

Beyond burned area: multidimensional fire monitoring reveals a staged transition in the Xingu region, Brazilian Amazon, 1985–2025

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Abstract

Fire in tropical forest frontiers is usually summarized through annual burned area, although the amount that burns, the size structure of burn scars, the seasonal timing and the cover types affected need not reorganize together. We tested this in the Xingu Integration Region, Pará, Brazil (250,792 km²), using forty-one years of 30-m Landsat burned-area and land-cover mapping (1985–2025) with climate, terrain and tenure data, combining change-point detection, circular statistics, index decomposition and two-stage random-forest modelling. Burned area shifted upward in 1996 (95% confidence interval 1996–2002), whereas dominance by scars of 10,000 ha or more shifted only in 2009 (2006–2013); the intervals do not overlap. Scars exceeding 50,000 ha occurred only in 2024. The burning season advanced by 0.99 months (0.15–1.83) and became more concentrated. Between the first and last decades, 51.4% of the increase was attributable to land-cover compositional change and 48.6% to higher class-specific burn rates; rate intensification within forest alone contributed 23.5% of the regional increase, from a contracting cover type. Land cover dominated the prediction of occurrence; accessibility overtook it for conditional magnitude at the 100-ha threshold. Predictive information associated with land tenure was largely inseparable from land cover: its unique contribution was not distinguishable from zero. The novelty is not that fire increased but that its components reorganized at different times and responded to different predictor structures. Monitoring should track these components separately rather than treat total burned area as a sufficient indicator of change.

Introduction

Fire in tropical forest frontiers is not simply becoming more extensive. Over recent decades, records from the Amazon, the Congo basin and insular Southeast Asia describe changes in the size distribution of individual events, in the timing and duration of the burning season, in the frequency with which the same ground burns again, and in the vegetation types affected (Field et al., 2016; Aragão et al., 2018; Andela et al., 2019; Tyukavina et al., 2022). These are distinct phenomena with distinct drivers, and they do not necessarily move together. A landscape can burn over a larger area without any change in how often a given hectare burns, if flammable cover has expanded. It can shift from many small fires to few large ones without any change in total area. It can burn earlier in the year without burning more.

Environmental monitoring nonetheless summarizes fire predominantly through annual burned area. Multi-decadal Landsat-based burned-area records are increasingly available at tens-of-metres resolution, and the metric underpins emissions inventories, protected-area effectiveness assessments and national reporting (van der Werf et al., 2017; Chuvieco et al., 2019; Long et al., 2019; Alencar et al., 2022). Its limitation is that it aggregates the processes above into a single number, and the aggregation is not neutral: two regions with identical burned-area trends can be undergoing entirely different transformations, requiring different responses.

Three conflations recur in regional fire assessments, and each has a methodological remedy that existing data already support.

The first is between monotonic trend and regime change. Regional assessments sometimes use long-term trend evidence in support of broader claims of fire-regime change (Archibald et al., 2013; Bowman et al., 2020; Jones et al., 2022). A trend test establishes that a series is increasing; it does not identify whether the increase was gradual or whether the system reorganized at discrete points. Formal change-point methods answer the second question, and applying them to several dimensions of the regime rather than to burned area alone reveals whether those dimensions changed together or in sequence — a distinction that is invisible in the aggregate and consequential for how monitoring is designed.

The second is between expansion of flammable cover and intensification of burning. Where forest has been converted to pasture at scale, burned area rises partly because more of the landscape is now the kind of surface that burns annually. Attributing the whole increase to intensified fire overstates the change in fire behaviour and misdirects the response toward ignition control when the operative process is conversion. Index decomposition methods, originally developed for energy and emissions accounting (Ang & Liu, 2001; Ang, 2005, 2015), provide an exact separation of the two, requiring only an annual burned-area product and a matching land-cover product. We adapt that framework to burned-area attribution, decomposing the change into an extent effect and a class-specific rate effect.

The third is between the occurrence of fire and its magnitude. Burned-area panels at landscape resolution contain a high proportion of zeros: most cell-years contain no mapped burning. A single regression on such data models a mixture of two processes — whether any mapped burning occurs within a cell, and how much burns conditional on occurrence — and reports one set of predictor importances for both. If those processes respond to different conditions, the mixture obscures both. Two-part formulations separate them and are well established in ecology (Cragg, 1971; Martin et al., 2005; Blasco-Moreno et al., 2019), but have received much less attention in burned-area attribution.

These remedies exist individually; their combined application within a single monitoring framework does not. We apply them jointly to a long, high-resolution record in a setting where land-cover transformation, environmental gradients, accessibility and territorial heterogeneity coexist at scales that permit their separate evaluation, and show what this integration reveals that aggregate burned-area monitoring conceals.

The Xingu Integration Region in the eastern Brazilian Amazon offers that setting. Four decades of consistent 30-m mapping cover a period during which pasture extent grew more than seventyfold while forest area contracted substantially, providing the contrast needed to separate fuel expansion from rate intensification. The region spans eight degrees of latitude, from dense humid forest in the north to the cerrado–forest transition in the south, so that fire can be examined against contrasting environmental backgrounds within a single administrative unit. Two federal highways structure access, and settlement was organized around them, providing a strong accessibility gradient that enters the models as a set of variables distinct from the environmental ones. Land tenure forms a heterogeneous mosaic in which Indigenous Territories, conservation units, rural settlements, public glebas and unregistered land occupy large and contiguous shares of the same region, allowing territorial contrasts to be examined across

substantial areas rather than at scattered margins. And the series contains an extreme year near its end, which makes robustness to the end of the series a necessary test rather than an optional one.

We assembled the full 1985–2025 burned-area record for the region and analysed it with change-point detection, circular statistics, index decomposition and a two-part model on a hexagonal panel of 2,561 cells.

The study addresses three questions:

Was the four-decade fire-regime reorganization simultaneous across dimensions, or staged through time? We test for breakpoints in fire quantity, in the size structure of events, in seasonal timing and in the cover composition of burning, and ask whether their confidence intervals coincide.

How much of the increase in burned area reflects a larger flammable landscape, and how much reflects more frequent burning within it? We decompose the change by cover class and quantify, in particular, how much of the regional increase arises from rising burn rates within forest that is simultaneously contracting.

Do fire occurrence and fire magnitude respond to the same conditions? We model them separately across three detection thresholds and compare the contribution of climate, topography, accessibility, land cover and land-tenure configuration to each, using block-level procedures appropriate to correlated predictors.

Throughout, we describe land-tenure categories as a spatial configuration rather than as governance, and use *land-tenure configuration* in preference to terms that imply institutional capacity. The data record where categories are and what burned within them; they do not record institutions, management practices, enforcement capacity or the decisions of the people who live in these territories. Inferences about why categories differ, and prescriptions about how any of them should be managed, would require evidence this study does not contain.

