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Widespread forest disturbance from windthrow in central African rainforests



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Natural disturbances are major drivers of tropical forest dynamics, yet their role in Central Africa's old-growth rainforests, the world's second largest tropical forest block, remains poorly quantified. Here we present the first regional assessment of windthrow, the uprooting or breakage of trees by wind. Using Landsat imagery from 2019 to 2020, we detected 74 windthrow events ≥ 30 ha, collectively affecting ~18,600 ha. These events were concentrated in eastern regions where mesoscale convective systems and extreme rainfall are most frequent. Sizes of windthrow events followed a Weibull distribution, with a single 3974 ha event accounting for one fifth of the total affected area. Event orientations aligned with prevailing storm outflows, and their timing coincided with peaks in extreme rainfall. For a subset of seven events with adequate temporal coverage before and after disturbance, near-infrared reflectance returned to pre-disturbance levels within months, indicating a rapid vegetation regrowth. Together, these findings show that windthrow is an important disturbance agent in Central Africa and must be considered in assessments of forest resilience under intensifying storm regimes.

Tropical rainforests store over 40% of global forest biomass¹ and are a critical part of the Earth's water and carbon cycles^{2–4}. While several studies document disturbance in the Amazon, the vast and carbon-dense rainforests of Central Africa remain poorly understood. In both regions, mesoscale convective systems (MCSs), organized clusters of thunderstorms, are the primary drivers of rainfall^{5,6}. In the Amazon, MCSs not only shape the seasonal carbon dynamics⁶ but also cause widespread tree mortality^{7,8} by generating extreme downbursts that trigger windthrow, the uprooting or snapping of trees⁹. Windthrow events affect forest structure, composition, and carbon cycling^{10,11} that over the past four decades have cumulatively affected ~0.06% (for events ≥ 30 ha) of the Amazon basin¹². In the Brazilian Arc of deforestation, windthrow events account for ~2.7% of total forest disturbance area¹³. Importantly, their frequency across the whole Amazon has quadrupled over the past four decades¹², with further increases projected under storm-intensifying conditions¹⁰.

Yet despite storing ~30% more aboveground biomass per unit area than the Amazon (395¹⁴ vs. 289¹⁵ Mg dry mass ha⁻¹) and experiencing frequent MCSs³, windthrow events have, to our knowledge, not been documented in the scientific literature for African rainforests. As a result, the

role of MCSs in shaping the dynamics and resilience of these globally important forests remains unknown.

African rainforests span approximately 2 million km², covering 13% of the continent's land area¹⁶, and store around 90% of its aboveground biomass and carbon². About 89% of these forests are located in Central Africa (see Supplementary Fig. 1), primarily within the Congo Basin and the broader Guineo-Congolian biogeographic region¹⁵. In Central Africa, MCSs contribute ~70% of annual rainfall³, shaping forest composition and aboveground biomass distribution^{14,16}. The frequency and intensity of extreme MCS-driven rainfall events have increased in Central Africa¹⁷, with further intensification projected^{17–19}. Understanding how these forests respond to intensifying MCSs is critical for predicting their resilience.

Results

More windthrow events in eastern Central Africa

We present the first regional assessment of large windthrow events (≥ 30 ha) across Central Africa. Our approach is based on extensive windthrow studies from the Amazon^{20,21}. We conducted a systematic regional analysis using Landsat and Sentinel imagery to map and quantify large windthrow events. We further quantified their spatial distribution relative to extreme

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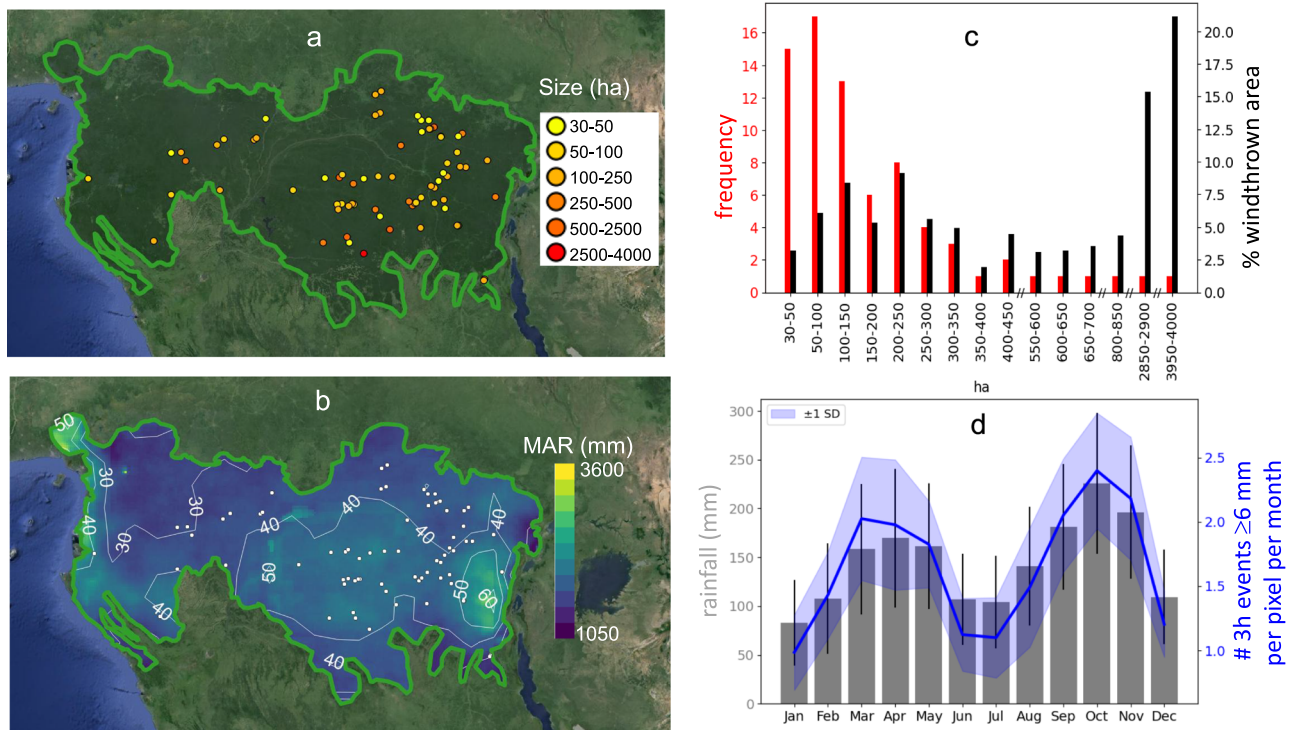


