



1 Rain-time operation, not rainfall alone, sets wind turbine blade rain- 2 erosion exposure: synchronized disdrometer and SCADA 3 measurements

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10

11 Abstract

12 Rain erosion of wind-turbine blade leading edges accumulates while the blades turn in rain,
13 yet exposure assessments prescribe a fixed rotor speed and rarely test how fast the turbines
14 actually turn while it rains. We coupled drop-resolved disdrometer rainfall to the operating records
15 of two whole wind farms over their common observation period: one wetter (Guangxi, 513 mm of
16 reconstructed rainfall) and one drier (Jiangsu, 242 mm). Rain-time operation does not merely
17 refine the exposure estimate; it sets its size. The observed tip speed replaces the fixed 90 m s⁻¹
18 reference, the rounded value of the fleet's observed operating-speed ceiling. Coupling it in lowers
19 the operation-coupled observed-period index (E_{SCADA}) to 18% of its fixed-speed value in Guangxi
20 and 47% in Jiangsu, so that reference overstates exposure by factors of 2.1–5.6. The microphysical
21 input matters far less: replacing the parameterized fall-velocity relation with the measured spectra
22 moves the same index by only 28–38%. The operating state can therefore change which site
23 appears worse. Under the common reference speed the wetter farm is roughly twice as exposed
24 (E_{90} 0.140 versus 0.066); with operation coupled in, the two point estimates change order (0.0251
25 versus 0.0311), although their bootstrap intervals overlap and the ranking is not statistically
26 separated. Exposure is concentrated in time: the 10% most exposed rain intervals carry 75–80% of
27 the total and the five most exposed rain events 78–90%. Capping the rain-time tip speed at 80 m



s⁻¹ removes 42–58% of the exposure while touching at most 48% of rain time, within the model framework and before power-loss or control constraints. Both indices are normalized to a literature reference coating and are screening quantities rather than lifetime predictions, and the threshold relation is extrapolated below its 90–150 m s⁻¹ calibration range. They supply the operational loading term that previous assessments had to assume.

1 Introduction

Wind-turbine blade leading edges experience repeated raindrop impacts while rotating at high speed. Each impact transfers kinetic energy to the coating surface, and once the accumulated energy exceeds the material-specific incubation threshold, the leading-edge protection system begins to erode (Keegan et al., 2013; Tempelis et al., 2025). The damage is cumulative and largely irreversible, so progressive roughening degrades blade aerodynamics and raises operation and maintenance costs, with reported annual energy production losses of about 1–4% for partly and fully degraded blades (Sareen et al., 2014; Mishnaevsky et al., 2021). How much of that penalty a site will actually incur is determined, before any damage is visible, by the erosive loading accumulated in service. That loading is not fixed by rainfall amount alone. The energy delivered per impact depends on drop size and on the speed at which the blade surface meets the drop. The number of impacts depends on how much rain the rotor sweeps through. Quantifying it from measured rainfall and measured operation is therefore the prerequisite for the coating selection, inspection scheduling and life prediction that erosion management requires, and it is the problem addressed here.

Research on leading-edge erosion loading has advanced along several lines. A first line derives the erosive driving term from precipitation statistics (rain gauges, radar climatologies and meteorological time series) and uses them to estimate erosion-relevant loading or coating lifetimes (Letson et al., 2020; Bartolomé and Teuwen, 2021; Verma et al., 2021). A second uses spatially complete precipitation products to build regional and offshore erosion atlases (Hannesdóttir et al., 2024). A third addresses the microphysical input directly. It shows that the assumed drop-size parameterization and the total rainfall both change the calculated blade lifetime appreciably, and that a fixed terminal-velocity relation discards the observed coupling between drop size and fall velocity (Tilg et al., 2022). Community reviews have since set out measurement and



58 intercomparison priorities for erosion campaigns (Pryor et al., 2022, 2024), and regional and site-
59 based studies have begun to base erosion estimates on locally measured rainfall (Caboni et al.,
60 2024; Caboni and van Dalum, 2025).

61 Each line nevertheless fixes, or omits, a term on which the impact energy depends.
62 Precipitation-statistics approaches characterize accumulation and rain rate, but generally do not
63 resolve the drop-size distribution that carries much of the impact energy. Two sites with similar
64 rainfall totals can therefore differ appreciably in erosive loading (Letson et al., 2020; Bartolomé
65 and Teuwen, 2021; Verma et al., 2021). Reanalysis- and radar-based atlases supply spatial
66 coverage, but inherit parameterized drop spectra that may misrepresent site-specific microphysics.
67 The parameterization also removes the coupling between drop size and fall velocity that raw
68 disdrometer spectra retain (Tilg et al., 2022; Hannesdóttir et al., 2024). Where measured rainfall is
69 used, the operating state of the turbines is generally prescribed rather than taken from the fleet's
70 own records; recent work still derives rotor speed from a nominal power curve (Pryor et al., 2022).
71 The rain-time rotor speed and power that scale the impact speed are therefore rarely represented.
72 Site-based studies have so far related erosion estimates to rainfall or meteorological variables
73 rather than to the time-aligned operating state of the turbines concerned (Caboni et al., 2024;
74 Caboni and van Dalum, 2025). The quantity that ultimately drives erosion (the impact speed
75 actually experienced by the blade during rain) therefore remains an assumed input, and the
76 resulting bias is unknown.

77 To address this gap, we couple representative Parsivel2 disdrometer observations with time-
78 aligned, farm-wide supervisory control and data acquisition (SCADA) records from two
79 contrasting Chinese wind farms. To our knowledge this is the first time-alignment of farm-wide
80 turbine operation with drop-resolved rainfall for erosion assessment. We separate a common-speed
81 microphysical screening index from an operation-coupled observed-period exposure index. This
82 lets us quantify how much the observed operating state changes the exposure estimate, how
83 concentrated exposure is across rain intervals and events, and how much a practical tip-speed cap
84 would reduce it. The framework thus supplies traceable, coating-dependent exposure inputs for
85 target-material erosion testing, erosion-safe-mode derating and the calibration of life models: the
86 loading term that previous assessments have to assume rather than measure.

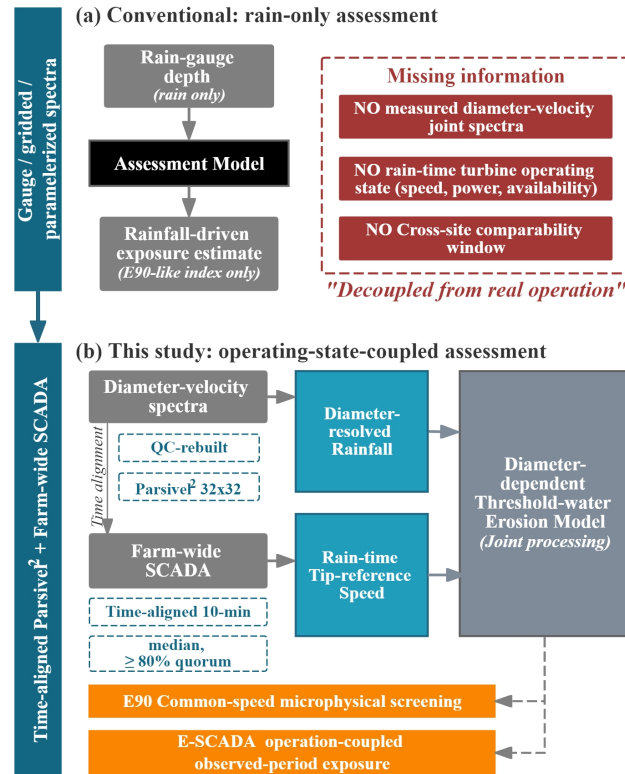


Fig. 1. Conceptual comparison of (a) rain-only and (b) operating-state-coupled leading-edge erosion exposure assessment.