Materials and methods

Study area

The Xingu Integration Region (Região de Integração do Xingu, hereafter XIR) covers 250,792 km² in the state of Pará, eastern Brazilian Amazon, and comprises ten municipalities: Altamira, Anapu, Brasil Novo, Medicilândia, Pacajá, Placas, Porto de Moz, Senador José Porfírio, Uruará and Vitória do Xingu (Fig. 1). Altamira alone accounts for 159,533 km², making the region strongly asymmetric in municipal size and extending it across roughly eight degrees of latitude, from 1.5° S to 9.6° S.

This latitudinal span produces a marked environmental gradient. The northern and central portions are dominated by dense ombrophilous forest under a humid climate with a short dry season, whereas the southern portion grades into the cerrado–forest transition, where naturally open and more fire-adapted vegetation formations become increasingly important. Background fire dynamics in these formations

differ from those of closed-canopy forest, and any regional analysis has to contend with that contrast; we return to it when interpreting spatial patterns.

The region is structured by two federal highways. The BR-230 (Transamazônica) crosses it east–west and has organized settlement since the 1970s, with rural settlement projects laid out perpendicular to the road. The BR-163 runs along the western margin. Land tenure forms a heterogeneous mosaic: Indigenous Territories occupy 38.4% of the territory, conservation units 29.0%, rural settlements 9.8%, and public glebas and unregistered land together 11.7%.

Data sources

Burned area was obtained from MapBiomas Fire Collection 5 (Alencar et al., 2022), an annual 30-m product derived from Landsat imagery covering 1985–2025. Land cover came from MapBiomas Collection 11 (Souza et al., 2020), at the same spatial resolution and for the same period; both collections were accessed in August 2026 through Google Earth Engine (Gorelick et al., 2017). Land tenure was taken from the 2025 Cartas da Terra land-tenure raster (Instituto para Governança Territorial e Políticas Públicas [iGPP], 2026), a nationally consistent reconstruction of tenure categories from cadastral, land-reform and protected-area registries. The layer has a 2025 reference year and is documented in a technical note published in 2026; the citable release is iGPP (2026). The raster processed here is the April 2025 release, deposited with the analysis code. Topography was derived from SRTM (30 m; Farr et al., 2007). Precipitation came from CHIRPS daily estimates (Funk et al., 2015) and atmospheric variables from ERA5-Land monthly aggregates (Muñoz-Sabater et al., 2021). The federal highway network was obtained from the DNIT georeferenced transport base (DNIT, n.d.) and municipal boundaries from the 2024 municipal mesh (IBGE, 2025).

The dry season was defined as June to November inclusive for all climate variables. Dry-season precipitation was summed over that window. Vapour pressure deficit was computed monthly from 2-m air temperature and dewpoint temperature using the Tetens–Magnus formulation, and then averaged across the window; computing the deficit from period-mean temperatures would underestimate the mean because saturation vapour pressure is convex in temperature.

Regional and hexagon-level climate variables were generated from the same monthly computation and the same June–November window, so that a single definition of dry-season vapour pressure deficit applies throughout the study.

Metric definitions

Burned area can be summarized in ways that are not interchangeable. We therefore distinguished three metrics and assigned each to a specific analytical purpose, using no metric outside that purpose.

Spatial union is the set of pixels that burned at least once in 1985–2025, each counted once: 38,341 km², or 15.29% of the region. It is used for statements about how much territory was ever affected, and for the recurrence analysis.

Annual sum is the sum of annual burned areas, allowing reburning between years: 86,147 km². It is derived from the land-cover-stratified product and is the only metric that resolves burned area by cover class. It is used for trends, change-point analysis and the decomposition.

Monthly sum is the equivalent total from the monthly product: 86,147 km². It is used for seasonality and circular statistics.

The annual and monthly totals agree to less than 0.001 km² across the series, so the two sources are interchangeable for every purpose in this study.

Forest was defined throughout as the combined extent of Forest Formation and Floodable Forest (MapBiomas classes 3 and 6), applied identically in the land-cover decomposition and in the hexagonal panel. This definition is narrower than the MapBiomas level-one Forest class, which additionally aggregates Savanna Formation (class 4), Mangrove (5) and Wooded Sandbank Vegetation (49). Savanna Formation carries a naturally recurrent fire regime, and including it would conflate anomalous fire in dense forest with expected fire in open formations — precisely the distinction this study sets out to make. The narrower definition is therefore adopted deliberately rather than as one of several equivalent options. Because alternative aggregations yield materially different intensification ratios, the definition is stated here and applied without variation throughout.

Savanna Formation (class 4) was retained as a separate reporting class and pasture corresponds to class 15. Cropland comprises all leaf-level temporary and perennial crop classes of Collection 11; two classes within the Farming level-one group are excluded from that aggregate. Forest Plantation (9) is mapped in the region but covers 23 km² across the whole series and was retained as a separate class rather than grouped with crops. Mosaic of Uses (21) is mapped in the region in Collection 11 and enters the decomposition as its own reporting class (Table 4); as a mixed-use class rather than a crop class, it was likewise retained outside the cropland aggregate. This aggregation defines the cropland predictor of the hexagonal panel only; the decomposition described below operates on the full set of level-two classes independently and does not depend on it.

Trend and change-point analysis

Monotonic trend in annual burned area was tested with the Mann–Kendall statistic (Mann, 1945; Kendall, 1975) and quantified with the Theil–Sen slope estimator (Sen, 1968) and its 95% confidence interval. Because the raw series is serially correlated (lag-1 autocorrelation 0.441), we also applied the Hamed and Rao (1998) variance correction. The resulting variance-correction factor was 1.000, so the corrected and uncorrected Mann–Kendall statistics are identical.

Monotonic trend does not establish a change of state, and we therefore tested for formal breakpoints. Two methods were used, with different inferential status. The non-parametric Pettitt (1979) test, which detects a shift in location without assuming a functional form, provides the primary inference. Segmented regression with a single breakpoint and a minimum segment length of five years was

computed as a descriptive comparison against the linear model; because its breakpoint is selected by exhaustive search over candidate years, the associated F statistic does not account for selection uncertainty and is not interpreted as a test. A 95% confidence interval for the break year was obtained by bootstrap under the alternative hypothesis, and refers throughout to the Pettitt estimate rather than to the segmented-regression breakpoint. The Pettitt break was estimated on the observed series; the mean of each resulting segment was fitted; residuals were resampled with replacement within segments; and the Pettitt break was re-estimated on each of 1,000 reconstructed series. Intervals are the 2.5th and 97.5th percentiles of the replicate distribution. Moving-block bootstrap was not used because block resampling destroys the two-regime structure the interval is meant to characterize.

Five dimensions of the fire regime were tested independently: fire quantity, as $\log(\text{annual burned area} + 1)$; large-scar dominance, as the annual share of burned area in scars $\geq 10,000$ ha; small-scar dominance, as the share in scars < 250 ha; the cover composition of fire, as the share of burned area in pasture; and seasonal timing, as the annual weighted circular mean month. Scars are annual units mapped from Landsat composites and clipped to the region: a single scar may aggregate fires unrelated in origin, so these classes describe mapped burn scars rather than individual fire events.