Fig. 1 | Windthrown trees in Central Africa. A windthrow of 78 ha occurred between 8 November and 17 December 2016 near 3.19° N, 12.83° E in the Dja Faunal Reserve, Cameroon. **a–c** Photographs of the windthrow taken by Dr. Brenda Larison (University of California, Los Angeles) from a helicopter some weeks after the event. The windthrow contour was manually delineated using the photographs and Landsat imagery by Dr. Vincent Deblauwe (Congo Basin Institute). **d–i** Satellite images show the windthrown region before and after the event. Changes in the

windthrown forests are represented as RGB composites of shortwave infrared, near-infrared (NIR), and red bands, from Landsat 8, Landsat 7, and Sentinel-2, respectively. The Sentinel-2 image was included to provide a denser time series and to show that vegetation regrowth had already covered the windthrow within one year. Cloud cover limited the availability of monthly image composites. Satellite imagery was processed in Google Earth Engine⁶⁹.

convective rainfall, characterized their size-frequency distribution, and assessed post-disturbance vegetation regrowth using near-infrared (NIR) reflectance as a proxy²² (see “Methods”). In a single windthrow case, helicopter photographs from Cameroon confirmed a windthrow event in 2016 (Fig. 1a–c), providing ground-truth evidence used only for this event to validate the methodology (Fig. 1d–i), which was then applied systematically across the region.

Using Landsat 8 imagery from 2019 to 2020, to achieve complete spatial coverage, we identified 74 windthrow events across Central Africa, cumulatively affecting 18,576 ha $\pm$ 4.3% (See “Methods”). These included both older events (occurring before 2019) and new events within the 2019–2020 period (see Methods). Windthrow events were concentrated in the eastern part of the region (Fig. 2a), where MCSs and extreme rainfall (rainfall $\geq$ 6 mm h⁻¹) are most frequent⁷ (Fig. 2b). A single large windthrow, spanning 3974 ha, accounted for 21% of the total disturbed area (Fig. 2c). After dating the windthrow occurrences (see “Methods”), we found that most events occurred between October–April, aligning with peaks in extreme rainfall events²³ (Fig. 2d). Of the 93% of windthrow events with discernible directionality (Methods), 55% were westward, 18% northward, 12% eastward, and 8% southward. Notably, all windthrow events $\geq$ 350 ha (9 cases) exhibited a westward orientation, consistent with the predominant movement of MCSs across the region³.

Windthrow and extreme rainfall

Across 33 windthrow events where the timing of their occurrence could be determined (see Methods), extreme rainfall was always observed (Fig. 3a, and Supplementary Fig. 2), with peak intensities averaging 15.6 $\pm$ 6.0 mm h⁻¹. We examined all rainfall events within 1–4 week occurrence windows. In most cases, multiple peaks were detected; however, in the few cases with only a single peak, rainfall reached 25.0 mm h⁻¹

(windthrow at lat: -1.17088°, lon: 21.3884° that occurred between December 16 and 23, 2019) and 20.7 mm h⁻¹ (windthrow at lat: -0.9167°, lon: 21.5621°, between July 30 and August 8, 2015). These cases illustrate that when a windthrow can be linked directly to a specific storm, the associated rainfall is consistently extreme, underscoring the role of intense convective events in generating windthrow.

Probability distributions of rainfall over different time intervals further reinforce this link (Fig. 3a and Supplementary Fig. 3). We used the Gamma probability distribution (see methods and Supplementary Table 1), which provides a flexible and physically meaningful representation of positively skewed precipitation data²⁴. In this distribution, the scale parameter θ (Fig. 3a) governs the rate at which the distribution decays. Smaller θ values correspond to steeper declines (faster decay and lower probability of extreme rainfall intensities), whereas larger θ values produce shallower declines and heavier tails. Based on this property, the three- and four-week windows around windthrow events exhibited the steepest declines ($\theta = 3.07$ and 2.95), while the one-week ($\theta = 4.17$) and especially the two-week ($\theta = 5.61$) windows showed shallower declines, indicating heavier tails and a higher relative frequency of extreme rainfall intensities close to the time of windthrow. All distributions were right-skewed as indicated by the k (shape parameter) < 1 .

