Probabilistic Tornado Risk Assessment for Wind Turbines in Germany

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Photo: Greg Johnson

https://www.weather-wind.com/

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1. Executive Summary

Germany's wind energy sector—Europe's largest, with over 28,000 onshore turbines and national targets to reach 115 GW by 2030—faces a growing but largely unquantified threat: tornadoes. With 30–60 tornadoes occurring annually, Germany ranks among the most tornado-active countries in Europe. Yet tornado risk is effectively absent from the catastrophe models that insurers and asset owners rely on to price and manage wind energy portfolios. Standard CAT frameworks cover European windstorm and hail, but treat tornado as a residual or unmodeled peril.

Weather Wind has developed a probabilistic Monte Carlo model that closes this gap. Built on peer-reviewed research published in *Natural Hazards* (Bouchard and Romanic, 2023), the model integrates three core components—tornado hazard climatology, wind turbine exposure, and a field data-built vulnerability function—to produce financial loss estimates directly usable for insurance pricing and capital planning.

The model simulates thousands of synthetic years of tornado activity across Germany, generating aggregated annual loss (AGG) and single-event occurrence loss (OCC) exceedance curves at return periods relevant to underwriters and reinsurers. Key findings include:

- Only about 10% of tornadoes are severe enough (F2 and stronger) to cause drastic damage or total collapse of wind turbines, but these events dominate the tail risk that drives capital requirements.
- Wind farm clustering in northern Germany increases correlated losses within single tornado events.
- Repowering—replacing older turbines with fewer, higher-capacity units—nearly doubles tail-region losses compared to simply adding more turbines of current capacity. This finding has direct implications for how portfolios should be priced as Germany's fleet modernizes.
- The model is sensitive to turbine installation costs, underscoring the need for standardized asset valuation data from the wind energy sector.

For insurers and reinsurers, the model provides quantitative inputs for tornado peril pricing, portfolio accumulation management, and incentivizing enhanced structural design standards. For wind farm operators and investors, it offers a tool to evaluate site-level risk and inform resilience strategies as the renewable transition accelerates.

Weather Wind delivers the atmospheric science and analytical rigor needed to quantify, price, and manage tornado risk for rapidly expanding wind energy sector.

2. The Problem: An Unmodeled Peril

Germany experiences 30–60 tornadoes per year, placing it among the most tornado-active countries in Europe. Research shows that Germany has the highest density of reported tornadoes on the continent, with occurrence concentrated in the north and northwest and an overall decrease toward the southeast. Tornadoes are most frequent between May and September, driven by severe convective storms associated with moisture convergence and strong wind shear. While the majority of events are weak (F0 on the Fujita scale), approximately one-third are strong enough to damage engineered structures, and roughly 10% are severe (F2 or stronger), capable of causing drastic damage or total collapse of wind turbines.

Table 1. Fujita[1] (F) tornado rating scale.

F Rating	Characteristic Wind Gust [m/s]	Damage Description
F0	18–32	Gale
F1	33–50	Moderate
F2	51–70	Significant
F3	71–92	Severe
F4	93–116	Devastating
F5	>117	Incredible

Climatological research further indicates that the environments favourable for severe convective storms—including tornadoes—are expected to increase across Europe by 5–20% per degree Celsius of global warming. Germany, together with France and Bosnia and Herzegovina, already has the highest frequency of environments favourable for significant tornadoes in Europe. As tornado climatologist Dotzek (2001) noted, tornado damage potential in Germany remains underestimated—a conclusion that has only become more consequential as the value of exposed infrastructure has grown.

That exposed infrastructure is substantial. Germany hosts the largest onshore wind energy fleet in Europe, with over 28,000 turbines and over 63 GW of installed capacity. With approximately 140 GWh of wind power generation as of 2024 (Figure 1), accounting for over 50% of national electricity generation from renewables. Put it differently, wind energy accounted for 23% of net German electricity production in 2021, and the country has committed to nearly doubling onshore capacity to 115 GW by 2030. This expansion includes significant repowering—replacing older turbines with larger, taller, higher-capacity machines that yield greater output but also concentrate

[1] This study uses the original Fujita (F) scale, which was the standard rating system in the European Severe Weather Database (ESWD) at the time the research was conducted (2022). In August 2023, the European Severe Storms Laboratory (ESSL) introduced the International Fujita (IF) scale for rating new tornado and wind damage events in Europe. The IF scale adopts the Damage Indicator and Degree of Damage framework from the Enhanced Fujita (EF) scale but uses instantaneous three-dimensional wind speeds rather than 3-second average horizontal gusts. The IF scale also allows half-step ratings (e.g., IF0.5, IF1.5) up to IF3. Historical ESWD reports retain their original F-scale ratings. The modelling framework presented here can readily be adapted to the IF scale as re-rated historical data becomes available.

more financial value per unit. As the footprint and value density of wind assets increase, so does their exposure to localized but destructive tornado events.

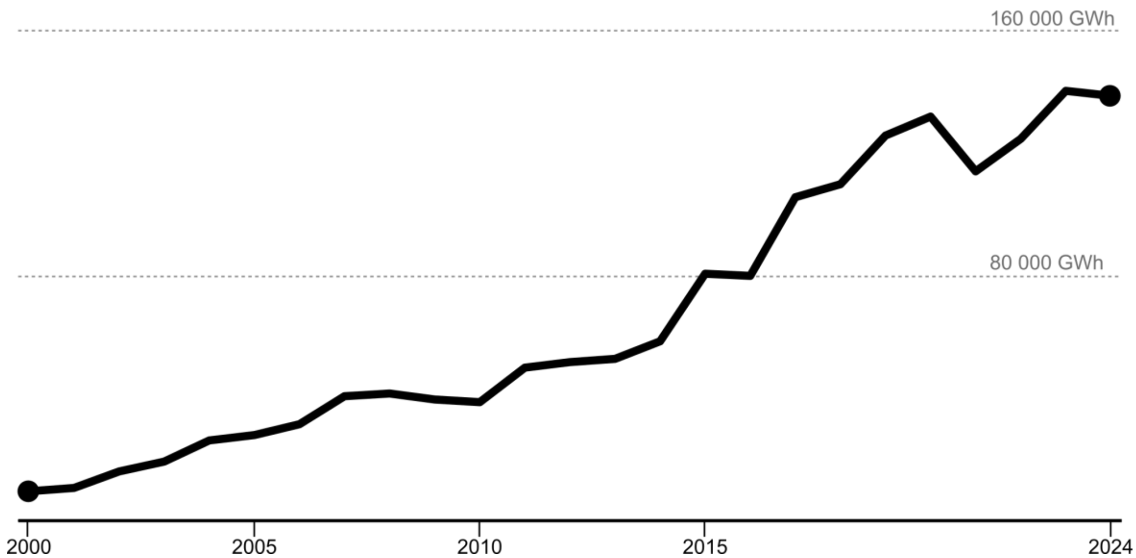

Figure 1. Evolution of wind energy electricity generation in Germany since 2000. Data source: International Energy Agency (2025). License: CC BY 4.0.