Both tests were applied to each dimension. Robustness to the end of the series – which contains the extreme year 2024 in its penultimate position – was assessed by re-estimating the Pettitt breakpoint on series truncated at 2024, 2023 and 2022.

Seasonal analysis

Month is a cyclical variable: December is adjacent to January, and a linear centre of gravity is therefore an inappropriate summary that underestimates displacement when the fire season straddles the calendar year. Seasonal timing was summarized with the area-weighted circular mean, obtained from the resultant vector of monthly burned area, and with the mean resultant length R , which measures the concentration of burning around that mean and ranges from zero (uniform across months) to one (all burning in a single month).

Three tests were applied. The Watson–Williams F test (Watson & Williams, 1956) compared the circular means of the two halves of the series, 1985–2004 and 2005–2025. The test assumes von Mises samples with a common concentration and is considered reliable only where the pooled mean resultant length exceeds about 0.45; the pooled mean resultant length was 0.935, well above that floor. Mardia's circular–linear correlation (Mardia, 1976) tested association between the annual circular mean and year, with the statistic $n \cdot r^2$ referred to a chi-squared distribution with two degrees of freedom. The Theil–Sen estimator was applied to the annual circular mean to quantify displacement per decade with a confidence interval. Annual circular means are expressed on a linear axis running from 0.5 to 12.5 months, so that a mean falling in early January sits adjacent to December, as it does on the circle, rather than at the opposite end of the axis. The annual means span 3.97 months, less than half a period, so the axis is unambiguous and no unwrapping is required before the linear tests.

Decomposition of burned-area change

Aggregate burned area can rise because more flammable land cover exists or because a given cover type burns more often. To separate these, we applied an additive Logarithmic Mean Divisia Index decomposition (Ang & Liu, 2001; Ang, 2015), expressing burned area as the sum across cover classes of the product of class extent and class-specific burn rate:

$$BA = \sum_c (E_c \cdot r_c), \text{ where } r_c = BA_c / E_c$$

The change between two periods decomposes exactly into an extent effect and a rate effect, weighted by the logarithmic mean of initial and final burned area by class. A three-factor form, separating total mapped area from compositional structure, was also computed. The decomposition is exact by construction; residuals below 1 km² yr⁻¹ confirmed correct implementation.

Because the result depends on the comparison windows, four window pairs were evaluated: the first and last years of the series (1985 and 2025); the first and last decades (1985–1994 and 2016–2025); the first and last five-year periods (1985–1989 and 2021–2025); and the first decade against 2014–2023, which excludes both the extreme year 2024 and the final year. The decomposition was computed both in aggregate and by cover class, the latter being necessary to distinguish compositional change in general from pasture expansion specifically.

The decomposition uses the thirteen level-two classes present in both the extent and burned-area products, together accounting for 99.999% of mapped extent; the single excluded class (aquaculture) covers 0.2 km² in 2024.

Spatial patterns and land-tenure contrasts

Spatial analyses were conducted on a regular hexagonal grid of 2,561 cells of mean planar area 106.1 km². All areas and distances were computed in the Albers Equal Area Conic projection for Brazil on the SIRGAS 2000 datum (standard parallels 2° S and 22° S, latitude of origin 12° S, central meridian 54° W, GRS80 ellipsoid), the convention adopted by the Brazilian national land-cover and deforestation monitoring programmes. This projection reproduces true ellipsoidal (GRS80) cell areas to within 1.4 × 10⁻⁵ km² per cell.

The grid is a regular hexagonal tessellation of whole cells and covers the region completely; cells at the margin extend beyond the regional boundary. Burned area in the panel is therefore computed within the intersection of each cell with the region, and panel totals are not interchangeable with regional totals.

Two area conventions coexist. Cell areas as exported from Earth Engine are geodesic areas on the authalic sphere of GRS80 rather than on the ellipsoid, and are on average 0.44% larger than the planar areas; the difference is a choice of reference surface rather than error and varies systematically with latitude. The planar convention is used throughout the panel, including the variable submitted to Local Moran's I: burned area in each cell is the burned fraction of the cell's area within the region multiplied by

the planar area of that intersection, and incidence divides it by the same planar area, so numerator and denominator share one definition; the exported geodesic areas are retained only as a diagnostic column. All ratios, category contrasts and classification metrics reported from the panel are invariant to the convention; only absolute burned-area totals are affected, and these are already stated as non-interchangeable with regional totals, which follow the pixel-area convention of the Earth Engine exports.

Spatial clustering was assessed with Local Moran's I (Anselin, 1995) on the cumulative burned footprint of each cell divided by the area of the cell lying within the region. The denominator matters at the boundary: cells cut by the regional limit extend over ground where burning is not counted, and on the absolute footprint they would appear artificially cold. The 7 cells with less than 0.1% of their area inside the region, excluded from the panel for the same reason, were excluded here as well, leaving 2,554 cells. Spatial weights were defined by a binary distance band applied to cell centroids and row-standardised, with sensitivity across bands of 25, 50 and 75 km. Significance was assessed by 999 conditional permutations with a fixed random seed. Because the local statistic applies one test per cell, testing 2,561 cells at a nominal 5% level would yield approximately 128 false positives in expectation under the global null, results are reported both nominally and after Benjamini–Hochberg false-discovery-rate correction (Benjamini & Hochberg, 1995). Cluster counts were also computed on the absolute footprint as a sensitivity check: at 50 km it yields 701 high–high and 1320 low–low cells after correction, against 709 and 1346 on the normalized variable, and a global Moran's I of 0.541 against 0.578.

Cumulative fire exposure by tenure category was summarized with a vulnerability index, defined as the ratio between a category's share of cumulative burned area and its share of territory, so that unity indicates burning proportional to extent. Two estimators were computed and are reported separately because they answer different questions and are not interchangeable. The area-based estimator uses pixel-level intersection of burned area and tenure category, and the dominant-hexagon estimator assigns each cell to the tenure category with the largest areal share within it and aggregates at cell level; it is the estimator to which the hexagonal panel and the clustering analysis correspond. A cell was assigned a dominant category only where the eight mapped categories jointly covered at least half of its area, since a largest share of a mostly unmapped cell does not establish dominance; 33 of 2,561 cells fell below this threshold; they are excluded from the vulnerability index and its bootstrap, and carried as an unreported residual class in the cluster-by-tenure cross-tabulation, where they remain in the denominators. Confidence intervals for the dominant-hexagon estimator were obtained from 1,000 bootstrap replicates over square spatial blocks of 50 km side, resampled with replacement, rather than over individual cells, since neighbouring cells are not independent and resampling them independently would produce intervals that are too narrow; intervals are the 2.5th and 97.5th percentiles of the replicate distribution. No interval is reported for the area-based estimator, which cannot be resampled spatially from the available tabulation.