Windthrow and inverse Weibull

The return time and size of windthrow events were positively correlated. Smaller events (30–100 ha) recur on timescales of centuries, while events larger than 500 ha have return times exceeding 10⁵ years (Fig. 3b). Compared to windthrow events in the Amazon²⁵, windthrow events in Central Africa are less frequent, likely reflecting regional differences in storm dynamics. MCSs, key drivers of windthrow, are more prevalent in the Amazon, where the most active regions experience over 100 events per year, compared to

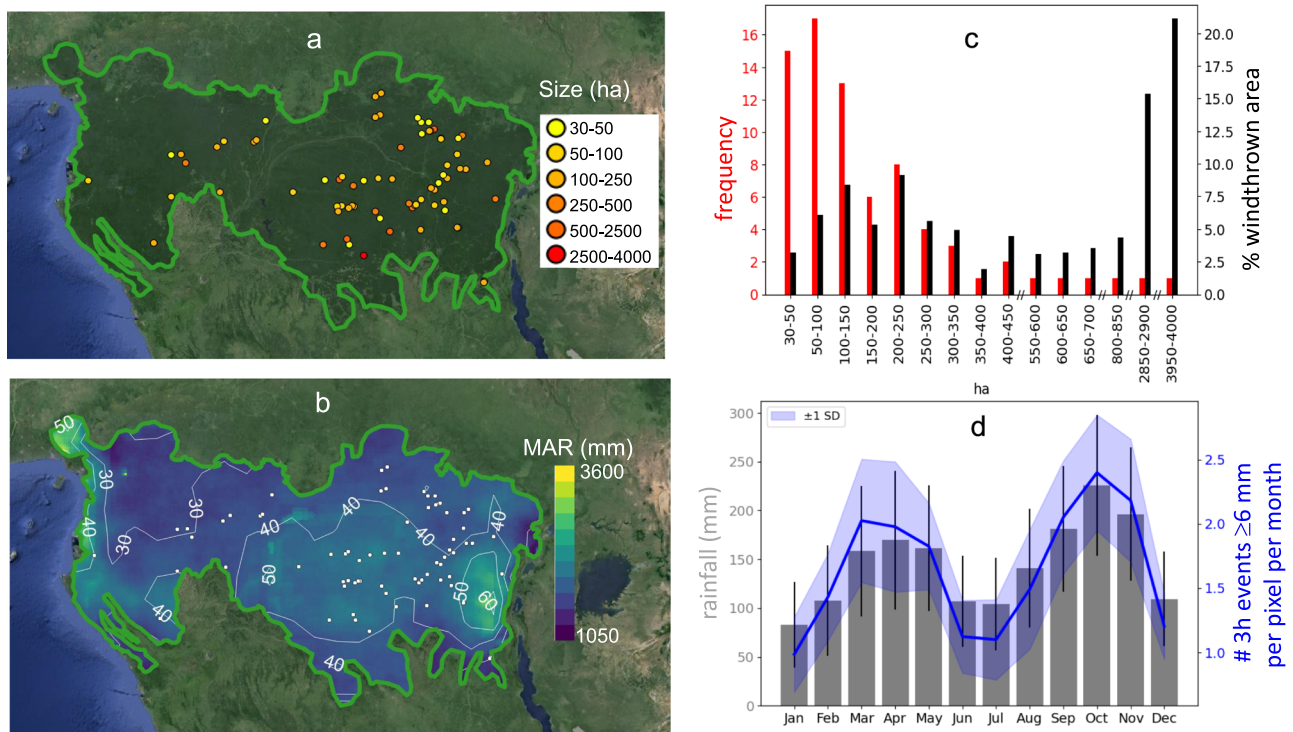


Fig. 2 | Characteristics of windthrow in Central Africa. **a** Spatial distribution of windthrow occurrences and their sizes. **b** Spatial association of the occurrence of windthrow events, mean annual rainfall (MAR), and mean annual number of extreme rainfall (rainfall $\geq 6 \text{ mm h}^{-1}$, contour lines) for the period 2001–2019. The locations of the windthrow events are represented by white dots. **c** Histogram of

windthrow frequency by size (red bars) and contribution to the total windthrown area (black bars). **d** Mean monthly rainfall (gray bars) and standard deviation (gray lines), along with the average number of extreme rainfall events (blue) and their standard deviation for the period 2001–2019. Details in “Methods”.

about 70 in Central Africa³. Additionally, persistent cloud cover during Central Africa’s two distinct wet seasons (Fig. 2d) may also limit windthrow detection, contributing to the lower observed frequency of events.

Sizes of windthrow events followed a right-skewed distribution, best described by an Inverse Weibull model (Fig. 3c, see “Methods” and Supplementary Table 2), consistent with findings from Central America²⁶ and the Amazon¹². The inverse Weibull model outperformed the power-law model (also used in tropical studies^{27–29}), particularly for events between 30 and 100 ha. For larger windthrow events (≥ 500 ha), however, both models showed similar fits (Fig. 3c).

Rapid regrowth

Based on analyses of seven windthrow events for which sufficient Landsat observations existed to capture both pre- and post-disturbance conditions (see Methods), we found that vegetation regrowth was rapid (e.g., Fig. 1d–i). Data availability was restricted not only by frequent cloud cover but also by the limited temporal density of Landsat acquisitions, which reduced the number of events that could be analyzed. We used near-infrared (NIR) reflectance as a proxy for vegetation regrowth, as it is sensitive to leaf regreening and less prone to saturation than standard vegetation indices²². Immediately after windthrow (time = 0), NIR values sharply declined due to canopy loss and exposed wood and soil (Fig. 3d). NIR values increased within two months and returned to pre-disturbance levels within six months. This rapid increase contrasts with the Amazon, where windthrow impacts can persist for up to a year before NIR begins to rise²², highlighting fundamental differences in post-disturbance dynamics between these regions.