Despite this convergence of hazard and exposure, tornado risk is largely absent from the catastrophe models used across the insurance and reinsurance industry to price and manage wind energy portfolios. Standard European CAT models focus on extratropical windstorm, hail, and— in some cases— convective wind gusts, but do not explicitly model tornado frequency, track geometry, or the interaction between tornado wind fields and individual turbine structures. This means that a peril capable of destroying multiple turbines in a single event is being treated as unmodeled residual risk. This gap will present real financial consequences as wind energy portfolios grow.

This whitepaper presents Weather Wind's approach to closing that gap. Using a probabilistic Monte Carlo model grounded in peer-reviewed research (Bouchard and Romanic, 2023, published in *Natural Hazards*), we combine observed tornado climatology, the national wind turbine exposure map, and a novel vulnerability function to quantify tornado-related financial losses across Germany's wind energy fleet. The results provide insurers with pricing-relevant metrics—aggregated and occurrence loss exceedance curves—and give asset owners a tool to evaluate and manage tornado risk at the portfolio level.

3. Model Architecture

Weather Wind's tornado risk model follows the standard catastrophe modelling framework used across the insurance industry:

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}.$$

Each component is modeled independently and then combined through Monte Carlo simulation to produce probabilistic loss estimates. The model generates thousands of synthetic years of tornado activity, each containing a realistic number of tornado events with statistically representative locations, track geometries, and wind speeds. For every simulated tornado, the model identifies which wind turbines fall within the tornado's path, determines the wind speed each turbine experiences based on its position within the tornado's intensity zones, calculates physical damage using the vulnerability function, and converts that damage into financial loss using component-level cost data.

The three model components are:

Hazard (Section 4) defines where, how often, and how intensely tornadoes occur across Germany. It draws on 24 years of observed tornado data from the European Severe Weather Database (1998–2021) and uses fitted statistical distributions to simulate annual tornado counts, spatial locations, track lengths and widths, bearing angles, and wind speeds.

Exposure (Section 5) maps the locations and installed capacities of Germany's onshore wind turbine fleet. Turbine-level data determines both the probability of intersection with a simulated tornado track and the financial value at risk.

Vulnerability (Section 6) translates tornado wind speeds into physical damage through a continuous damage function developed specifically for this study. The function is based on field survey data of wind turbines damaged by tornadoes and represents the first published vulnerability curve for this hazard-structure combination.

Losses are aggregated in two ways standard to the insurance industry. The **Aggregated Loss (AGG)** is the total of all tornado-related losses in a simulated year. The **Occurrence Loss (OCC)** is the single largest event loss in that year. Both are plotted as exceedance curves against return periods, providing the metrics underwriters and capital managers use to set premiums, reserves, and reinsurance attachment points.

The full methodology is detailed in Bouchard and Romanic (2023), published in *Natural Hazards*. The sections that follow summarize each component with emphasis on the inputs, assumptions, and outputs most relevant to insurance applications.

4. Hazard Assessment

The hazard module simulates the frequency, location, intensity, and physical dimensions of tornadoes across Germany (Figure 2a). Rather than relying on a single deterministic scenario, the model generates thousands of synthetic tornado seasons that are statistically consistent with observed climatology, capturing the full range of plausible outcomes—including rare, high-impact years that have not yet been observed but are physically realistic.

Annual tornado frequency. The number of tornadoes per year is modeled using a negative binomial distribution ($r = 8.63, p = 0.15$), fitted to 24 years of observed data from the European Severe Weather Database (ESWD, 1998–2021). A change-point detection method identified an abrupt shift in reporting rates around 1998—likely driven by improved reporting rather than a physical climate change—so only the post-1998 record is used, yielding a mean of 48 tornadoes per year (Figure 2a). The negative binomial distribution in Figure 2b accounts for the year-to-year variability (overdispersion) in tornado counts that a simpler Poisson model would not capture.

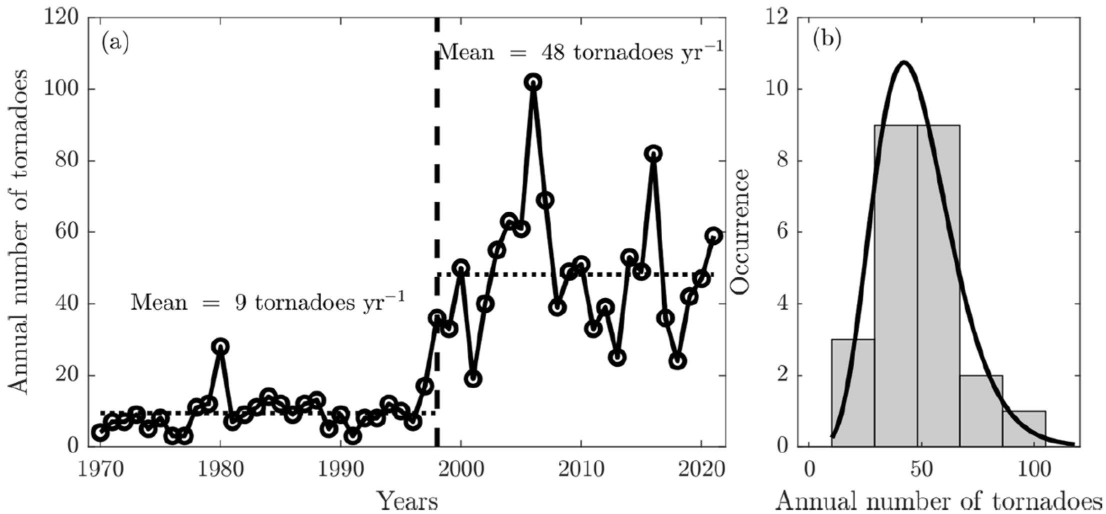

Figure 2. (a) Annual occurrence of all registered tornadoes over Germany from 1970 to 2021. (b) Histogram of the annual number of tornadoes in the period 1998–2021 fitted with a negative binomial distribution. Data source: ESWD (2022).

Spatial distribution. Tornado touchdown locations are not placed randomly across Germany. Instead, the model uses a kernel density estimator (KDE) based on observed touchdown coordinates to preserve the spatial patterns evident in the historical record: higher tornado density in the north and northwest, with occurrence decreasing toward the southeast (Figure 3). For each simulated tornado, an observed event is randomly sampled from the database and its coordinates are nudged using a bivariate normal distribution, introducing randomness while maintaining climatological realism. This approach is a significant improvement over uniform random placement, which would overestimate risk in low-activity regions and underestimate it where tornadoes actually concentrate.