Predictive modelling of fire occurrence and magnitude

A hexagon-year panel was assembled comprising 105,001 observations (2,561 cells × 41 years) and nineteen predictors grouped into five blocks: climate (dry-season vapour pressure deficit and precipitation, 2 variables), topography (mean elevation and slope, 2), accessibility (distance from the cell centroid to the BR-230, to the BR-163 and to the nearest municipal seat, 3), land cover (areal shares of pasture, forest, cropland and savanna, 4) and land tenure (areal shares of the eight analytical categories, 8). Thirty-three cells in which the eight tenure categories jointly covered less than half the cell area were assigned to a residual class, and a further seven whose intersection with the region was negligible were excluded, leaving 103,361 observations across 2,521 cells.

Land cover and climate vary annually; topography, accessibility and tenure are time-invariant. Tenure shares are compositional and, together with the excluded residual, sum to unity within each cell; all eight are retained. Tree-based ensembles do not require a reference category, and omitting one share would discard potentially predictive information without providing the interpretive benefit that a reference level confers in a regression.

Zero burned area was recorded in 63.8% of panel observations, with the proportion varying from 16% to 85% across tenure categories. A hurdle formulation (Cragg, 1971; Mullahy, 1986) was therefore fitted to test whether predictor blocks contribute differently to fire occurrence and to conditional magnitude. The first stage modelled the probability that burned area exceeds a threshold T using random forest classification (Breiman, 2001); the second modelled $\log(\text{burned area} + 1)$ conditional on exceeding that threshold, on the same scale as the single-model regression, so that the two are directly comparable. Three absolute thresholds were used: $T = 0$, taken as the primary analysis and corresponding to any detected burning, with $T = 0.1 \text{ km}^2$ and $T = 1 \text{ km}^2$ — that is, 10 ha and 100 ha — as sensitivity analyses. Thresholds are expressed as absolute burned area rather than as a fraction of cell area, because the area of each cell falling within the region varies for cells at the regional boundary.

The occurrence stage was evaluated by area under the ROC curve, area under the precision–recall curve reported alongside the positive-class prevalence that forms its baseline, Brier score, balanced accuracy and the confusion matrix at a 0.5 cut-off; probability calibration was assessed by comparing mean predicted probability with observed frequency within deciles of predicted probability. For the magnitude stage, root mean squared error is reported on the modelling scale and, after back-transformation, in km^2 . Because the response is $\log(BA + 1)$, the back-transformation with Duan's (1983) smearing estimator s is $BA = \exp(\hat{y}) \cdot s - 1$. Identical spatio-temporal partitions were used for both stages and for all three thresholds, and performance is reported for the single held-out spatio-temporal test set.

A single random forest regression on log-transformed burned area, $\log(\text{burned area} + 1)$, fitted to all observations, is reported alongside the two stages as a comparison and is the model on which the block-level contribution analysis below is computed. Model performance was evaluated under three partitioning regimes rather than one, following the case for validation structured by the dependence in the data (Roberts et al., 2017; Ploton et al., 2020). The temporal regime withholds a random 30% of years, so that test observations are unseen years in known locations. The spatial regime withholds a

random 30% of cells, giving unseen locations in known years. The spatio-temporal regime withholds both simultaneously, and its test set comprises only observations in cells and years both absent from training. The third is the most demanding, and is the only regime used for the attribution results reported here, because time-invariant predictors allow a model to learn cell identity when the same cells appear in both partitions. Partitions were drawn once with a fixed seed and reused unchanged across every model, so that differences between models cannot arise from partitioning.

All forests, in both the attribution models and the two hurdle stages, used a single fixed configuration (500 trees, maximum depth 30, minimum leaf size 2, bootstrap resampling, seed 42), with squared-error splitting for regression and Gini impurity for classification.

Because the comparisons of interest are between predictor sets evaluated on identical partitions rather than between tuned configurations, no hyperparameter search was performed; this also avoids the spatial leakage that arises when tuning folds are drawn by randomly shuffling cell-year rows.

Because the predictors are strongly correlated – tenure shares are compositional and covary with land cover – individual permutation importance measures redundancy rather than irrelevance (Strobl et al., 2008), and can be negative when permuting a variable improves held-out performance. Predictor-block contributions were therefore evaluated with two complementary procedures. Block ablation fitted models on nested predictor sets and compared their performance on the common test set. For the two blocks of interest – land cover C and land tenure T , both conditional on a baseline B comprising climate, topography and accessibility – the increments were combined into a two-block predictive commonality decomposition (Ray-Mukherjee et al., 2014):

$$U_C = R^2(B + C+T) - R^2(B + T)$$

$$U_T = R^2(B + C+T) - R^2(B + C)$$

$$S_{CT} = R^2(B + C) + R^2(B + T) - R^2(B) - R^2(B + C+T)$$

where U denotes the unique contribution of a block and S the contribution shared between them. The decomposition is symmetric in C and T and does not depend on the order in which blocks are introduced, but it is conditional on B being present in every model, and this conditioning is stated wherever the values are reported. It partitions predictive performance, not variance in any causal sense.

Grouped permutation importance permuted all variables within a block simultaneously and recorded the resulting loss in performance, averaged over ten repetitions. The scoring function was the coefficient of determination for regression models and the area under the ROC curve for classification models, specified explicitly rather than left to the default, which for classifiers is accuracy and is misleading under class imbalance. Direction of effect was assessed with accumulated local effects (Apley & Zhu,

2020), which remain interpretable under correlated predictors, rather than with partial dependence, which extrapolates into combinations of predictor values that do not occur.

Software and reproducibility

Analyses were performed in Python 3.9.16 using numpy 1.23.5, pandas 1.5.3, scipy 1.10.0, scikit-learn 1.2.1 (Pedregosa et al., 2011), geopandas 0.12.2, and libpysal 4.8.1 with esda 2.5.1 (Rey & Anselin, 2010). Satellite data were processed in Google Earth Engine. All random procedures used seed 42 unless otherwise stated.

Analysis scripts, frozen metric definitions and an audit manifest recording input file hashes, library versions and the analytical source of each reported quantity are available at <https://doi.org/10.5281/zenodo.22082084>. All reported quantities were recomputed from source-precision values; derived statistics were never computed from figures rounded for presentation.

Results and discussion

A staged reorganization of the fire regime

Between 1985 and 2025, annual burned area in the XIR summed to 86,147 km². Because fire recurs, the spatial union of all burned pixels is much smaller: 38,341 km², or 15.29% of the region. Roughly one seventh of the territory burned at least once over four decades and a year, and within that footprint reburning is the norm rather than the exception — 45.85% of the burned footprint burned exactly once and **54.15% burned two or more times**, with a maximum of 39 fire years recorded in a single 30-m pixel. Nearly one tenth of the footprint (9.69%) burned five times or more.

Annual burned area increased monotonically across the series (Mann–Kendall $Z = 5.36$, $p < 10^{-6}$). The Theil–Sen slope was 91.0 km² yr⁻¹ (95% CI 61.0–128.2) and the least-squares slope 114.6 km² yr⁻¹ ($R^2 = 0.464$), the difference reflecting the leverage of extreme years on the least-squares fit. Lag-1 autocorrelation of the raw series was 0.441; the Hamed–Rao variance-correction factor was 1.000, leaving the test statistic unchanged.