Discussion

Disturbance patterns across African rainforests are diverse, dynamic, and remain poorly quantified. Paleocological evidence indicates that these forests have endured repeated waves of severe disturbance over millennia,

driven by droughts, fires, and human activity^{30–33}. Today, Central African forests face multiple pressures. Defaunation, especially the decline of elephants and other important seed dispersers^{34,35}, agricultural expansion^{36,37}, and selective logging are prominent^{15,38}. Anthropogenic disturbance is now dominant, with small-scale agricultural clearing accounting for 84% of disturbed area, annual loss rates in primary forests doubling between 2000 and 2014, and smallholder clearing in the Democratic Republic of Congo alone responsible for nearly two-thirds of total basin forest loss³⁶. Over 61% (45,954 km²) of the forest disturbances in the region occurred near roads or outside formal land allocations from 2000 to 2022³⁹, as road length within the basin nearly doubled since the early 2000s⁴⁰. In terms of natural disturbance drivers, the Congo Basin experiences exceptional lightning activity, which disproportionately affects large canopy trees that are critical for carbon storage and forest structure, though the scale of this effect remains unquantified. Evidence elsewhere in the tropics suggests each strike may kill and damage multiple trees⁴¹. Against this backdrop, windthrow stands out as a storm-driven disturbance that produces extensive canopy openings (≥ 30 ha), underscoring its distinct role within Africa’s disturbance regime. Over the comparative multi-decadal framework used here, large windthrow events (≥ 30 ha) cumulatively affected ~18,600 ha, corresponding to approximately 0.01% of Central African rainforest area, a substantially smaller fraction than reported for the Amazon (~0.06%) using the same approach.

The spatial overlap between windthrow events and extreme rainfall suggests that MCS-driven downbursts are an important disturbance agent, consistent with observations in the Amazon^{7,8}, Central America²⁶, and southern African ecosystems⁴². While local factors such as soil properties (Central Africa is dominated by relatively uniform ferralsols⁴³), root anchorage⁴⁴, forest structure^{45–47}, liana loads⁴⁸, and historical land-use may modulate forest susceptibility to windthrow, MCS-driven downbursts appear to be the dominant cause. MCS driven winds are likely to cause a

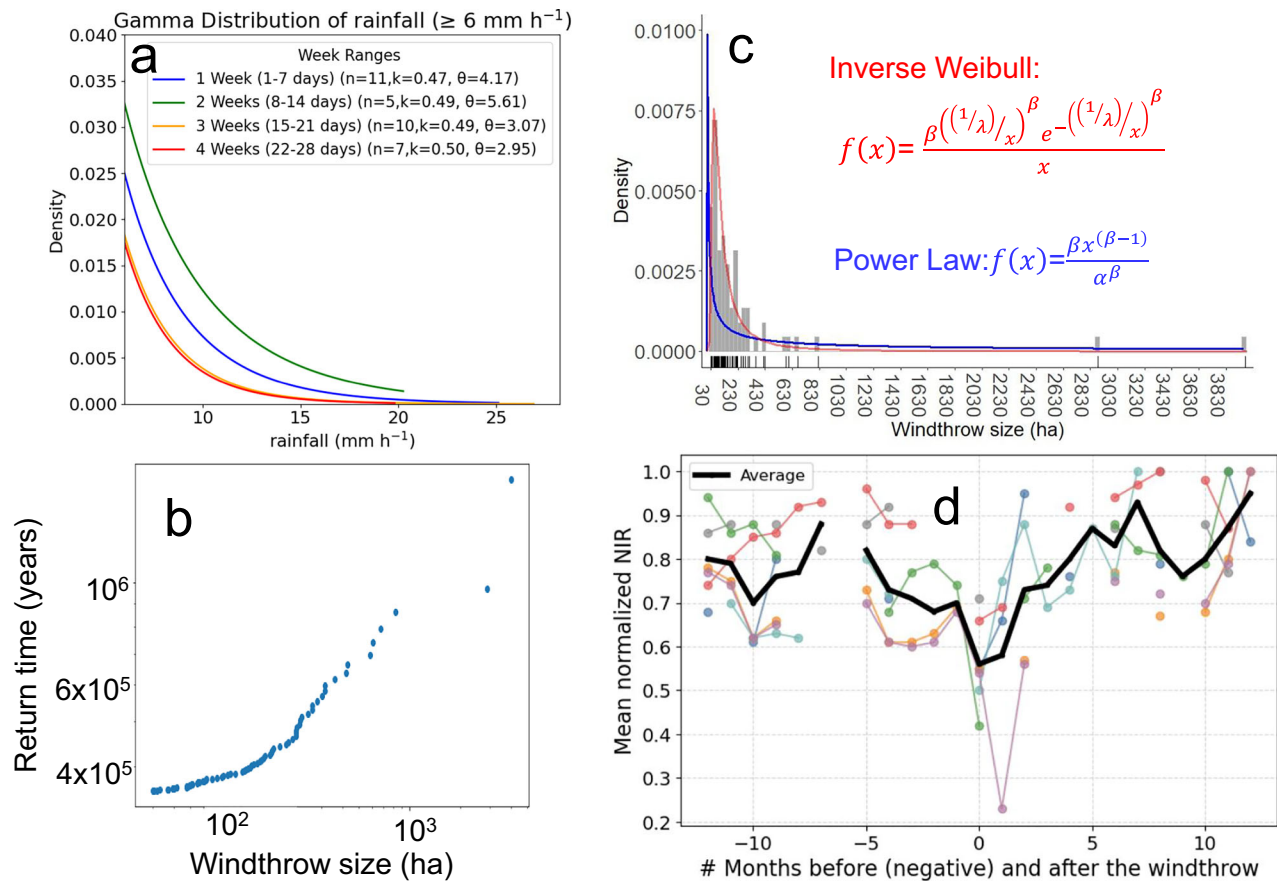


Fig. 3 | Rainfall patterns, frequency, size, and post-disturbance regrowth of African windthrow. **a**, Rainfall intensities associated with windthrow events across 1–4 week intervals, modeled using the Gamma probability distribution $f(x; k, \theta) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-x/\theta}$ where θ is the scale parameter that controls the steepness of decline, and k is the shape parameter that controls the form of the distribution (Supplementary Table 1). Windthrow counts (n) are shown for each interval. The 6 mm h^{-1} threshold marks extreme rainfall from mesoscale convective systems⁹⁰ (see “Methods”; Supplementary Fig. 3). **b** Return interval versus windthrow size over 30