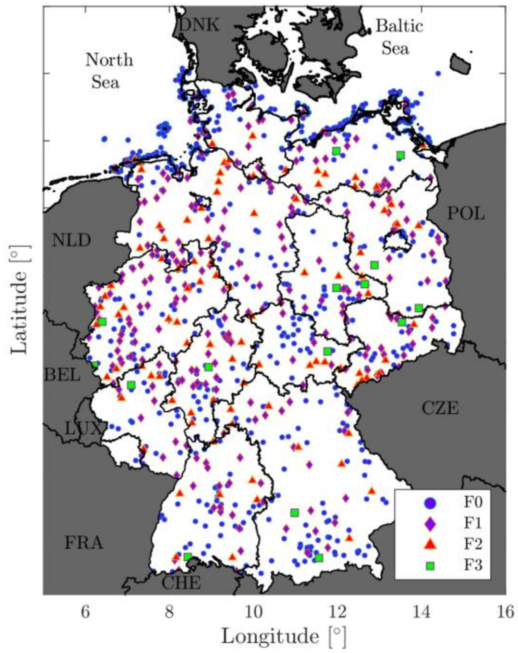

Figure 3. Map of Germany showing tornado locations in the period 1998–2021 categorized by their EF scale. Source: European Severe Weather Database.

Track geometry. The length and width of each simulated tornado path are drawn from Weibull distributions parameterized by tornado intensity, based on the extensive United States (US) tornado path data compiled by Brooks (2004). Comparison between German and US tornado path dimensions shows similar statistical behaviour, consistent with findings by Dessens and Snow (1993) for France. Both path length and width increase with tornado intensity—an F3 tornado has a mean path length of approximately 22.5 km and mean width of 264 m, compared to 1.4 km and 28 m for an F0.

Bearing angle. The direction of tornado travel is modeled using a kernel probability distribution fitted to thunderstorm trajectory data from Hagen and Finke (1999), yielding a mean bearing angle of 242°—indicating a prevailing southwest-to-northeast movement consistent with the dominant storm tracks over Germany.

Wind speeds and intensity variation along the track. Tornado wind speeds are generated from a log-normal distribution fitted to damage-derived wind speed estimates from Elsner et al. (2014). Critically, the model does not assume uniform wind speeds across the tornado path. Following the method of Standohar-Alfano and Lindt (2015), each tornado footprint is segmented into concentric intensity zones (Figure 4), with the highest-rated winds concentrated in the core and progressively weaker winds toward the periphery. A wind turbine's damage therefore depends not just on whether a tornado passes nearby, but on precisely where within the tornado's footprint it is located.

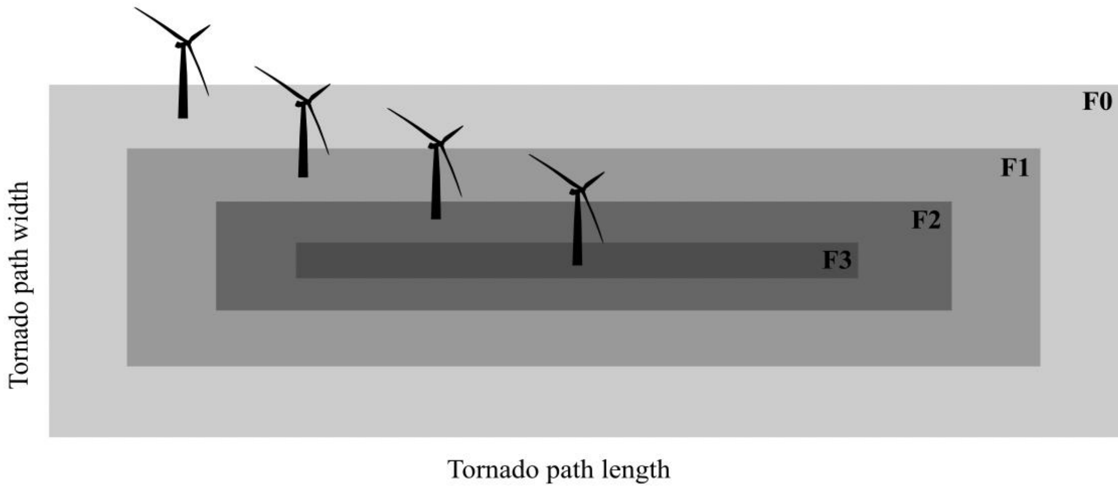

Figure 4. Conceptual blueprint of a segmented F3 tornado (not to scale). The depicted wind turbines encounter four wind speed regimes, with each regime representing a distinct F-scale intensity zone.

What the hazard module does not currently include. Tornado outbreaks—events in which multiple tornadoes form within the same convective system—are not explicitly modeled in the present Germany framework due to limited statistical data on outbreak characteristics in Europe. Each tornado is treated as an independent event. This feature is currently being implemented in a companion model under development for Canada, where outbreak data is more readily available, and will be incorporated into the Germany model as European outbreak data improves.

5. Exposure

The exposure module identifies the location, capacity, and financial value of every onshore wind turbine in Germany that could be affected by a simulated tornado. In catastrophe modelling, exposure defines what is at risk—and for a peril as spatially concentrated as a tornado, turbine-level resolution is essential.

Wind turbine fleet. The model uses turbine-level data from the Helmholtz Centre for Environmental Research (UFZ), which provides the geographic coordinates and nominal capacity of 24,456 onshore wind turbines installed across Germany as of 2015. The highest concentration of turbines is found in the north and northwest (Figure 5)—regions that also coincide with the highest tornado activity (Figure 3)—creating a spatial correlation between hazard and exposure that is central to the risk picture. Installed capacities range from less than 1 MW to over 3 MW, with approximately 63% of turbines rated between 1 and 3 MW.