2 Materials and methods

2.1 Study area and observation instruments

The study uses representative observations from the Tengxian and Guanyun wind farms. The first liquid-rain intervals were recorded on 27 May 2026 (Guangxi) and 20 May 2026 (Jiangsu), with both disdrometers operating from 24 April 2026 (Tables 1 and 2). The instruments were installed at 15 m above the local ground (Guangxi) and 10 m above the roof surface (Jiangsu). The corresponding hub heights are 100/110 m in Guangxi and predominantly 155 m in Jiangsu (with a small number of 140 and 145 m locations). The disdrometers logged continuously from 24 April 2026, during installation and commissioning. Disdrometer observations and the Guangxi SCADA export extend to 31 July 2026, whereas the Jiangsu SCADA export ends on 21 July 2026.



The Guangxi site is the Tengxian wind farm in Wuzhou (110.86° E, 23.76° N), comprising 37 direct-drive GW165 turbines rated at 4.0 MW. The Jiangsu site is the Guanyun wind farm in Lianyungang (119.54° E, 34.34° N), comprising 25 direct-drive GW165 4.0 MW turbines. Each Parsivel² instrument was installed on the roof of the onsite substation (booster station) to continuously record drop diameter and fall velocity for the wind-farm area. The Guangxi unit was secured to a roof-cast concrete foundation with an embedded anchor cage, whereas the Jiangsu unit was secured by expansion bolts installed through roof drill holes. According to the operator, the Guangxi Parsivel is about 5 km from the Tengxian turbines, whereas the Jiangsu unit is sited within the farm area around which the turbines are distributed; per-turbine distances and clock logs were not disclosed. Both instruments are roof-mounted with clear exposure above the local parapet (operator photographic documentation).

Table 1 documents the observation coordinates and installation settings. An elevated rooftop location provides a practical position for continuous in-farm observations, but does not remove effects from surrounding buildings, roof edges, local terrain or near-surface flow. The observations consequently constrain regional precipitation input and are not extrapolated as unbiased rotor-height spectra or local blade-flow conditions. The comparison does not presuppose which site is more erosive; it applies a common quality-control, speed-conversion and reference-material framework to determine how rainfall and operation affect the ranking.

Table 1. Observation coordinates and installation settings.

Region	Wind farm	Observation coordinate	Turbines	Disdrometer setting
Guangxi	Wuzhou Tengxian	110.86° E, 23.76° N	37, 4.0 MW	roof-cast concrete foundation with embedded anchor cage
Jiangsu	Lianyungang Guanyun	119.54° E, 34.34° N	25, 4.0 MW	roof-drilled expansion bolts

Parsivel² is an optical laser-extinction disdrometer that records particles crossing a sampling beam in predefined diameter and velocity classes (Löffler-Mang and Joss, 2000). Its 32 × 32 raw-count matrix retains joint drop-diameter and fall-velocity information needed for precipitation-phase selection, rainfall reconstruction, drop-size statistics and velocity-diameter consistency checks. Unlike accumulated rainfall alone, the matrix preserves the scale and motion information required to describe raindrop impacts on a rotating blade (Pires et al., 2026). Sampling uncertainty



of optical disdrometers is non-negligible: small drops can be missed or over-counted near the detection limit, and the finite sampling area limits the representativeness of short records (Jaffrain and Berne, 2011; Letson and Pryor, 2023). These sampling and edge-occlusion effects are considered in the quality control interpretation and in the uncertainty discussion of the reconstructed rainfall. The analysis fields derived from these records are defined in Section 2.2 (Table 2).

2.2 Data types and fields

The raw records are in Campbell TOA5 logger format and contain time, accumulated rainfall, weather code, rain rate and 1024 diameter-velocity channel counts. The 1024 channels are reconstructed as a 32×32 matrix and transposed to diameter rows and velocity columns. Table 2 lists the fields used in the analysis.

Table 2. Analysis fields of this study.

Source	Field or derived quantity	Role	Observation period
Disdrometer	Time, weather code, accumulated rainfall, rain rate, 32×32 counts	Rain selection, closure, diameter-velocity reconstruction	24 April–31 July 2026; first liquid rain 20 May (Jiangsu) / 27 May (Guangxi)
SCADA	Time, completeness, rotor-speed channel (rpm), nacelle wind speed, grid-side active power, status	Operational quality control and rain-time reference speed	1 April–31 July 2026 (Guangxi) / 21 July 2026 (Jiangsu)
Coupled data	10-min rainfall, diameter-resolved rainfall, farm-median operating variables	Interval-specific erosion-model input	Rain–SCADA overlaps

2.3 Quality control and diameter-velocity reconstruction

Identifiable liquid-precipitation records were retained after removing invalid records, non-liquid weather codes and spectra failing basic consistency checks. Counts $n_{i,j}$ were reconstructed by diameter-bin center D_i and velocity-bin center v_j . The liquid terminal-velocity relation was used as a spectrum-shape check, with the known sampling uncertainty of optical disdrometers considered in the quality control (QC) interpretation. Weather-code screening retained only records flagged as liquid precipitation; mixed-phase, frozen and ambiguous codes were excluded to avoid contamination of the drop-size statistics by solid hydrometeors.

$$v_t(D_i) = 4.874 D_i \exp(-0.195 D_i) \quad (1)$$



where v_t is in m s^{-1} and D_i is in mm; such terminal-velocity relations are widely used in raindrop microphysics (Gunn and Kinzer, 1949; Atlas et al., 1973; Beard, 1976).

$$A_i = 180(30 - \frac{D_i}{2}) \quad (2)$$

with A_i in mm^2 . Together with sampling duration, channel velocity and drop volume, the matrix yields diameter-resolved rainfall $R_{i,k}$ in each 10-min interval k . The beam cross-section A_i follows the Parsivel² specification (measuring area 54 cm^2 , i.e. $180 \text{ mm} \times 30 \text{ mm}$), and edge-channel counts were handled conservatively because partial beam occlusion biases small-drop counts upward and is a known source of reconstructed-rainfall overestimation.

2.4 Rainfall closure and microphysical statistics

Rainfall closure is defined as the ratio of spectrum-reconstructed to accumulated rainfall. A closure slightly above 100% is expected because small-drop over-counting, the finite sampling area and spectrum-reconstruction bias all tend to inflate the reconstructed rainfall relative to the accumulated instrument reading (Jaffrain and Berne, 2011; Letson and Pryor, 2023). The closure values are therefore reported as a quality metric rather than interpreted as an instrument calibration. We treated record-to-record accumulator increments exceeding 10 mm per 5-min record as counter discontinuities and excluded them from the accumulated total; this affected a single counter discontinuity in the Jiangsu record (Supplementary Table S4).

$$C_R = \frac{R_{\text{spec}}}{R_{\text{acc}}} \times 100\% \quad (3)$$

Number fraction, rainfall fraction, rainfall median diameter $D_{50,\text{rain}}$, $D_{90,\text{rain}}$ and mass-weighted mean diameter are calculated. The latter is

$$D_m = \frac{\sum_i D_i R_i}{\sum_i R_i} \quad (4)$$

These metrics distinguish the diameter range that dominates occurrence from the range that dominates water mass and is therefore more directly relevant to erosion loading. The mass-weighted mean diameter D_m is computed from the raw 32×32 drop counts accumulated over the liquid diameter domain (0.20–8.00 mm) and over records with a positive logger rain-intensity flag. Because the reconstructed water volume is proportional to the drop count weighted by D^3 , the



168 volume-weighted expression in Eq. (4) is algebraically identical to $\sum N_i D_i^4 / \sum N_i D_i^3$. It is not
 169 computed from pre-weighted rainfall depths.