years, based on the inverse cumulative probability distribution²⁵ (see “Methods”). **c** Size distribution fitted with an inverse Weibull ($\beta = 1.29$, 95% CI: 1.09–1.59; $\lambda = 0.012$, 95% CI: 0.010–0.148) and a power law ($\alpha = 3320.7$, 95% CI: 3320.7–3970.2; $\beta = 0.26$, 95% CI: 0.23–0.37) (Supplementary Table 2). **d** Changes in near-infrared (NIR) reflectance before and after seven events (colored lines) from Landsat 8. NIR values averaged over a 4×4 -pixel window, normalized to the maximum, and smoothed monthly (black line).

range of damage from branch and single tree fall events to multiple tree falls⁴⁹. Recent evidence from repeated high spatial resolution airborne lidar studies in the Brazilian Amazon indicated that wind-driven disturbances covered 1.25% of the surveyed area annually¹³. Assuming that large and small wind-driven disturbances are spatially correlated, the more frequent occurrence of windthrow events in eastern Central Africa indicates that the forest is likely to be more dynamic compared to western Central Africa, potentially contributing to the Eastern region’s lower biomass (see Supplementary Fig. 4). A similar pattern is observed in the Amazon, where western forests experience more frequent windthrow²⁰, have lower biomass², and faster carbon turnover⁵⁰ than the eastern Amazonian forests where windthrow events are less frequent²⁰. Other factors, such as forest age and land-use pressures, may also contribute to regional biomass differences; however, our study does not analyze biomass directly. Rather, we draw on evidence from the Amazon, where windthrow frequency has been linked to lower biomass and faster turnover, to suggest that disturbance regimes can be an important driver of large-scale biomass patterns across tropical forests.

Notably, despite higher rainfall and therefore more persistent cloud cover in eastern Central Africa, conditions that would be expected to hinder windthrow detection, this region exhibits the highest occurrence of windthrow events, indicating a genuine spatial signal rather than a detection artifact.

Windthrow events are unlikely to recur at the same location, and our analysis confirmed that recurrence at the same location is rare (Fig. 3b),

consistent with findings from the Amazon²⁵. By mapping windthrow regionally, we revealed broader patterns of ecosystem vulnerability across Central Africa. In the Amazon, studies have documented varying spatial distributions as well as temporal shifts in windthrow frequency¹², highlighting the need to monitor these disturbances across both spatial and temporal scales. Future work in Africa, including studies with high resolution repeat lidar, should build on this foundation to explore temporal dynamics and potential links to large-scale biotic and abiotic drivers, including shifts in climate and vegetation composition and dynamics^{10,12,28} across tropical forests.

Compared to the Amazon, Central African rainforests receive lower annual rainfall (2500 mm vs 1750 mm)²³, and have lower stem density (600¹⁵ vs 426¹⁴ stem ha^{-1} for trees $\geq 10 \text{ cm}$ diameter) on average, but contain relatively more large trees ($\geq 70 \text{ cm}$ diameter)⁵¹. This structure would suggest slower recovery after windthrow. Therefore, the recovery of NIR in Central Africa within six months, compared to the one-year recovery period observed in the Amazon⁵², was unexpected. This faster establishment and growth of early-successional plants may be partly explained by Central Africa’s bimodal rainfall regime, which provides more regular moisture, reduces the duration of dry periods, and may promote vegetative strategies for faster regrowth compared to the more seasonal Amazon basin¹⁵. Given the limited temporal density of Landsat imagery, constrained both by frequent cloud cover and by gaps in image availability, our analysis could only include a subset of cases ($n = 7$) and

cannot systematically isolate dry-season responses; however, the bimodal rainfall regime itself reduces such seasonal contrasts.

Rapid vegetation regrowth in Central Africa may partly reflect long-term ecological filtering. During the Late Holocene, around 2500 years BP, Central Africa's forests experienced a dramatic contraction that is theorized to reflect some combination of regional droughts and human activities^{53,54}. This contraction removed many drought-sensitive taxa and favored fast-growing, disturbance-tolerant species, potentially altering forest composition in ways that persist today. Modern-day forests in this region may thus retain a composition shaped by this filtering, favoring species with enhanced recolonization abilities following windthrow. Moreover, studies indicate that extensive human occupation and land management occurred throughout the Congo Basin during the Iron Age, leading to localized clearing, burning, and cultivation⁵⁵. These activities, followed by a population collapse around 400 CE, likely helped various robust pioneer taxa to dominate many forest areas. Amazonian forests, in contrast, though also hosting extensive human populations that influenced forest composition⁵⁶, lacked a major synchronized episode of forest degradation and loss, and thus, we suggest, likely retained many more slow-growing species. These historical contrasts could contribute to the observed differences in present-day recovery trajectories illustrated by NIR reflectance recovery.