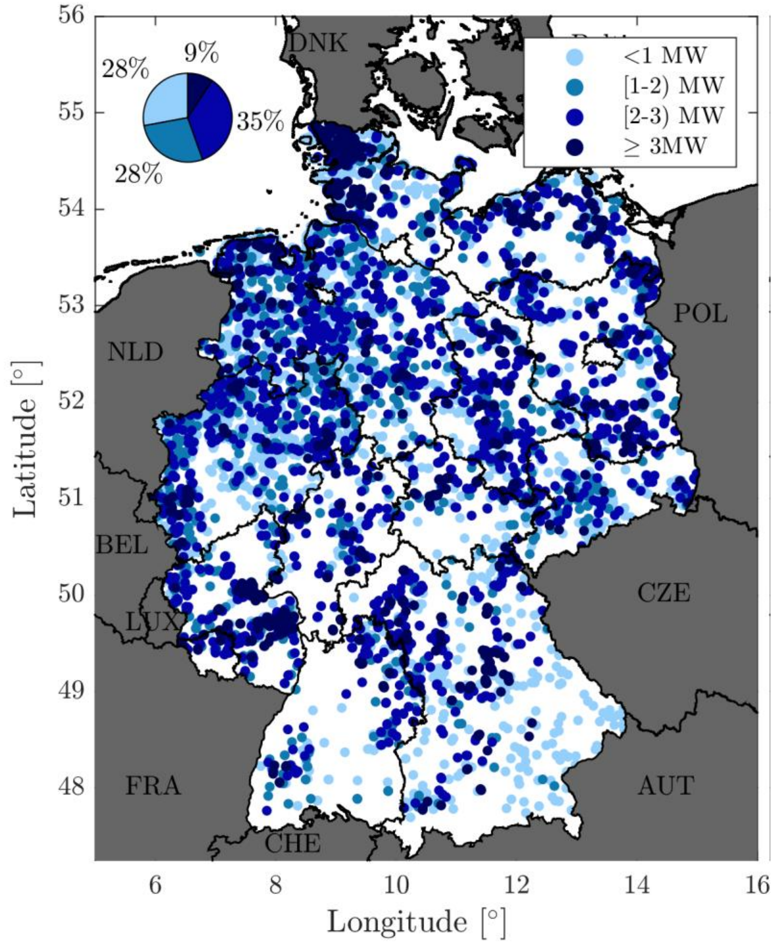

Figure 5. Map of Germany showing a wind turbine locations and their nominal power, including a pie chart of the proportion of different installed capacities in the total number of wind turbines. Data source: Helmholtz Centre for Environmental Research (2015).

Asset valuation. Each wind turbine is assigned a total replacement value based on its nominal capacity and a per-kilowatt cost drawn from industry data. The total cost value, V, of a turbine is calculated as:

$$V = C \times R,$$

where C is the nominal capacity in kilowatts and R is a cost rate per kilowatt, randomly sampled from a normal distribution with a mean of €1,250/kW, a standard deviation of 15%, and bounded between €1,100 and €1,400/kW. This range reflects the variability in total installed costs across different turbine types and manufacturers, and captures not just the turbine hardware but also grid connection, civil works, licensing, and engineering costs. The randomization ensures that the model does not assume a single uniform price across the entire fleet, which would understate the natural variability in asset values.

Why exposure matters for tornado risk. Unlike broad-footprint perils such as extratropical windstorms, a tornado's damage swath is narrow—typically tens to hundreds of meters wide. This means that whether a tornado causes any loss at all depends on whether its track physically intersects a turbine's rotor-swept area. For an individual turbine, this probability is very low in any given year. However, across a portfolio of tens of thousands of turbines and dozens of annual tornadoes, the cumulative probability of interaction becomes meaningful. The model calculates that over a 20-year turbine lifespan, the probability of at least one tornado strike on an average-sized turbine in Germany is approximately 0.05% for F1, 0.07% for F2, and 0.03% for F3 tornadoes. While these figures appear small for a single asset, they translate to non-trivial expected losses when scaled across the national fleet—and the losses per event can be severe.

Exposure evolution. The model's 2015 exposure map in Figure 5 serves as the baseline, but Germany's wind fleet has grown substantially since then and will continue to expand toward the 115 GW target. Section 8 of this whitepaper examines two future exposure scenarios—doubling the number of turbines, and repowering with fewer but larger units—to quantify how fleet expansion changes the risk profile. Periodic refreshes of the exposure database are recommended to maintain pricing accuracy as the fleet evolves.

6. Vulnerability

The vulnerability module is the bridge between physical hazard and financial loss. It answers a deceptively simple question: given that a tornado of a certain wind speed strikes a wind turbine, how much damage should we expect? The answer is captured in a continuous vulnerability function—first developed in this study—that relates tornado wind speed to a damage index ranging from 0 (no damage) to 1 (total replacement required). An example of collapsed wind turbine due to a tornado is shown in Figure 6.

Degrees of Damage. The foundation of the vulnerability curve is empirical. Marshall et al. (2022) surveyed wind turbines damaged by tornadoes and categorized the observed damage into five Degrees of Damage (DOD), each associated with a typical resistance wind speed and a set of affected turbine components.

Figure 6. Wind turbine damaged by an F2 tornado near Greenfield, Iowa, May 21, 2024. Source: NWS.

These DOD categories are discrete (Figure 7), but real-world damage exists on a continuum. To make the data usable for probabilistic modelling, we fitted a generalized logistic function— the Richard's curve—to the DOD data points, producing a smooth, monotonically increasing vulnerability curve in Figure 7.

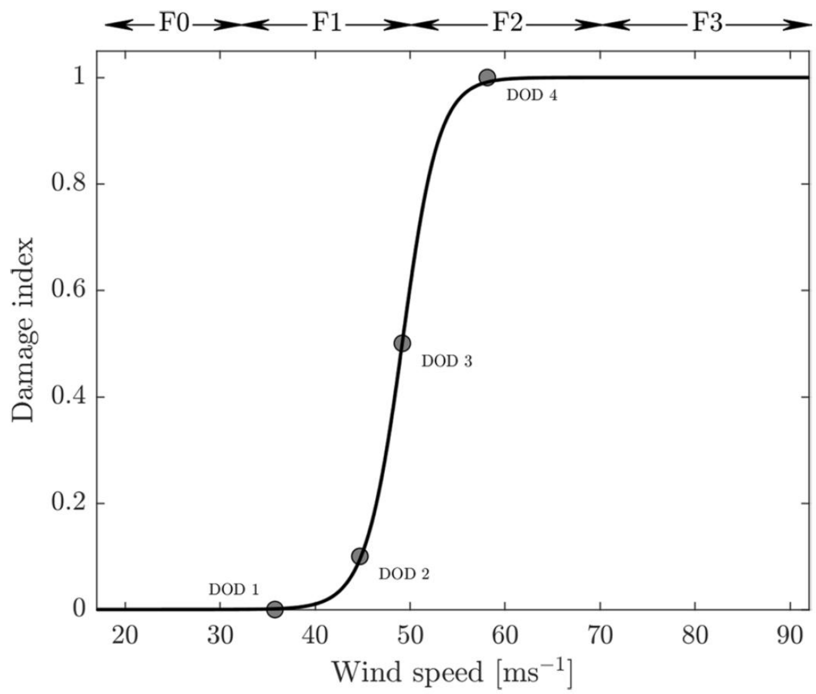

Figure 7. Vulnerability curve for wind turbines under tornadic wind loading, developed in Bouchard and Romanic (2023). This is the first published continuous vulnerability function for this hazard-structure combination.