170 **2.5 SCADA screening and temporal alignment**

171 Farm-wide SCADA provides 10-min turbine state, completeness, reported speed, nacelle
 172 wind speed, grid-side active power and availability. Records with completeness below 0.90 or with
 173 physically implausible rotational speed, wind speed or power were excluded. At each timestamp
 174 the farm operating state is the median over the reporting turbines, and a timestamp is retained only
 175 if at least 80% of the turbines report valid data. These two thresholds (record completeness ≥ 0.90
 176 and an 80% reporting quorum) balance robustness against individual turbine faults,
 177 communication loss and curtailment against the need to retain enough intervals for the rain-time
 178 statistics.

179 The disdrometer records were aggregated onto the same 10-min grid. We define liquid
 180 rainfall on the reconstructed spectrum: we sum diameter-resolved liquid depth over the 0.20–8.00
 181 mm diameter bins (Parsivel² class centers 0.312–7.500 mm) and assign raw records to left-closed
 182 10-min intervals. An interval counts as rain when its summed liquid depth exceeds zero. This rule
 183 is intentionally independent of the logger rain-intensity flag. Rain events are defined as contiguous
 184 blocks of liquid-rain intervals, with a new event starting after a gap of more than 3 h between
 185 consecutive intervals. Alternative event flags, diameter lower bounds and logger-intensity
 186 thresholds are reported in Supplementary Table S3. To keep the two sites' screening indices
 187 comparable, both sites are analyzed over the common SCADA coverage period ending on the
 188 Jiangsu export endpoint (21 July 2026, 23:50 local time; hereafter the common window).
 189 Operation-coupled calculations are restricted to these available overlaps and do not extrapolate
 190 across intervals without SCADA records (Supplementary Table S3).

191 SCADA availability was assessed against every liquid-rain timestamp within the common
 192 window. Intervals whose timestamps are present but whose turbines all fail the completeness
 193 threshold are treated as unavailable, and intervals after a site's export endpoint are not extrapolated.
 194 The available exports contain no maintenance, outage or communication logs, so these intervals
 195 are reported as unavailable rather than reclassified by cause. The operator reports that they
 196 coincide with maintenance shutdowns and automatic-control state changes, but the corresponding
 197 logs are confidential. Rain-intensity representativeness of the excluded intervals was tested with



198 two-sample Kolmogorov–Smirnov comparisons of the 10-min interval-maximum rain intensity;
199 the resulting availability counts and test outcomes are reported in Section 3.5 and Supplementary
200 Fig. S1.

201 **2.6 Tip-reference and relative impact speed**

202 For a common comparison, the reference rotor diameter is $D_{\text{rot}} = 165$ m

$$U_{\text{tip},k} = \frac{\pi D_{\text{rot}} n_k}{60} \quad (5)$$

203 Both study sites use permanent-magnet direct-drive GW165 turbines of the Goldwind GP21
204 platform, in which the rotor hub drives the generator directly without a gearbox (Polinder et al.,
205 2013). The archived SCADA channel is labeled generator speed; for this direct-drive configuration
206 the generator and rotor speeds are synchronous (1:1), so no gearbox conversion is required. The
207 165 m rotor diameter is used as the common reference geometry for the 4 MW-class comparison;
208 the operator confirms that both fleets are GW165-4.0 MW units of the same platform. This is a tip-
209 reference calculation and does not resolve the local spanwise blade speed or blade-flow conditions.
210 The present results are deliberately expressed relative to the common 4 MW reference rotor so that
211 the two sites remain comparable. The derived tip-reference speed uses the common reference rotor
212 ($\pi D_{\text{rot}} n / 60$) and is not the local blade-section speed; “tip speed” is used below as its short form.

$$V_{\text{imp},i,k} = \sqrt{U_{\text{tip},k}^2 + v_t(D_i)^2} \quad (6)$$

213 Eq. (6) omits yaw, transient pitch, rain horizontal velocity, droplet slowdown and three-
214 dimensional flow deflection, and is consequently a screening-level relative speed rather than a
215 computational-fluid-dynamics (CFD)-resolved local impact speed. Neglecting droplet slowdown
216 near the blade surface tends to overestimate the relative impact speed. Barfknecht and von Terzi
217 (2024) show that this simplification is conservative for screening purposes, because the kinetic
218 energy transferred to the coating is bounded by the free-stream impact condition. Numerical
219 simulations of droplet impingement and surface degradation provide complementary constraints
220 on the impact kinematics (Doagou-Rad and Mishnaevsky, 2020; Verma et al., 2020a, b).

221 Rain-time wind speed is reported from the SCADA nacelle anemometer as measured, without
222 vertical extrapolation; wind speed does not enter the exposure calculation. The quality-controlled
223 SCADA records show an operational speed ceiling whose 99.5th percentiles correspond to 90.5



and 90.8 m s^{-1} in Guangxi and Jiangsu (quantified in Section 3.4). The fixed 90 m s^{-1} benchmark used for E_{90} is the rounded value of this observed operational ceiling, not a typical rain-time operating point. Design-rated rotor-speed and power-curve data are proprietary and were not available. The sensitivity of the reported indices to the chosen reference speed is quantified in Supplementary Table S5.

2.7 Diameter-dependent rain-erosion exposure model

We use the diameter-dependent allowed-impingement relation reported in the raindrop-erosion tests of Bech et al. (2022); for a review of the Springer-type erosion model see Hoksbergen et al. (2022).

$$H_{\text{crit},i,k} = H_{100}(D_i) \left(\frac{V_{\text{imp},i,k}}{100 \text{ m s}^{-1}} \right)^{-m(D_i)} \quad (7)$$

where

$$H_{100}(D_i) = 21.7 - 17.1 \frac{D_i - 2.3}{1 + |D_i - 2.3|} \quad (8)$$

and

$$m(D_i) = 8.9 - 3.1 \frac{D_i - 2.1}{1 + |D_i - 2.1|} \quad (9)$$

$H_{100}(D_i)$ is the allowed impingement of the reference coating at 100 m s^{-1} and $m(D_i)$ is its diameter-dependent speed exponent, with D_i expressed in mm. The equivalent water layer reaching the leading-edge path is approximated as $H_{i,k} = (R_{i,k}/1000) \cdot (U_{\text{tip},k}/v_t(D_i))$. The reference-coating parameters $H_{100}(D_i)$ and $m(D_i)$ are those fitted by Bech et al. (2022) to their multi-diameter whirling-arm tests of a commercial polyurethane topcoat; their tested diameter and impact-speed domain defines the validity range of the present index. Because all exposure terms enter as ratios of water layers, only the relative magnitudes of $H_{100}(D_i)$ matter and the absolute scaling of $H_{100}(D_i)$ cancels out; the present results are therefore reported as a dimensionless screening index.

$$H_{i,k} = \frac{R_{i,k}}{1000} \frac{U_{\text{tip},k}}{v_t(D_i)} \quad (10)$$

The operation-coupled observed-period index is



$$E_{\text{SCADA}} = \sum_k \sum_i \frac{H_{i,k}}{H_{\text{crit},i,k}} \quad (11)$$

A common-speed benchmark E_{90} is also calculated by setting $U_{\text{tip}} = 90 \text{ m s}^{-1}$, the fixed reference of Section 2.6. Both indices are observed-period screening indices for the literature reference coating, not lifetimes of the field blade-material systems, whose coating systems are not characterized in this study; all parameters and their defining sections are consolidated in Table 3. E_{90} isolates the microphysical input over the full rain record, whereas E_{SCADA} is restricted to the rain–SCADA overlaps. Because the two indices are defined over different sample scopes, the all-valid-window E_{90} and E_{SCADA} should not be compared directly. The ratio E_{SCADA}/E_{90} computed on the identical QC-matched intervals is a well-defined matched-window compression statistic; it is reported with its bootstrap uncertainty in Section 3.5.

