendar days; any station-wide data-quality problem, such as an instrument fault, an observer transcription habit, or a relocation, that affects a given day's record could in principle affect both series simultaneously and in a correlated way, which would not show up as an obvious artefact in either series alone but could, in principle, inflate or deflate the cross-correlation we report. We have not attempted to test for this specific failure mode, and flag it as an open question rather than a resolved one.
- **Possible inhomogeneity at Agadez.** A separate analysis of the same 2015–2024 records suspects that the Agadez sunshine series for 2015–2018 is inhomogeneous, judging from its decoupling from the diurnal temperature range [8]. These four years make up close to half of the 2015–2023 record used here. We have not tested formally for a break, but excluding them (Section 3.1) leaves the deseasonalized Agadez correlation weak, with a bootstrap interval that still includes zero, while the raw correlation becomes stronger (-0.237). Any such break would also enter the solar proxy and therefore the Agadez correlations of Section 3.1.
- **Daily-total resolution and no dispatch simulation.** Every result in this paper operates on daily or monthly aggregates and generic power-curve proxies; it does not simulate an actual hybrid system against demand, storage, or backup generation, and none of its correlation or stability results should be read as a storage-sizing or backup-reduction estimate.
- **Generic turbine and uncalibrated solar coefficients.** The wind-energy proxy uses a generic turbine power curve at an unverified hub height (Section 2.2), and the solar proxy uses generic, locally uncalibrated Ångström–Prescott coefficients (Section 2.3). Both are standard simplifications in a setting with no on-site calibration instruments, and both would need to be relaxed, with site-specific turbine data and a locally calibrated solar

model, before the proxies used here could support a bankable hybrid-system design rather than an exploratory complementarity characterization.

- **Geometric, not measured, sub-daily solar profile.** Section 2.6's replacement for the fixed sinusoid is a clear-sky geometric idealisation, not a measured sub-daily irradiance record, and should not be over-interpreted as demonstrating a specific real-world intra-day complementarity magnitude.
- **Block-bootstrap block length.** We resample whole month-year blocks, which respects month-scale serial dependence but may still understate uncertainty if dependence extends across months within a season; we did not have scope within this analysis to test sensitivity to block length systematically.

5 CONCLUSION

A pooled daily correlation between wind and solar resource at these three Nigerien stations is negative and conventionally significant everywhere, but that headline result is, at two of the three stations, substantially an artefact of shared seasonality rather than evidence of a genuine day-to-day anti-phase relationship: after deseasonalization the signal is not statistically robust at Agadez and is weak and borderline at Bilma. N'Guigmi is the exception, retaining a materially negative, bootstrap-robust association even after the seasonal cycle is removed, and is the station we would point to first if asked where a genuine daily-scale complementarity effect is most likely to be real rather than a sample-size artefact. Separately, and we think importantly, the practical stabilising value of a wind-solar hybrid mix at monthly resolution comes predominantly from solar power's comparatively low seasonal variability rather than from any anti-phase correlation, a distinction the correlation-coefficient framing common in this literature tends to obscure. We offer this as a methodologically cautious, station-differentiated characterization of wind-solar complementarity along Niger's Sahara-to-Sahel gradient, not as a system-design result, and we think the central lesson generalises beyond this dataset: a long daily record is not automatically a large independent sample, and a statistically significant pooled correlation is not automatically an operationally meaningful one.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The author declares no conflict of interest. The author is also affiliated with Innovatech Smart Energies, an engineering consultancy; this affiliation had no role in the design of the study, the analysis or interpretation of the data, or the decision to publish.

Data and code availability

The daily wind-energy and solar-irradiance proxy series, the correlation and bootstrap pipeline, and the C_{stab} calculation described in Sections 2.2-2.5 are available from the corresponding author on reasonable request. Software: Python 3.13, pandas 3.0 [19], NumPy 2.5 [20], SciPy 1.18 [21], Matplotlib 3.11 [22]. Bootstrap random seed fixed at 7 for exact reproducibility of Table 2's confidence intervals.

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