Why this matters. Prior to this work, no published continuous vulnerability function existed for wind turbines under tornadic wind loading. Vulnerability curves are well established for other hazard-structure combinations (e.g., buildings in hurricanes, structures in debris flows), but the specific interaction between the concentrated, rotating wind field of a tornado and the tall, slender geometry of a wind turbine had not been formally modelled. This gap meant that any attempt to quantify tornado losses to wind energy assets required ad hoc assumptions about damage. The curve presented here—grounded in post-tornado damage survey data—provides the first empirically anchored alternative.

What the curve tells us. The vulnerability function reveals that F0 tornadoes (wind speeds below 32 m/s) cause no damage to wind turbines. F1 tornadoes produce the widest range of possible damage outcomes—from negligible to moderate—depending on where the wind speed falls within the F1 range. F2 tornadoes cause considerable to total damage. At F3 wind speeds, damage reaches the maximum ($D = 1$; Figure 6), meaning total replacement is required. Because F3 already causes complete destruction, tornadoes rated F4 or F5 would not produce additional losses beyond replacement cost—which is why the absence of F4+ events from the German record does not limit the model's loss estimates.

From damage to financial loss. Physical damage is converted to monetary loss using component-level cost data. Table 2 shows the typical percentage contribution of each major component to the total installed cost of a horizontal-axis onshore wind turbine.

Table 2. Percentage contributions of main components to the total capital cost of typical horizontal-axis onshore wind turbine.

Component	% of Total Cost	Description
Tower	26.3	Structure supporting the wind turbine
Rotor blades	22.2	Airfoil-shaped blades capturing wind energy
Gearbox	12.9	Boosts rotor shaft speed for the generator
Power converter	5.0	Converts DC to AC for the grid
Transformer	3.6	Steps up voltage for grid transmission
Generator	3.4	Converts mechanical to electrical energy
Main frame	2.8	Supports the drive train
Pitch system	2.7	Adjusts blade angle
Main shaft	1.9	Transfers rotor torque to the gearbox
Rotor hub	1.4	Holds blades in position
Nacelle housing	1.4	Covers the drive train
Brake system	1.3	Stops the rotor when needed
Yaw system	1.3	Orients the nacelle into the wind
Rotor bearings	1.2	Balance wind-imposed forces
Screws	1.0	Secure structural connections
Cables	1.0	Link turbine to electrical substation
Other	10.6	Foundation, grid connection, etc.

Each DOD state maps to a specific set of damaged components, and the cumulative cost of those components determines the financial loss for that damage level. The loss rule is straightforward: if the damage index, D, is below 0.7, the loss equals the damage index multiplied by the total turbine value. If the damage index reaches or exceeds 0.7, the entire turbine is deemed a total loss requiring full replacement. This threshold reflects the practical reality that once the tower (26.3% of value) and most drive train components are compromised, repair is no longer economically viable.

Accounting for uncertainty. A single deterministic curve cannot capture the full variability of real-world damage outcomes. Different turbine designs, foundation types, soil conditions, blade orientations at the moment of impact, and debris effects all introduce uncertainty. To address this, the model offers two vulnerability approaches. The first is a deterministic relationship (DR) that applies the vulnerability curve directly. The second is a randomized deterministic relationship (RDR) in which the damage index, D, is treated as a normally distributed random variable centred on the deterministic value with a standard deviation of 15%, bounded between 0 and 1. This stochastic treatment provides a more realistic spread of loss outcomes, particularly for the moderate-damage events (F1–F2 range) where real-world variability is greatest. Both approaches are carried through the full simulation to assess how vulnerability uncertainty propagates into loss estimates.

7. Results: Loss Exceedance Analysis

With hazard, exposure, and vulnerability combined through Monte Carlo simulation, the model produces probabilistic loss estimates across thousands of synthetic years. Results are expressed using the two standard insurance metrics introduced in Section 3: Aggregated Loss (AGG)—the total of all tornado-caused losses in a simulated year—and Occurrence Loss (OCC)—the single largest event loss in that year. Both are plotted as exceedance curves against return periods, providing the tail-risk metrics that underwriters and capital managers use for pricing, reserving, and reinsurance structuring.

The results presented here are based on an average of 60 independent model runs, each spanning 1,000 simulated years. This large simulation volume ensures stable estimates across the return-period spectrum and allows quantification of model uncertainty through the spread around the mean.

Deterministic vs. stochastic vulnerability. The model was run using both vulnerability approaches described in Section 6—the deterministic relationship (DR), which applies the vulnerability curve directly, and the randomized deterministic relationship (RDR), which treats the damage index as a normally distributed random variable around the deterministic value. Comparing the two in Figure 8 provides insight into how vulnerability uncertainty propagates into financial loss estimates.

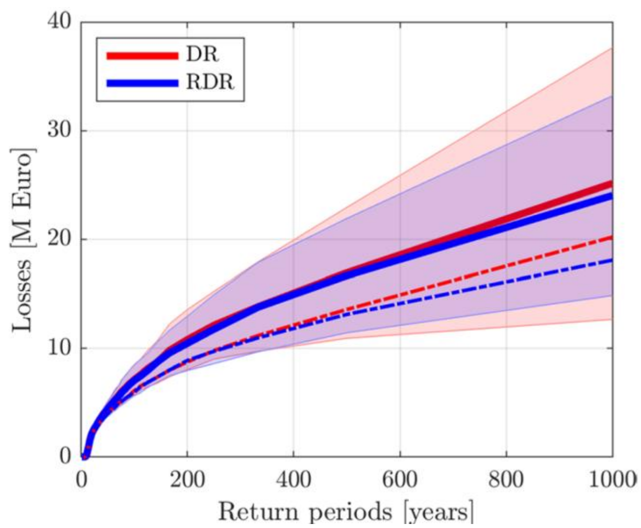

Figure 8. Probability exceedance curves showing AGG (full lines) and OCC (dot-dashed lines) losses associated with the DR (red) and RDR (blue) vulnerability modeling approaches. The profiles are based on an average of 60 1000-year return period model runs. The shaded regions represent one standard deviation around the mean AGG losses.

For short return periods (frequent, moderate-loss years), the two approaches produce similar results. The distinction becomes meaningful in the tail—return periods beyond approximately 200–500 years—where the DR method yields higher mean OCC losses and greater variability around the mean AGG losses than the RDR method. This divergence arises from the shape of the vulnerability curve. At the steep mid-section of the curve (F1–F2 wind speeds), the RDR's random re-sampling tends to smooth out losses: it increases damage slightly for weaker events but reduces it for stronger events, because losses are capped at full replacement cost. The net effect is that the stochastic approach produces a narrower and slightly lower band of tail losses.