Table 3. Key parameters and symbols of the observed-period exposure framework.

Category	Parameter/symbol	Meaning	Value	Source
Reference rotor	Drot	Common reference rotor diameter	165 m (GW165 platform, 4 MW class)	Section 2.6
	Drivetrain	Direct-drive permanent-magnet synchronous generator (PMSG), 1:1 (no gearbox conversion)	Speed channel equals rotor speed	Section 2.6
	Common-speed baseline	Fixed tip speed for E_{90}	90 m s^{-1}	Section 2.7
Model and material	$v_t(D_i)$	Terminal-velocity relation	Exponential liquid terminal-velocity relation (Eq. 1)	Section 2.3
	$H_{i,k}$	Equivalent water layer per diameter class	$H_{i,k} = (R_{i,k}/1000) \cdot (U_{\text{tip},k} / v_t(D_i))$	Section 2.7
	$H_{100}(D_i), m(D_i)$	Reference-coating threshold and speed exponent	Bech et al. fits (commercial polyurethane topcoat on glass-fibre epoxy; validity domain = test domain)	Section 2.7
Model and material	$V_{\text{imp},i,k}$	Relative impact speed per diameter class	$V_{\text{imp},i,k} = \text{sqrt}(U_{\text{tip},k}^2 + v_t(D_i)^2)$ (Eq. 6)	Section 2.7
Model and material	$H_{\text{crit},i,k}$	Allowed-impingement (critical) water layer per diameter class	$H_{\text{crit},i,k} = H_{100}(D_i) / V_{\text{imp},i,k m}(D_i)$ (Eq. 7)	Section 2.7

Note. All parameters are as defined in Sections 2.3–2.7. The complete parameter and source-traceability table, including instrument, screening-threshold and result entries, is provided in Supplementary Table S4; numerical exposure outputs are reported in Table 4.

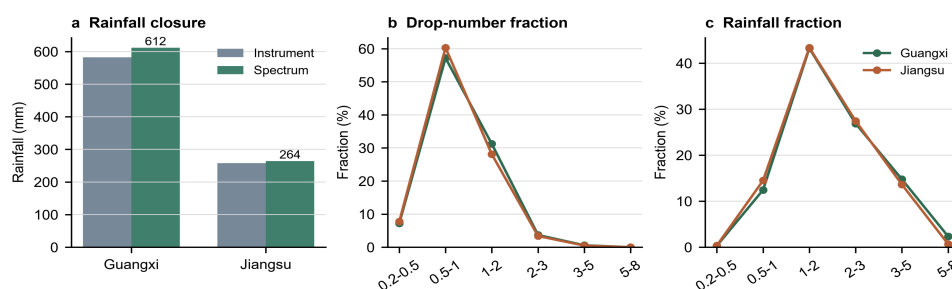


3 Results

Rooftop observations provide a practical in-farm record of near-surface precipitation microphysics; results are reported for the common window ending on 21 July 2026 unless stated otherwise.

3.1 Rainfall closure and drop-size distribution

Quality-controlled 32×32 matrices reproduce accumulated liquid rainfall at both sites to within 5%, so the reconstructed spectra are used as the rainfall input throughout the exposure calculation. Over the full disdrometer record (to 31 July 2026) the spectrum-reconstructed rainfall is 611.74 mm in Guangxi and 264.25 mm in Jiangsu, against instrument totals of 582.27 and 257.68 mm (closure 105.06% and 102.55%). Within the common window used for the exposure calculation (to 21 July 2026) the reconstructed totals are 513.00 and 242.07 mm, so the water-input contrast is a factor of 2.3 over the full record and 2.1 over the common window (Fig. 2).



270

Fig. 2. Rainfall closure, drop-number fraction and diameter-resolved rainfall contribution. (a) compares instrument and spectrum-reconstructed rainfall; (b) and (c) distinguish occurrence from rainfall contribution.

Both sites have a drop-number maximum at 0.5–1 mm, whereas 1–3 mm drops dominate rainfall contribution. D_m is 2.07 mm in Guangxi and 1.96 mm in Jiangsu. The rainfall-median and 90th-percentile diameters are $D_{50,rain} = 1.73$ mm (Guangxi) and 1.67 mm (Jiangsu), and $D_{90,rain} = 3.28$ mm and 3.09 mm. Thus, in addition to higher total rainfall, Guangxi gives greater weight to larger drops that influence both water mass and the diameter-dependent threshold relation. The 1–3 mm range that dominates rainfall contribution coincides with the most diameter-sensitive part of the Bech et al. (2022) threshold relation.

280



3.2 Diameter-velocity spectra

Fig. 3 shows the quality-controlled 32×32 spectra. The main liquid-rain band follows the terminal-velocity tendency, with higher fall velocity at larger diameter. Contributions in the medium-to-large diameter range are more evident in Guangxi, while the Jiangsu spectrum is relatively concentrated. The measured velocity matrix is used here for phase identification, QC/consistency filtering and rain-rate reconstruction; the exposure model itself uses the diameter-resolved terminal-velocity relation (Eq. 1) so that the two sites are compared under an identical kinematic assumption. A sensitivity of the exposure indices to observed versus parameterized fall speeds is reported in Section 3.5 and Supplementary Table S7, using the measured 32×32 velocity-diameter matrices.

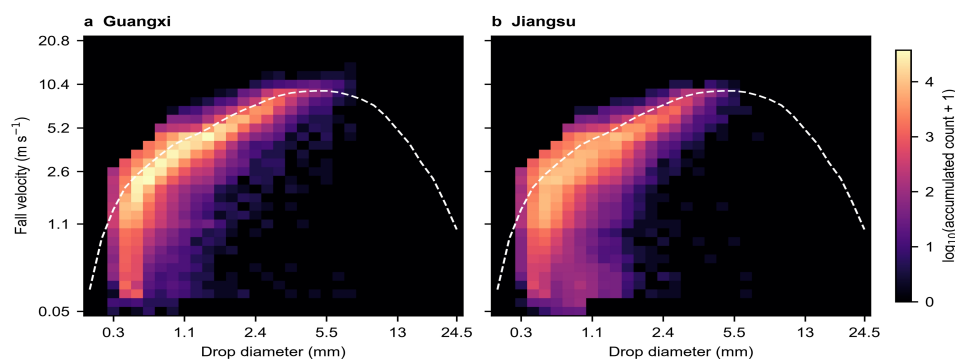


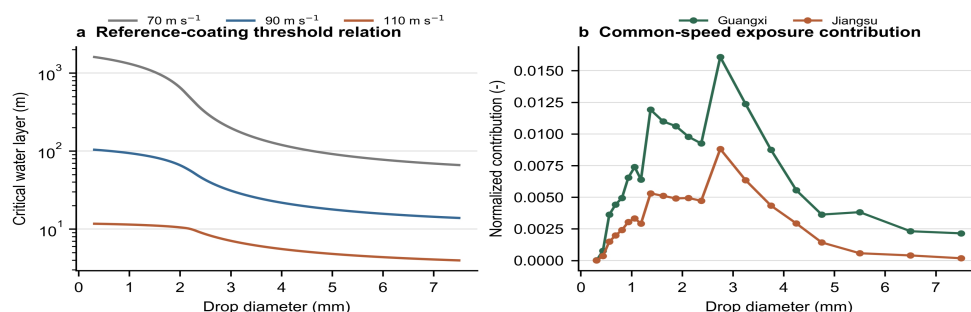
Fig. 3. Quality-controlled 32×32 diameter-velocity distributions for Guangxi and Jiangsu. Color denotes relative accumulated count intensity; the white dashed curve is the terminal-velocity relation.