Recovery of near-infrared (NIR) reflectance reflects rapid infilling by regenerating vegetation, including understory, herbaceous, and shrub layers, and should not be interpreted as recovery of canopy structure or aboveground biomass. After canopy closure, NIR continues to increase, followed by a decrease as succession proceeds²². Ecological context and biogeographic history likely also play important roles^{22,57–59} for fast NIR recovery in Central Africa. A key structural difference between regions lies in the understory composition. While Amazonian gaps are often dominated by slow-growing palms, Central Africa features dense shrub layers and abundant herbaceous species, including fast-growing clonal taxa such as *Marantochloa* spp. and *Haumania* spp., which rapidly fill gaps and yield high NIR reflectance within months^{57,60}. In contrast, although understory palms often survive windthrow events, they are slower to spread across gaps and drive changes that affect the spectral signals⁶¹. Persistent post-windthrow mortality may further slow forest recovery in the Amazon¹¹. Together, these differences likely explain the faster NIR recovery observed in Central Africa compared with Amazonian forests⁶². Although post-disturbance rainfall may vary among events, the limited available cases all showed a consistent pattern of rapid NIR recovery. Integrating ground-based biomass and species composition data with multisensor remote sensing of vegetation structure and dynamics (e.g., vegetation height, crown damage, and regrowth) from drones, aircraft, and satellites is essential for capturing the ecological mechanisms involved in post-windthrow dynamics.

MCSs have intensified in Central Africa³, tripling in frequency since the 1980s⁶³ and exhibiting earlier seasonal onset¹⁷. These trends are expected to accelerate under future climate conditions^{17,18}. As a result, Central Africa is likely to experience an increase in windthrow events⁷. Yet, compared to the Amazon, African forests remain significantly understudied, especially in relation to natural disturbance regimes and their consequences. Addressing this gap is critical, as changes in storm intensities and frequencies could fundamentally alter the structure, function, and long-term carbon storage capacity of one of the world's most vital yet least understood tropical forest regions, with profound implications for both the forest and for the climate.

Our study provides the first regional assessment of large windthrow events in Central Africa. However, we acknowledge that our detection approach is conservative. Persistent cloud cover and rapid post-disturbance regrowth strongly influenced the identification of windthrow events. Accurately delineating the disturbed areas requires more detailed analysis, as challenges arise from the delineation of the disturbed area, the resolution, and spectral characteristics of the satellite imagery used. Future work that incorporates field validation and higher-resolution multitemporal imagery, together with detailed analysis of the west–east gradient in windthrow

frequency, will be crucial for refining these estimates and quantifying regrowth, biomass loss, and species composition shifts.

We conclude that large windthrow events, recognized as a driver of forest dynamics in the Amazon, also occur across Central Africa and are closely linked to the occurrence of extreme mesoscale convective rainfall. These disturbances exhibit regional occurrence patterns and show rapid post-disturbance regrowth, likely influenced by the region's climate, functional trait composition, and species turnover. Functional traits, such as fast growth rates, resprouting ability, or clonal propagation, have been shown to shape demographic responses of tropical trees after disturbance⁶⁴. The clear link between extreme rainfall and windthrow highlights the critical role of convective storms in generating disturbance, with important implications for forest structure, carbon dynamics, and biomass distribution in Central African tropical forest ecosystems. As MCS activity intensifies with ongoing atmospheric changes, storm-driven disturbances may become a dominant force shaping the resilience and carbon balance of tropical forests globally. These findings highlight the need to integrate windthrow dynamics into Earth system models and carbon accounting frameworks⁶⁵, and to expand in situ networks for tracking post-disturbance recovery and long-term carbon consequences⁶⁶. As convective storms intensify, windthrow events may become a dominant force shaping the structure, carbon balance, and resilience of Central Africa's rainforests.

Methods

Study area

Our study area consists of the rainforests of Central Africa, including the Democratic Republic of the Congo, Republic of Congo, Central African Republic, Cameroon, Gabon, and Equatorial Guinea. To identify forest areas, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6.1 product, a combined dataset from the Terra and Aqua satellites that offers global land cover classifications at yearly intervals^{67,68}. Accessible through the Google Earth Engine (GEE)⁶⁹, the MCD12Q1 data provides 17 vegetation classifications. We used land cover for 2020 and employed the International Geosphere-Biosphere Programme (IGBP) classification scheme to define African rainforests identified as evergreen broadleaf forests. Central Africa was chosen as the primary region of interest because of its concentration of 89% of Africa's rainforests^{15,70} (Supplementary Fig. 1). Central Africa forests are increasingly threatened by deforestation⁷¹ and road expansion⁴⁰. African rainforests have demonstrated notable resilience to droughts, and the overall carbon sink has been maintained, albeit at a reduced rate relative to Amazonian and Asian forests⁷².

Windthrow detection

In the Amazon, windthrow events have been identified using a combination of Landsat spectral bands of shortwave infrared (SWIR, ~1.57–1.65 μm), near infrared (NIR, ~0.85–0.88 μm), and Red (~0.64–0.67 μm)^{20,52}, and it was uncertain whether this approach could be directly applied to African forests. In 2016, a windthrow event occurred in Cameroon, and an aerial survey via helicopter captured high-resolution photographs of the affected area; these images provided independent confirmation of this event by clearly documenting a large area covered by uprooted and snapped trees (Fig. 1a–c). These photographs were used solely to validate this specific event.

For the detection of windthrow events, we followed our previous studies in the Amazon²⁰ using the same band combinations. Windthrow events were identified based on their spectral characteristics^{20,52} and their distinctive fan shape, which emanates from a central area³² (Supplementary Fig. 5a). Spectral mixture analysis (SMA)⁷³ was applied to bands 2 to 7 from Landsat 8 for the period 2019–2020 to identify windthrow events. Image-derived endmembers of photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and shade were used. One set of endmembers was used to identify windthrow²⁰. The fractions of PV and NPV were then normalized, removing the shade endmember, resulting in PV/(PV + NPV) and NPV/(PV + NPV)⁷⁴. These were used to distinguish

between new (PV) and old (NPV) windthrow. The delineation of windthrow is described in the following paragraphs (also Supplementary Fig. 5a). Only windthrow ≥ 30 hectares were included in our analysis, consistent with studies in the Amazon^{12,52}.