Mean annual burned area rose from 450 km² yr⁻¹ in 1985–1989 to 5,002 km² yr⁻¹ in 2021–2025, an 11.1-fold increase. This ratio is strongly dependent on the comparison window (Table 1). Comparing first and last decades gives 9.0-fold; the pre-2024 windows give 10.2-fold on quinquennia (2019–2023) and 8.0-fold on decades (2014–2023). The estimate therefore ranges from 8.0- to 11.1-fold across comparison windows, and the decomposition below separates the processes the ratio aggregates.

Table 1
Sensitivity of the intensification ratio to the comparison window

Comparison	Ratio
First and last five-year periods (1985–1989, 2021–2025)	11.11
First and last decades (1985–1994, 2016–2025)	8.96
Pre-2024 five-year window (2019–2023)	10.17
First decade against 2014–2023	8.00

Monotonic increase, however, is not a change of regime, and the distinction matters because studies of tropical fire routinely infer the latter from the former. We therefore tested for formal breakpoints in five independent dimensions (Table 2). All five returned significant breaks, and the breakpoints are largely insensitive to the end of the series: of 20 combinations of dimension and truncation, 16 return the full-series year unchanged, and the pasture and seasonal breaks do not move at all. The burned-area break is the exception and is reported as such: it falls in 1996 for the full series and moves to 1999 when 2025 is removed, returning to 1996 under earlier truncations, so the estimate is sensitive to a single terminal year.

Table 2
Change-point tests across dimensions of the fire regime

Dimension	Pettitt	p	Segmented breakpoint	Bootstrap 95% CI
log(annual burned area + 1)	1996	0.0006	2006	1996–2002
Share of area in scars $\geq 10,000$ ha	2009	0.0037	2013	2006–2013
Share of area in scars < 250 ha	2003	0.0006	2019	1999–2007
Share of burned area in pasture	2004	0.000026	1995	2002–2007
Circular mean fire month	2002	0.0162	2003	1996–2009

The breakpoints do not coincide (Fig. 2). The bootstrap interval for the burned-area break (1996–2002) does not overlap that for the share of area in large scars (2006–2013), placing more than a decade between the two point estimates. Fire quantity changed first; the size structure of fire changed later. This is the central temporal result, and it is why we describe the change as a **staged transition** rather than a regime shift: the system did not move between states at one moment but reorganized in sequence, with an increase in burned area in the mid-1990s followed by a restructuring of the burn-scar size distribution in the late 2000s.

The size structure shifted progressively and substantially. Scars smaller than 250 ha accounted for 75.32% of burned area in 1985–1994, falling to 68.62%, 59.86% and 40.37% in successive windows,

while scars of 5,000 ha or more rose from 0.22% to 4.20%, 8.51% and 29.28%. Fire moved from many small events to fewer large ones.

The extreme tail, however, appeared only at the very end. Scars of 10,000 ha or more – the class whose dominance changed formally in the late 2000s (Table 2) – represented 57.6% of burned area in 2024, against a maximum of 22.3% in any other year of the series. Scars exceeding 50,000 ha occurred in a single year of the 41, 2024, when they accounted for 45.4% of that year's 10,216 km². Both extremes postdate the 2009 large-scar breakpoint by more than a decade, so 2024 amplified a restructuring of the burn-scar size distribution that was already under way rather than initiating it.

The non-coincident breakpoints show that long-term fire monitoring should track both total burned area and the distribution of burn-scar sizes.

An earlier and more compressed fire season

Fire in the region is sharply seasonal. Between August and December fell 87.80% of cumulative burned area, against 3.76% between February and May, with a minimum in April (0.64%, 556 km²).

Seasonal timing shifted earlier across the series (Fig. 3). The area-weighted circular mean month moved from 10.56 (November) in 1985–1994 to 9.45 (September) in 2005–2014, remaining at 9.49 in 2015–2025; the modal peak month shifted from November to September between the second and third decades (Table 3). Across the full series the Theil–Sen slope on the annual circular mean was – 0.248 month per decade (95% CI – 0.457 to – 0.037), a total displacement of **0.99 months** (95% CI 0.15–1.83). The shift was significant under a Watson–Williams comparison of the two halves of the series ($F = 10.91$, $p = 0.0021$) and under Mardia's circular–linear correlation against year ($r = 0.435$, $p = 0.0208$).

Table 3
Circular seasonal statistics by period

Period	Circular mean month	R	Modal peak
1985–1994	10.56 (Nov)	0.653	Nov
1995–2004	10.19 (Oct)	0.595	Nov
2005–2014	9.45 (Sep)	0.728	Sep
2015–2025	9.49 (Sep)	0.708	Sep

The season also became more concentrated (Table 3). The mean resultant length R , which measures how tightly burned area clusters around the seasonal mean, rose from 0.606 in 1985–2004 to 0.713 in 2005–2025, a trend of + 0.020 per decade. Fire did not simply move earlier: a larger annual burned area is now delivered within a narrower window.

The two changes compound operationally. An earlier and more concentrated season compresses the window in which prevention and suppression resources must respond, and shifts it away from the

historical centre against which deployment schedules, equipment staging and burning-restriction calendars are typically set.

As a methodological sensitivity check, treating calendar month as a linear variable returns a non-significant change-point ($p = 0.242$), because January burning in the early decades pulls a linear mean toward the start of the year across a discontinuity that has no meaning for a cyclical variable. The distortion is substantial enough to reverse the conclusion, and circular statistics are therefore not an optional refinement for seasonal fire timing.

Pasture expansion and forest burn-rate intensification act through different pathways

An aggregate increase in burned area can arise because more flammable land cover exists, or because a given cover type burns more often. These have different implications and different policy responses, and the distinction is rarely made explicit in regional fire assessments. We separated them by index decomposition.

Land-cover change over the period was dominated by forest-to-pasture conversion. Pasture extent grew from 424 km² in 1985 to 32,224 km² in 2025, a 76-fold increase. Forest contracted from 239,659 km² to 205,707 km². Forest loss (– 33,952 km²) and pasture gain (+ 31,799 km²) are of similar magnitude, differing by 6.8%, which is consistent with widespread forest-to-pasture conversion, although aggregate area balances alone do not establish one-to-one transitions.

Comparing first and last decades ($\Delta = 3,896 \text{ km}^2 \text{ yr}^{-1}$), the decomposition attributed **51.4% of the increase to land-cover compositional change and 48.6% to increased burn rates**, with a residual below 1 km² yr⁻¹. Under the five-year windows used for the headline ratio the split was 54.0% / 46.0%; under the pre-2024 window (2014–2023), 55.6% / 44.4%. Approximately half of the rise in burned area therefore reflects the existence of more pasture rather than more intense burning — a result that cannot be recovered from the aggregate series.