3.3 Microphysical difference under a common speed

When the reference tip speed is fixed at the 90 m s^{-1} reference value, the model compares diameter-resolved rainfall and fall-velocity inputs only. Over all valid rain intervals in the common window the normalized exposure is 0.1413 in Guangxi and 0.0656 in Jiangsu, a ratio of 2.15 from the exact values. Over the QC-matched rain-SCADA intervals used in Section 3.5 the values are 0.1404 and 0.0656 (Table 4), a difference of less than 1% from the all-valid values (967 versus 961 Guangxi intervals). The E_{90} ratio of 2.15 is slightly lower than the ratio of reconstructed rainfall depths (2.32), indicating that the coarser Guangxi spectrum does not amplify the water-loading difference under common-speed screening. The higher Guangxi value therefore reflects



water loading rather than spectral shape. It is not a ranking of operating-turbine exposure. Extending the Guangxi record to its full export through 31 July raises the extended-record E_{90} (record beyond the common window) to 0.170. The Jiangsu full-window all-valid E_{90} is 0.0712 while its matched E_{90} remains 0.0656 because SCADA ends on 21 July. The extension is retained as a sensitivity result (Supplementary Table S1). Fig. 4 illustrates the diameter contributions under the common-speed condition.



310

311 **Fig. 4. Input-output relationship of the diameter-dependent threshold-water model and diameter**
 312 **contributions under the common-speed condition.**

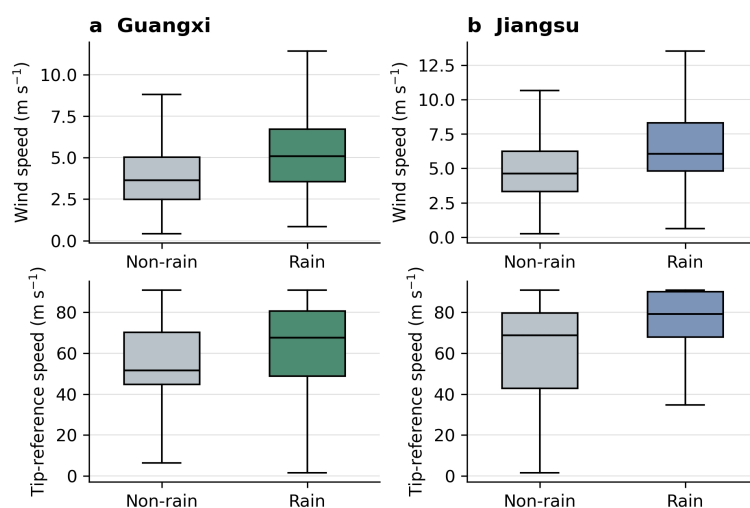
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314 3.4 Rain-time SCADA operation

315 Mann–Whitney U tests confirm that the rain-time median of each quantity differs
 316 significantly from its non-rain (dry) counterpart ($p < 0.001$ for all eight comparisons;
 317 Supplementary Table S2). The quality-controlled records show an operational speed ceiling of
 318 about 10.5 rpm in both fleets, equivalent to 90.7 m s⁻¹ (99.5th percentiles 90.5 and 90.8 m s⁻¹). Fig.
 319 5 compares quality-controlled non-rain and QC-matched SCADA intervals for wind speed and tip-
 320 reference speed (panels a–d). The median rain-time values are 5.11 m s⁻¹ and 67.58 m s⁻¹ in
 321 Guangxi and 6.08 m s⁻¹ and 79.17 m s⁻¹ in Jiangsu. Median rain-time rotor speed and grid-side
 322 power are 7.82 rpm and 555.1 kW in Guangxi and 9.16 rpm and 1005.9 kW in Jiangsu
 323 (Supplementary Table S2). In 83.35% (Guangxi) and 91.46% (Jiangsu) of rain intervals the farm-
 324 median power exceeds 100 kW; averaged over intervals, 76.7% and 88.2% of the reporting
 325 turbines exceeded 100 kW. By rain-rate class (Fig. 6), median tip-reference speeds are 67.1, 70.4
 326 and 64.5 m s⁻¹ and median grid-side powers 556, 628 and 392 kW in Guangxi for 0–1, 1–5 and ≥ 5
 327 mm h⁻¹, versus 79.0, 82.0 and 81.2 m s⁻¹ and 773, 1332 and 1290 kW in Jiangsu.



328 Rain therefore frequently coincides with power-producing rotation rather than predominantly
 329 stopped turbines. Because rain-time power remains far below the 4 MW-class rating at both sites,
 330 the turbines operate mostly in the partial-load regime during rain; the reported power and tip-
 331 reference speeds are representative of the observed periods rather than of all-weather operation.
 332 Supplementary Fig. S2 shows the joint distribution of rain intensity and farm-median wind speed
 333 for the QC-matched intervals at both sites. A turbine-level check using the per-turbine records
 334 confirms that farm-median aggregation does not create the observed compression. Rain-time
 335 median rotor speed spans 5.50–9.09 rpm across the 37 Guangxi turbines and 8.49–9.35 rpm across
 336 the 25 Jiangsu turbines, with farm-median values of 7.82 and 9.16 rpm inside the central half of
 337 the turbine medians. Turbine-level E_{SCADA} ranges 0.007–0.058 (Guangxi) and 0.026–0.039
 338 (Jiangsu), so every turbine retains compression relative to the fixed-speed benchmark
 339 (Supplementary Table S8).

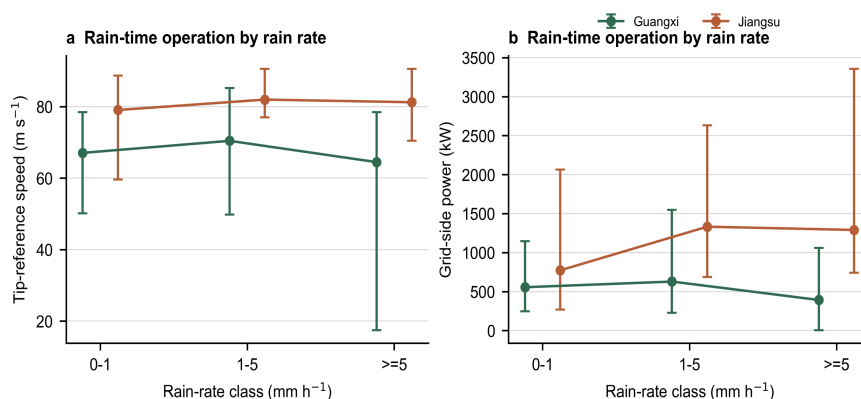


340

341 **Fig. 5. Wind speed and tip-reference speed for quality-controlled non-rain (dry) and QC-matched SCADA**
 342 **intervals within the common window. Boxes show the interquartile range; horizontal lines and labels show**
 343 **medians.**

344

345 Fig. 6 summarizes operation by rain-rate class. These are observed co-occurrences, not causal
 346 effects of rain intensity on power or rotation, because ambient wind, dispatch, faults and
 347 curtailment also govern operation. They serve to identify the measured combinations of rainfall,
 348 drop spectrum and rotational input that enter the model.