Each identified windthrow was verified using Landsat imagery (16-day revisit for Landsat 5 and 7; ~8-day revisit from 2013 onward when combining Landsat 7 and 8), based on their fan-shaped pattern (diverging from a central area with scattered debris at the tail) and to distinguish them from pre-existing clearings or other disturbances, as well as to determine their timing of occurrence. When available, Sentinel-2 imagery was also used to refine event timing, given its higher revisit frequency (~5 days at the equator from the combined Sentinel-2A, launched in 2015, and Sentinel-2B, launched in 2017). This verification was carried out based on a RGB band combination, specifically SWIR, NIR, and Red bands. Using this combination, old windthrow events appear bright green due to the presence of understory and pioneer tree species reflecting more near-infrared light, while new windthrow events appear red due to high shortwave infrared reflectance resulting from exposed bare wood and soil²² (see Supplementary Fig. 5a, b).

We employed a conservative methodology to identify windthrow events. Any event for which the timing of occurrence could not be determined within five months window for its year of occurrence was excluded from our analysis. In Central Africa, where two wet seasons per year and persistent cloud cover limit clear observations, this likely underestimates event numbers but reduces the risk of misclassifying land-use change as windthrow (see Supplementary Fig. 6). However, the five-month criterion minimizes the risk of misclassifying land-use change as windthrow, because some clearings could otherwise appear similar if detected only after several months. In the Amazon, tropical grain and legume crops require more than four months to reach harvest⁷⁵, with canopy closure occurring about 75 days after planting⁷⁶. In Central Africa, given that the vast majority of forest conversion for agriculture is for small-scale cropping systems (~1–2 ha) and occurs along roads^{36,39}, and crops in larger plots are primarily perennial tree crops that require more than five months to establish sufficiently large crowns to cover bare soil after clearing (e.g., cocoa, oil palm, rubber), we believe it is unlikely that ~30 hectares of old-growth forest could be cleared and planted within about two months with a subsequent three months to establish a crop canopy and therefore appear similar to an older windthrow. This prevents us from misclassifying abrupt canopy openings caused by windthrow events compared to slower transitions associated with land conversion.

For almost all windthrow events ($n = 69$), we determined their direction by manually delineating the primary gap using a triangle to capture the fan shape (see Supplementary Fig. 5a). The direction of the windthrow was determined by tracing from the vertex (tail), marking the start of the fan-shaped pattern, to the center of the fan (Supplementary Fig. 5a), following a previous study²⁰. This approach captures the primary orientation of the windthrow. The direction was expressed using the geographic convention, where true north is 0°, and angles increase clockwise. For five windthrow events, the direction was difficult to determine due to the irregular shape of the event; we therefore delineated only a polygon encompassing the main disturbed area (Supplementary Fig. 5b).

We calculated the area of each windthrow using two approaches in GEE: a geometry-based calculation (`geometry.area()`), which measures polygon area directly, and a raster-based calculation (`ee.Image.pixelArea()`), which sums pixel areas within the polygon. Both methods were applied in EPSG:4326 (latitude/longitude), the standard for global-scale satellite datasets, and in UTM (Universal Transverse Mercator), which minimizes local distortion for local features. Since some windthrow events span several kilometers (e.g., Supplementary Fig. 5a), projection choice can affect area estimation; therefore, we calculated areas in both EPSG:4326 and UTM to evaluate the influence of projection on our results, as both projections are widely used in geospatial analyses. For each windthrow, GEE directly provides all four estimates (two methods $\times$ two projections), making it straightforward to compare them. These comparisons showed that

differences were consistently small, averaging ~0.5% of the windthrow area. We therefore report the mean across all method–projection combinations as the area estimate and use the observed ~0.5% difference as the per-event uncertainty. When propagated across the 74 windthrow events, this yielded an overall uncertainty of 4.3% for the total windthrown area.

To estimate the speed of NIR recovery, we used the average NIR reflectance from a 4×4 pixel box centered on the most disturbed area (i.e., where ΔNPV was highest). Although the Normalized Difference Vegetation Index⁷⁷ is widely used to analyze vegetation changes, NIR more effectively detects windthrow events and subsequent regrowth²² and is less prone to mixed-pixel issues because NIR reflectance better isolates the vegetation portion⁷⁸. We calculated mean NIR values for each 4×4 pixel box over the 12 months preceding and following each windthrow event. Only events with at least five months of available NIR observations within the 12-month pre-disturbance window and at least five months within the 12-month post-disturbance window were analyzed. To avoid spectral inconsistencies across sensors, we restricted the dataset to Landsat 8. As a result of these constraints and the limited temporal density of cloud-free Landsat imagery in Central Africa, only seven windthrow events met these criteria (Fig. 3d).

The analysis of Landsat images (calibrated top-of-atmosphere reflectance), Sentinel images, SMA analysis, windthrow delineation and area calculations, and regrowth were all conducted in Google Earth Engine (GEE), which provides the data, tools, and algorithms required for these tasks.

Probabilistic function

Gamma distributions of extreme rainfall events (Fig. 3a) were fitted by maximum likelihood with the location parameter fixed at zero, constraining the distribution to non-negative rainfall values and ensuring physically meaningful parameter estimates. Goodness-of-fit was evaluated using the Kolmogorov–Smirnov and Cramér–von Mises statistics^{79,80}, complemented by likelihood-based metrics, the Akaike Information Criterion-AIC⁸¹ and the Bayesian Information Criterion-BIC⁸². The fitted parameters and goodness-of-fit metrics are provided in the Supplementary Table 1.