The class-level decomposition (Table 4, Fig. 4) shows that the two components are distributed very unevenly.

Table 4
Decomposition of the change in mean annual burned area by land-cover class, first to last decade ($\text{km}^2 \text{yr}^{-1}$)

Class	Extent effect	Rate effect	Total	% of Δ
Pasture	1,879	530	2,408	61.8
Forest (classes 3 and 6)	-60	916	856	22.0
Mosaic of uses	171	235	406	10.4
Savanna formation	-3	133	129	3.3
Other classes	19	78	96	2.5
Total	2,004	1,892	3,896	100

Pasture accounted for 61.8% of the increase, of which 78% derived from area expansion and 22% from higher burn rates. Mosaic of uses accounted for 10.4%, exceeding savanna formation. Forest contributed a net 22.0% **despite losing area**: contraction of extent contributed $-60 \text{ km}^2 \text{yr}^{-1}$, while intensification of burning within remaining forest added $+916 \text{ km}^2 \text{yr}^{-1}$. **Rate intensification within forest alone therefore accounts for 23.5% of the total regional increase** — close to a quarter, delivered by a cover type that shrank by $33,952 \text{ km}^2$ over the same period.

Burn rates diverged sharply between cover types. Between first and last decades, mean annual burn incidence rose from 0.086% to 0.506% yr^{-1} in forest, a **5.8-fold increase**, against 5.34% to 9.23% yr^{-1} in pasture, a 1.7-fold increase. The forest figure is sensitive to specification — 5.9- and 6.6-fold under alternative forest definitions, and **3.8-fold under the pre-2024 window** — but exceeds pasture intensification by at least a factor of two under every specification tested.

Aggregate burned-area trends are not comparable across regions with different conversion histories: a region that has converted extensively will show rising burned area largely through fuel expansion, while a region that has not may show a similar trend through intensification alone. Reporting the aggregate without decomposition conflates the two, and the policy responses they imply — controlling conversion versus controlling ignition and degradation — are different. The decomposition applied here requires only an annual burned-area product and a matching land-cover product, both of which are now available for most tropical forest regions.

The forest result connects to the recurrence pattern reported above, where more than half the burned footprint burned at least twice. Rising burn rates within a contracting forest area, combined with widespread regional recurrence, are consistent with the positive fire–degradation feedback documented for Amazonian forests (Cochrane & Laurance, 2008; Silv rio et al., 2013; Brando et al., 2014; Alencar et al., 2015), although the present analysis does not establish that the forest cells with rising rates are the same cells that burned repeatedly.

Climate association differs by temporal scale

Dry-season vapour pressure deficit correlated strongly with annual burned area (Spearman $\rho = 0.637$, $p < 10^{-5}$; Pearson $r = 0.661$). Because both series trend upward across the period, we also report detrended coefficients. After detrending, the VPD association weakened substantially and was no longer significant under either estimator ($\rho = 0.257$, $p = 0.105$; $r = 0.304$, $p = 0.054$). A leave-one-out analysis confirms the fragility of the detrended association: omitting each year in turn, the Spearman coefficient was significant in only 1 of the 41 omissions and the Pearson coefficient in 11, so the interannual VPD signal is not established once the shared trend is removed.

Dry-season precipitation showed the opposite pattern. No association appeared in the raw series ($\rho = -0.257$, $p = 0.105$; $r = -0.312$), but after detrending the association was negative and significant under both estimators ($\rho = -0.399$, $p = 0.010$; $r = -0.396$, $p = 0.010$), and the association was significant under all 41 leave-one-out omissions for both estimators.

The two variables were therefore associated with different components of temporal variation. The raw VPD coefficient of 0.637 is substantially an expression of shared trend, whereas dry-season rainfall was associated with interannual departures from the long-term trajectory and is invisible in the raw series because that trend dominates it. Reporting only the raw VPD coefficient — the more common practice — conflates trend co-movement with interannual association and overstates the strength of the climate signal at the scale on which fire management operates.

Spatial clustering and the land-tenure gradient

Local Moran's I on the cumulative burned fraction of each cell — the burned footprint divided by the area of the cell within the region — across the 2,554 cells retained after the denominator cut described in Methods identified 714 high–high and 1350 low–low clusters at a 50 km distance band (Fig. 5a, b; global Moran's $I = 0.578$, $p = 0.001$, 999 permutations, no islands, mean 64.7 neighbours). The pattern was insensitive to false-discovery-rate correction, which reduced these to 709 and 1346 cells, and remained structurally stable at the 25 and 75 km bands (Fig. 5b), although counts of spatial outliers rose with neighbourhood width. Outliers are reported at the 50 km band throughout, on the within-region denominator: on the absolute footprint, whole cells cut by the regional limit hold little burned area and read as cold among hot neighbours, a margin artefact the denominator removes. Tenure composition inside the high–high clusters is itself uneven: public glebas are over-represented by a factor of 3.31 relative to their share of all cells (Fig. 5c).

Cumulative fire exposure differed markedly among tenure categories. Using a pixel-based vulnerability index — the ratio between a category's share of burned area and its share of territory, so that unity indicates burning proportional to extent — public glebas recorded 4.51 and Indigenous Territories 0.083, a **54.7-fold gradient**. Public glebas and unregistered land together occupy 11.7% of the region but account for 46.3% of cumulative burned area.

The magnitude of this gradient depends on the unit of analysis. Recomputed on a dominant-category-per-hexagon basis, the same contrast was 26.6-fold (glebas 3.26, Indigenous Territories 0.123, 95% CI

from spatial block bootstrap 17.9–41.7). The difference between the estimators is measurable rather than a matter of judgement. For each category we computed **capture**, the fraction of its total area falling inside the cells it dominates: it ranges from 97.8% for Indigenous Territories, which form large contiguous blocks, to 33.7% for public undesignated forest, which is spatially fragmented and is therefore mixed with neighbouring categories in the cells it dominates. Where capture falls below one half — public undesignated forest and private land — the area-based index is the reportable estimate. Aggregation is also one-directional, pulling high-index categories down and low-index categories up, so **the hexagonal gradient is a lower bound**; it is reported as the headline figure only because it is the estimator for which a spatial block bootstrap is available.

Military areas, outside the eight analytical categories, recorded an index of 4.39 despite representing maximal formal state presence — consistent with their location in the southern cerrado–forest transition. Exposure indices of this kind conflate tenure category with vegetation-driven susceptibility, which the following subsection addresses directly.

Tenure contrasts are concentrated in fire occurrence rather than conditional magnitude

Zero burned area was recorded in 63.8% of cell-year observations, and the proportion of zeros varied more than fivefold across tenure categories — 84.5% in Indigenous Territories against 16.1% in public glebas. This structure motivated separating the probability that fire occurs from the amount that burns once it does.