349

350 **Fig. 6. Tip-reference speed and grid-side active power by rain-rate class. Points and labels show medians;**
 351 **vertical spans show the interquartile range.**

352

353 3.5 SCADA-coupled observed-period exposure

354 SCADA availability within the common window was high: 961 of 967 Guangxi rain intervals
 355 (99.38%) and all 609 Jiangsu intervals were QC-matched (Supplementary Fig. S1). The intervals
 356 excluded from the Guangxi sample are statistically indistinguishable in rain intensity from the
 357 retained ones (Kolmogorov–Smirnov $D = 0.39$, $p = 0.25$), whereas the 108 Jiangsu intervals
 358 beyond the export endpoint (22.18 mm) differ significantly ($D = 0.19$, $p = 0.002$; Supplementary
 359 Table S4). Table 4 and Fig. 7 compare the common-speed and operation-coupled results over these
 360 QC-matched overlaps within the common window. At the fixed 90 m s^{-1} reference, normalized
 361 exposure of the literature reference coating is 0.140 in Guangxi and 0.066 in Jiangsu; with the
 362 interval-specific rain-time tip speeds, E_{SCADA} falls to 0.0251 and 0.0311. The matched-window
 363 compression ratio E_{SCADA}/E_{90} is 0.179 (95% paired percentile-bootstrap interval [0.066, 0.334] at
 364 event level) in Guangxi and 0.474 (event-level interval [0.198, 0.740]) in Jiangsu. Both event-level
 365 intervals lie below one, so compression relative to the fixed benchmark is supported at event level
 366 within each site, but the two intervals overlap; the cross-site ranking and the exact compression
 367 magnitudes are therefore not statistically separated. Interval-level and event-level bootstrap results
 368 are tabulated in Supplementary Table S6.

369 A fall-speed sensitivity replaces the parameterized terminal-velocity relation with the
 370 observed 32×32 fall-velocity distribution. It raises E_{90} by about 21% and 33% and E_{SCADA} by



about 28% and 38% in Guangxi and Jiangsu, respectively, but shifts the matched-window compression ratio by only +5.6% (0.179 to 0.189) and +3.4% (0.474 to 0.490), leaving the within-site compression and the cross-site ranking unchanged (Supplementary Table S7). The operation-coupled point estimates therefore reverse the common-speed ranking (0.0251 versus 0.0311), although the bootstrap intervals overlap (Section 4.1).

Table 4. Calculation results over valid rain–SCADA overlaps within the common window (ending 21 July 2026).

Site	Rain intervals (n)	Rain duration (h)	QC-matched rainfall (mm)	median U_{tip} (m s ⁻¹)	E_{90}	E_{SCADA} (95% CI)
Guangxi	961	160.17	508.83	67.58	0.140	0.025 [0.019, 0.032]
Jiangsu	609	101.50	242.07	79.17	0.066	0.031 [0.022, 0.044]

Note. E_{90} and E_{SCADA} refer to the common-window matched period. Over all valid rain intervals in the window, E_{90} is 0.141 in Guangxi and 0.066 in Jiangsu, rising to 0.17 when the Guangxi record is extended to 31 July (0.07 for Jiangsu over all valid intervals; its matched-window value remains 0.066 because SCADA ends on 21 July). The Guangxi increase reflects 98.7 mm of rain in the 109 intervals that lie outside the common window, of which 108 are QC-matched and one is unmatched (Supplementary Table S1). For Jiangsu, the 609 matched intervals and the point estimates are identical in both windows; the small difference between the common-window CI [0.0216, 0.0442] and the full-window value [0.0216, 0.0438] reflects the Monte Carlo resampling order of the shared seeded bootstrap stream.

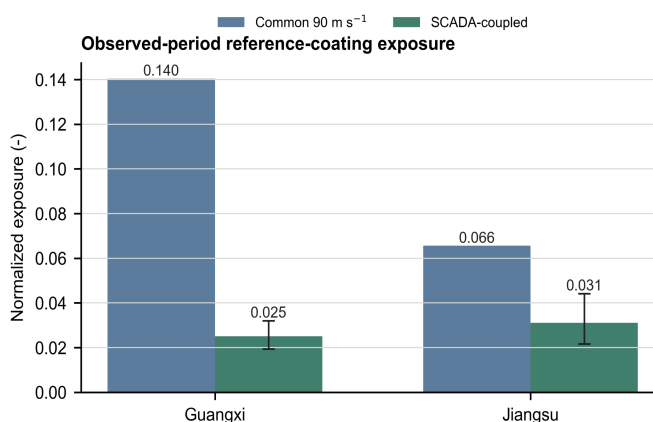




Fig. 7. Observed-period normalized exposure for the fixed common-speed (90 m s^{-1}) and rain-time SCADA-coupled conditions over the common window (ending 21 July 2026). E90 values in Table 4 are computed over the QC-matched rain–SCADA intervals, whereas the all-valid-window E90 reported in Section 3.3 is computed over all valid rain intervals within the window. Error bars on the SCADA-coupled bars show interval-level 95% percentile-bootstrap intervals; event-level intervals are given in Supplementary Table S6.

Exposure is strongly concentrated in a small number of rain intervals and events. Under the operation-coupled index, the 10% most exposed QC-matched intervals contribute 80% (Guangxi) and 75% (Jiangsu) of the total observed-period exposure. A single rain event accounts for 47% and 53% of the site totals, and the five most exposed events together contribute 78% (Guangxi) and 90% (Jiangsu) (Fig. 8b). Across the record, 63 (Guangxi) and 35 (Jiangsu) rain events satisfy the 3 h separation rule. These events combine the largest rain depths with rain-time tip speeds close to the operational ceiling. Exposure assessment and erosion-safe-mode operation therefore both target a small subset of the rain climatology rather than all rain intervals uniformly.

Recomputing E_{SCADA} with a capped interval-specific tip speed quantifies the derating leverage within the present screening framework (Fig. 8a). Capping the rain-time tip speed at 80 m s^{-1} reduces the observed-period exposure index by 42% in Guangxi and 58% in Jiangsu while affecting 26% and 48% of the rain time; a 75 m s^{-1} cap gives reductions of 60% and 75%. These capped-speed estimates describe model-framework exposure reduction before power-loss, torque-feasibility or control-latency constraints, and the sensitivity of the compression ratio to the fixed reference speed is reported in Supplementary Table S5.

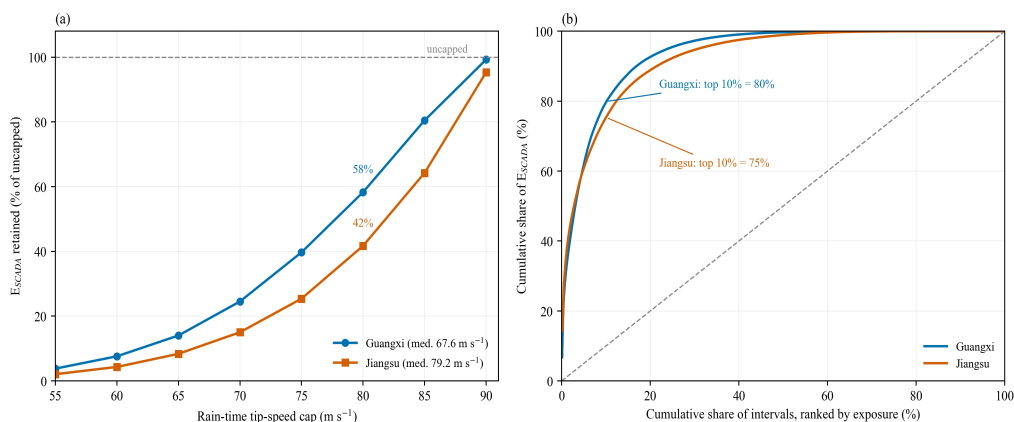




Fig. 8. (a) Observed-period exposure retained when the rain-time tip speed is capped at the indicated value, expressed relative to the uncapped E_{SCADA} ; the percentage of rain time whose actual speed exceeds each cap is given in the text. (b) Cumulative share of E_{SCADA} against the share of intervals ranked by decreasing exposure, illustrating the concentration of erosion-relevant exposure in a few intervals and events.