This finding has a practical implication for insurers: the choice of vulnerability treatment matters most for the low-frequency, high-severity events that drive capital requirements and reinsurance attachment points. The deterministic approach is more conservative in the tail and may be preferred for prudent reserving (Figure 8). The stochastic approach provides a more realistic representation of the spread of outcomes and may be more appropriate for portfolio-level pricing.

Key findings from the loss exceedance curves: Both AGG and OCC curves rise steeply for return periods below 200 years and begin to flatten beyond 500 years, though positive gradients remain at the 1,000-year return period, suggesting that losses beyond 25 million euros are plausible for even longer return periods. Approximately two-thirds of simulated tornadoes are F0—the weakest category—which causes no damage to wind turbines (Figure 9). Only about one-third of annual tornadoes have the potential to cause any financial loss. Within that damaging subset, roughly 10% of all tornadoes are F2 or stronger and capable of causing severe damage or total collapse. These rare but intense events dominate the tail of the loss distribution.

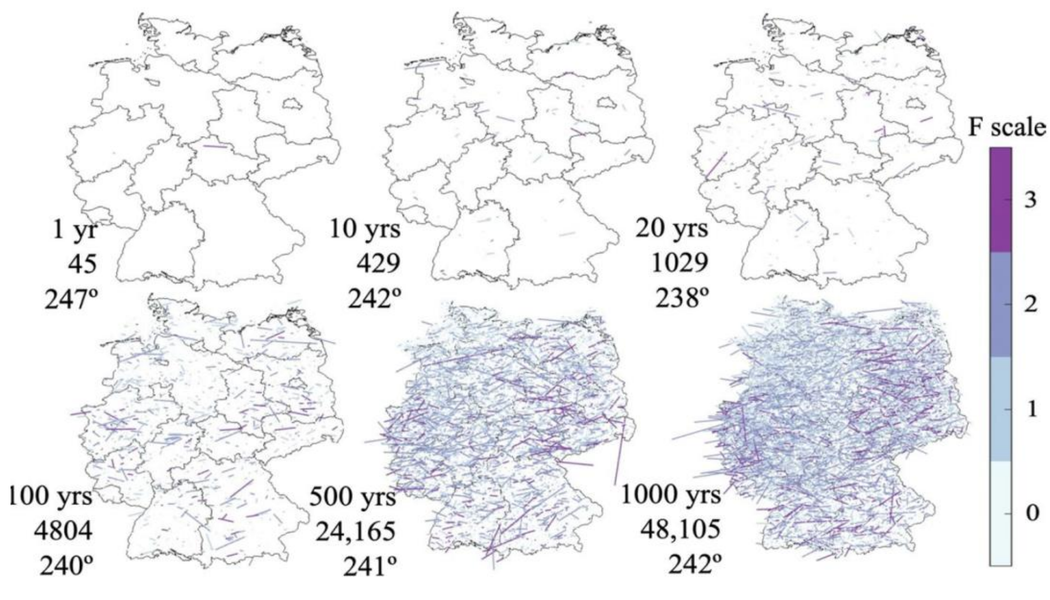

Figure 9. Modeled tornado tracks over Germany for return periods of 1, 10, 20, 100, 500, and 1000 years. The total number of modeled tornadoes and mean bearing angles of tornado tracks are indicated in the bottom-left of each figure.

Most simulated years produce modest total losses. The years that generate significant aggregate losses are driven by one or a small number of severe tornadoes (F2–F3) whose tracks happen to intersect wind farm clusters—particularly in northern and northwestern Germany, where both tornado density and turbine concentration are highest. This spatial correlation between hazard and exposure is a key driver of portfolio-level risk.

The seasonal timing of tornadoes provides a partial natural hedge. Tornado activity peaks in summer months (June–August), when wind turbine capacity factors are at their lowest (around 10%) and revenue from electricity generation is reduced. However, German electricity demand remains relatively stable year-round—only about 12% lower in August than the February peak—so the grid-impact and business-interruption implications of summer tornado damage should not be dismissed.

8. Scenario Analysis: How Fleet Expansion Changes the Risk

Germany's commitment to nearly doubling onshore wind capacity by 2030 raises an immediate question for insurers and asset owners: how will the expansion change the tornado loss profile? The answer depends not just on how many turbines are added, but on what kind of turbines replace or supplement the existing fleet. To investigate this question, we modeled two expansion scenarios using the DR vulnerability approach.

Scenario 1—More turbines of similar capacity (2NUM). The number of wind turbines is doubled while maintaining a capacity distribution similar to the currently installed fleet. New turbines are distributed uniformly across the exposure map, and their capacities are randomly sampled from the existing database. This scenario represents a straightforward scaling of the current fleet.

Scenario 2—Fewer but larger turbines through repowering (2CAP). The total installed capacity is increased to 100 GW by replacing turbines with fewer, higher-capacity modern units. Individual turbine capacities are normally distributed with a mean of 5.2 MW (bounded between 4 and 8 MW), reflecting the trend toward larger machines—including 7.5 MW onshore units already operational at sites such as Magdeburg-Rothensee and Ellern in Germany. This scenario reduces the total number of turbines by approximately 27% compared to the current fleet while roughly doubling total capacity.

The critical finding: repowering nearly doubles tail losses compared to simply adding turbines. Figure 10 shows that across the full range of return periods, the repowering scenario (2CAP) produces significantly larger losses than the doubling scenario (2NUM), with 2CAP values approaching double the 2NUM losses in the tail region. Both scenarios show steep gradients at the 1,000-year return period, indicating that losses beyond those modeled here are plausible.

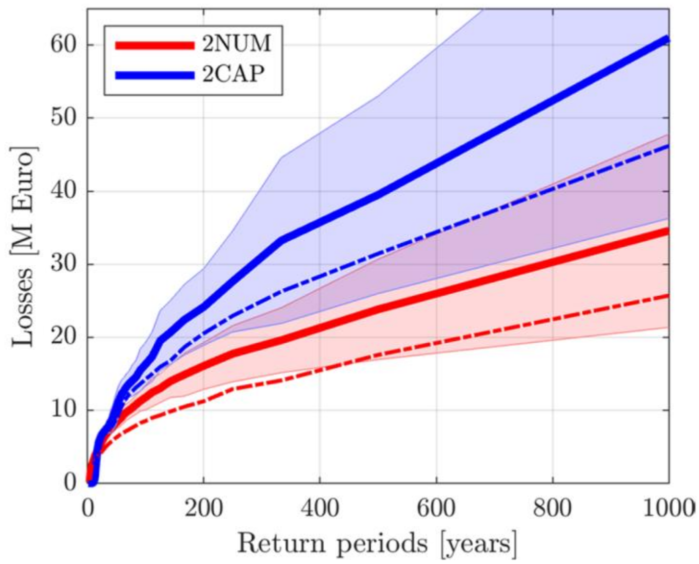

Figure 10. AGG (full lines) and OCC (dot-dashed lines) loss profiles for modified exposure map: doubling the number of wind turbines with capacities similar to the currently installed units (red) and new repowered wind turbines adding to a total capacity of 100 GW (blue).