The descriptive pattern is unambiguous (Table 5, Fig. 6c). As the occurrence threshold rises, the tenure contrast in fire **probability widens** — 5.4-fold at any detected burning, 12.0-fold at 10 ha, 22.4-fold at 100 ha — while the contrast in **conditional magnitude collapses**, from 4.9-fold to 2.3-fold to 1.4-fold. At the 100 ha threshold, mean burned area given fire is similar across categories and is in fact highest in public undesignated forest (6.89 km²) and strict-protection conservation units (6.50 km²) rather than in private land (3.84 km²).

Table 5

Fire probability and conditional magnitude by tenure category. ☐ Capture below 50% (public undesignated forest 33.7%, private land 37.1%): for these two categories the dominant-hexagon assignment describes the neighbourhood as much as the category, and the values are reported for completeness rather than as estimates of the class.

Tenure	P(fire) > 0	E(BA fire) > 0	P(fire) > 1 km ²	E(BA fire) > 1 km ²
Public glebas	83.9%	3.20 km ²	42.7%	5.94 km ²
Private land ☐	68.3%	1.75	27.7%	3.84
Rural settlement	71.8%	2.58	33.7%	5.14
Unregistered land	66.9%	3.57	35.3%	6.48
Public undesignated forest ☐	65.1%	3.21	28.8%	6.89
Sustainable-use UC	28.2%	1.29	5.5%	5.91
Strict-protection UC	17.9%	1.89	4.9%	6.50
Indigenous Territory	15.5%	0.65	1.9%	4.38
Glebas / Indigenous ratio	5.4×	4.9×	22.4×	1.4×

Because the divergence strengthens rather than weakens as the threshold rises, it cannot be attributed to detection sensitivity or edge effects near the minimum mapping unit, which would produce the opposite pattern: a contrast concentrated in the smallest detections and dissolving as they are excluded.

Random forest models reproduced this asymmetry. Occurrence was predicted with an area under the ROC curve of 0.929 at the primary threshold and 0.943 at 100 ha, with well-calibrated probabilities. Conditional magnitude was predicted considerably less well: $R^2 = 0.371$, 0.284 and 0.224 at the three thresholds. Prediction error on the magnitude stage was similar across thresholds in log units while error in km² increased with them, because higher thresholds select larger scars: relative error is stable and absolute error is not.

Grouped permutation importance revealed an inversion between the two stages (Table 6). Land cover dominated occurrence at every threshold while accessibility contributed almost nothing; for conditional magnitude accessibility became a major predictor and at the 100 ha threshold **exceeded land cover** (ΔR^2 0.318 against 0.218). Accessibility here comprises distance to the two federal highways and to the nearest municipal seat, and the contrast is predictive rather than causal: the block contributed little to discriminating where fire occurs, and a great deal to predicting how much burns where it does. Climate and topography contribute little at either stage, with losses below 0.02 throughout. Grouped permutation importance measures the degradation caused by shuffling a block and is therefore bounded below by zero in expectation; it does not carry the direction of an effect, and a small value is evidence of weak predictive contribution rather than of a protective one.

Table 6
Grouped permutation importance by stage and threshold

Block	Occurrence > 0 (ΔAUC)	Magnitude > 0 (ΔR^2)	Magnitude > 1 km ² (ΔR^2)
Land cover	0.288	0.666	0.218
Accessibility	0.011	0.234	0.318
Land tenure	0.003	0.053	0.012
Climate	0.003	0.020	0.019
Topography	0.004	0.020	0.003

A single regression on log-transformed burned area over the same partition achieved $R^2 = 0.527$, higher than either stage in isolation, but it conflates the two processes: the value of the two-part formulation lies in showing that occurrence and magnitude have distinct predictor structures, not in improving aggregate prediction.

Tenure information is largely shared with land cover

Model performance was evaluated under three partitioning regimes to separate temporal from spatial generalization: $R^2 = 0.597$ for unseen years in known locations, 0.622 for unseen locations in known years, and **0.528 for unseen locations in unseen years**. The last figure is a single draw of the partition: across 50 independent draws its median is 0.471 with a 95% interval of 0.256 to 0.563. The last is the most demanding, and all attribution results use it. The modest decline from the temporal to the spatio-temporal regime indicates that spatial leakage, while present, does not dominate performance.

Block ablation (Table 7) shows that land tenure carries substantial spatial information in isolation but little that is separable from land cover. Added to a baseline of climate, topography and accessibility, tenure alone raised R^2 by 0.056 and land cover by 0.204; jointly they raised it by 0.227. The two-block commonality decomposition conditional on that baseline gives a shared component of 0.0324 and a unique tenure contribution of 0.0236.

Because these are single-draw estimates, we repeated the spatio-temporal partition 50 times with identical hyperparameters, the unique tenure contribution has a median of 0.0147 and a 95% interval of -0.0085 to 0.0312, which spans zero; it is non-positive in 5 of the 50 partitions. The shared fraction ranges from 21% to 121%, an amplitude larger than any difference one would wish to interpret from it.

No point estimate of the shared fraction is therefore reported: under this design the predictive information associated with land tenure is largely **not separable** from land-cover composition.

Table 7
Predictive performance of predictor-block combinations under spatio-temporal validation. Four decimal places are given because the commonality components are differences between these values

Predictor set	R ²
Climate + topography	0.0367
B = climate + topography + accessibility	0.3004
B + land cover (C)	0.5042
B + land tenure (T)	0.3565
B + C + T	0.5279

Climate and topography alone explain almost none of the variance ($R^2 = 0.0367$): these variables vary weakly among cells and their relevant variation is temporal, which a spatially-partitioned test cannot exploit.

The interpretation follows directly. Land tenure is not irrelevant to fire — a block that raises R^2 from 0.300 to 0.356 on unseen cells in unseen years carries real spatial information. But that information is almost entirely recoverable from land-cover composition. The large shared component indicates that tenure categories and land-cover composition carry strongly overlapping spatial information, a pattern consistent with, but not demonstrating, an indirect pathway linking territorial configuration, land-cover composition and fire. Together with the occurrence result above, tenure-associated contrasts appear concentrated in whether fire occurs, while land cover dominates the prediction of occurrence and accessibility becomes substantially more important for conditional magnitude.

This is an association consistent with an indirect pathway, not a demonstrated causal mediation, and the design does not permit the stronger claim. The tenure layer is a contemporary snapshot applied retrospectively across four decades. Categories were designated at different times, and some units predate the beginning of the satellite record, leaving no observable pre-designation period for them. Establishing that designation changed fire trajectories, rather than that present-day categories differ in cumulative exposure, would require a tenure panel resolved by designation date. That analysis is possible with existing records and is the natural extension of this work.

Conclusions

Four decades of 30-m burned-area mapping across the Xingu Integration Region show that the fire regime did not change at a single moment. Burned area broke upward in the mid-1990s, while the share of area contained in scars of 10,000 ha or more broke roughly a decade later; the bootstrap confidence intervals for the two breakpoints do not overlap. Fire quantity changed first and the size structure of fire changed afterwards, so the transition was staged rather than abrupt.