4 Discussion

4.1 Microphysical and operation-coupled exposure

Coupling the observed rain-time operating state reduces the matched-window exposure index to 18% of its fixed-speed value in Guangxi and 47% in Jiangsu, and this factor of 2.1–5.6 is the central quantitative result of the study. The two indices address separate questions: E_{90} holds the rotor kinematics fixed at the common 90 m s^{-1} reference and therefore isolates how rainfall microphysics (drop-size spectrum, fall-velocity coupling and liquid-water loading) maps onto the diameter-dependent exposure integral (Section 2.7). E_{SCADA} replaces the fixed speed with the observed interval-specific rain-time tip-reference speed, so it represents the exposure actually experienced by operating turbines during the observed rain periods. Both indices are normalized to the same literature reference coating (Bech et al., 2022); the gap between them is therefore an empirical measure of the operating-state contribution that is independent of the still-unidentified field coating system. This is consistent with the energetic characterization of Bartolomé and Teuwen (2021), who found that wind speed, through its control of rotor speed, was the main contributor to the erosive variables, whereas rainfall intensity played only a secondary role.

The magnitude of the compression and its site contrast follow from the nonlinear structure of the model. The equivalent water layer $H_{i,k}$ scales linearly with $U_{tip,k}/v_t(D_i)$ (Eq. 10), whereas the allowed-impingement threshold H_{crit} decreases steeply with increasing impact speed through the fitted exponent $m(D_i)$ of the Bech et al. (2022) relation. A rain-time tip speed that lies below the fixed benchmark therefore lowers the exposure twice, through the swept water layer and through the threshold relation. The Guangxi median rain-time tip speed is 25% below the 90 m s^{-1} benchmark (67.58 versus 90 m s^{-1}) and the site retains 18% of the fixed-speed exposure, whereas the Jiangsu median, 12% below the benchmark (79.17 versus 90 m s^{-1}), retains 47%.



439 The direction of this bias mirrors the erosion-safe-mode studies. In those, reducing tip speed
440 during high-rain-rate periods recovered about 70% of the erosion-related profit loss (Hasager et al.,
441 2021). Curtailing only during extreme precipitation events extended leading-edge life from a few
442 years to the design life at negligible annual energy production cost (Bech et al., 2018). The exact
443 retention ratio depends on the full rain-time speed distribution, not on the median alone. Even so,
444 this strong sensitivity to the speed reference is consistent with Barfknecht and von Terzi (2025),
445 who showed that the damage rate scales approximately with $V^{(\beta+1)}$ with β of order 10. It is also
446 consistent with the diameter- and velocity-dependent threshold relation of Bech et al. (2022), so
447 that a moderate reduction in tip speed produces a disproportionately large reduction in damage.
448 The present contribution removes the drop-spectrum assumption with measured 32×32 spectra
449 and constrains the operating-state term with time-aligned SCADA records instead of an assumed
450 rain–wind coupling.

451 The operation-coupled point estimates (0.0251 versus 0.0311) reverse the common-speed
452 ranking, but their 95% bootstrap intervals overlap, so the cross-site ranking of observed-period
453 exposure remains open within the observed periods; with 63 and 35 rain events, event-level
454 resampling widens the intervals further (Section 4.4). The comparison nevertheless shows why
455 rainfall alone cannot rank erosion-relevant loading. It extends the station comparison of Bech et al.
456 (2022), whose drop-size-dependent model produced a factor-3 variation in added damage per
457 meter of rain between northern-European stations because of differences in concurrent wind
458 during rain. It also extends that of Caboni et al. (2024), who linked shorter incubation at coastal
459 sites to higher wind speeds during rainfall. Under common-speed screening, Guangxi is more
460 exposed by a factor of about 2.1; once operation is coupled in, the two sites become statistically
461 indistinguishable. Any single-site ranking claim must therefore be tied to the metric from which it
462 is derived, and material testing, maintenance planning and derating logic should be informed by
463 the exposure statistics rather than by rainfall totals alone.

464 **4.2 Physical mechanisms, relation to previous work and the material boundary**

465 Physically, rain erosion accumulates only when repeated droplet impacts deliver sufficient
466 kinetic energy above the coating incubation threshold (Keegan et al., 2013; Tempelis et al., 2025).
467 The relevant loading is therefore set jointly by the drop-size-dependent impact energy and by the
468 number of impacts, the latter being governed by liquid-water loading and by the blade speed at
469 which that water is swept through the droplet field. Because fall velocity increases with drop



diameter (Gunn and Kinzer, 1949; Atlas et al., 1973) and the allowed-impingement threshold decreases with both diameter and impact speed (Bech et al., 2022), the largest drops contribute disproportionately to the exposure integral. The 1–3 mm class, which dominates the rainfall contribution at both sites (Section 3.1), is also the most diameter-sensitive part of the Bech et al. (2022) relation.

Modeling studies have established that the kinetic energy transferred by hydrometeor impacts is jointly controlled by the drop-size distribution and the rotor speed, and that joint precipitation–wind statistics remain sparsely observed (Pryor et al., 2022, 2024). This dependence has rarely been verified with farm-level operational data.

Verma et al. (2021) attributed the three-to-four-fold shorter coating lifetime of coastal sites mainly to heavy rain coinciding with high wind speeds. Hasager et al. (2021) quantified the exposure-reduction potential of erosion-safe mode from the same joint dependence in the North Sea and Baltic Sea. Atlas and parameterization studies show that the drop-size parameterization alone can change lifetime estimates by a factor of 44 (Tilg et al., 2022). The choice of precipitation dataset and resolution, by contrast, changes damage estimates by tens of percent (Hannesdóttir et al., 2024; Caboni and van Dalum, 2025).

Our results translate these model-based findings into direct observation: at Jiangsu, rain-time tip-reference speeds and power production during rain are higher, and this operating-state contrast reverses the common-speed ranking at point-estimate level (the cross-site E_{SCADA} intervals overlap; Section 3.5). The compression ratios in Section 3.5 quantify at farm scale how much of the fixed 90 m s^{−1} benchmark exposure is avoided because turbines rarely approach their operational speed ceiling during rain. The joint dependence is site-dependent. The rank correlation between rain intensity and farm-median wind speed is significant in Jiangsu (Spearman’s $\rho = 0.24$, $p = 1.9 \times 10^{-9}$) but not in Guangxi ($\rho = 0.036$, $p = 0.271$; Supplementary Fig. S2). The erosion-safe-mode leverage may therefore be smaller at the subtropical site.

Because E_{90} and E_{SCADA} are screening indices rather than lifetimes, they complement rather than compete with absolute-lifetime frameworks (Verma et al., 2021; Contreras López et al., 2023). The reference-coating parameterization (Bech et al., 2022) can be replaced by target-material data obtained in controlled multi-diameter rain-erosion tests following the ASTM G73 methodology (Elhadi Ibrahim and Medraj, 2020). The field-observed rainfall and operating-state inputs reported



here can then be propagated directly through such frameworks. The reference-coating relation of Bech et al. (2022) was fitted over impact velocities of 90–150 m s⁻¹. A substantial part of the observed rain-time tip-speed distribution (median 67.6 m s⁻¹ in Guangxi) and both capping scenarios lie below that range. The compression ratios reported here therefore rest on a limited extrapolation of the threshold exponent and should be read as screening-level. As Mishnaevsky et al. (2021) stress, in-service leading-edge protection systems differ in thickness, substrate, geometry and repair history, so the laboratory reference coating bounds the transferability of these indices. The material boundary is decisive. The present parameters refer to a commercial polyurethane topcoat on glass-fiber epoxy tested by Bech et al. (2022). They neither identify nor represent the field leading-edge protection system, including its thickness, substrate, leading-edge geometry, defects, temperature, humidity, repairs and damage evolution. The indices are therefore reported strictly for the literature reference coating.