This result is counterintuitive at first glance—the repowering scenario has fewer turbines, which means fewer potential tornado-turbine intersections. However, the loss model is driven by asset value too, not only contact frequency. Each repowered turbine carries substantially higher replacement cost (recall: $V = C \times R$), and because financial loss scales directly with turbine value through the vulnerability function, the concentrated value per unit in the 2CAP scenario amplifies losses far more than the increased contact frequency in the 2NUM scenario.

What this means for insurers: Portfolios weighted toward modern, high-capacity turbines carry higher per-event loss potential than portfolios with many smaller units, even if the total installed capacity is the same. This decision has direct implications for pricing: a simple capacity-based premium rate may understate risk for repowered portfolios. Underwriters should consider not just total insured capacity but the distribution of per-unit values—particularly for wind farms in tornado-active corridors of northern Germany.

The model is also notably sensitive to turbine installation costs, which are the primary driver of financial loss once physical damage is determined. This result underscores the importance of accurate, standardized asset valuation data from the wind energy sector. Variability in reported costs across manufacturers and project types is a significant source of uncertainty in loss estimates, and closer collaboration between insurers and wind farm operators on asset data would improve pricing accuracy.

Sensitivity testing with a fixed tornado path. To further validate the model's behaviour, we conducted controlled experiments in which a tornado of fixed dimensions (2,500 m length, 270 m width) was repeatedly placed over the same 17-turbine wind farm in Schleswig-Holstein, Germany. Tornado intensity (F1–F3), turbine capacity (halved, unchanged, doubled), and vulnerability treatment (DR and RDR) were varied across 18 scenarios, each consisting of 30 runs of 1,000-year simulations.

The results confirmed three properties of the model. First, losses scale linearly with turbine capacity across all scenarios—doubling capacity doubles the mean loss. Second, the DR and RDR approaches produce nearly identical loss distributions for F1 tornadoes but diverge systematically for F2 and F3, with RDR producing lower and more tightly distributed losses, consistent with the findings in Section 7. Third, F1 tornado loss distributions exhibit a Poisson-like shape truncated at zero (because the lower bound of F1 wind speeds causes no damage), while F2 and F3 distributions are approximately normal, centered on high loss values. These controlled results give confidence that the model behaves predictably and consistently, and that its outputs respond logically to changes in input parameters.

9. Recommendations for Insurers and Asset Owners

The results presented in this whitepaper point to several concrete applications for organizations that underwrite, manage, or invest in wind energy assets in Germany.

Incorporate tornado as an explicitly priced peril. Tornado risk is underrepresented in most catastrophe models deployed for European wind energy portfolios, which focus on extratropical windstorm and hail. Our model provides the probabilistic loss metrics—AGG and OCC exceedance curves, event-level losses, and return-period estimates, to name a few—needed to price tornado as a standalone peril or to supplement existing CAT model output. These metrics can feed directly into actuarial workflows for premium calculation, reserve setting, and technical pricing of excess-of-loss and aggregate covers. The model's output format is compatible with the catastrophe modelling frameworks used across the industry, including open platforms such as Oasis LMF.

Differentiate pricing by portfolio composition, not just total capacity. The scenario analysis in Section 8 demonstrates that two portfolios with identical total insured capacity can have materially different tornado loss profiles depending on per-unit turbine value. Portfolios concentrated in modern, high-capacity repowered turbines carry higher per-event loss potential than portfolios of many smaller units. Underwriters should request and incorporate per-turbine capacity and valuation data—not just aggregate MW—when pricing wind energy accounts exposed to tornado risk.

Identify and manage spatial accumulation. The model reveals that the highest tornado activity in Germany overlaps geographically with the highest concentration of wind turbines—both are concentrated in the north and northwest. This spatial correlation means that single-event losses are amplified by wind farm clustering. Insurers managing multi-account portfolios should use the model's spatial output to identify accumulation hotspots, assess correlated loss potential across accounts, and set appropriate per-event and aggregate limits for tornado-exposed regions.

Incentivize enhanced structural resilience. The vulnerability curve shows that the steepest region of damage increase occurs in the F1–F2 wind speed range (approximately 36–60 m/s). Even modest improvements to structural resistance in this range—for example, strengthened yaw systems, reinforced blade root connections, or enhanced nacelle housing—would shift the vulnerability curve downward, reducing expected losses disproportionately relative to the engineering cost. Insurers can use this insight to design premium discounts or risk-sharing programs that reward operators who adopt enhanced design standards, creating a virtuous cycle of reduced risk and lower claims costs.

Refresh exposure data periodically. As Germany's wind fleet expands through new installations and repowering, the exposure map underlying the model will require periodic updates. The sensitivity of loss estimates to turbine capacity and cost data (Section 8) means that outdated exposure information can materially misstate risk. We recommend annual or biannual portfolio refreshes, particularly for accounts undergoing significant repowering activity.

Account for business interruption alongside physical damage. The current model quantifies direct physical damage losses. However, the seasonal analysis shows that while tornado peak season coincides with low capacity factors, Germany's electricity demand remains relatively stable year-round. A tornado destroying several turbines during summer would still affect contractual generation obligations and grid commitments. Extending the analysis to include business interruption and revenue loss would provide a more complete picture of tornado-related financial exposure—an extension Weather Wind can deliver as a future model enhancement

10. Limitations and Potential Improvements

The modelling framework presented in this whitepaper provides robust probabilistic estimates of tornado-related losses to wind turbines in Germany. Like any model, it rests on assumptions and data inputs that introduce uncertainty. Transparency about these limitations is essential for appropriate use of the results—and each limitation also represents a defined pathway for future improvement.

Vulnerability characterization. The vulnerability curve developed in this study is the first published continuous function for wind turbines under tornadic loading, but it is built from a limited set of post-tornado damage survey data (Marshall et al., 2022). Modern turbines are taller, have larger rotor diameters, and use different materials and construction methods than those represented in historical damage surveys. As more turbines are exposed to tornadoes and more damage data becomes available—particularly for the latest generation of 5+ MW machines—the vulnerability function can be refined with greater confidence in the high-damage states that drive tail losses. Future structural testing, computational fluid dynamics modelling of tornadic wind-structure interaction, and collaboration with turbine manufacturers on component fragility data would all contribute to reducing vulnerability uncertainty.