Fitting windthrow distributions with established statistical models allows direct comparison between African and the Amazon forests, shedding light on universal scaling patterns and regional ecological differences. We identified the best statistical distribution model to characterize the size distribution of windthrow using Akaike Information Criterion (AIC, see Supplementary Table 2), a widely used metric for model selection calculated within the univariate ML 1.1.2 package in R⁸³. Our results showed that the inverse Weibull better fit our observations. Weibull distributions reflect the physical limits of extreme wind events, which are constrained by the maximum kinetic energy transferable from the atmosphere to the forest⁸⁴.

Local occurrence of windthrow events

We estimated the return intervals of windthrow events in Africa over a 30-year period by analyzing event sizes and their cumulative impact on forest cover. First, we sorted windthrow events in descending order and computed their cumulative affected area. We then calculated the annualized cumulative area by dividing by 30 years and estimated the probability of occurrence per year as the ratio of annual cumulative area to total forest area. The return interval for each event size was derived as the inverse of this probability. Finally, we visualized the relationship between windthrow size and return interval using a log-log scatter plot, providing insight into the recurrence of disturbances across different event magnitudes. We acknowledge that this calculation of return interval implicitly assumes (a) constant detectability through time, (b) windthrow events occurring across a 30-year period¹⁰, and (c) negligible spectral change due to vegetation regrowth. These factors would underestimate the affected area and overestimate the estimated return intervals. We chose this approach to ensure our results are comparable to those obtained using a similar method over the Amazon²⁵.

Following previous Amazon-wide windthrow analyses^{10,20}, we adopt a 30-year reference period solely to ensure methodological consistency and enable direct regional comparison, as using a different reference period

would preclude like-for-like comparison of return intervals across regions. This reference period does not represent a Central Africa-specific recurrence interval; therefore, the resulting return intervals should be interpreted as comparative metrics rather than absolute estimates of windthrow frequency. In Central Africa, continuous Landsat imagery suitable for windthrow detection spans less than a decade (see Supplementary Fig. 7), which is insufficient to capture the full detectability lifetime of windthrow scars given the multi-decadal forest regrowth following disturbance in Africa^{85,86}.

Mean rainfall

For the period 2001–2019, we calculated mean annual rainfall (MAR, Fig. 2b) and mean monthly rainfall (Fig. 2d) using the monthly precipitation product from the Global Precipitation Measurement (GPM) mission's Integrated Multi-satellite Retrievals for GPM (IMERG) Version 7, at 0.1° spatial resolution^{87,88}. IMERG leverages GPM's next-generation satellite observations of global rain and snow to produce consistent global rainfall estimates. It integrates data from multiple sources, including passive microwave measurements, microwave-calibrated infrared observations, and rain gauge analyses⁸⁷. MAR was computed by summing monthly precipitation per pixel over the 2001–2019 period and dividing by the number of years. Mean monthly rainfall was computed similarly for each calendar month, with pixel values averaged across the Central Africa study region. GPM IMERG data are available in GEE, and all calculations were conducted within this platform.

Extreme rainfall events

We computed the mean annual (Fig. 2b) and mean monthly (Fig. 2d) number of extreme rainfall rate events ($\geq 6 \text{ mm h}^{-1}$) using the 3-hourly precipitation product from the Tropical Rainfall Measuring Mission (TRMM) 3B42 dataset^{87,89}. The calculation was done by adding the number of rainfall rate events $\geq 6 \text{ mm h}^{-1}$ per pixel for the period 2001–2019, and dividing this total by the number of years. Mean monthly extreme rainfall events were computed similarly for each month, with pixel values averaged across the Central Africa study region. We were not aware of studies on Africa defining extreme rainfall events at the hourly time scales and associated with MCSs; therefore, we used the value of 6 mm h^{-1} for these conditions found in the Amazon⁹⁰. TRMM 3B42 data are available in GEE, and all computations were performed in this platform.

Windthrow timing and associated rainfall

For each identified windthrow, we used imagery from Landsat 5, 7, 8, and Sentinel-2 to estimate the most probable time of occurrence. Events that could not be dated within a one-month window were excluded from our analysis, as we could not confidently link them to a specific rainfall event. In total, 33 windthrow events met this criterion. Windthrow events that occurred within a one-week window were grouped and labeled as Week 1, and a similar procedure for Week 2, Week 3, or Week 4. For each of these weeks, we obtained the corresponding instantaneous 30 min rainfall rates from the Integrated Multi-satellite Retrievals for GPM (IMERG) Half Hourly 0.1 degree $\times$ 0.1 degree V07 data^{87,91}. These data are available in GEE, and all analyses were conducted on this platform.

Data availability

All data supporting the findings of this study are freely available from the sources cited in the manuscript.

Code availability

All analyses were performed using standard Google Earth Engine (GEE) functionality with simple scripts that can be easily reproduced by following the methods described in the manuscript. Because the analyses rely solely on basic GEE operations, equivalent workflows can be readily generated using publicly available tools or AI-assisted code generation.

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Author contributions

R.N.J. and Y.F. conceived and designed the study. R.N.J., Y.F., and J.U.M. analyzed the data and produced the figures. R.N.J., Y.F., J.U.M., D.M.M., M.K., E.O., and D.S. contributed to writing the manuscript. R.N.J., Y.F., M.K., E.O., and D.S. revised and edited the final version.

Competing interests

The authors declare no competing interests.

Additional information

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