4.3 Operational implications and erosion-safe-mode leverage

Erosion-safe-mode derating is effective because exposure is both strongly nonlinear in tip speed and concentrated in a small number of rain events (Bech et al., 2022; Barfknecht and von Terzi, 2025), and the present record confirms both properties at farm scale. Barfknecht and von Terzi (2025) showed that large droplets are considerably more damaging per unit water volume, and the mass-weighted mean diameters observed here (2.07 and 1.96 mm; Section 3.1) place a substantial fraction of the rain-time water mass in damage-relevant size classes. Reducing the tip speed during rain acts twice: it lowers the impact speed that enters the threshold relation and reduces the equivalent water layer swept per interval (Eq. 10). The derating leverage quantified in Section 3.5 is therefore governed by the farm-specific rain-time operating distribution rather than by rainfall alone. The same two-term structure dominates Springer-type damage accumulation (Tempelis et al., 2025; Hoksbergen et al., 2022). Hoksbergen et al. (2022) caution, however, that the fitted constants of that model are not physically representative. That is one reason this study reports a normalized screening index rather than a lifetime.

In practice, derating need not be applied throughout all rain time. Most of the observed-period exposure is carried by a small minority of the record: 75–80% by the 10% most exposed intervals, and a large share by a handful of extreme rain–wind co-occurrences (Section 3.5). A control strategy could identify those co-occurrences in real time, using precipitation nowcasting as proposed for erosion-safe mode by Tilg et al. (2020) and the drop-size-dependent considerations of



531 Barfknecht and von Terzi (2025). Such a strategy could capture most of the exposure reduction
 532 while affecting only a small fraction of rain time.

533 This concentration reproduces a pattern already reported in the modeling literature. About
 534 half of the modeled damage has been attributed to only 10% of rain events (Barfknecht and von
 535 Terzi, 2025), and 50% of impact kinetic energy has been found to occur in 6–12 h per year (Letson
 536 and Pryor, 2023). Erosion-safe-mode studies recover most of the erosion-related profit loss by
 537 curtailing only during such periods (Hasager et al., 2021).

538 The site contrast is informative. Jiangsu, whose rain-time operation lies closer to the
 539 operational ceiling, has more to gain from capping but also more rain time affected. Guangxi’s
 540 median rain-time operation already lies well below it, so capping removes less exposure and
 541 affects less rain time. In both cases the reduction is concentrated in a few extreme events rather
 542 than spread uniformly over the rain climatology; energy and control feasibility of such caps are
 543 outside the present screening scope.

544 **4.4 Robustness, scope and outlook**

545 The main result is robust to the checks the data permit. Per-turbine medians reproduce within-
 546 site compression for every turbine (Supplementary Table S8), so the farm-median basis is not an
 547 aggregation artifact. The concentration structure rests on record-internal contrasts that resampling
 548 cannot remove. Replacing the parameterized fall velocity with the observed 32×32 distribution
 549 changes the absolute indices by 21–38%, while shifting the compression ratios by only +3.4–5.6%.
 550 Event-level resampling widens the exposure intervals, but both sites retain compression relative to
 551 the fixed benchmark and only the cross-site ranking remains unresolved.

552 Three features of the dataset set the scope of the quantitative claims. Rainfall closure is an
 553 internal check of the Parsivel2 reconstruction rather than an independent validation, and
 554 disdrometer sampling uncertainty and edge effects (Jaffrain and Berne, 2011; Letson and Pryor,
 555 2023) remain the principal limit on the microphysical input. The roof-level siting samples near-
 556 surface spectra rather than rotor-height flow, with a larger spatial offset in Guangxi, so the
 557 matched records represent farm-wide operation co-occurring with roof-site rain. Finally, the 90 m
 558 s⁻¹ reference is anchored to the observed operational ceiling because the design-rated value is
 559 proprietary, and neglecting droplet slowdown near the blade makes the calculated impact speed
 560 conservative rather than permissive (Barfknecht and von Terzi, 2024).



The framework transfers directly to any farm that holds SCADA records, and its extensions are well defined. They are: replacing the reference coating with target-material data from controlled multi-diameter tests; resolving the fall-velocity distribution from the full per-record 32×32 matrices; and testing the screening outputs against blade-health records over multiple rain seasons. Together with the field and laboratory intercomparison priorities set out for this problem (Pryor et al., 2022, 2024), these steps define the route from the present exposure index to life and inspection-interval prediction. That route requires four further ingredients: controlled multi-diameter tests of the target material following the ASTM G73 methodology (Elhadi Ibrahim and Medraj, 2020); damage-accumulation models (Slot et al., 2015; Hoksbergen et al., 2022); computational droplet-impingement and degradation analysis (Doagou-Rad and Mishnaevsky, 2020; Verma et al., 2020a, b; Contreras López et al., 2023); and uncertainty quantification of leading-edge-erosion impacts (Maniaci et al., 2020). These field observations do not overturn the model-based picture of rain erosion; they supply the operational term that picture has assumed. That term is large enough to change the ranking of two sites differing by a factor of 2.3 in rainfall, consistent with the input sensitivity and wind–rain dependence quantified for European sites (Castorrini et al., 2024; Visbech et al., 2025).

5 Conclusions

This study develops a field-input framework that couples drop-resolved disdrometer observations with time-aligned farm-wide 10-min SCADA operation and a diameter-dependent rain-erosion model. It applies that framework at two Chinese wind farms to quantify how the rain-time operating state controls observed-period erosion exposure. The main conclusions are as follows.

(1) The rain-time operating state, not rainfall microphysics alone, sets the size of observed-period erosion exposure. Rain-time operation differs significantly from non-rain operation (Mann–Whitney U, $p < 0.001$ for all eight comparisons). Coupling it into the exposure calculation compresses the matched-window index to 18% of its fixed-speed value in Guangxi and 47% in Jiangsu. An assessment that assumes the 90 m s^{-1} reference throughout therefore overstates observed-period exposure by factors of 2.1–5.6.

(2) Coupling the observed operation inverts the cross-site ranking. Under the common 90 m s^{-1} benchmark Guangxi is about 2.1 times more exposed than Jiangsu. Under the operation-



coupled index the two sites converge and change order (0.0251 versus 0.0311). Their bootstrap intervals overlap, so the ranking is not statistically separated; which farm ranks as the more exposed one therefore depends on whether the operating state is included.

(3) Exposure is carried by a small minority of the record and is therefore operationally controllable. The 10% most exposed intervals account for 75–80% of the exposure and the five most exposed rain events for 78–90%; capping the rain-time tip speed at 80 m s⁻¹ cuts the index by 42–58% while affecting at most 48% of rain time.

(4) Drop-resolved rainfall combined with farm-wide SCADA operation yields a traceable exposure input for erosion management. The framework supplies coating-dependent exposure inputs for target-material erosion testing, erosion-safe-mode derating and the calibration of life models. It turns a loading term that previous assessments had to assume into one measured from the rain and the operation a farm actually experiences.

Data availability

The raw Parsivel² disdrometer data and the wind-turbine SCADA data are confidential property of Goldwind Science & Technology Co., Ltd. and are not publicly available; access may be considered by the data owner for legitimate research purposes subject to confidentiality and data-security requirements. The derived 10 min interval tables and the analysis code that reproduce the reported indices are available from the corresponding author on reasonable request, subject to the data owner's approval.

Author contribution

Yisheng Liu: conceptualization, methodology, software, formal analysis, visualization, and writing (original draft, review, and editing). Xinchang Jia: data curation, formal analysis, and investigation. Xiaoya Liu: methodology, supervision, and writing (review and editing). Meng Jin: conceptualization, project administration, funding acquisition, and resources. Fang Liu: investigation. Yafei Li: methodology and supervision. All authors discussed the results and approved the final manuscript.

Competing interests

The authors declare that they have no conflict of interest.



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