Tornado outbreaks. The current framework simulates each tornado as an independent event. It does not account for tornado outbreaks—episodes in which a single convective system produces multiple tornadoes within a short time window and geographic area. Outbreaks introduce correlated losses that the independent-event assumption may understate, particularly for spatially concentrated wind farm portfolios. This feature is currently being implemented in a companion model under development for Canada, where more extensive outbreak data is available from established North American severe weather databases. The outbreak module will be incorporated into the Germany model as European outbreak statistics improve—an area where the expanding

European Severe Weather Database (ESWD) is expected to contribute increasingly useful data in the coming years.

Secondary damage mechanisms. Blade fragmentation, debris impact on adjacent turbines, and cascading mechanical failures across a wind farm are not explicitly modeled. In a dense wind farm struck by an F2 or F3 tornado, flying debris from a destroyed turbine could damage neighbouring units that might otherwise have sustained only moderate wind loading. Incorporating debris-field modelling would capture this additional source of correlated loss and is a natural extension of the Monte Carlo framework.

Repair and downtime modelling. The present model converts physical damage directly into financial loss based on replacement cost. It does not dynamically represent the operational realities of post-tornado recovery: supply-chain lead times for major components (blades, gearboxes, generators), crane availability and mobilization, staged repair scheduling across multiple damaged turbines, or grid reconnection timelines. A system dynamics module incorporating these factors would allow the model to quantify business interruption losses — not just physical damage — including post-event recovery timelines, lost revenue from generation downtime, workforce and crane deployment constraints, and interaction effects when multiple turbines require simultaneous repair. This extension is not included in the present deliverable but can be incorporated based on client needs and data availability.

Exposure data currency. The baseline exposure map uses 2015 turbine location and capacity data from the Helmholtz Centre for Environmental Research (UFZ). Germany's wind fleet has grown substantially since then. While the scenario analysis in Section 8 explores future expansion paths, periodic model refreshes with current fleet data are recommended to maintain pricing accuracy. As open-source turbine registries and industry databases improve, incorporating real-time or near-real-time exposure data will become increasingly feasible.

Spatial modelling of rare tornadoes. The kernel density approach to spatial distribution performs well for F0 and F1 tornadoes, which have large sample sizes in the ESWD database. For F2 tornadoes (100 events in the 1998–2021 record) and particularly F3 tornadoes (15 events), the spatial model shows greater variability between simulation runs, reflecting the limited observational data. As the ESWD record lengthens and more events are documented, the spatial fidelity of rare tornado modelling will improve. In the interim, users should be aware that regional loss estimates for F3 tornadoes carry wider confidence intervals than those for weaker events.

Weather Wind's development roadmap. Weather Wind is actively developing a system dynamics module that couples with the Monte Carlo hazard framework to address precisely these questions. By modelling the interdependencies between damage states, recovery resources, grid impacts, and operational constraints as a dynamic system, this extension will provide clients with resilience metrics beyond direct loss—including expected recovery timelines, business interruption estimates, and the cascading effects of simultaneous damage to multiple turbines within a portfolio. This capability represents a natural evolution from *"what is the loss?"* to *"how quickly and at what cost can operations recover?"*

11. Weather Wind Consulting Services

Weather Wind is a consulting firm specializing in atmospheric science solutions for the insurance, energy, and engineering sectors. Founded by Prof. Dr. Djordje Romanic, the firm bridges the gap between academic research in atmospheric hazards, weather and climate forecasting, wind energy and wind engineering, on one side, and the quantitative tools that industry needs to make informed decisions about risk, on the other side.

Our core capabilities in natural hazard modelling span four areas:

Probabilistic Natural Hazard Modelling. Tailored Monte Carlo simulations for tornado, windstorm, hurricane, and hail risks—delivering loss exceedance curves, aggregate and occurrence metrics, and portfolio-level financial insights for underwriting and capital allocation. The tornado risk model for Germany presented in this whitepaper is one example of this capability. We have also developed probabilistic tornado loss models for 1- and 2-family residential homes in Oklahoma and Kansas (United States), as well as the wind turbine model for Germany presented in this whitepaper. A companion model for Canada incorporating tornado outbreak clustering is currently under active development. Each model is built on peer-reviewed methodology and calibrated to regional tornado climatology, exposure characteristics, and locally relevant vulnerability functions. Weather Wind is also coupling its hazard models with a system dynamics framework to analyze post-event resilience, recovery trajectories, and cascading operational impacts—extending the analysis beyond direct physical damage to capture the full lifecycle of loss and recovery.

Site-Specific Hazard and Design Wind Assessments. Comprehensive climatological analysis, extreme-value statistics, and IEC-compliant wind resource evaluations to support turbine siting, annual energy production estimates, and operational planning.

Wind Engineering and Structural Vulnerability. Development of fragility and vulnerability curves, component-level damage modelling, and load analysis for structures and infrastructure exposed to severe wind hazards—including the novel tornado vulnerability function for wind turbines presented in this whitepaper.

Weather and Climate Forecasting. High-resolution numerical weather prediction, nowcasting for construction and maintenance scheduling, and long-term climate trend analysis under non-stationary scenarios.

Weather Wind welcomes enquiries from insurers, reinsurers, asset owners, and wind farm developers seeking to quantify and manage tornado risk—or any atmospheric hazard—with rigorous, peer-reviewed science.

For a portfolio-specific tornado risk assessment or to discuss how the modelling framework can be adapted to your needs, contact us at office@weather-wind.com or visit www.weather-wind.com.

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—About the Author—

Dr. Djordje Romanic is the founder of Weather Wind and Associate Professor in the Department of Atmospheric and Oceanic Sciences at McGill University, Montreal, Canada. His research focuses on severe wind hazards—including tornadoes, downbursts, hurricanes, and thunderstorm outflows—and their interaction with the built environment. He has developed probabilistic catastrophe models for tornado risk in the United States, Germany, and Canada, with particular expertise in Monte Carlo simulation methods, wind climatology, vulnerability modelling, and financial loss estimation for the insurance sector. Research group webpage: https://web.meteo.mcgill.ca/~dromanic/.

Dr. Romanic's work has been published in leading international journals including *Natural Hazards*, *Natural Hazards Review*, *Reliability Engineering & System Safety*, *Monthly Weather Review*, *Renewable Energy*, *Weather and Climate Extremes*, and the *International Journal of Disaster Risk Reduction*, among others (Google Scholar h-index: 23). The tornado risk model for Germany presented in this whitepaper is based on Bouchard and Romanic (2023), published in *Natural Hazards*. His research has been supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), Fonds de recherche du Québec–Nature et technologies (FRQNT) and the Canadian Institutes of Health Research (CIHR), Environment and Climate Change Canada (ECCC), among others.

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