The increase in burned area had two distinct sources of comparable size. Approximately half arose from a larger flammable landscape, accompanying a seventyfold expansion of pasture, and approximately half from higher burn rates within existing cover. These are separable only by decomposition, and separating them changes the interpretation. Pasture accounted for the greater part of the total increase, but most of its contribution came from occupying more ground rather than from burning more often. Forest contributed more than a fifth of the net regional increase despite losing extent, entirely through rate intensification. Rising burn rates within contracting forest are the largest class-specific contribution to burn-rate intensification in the region, and they are invisible in the aggregate series.

Fire occurrence and conditional fire magnitude showed distinct predictor structures and should be monitored as separate quantities. Across the hexagonal panel, land-cover composition dominated the prediction of whether a cell burned at all, while accessibility contributed little to occurrence but became a major predictor of how much burned once fire was present. Contrasts between land-tenure categories were concentrated in occurrence rather than in conditional magnitude and strengthened as the detection threshold rose, a pattern inconsistent with an explanation driven by sensitivity to the smallest mapped detections; most of the predictive information carried by tenure configuration is nonetheless shared with land-cover composition rather than unique to it.

The burning season also advanced by approximately one month across the series and became more concentrated, so that a larger burned area is now delivered within a narrower window. Establishing this required treating calendar month as a cyclical rather than a linear variable; the linear treatment returns no significant change.

The added value of these findings is a specification for what long-term fire monitoring must record. Annual burned area alone cannot distinguish a landscape that burns more from one that has more to burn, cannot reveal a reorganization of event sizes occurring beneath a steady total, cannot detect a season moving earlier, and cannot separate the conditions associated with whether burning occurs from those associated with how much burns once it does. Each of these requires a distinct metric, and each is obtainable from products already in routine operational use. Monitoring programmes that report burned area alone can detect that the total is changing while remaining unable to identify which component of the fire regime has changed.

Declarations

Ethics approval

and consent

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Author Contribution

Conceptualization: L.F.M.M., G.A.V., M.M.N.A. Methodology: L.F.M.M., V.L.S.A., A.A.C.A., G.A.V. Software: L.F.M.M. Formal analysis: L.F.M.M., V.L.S.A. Investigation: L.F.M.M. Data curation: L.F.M.M., V.L.S.A. Visualization: L.F.M.M. Writing – original draft: L.F.M.M. Writing – review and editing: V.L.S.A., A.A.C.A., M.M.N.A., G.A.V. Supervision: G.A.V., M.M.N.A., A.A.C.A. All authors read and approved the final manuscript.

Data Availability

The burned-area, land-use/cover, climate and terrain inputs are public products (MapBiomas Fire Collection 5, MapBiomas Land Use/Cover Collection 11, CHIRPS, ERA5-Land, SRTM; the land-tenure raster is the iGPP Cartas da Terra release of 2025). Every regional and hexagon-level export used in the analysis (1985–2025), the Earth Engine scripts that produced them, the assembled hexagon-year panel (105,001 observations), all derived tables, the registry of reported quantities (METRICAS_v2) and the audit manifest recording the hash of every input and output are deposited at <https://doi.org/10.5281/zenodo.22082084> under a CC BY 4.0 licence.

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Figures

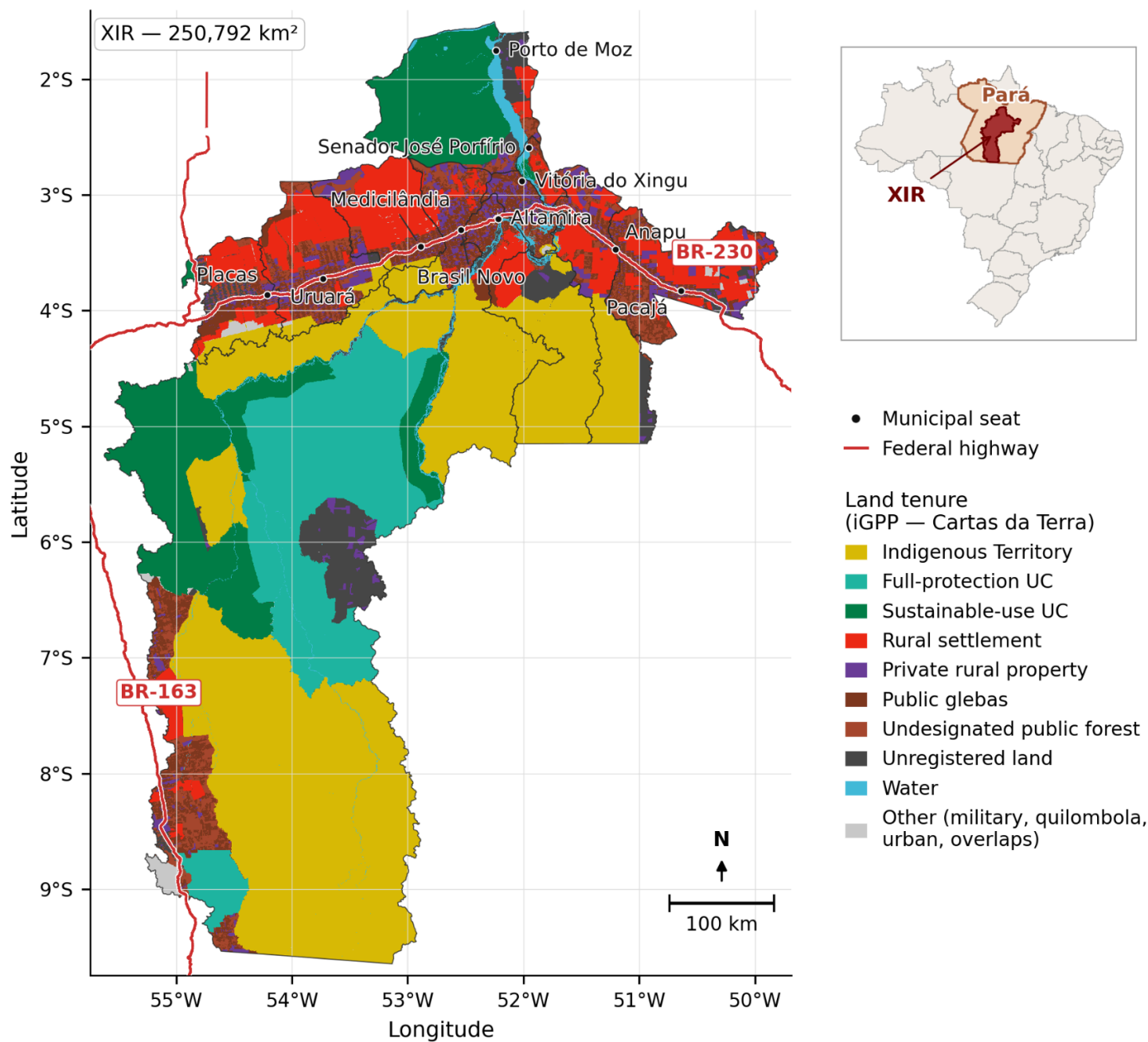


Figure 1

Land-tenure mosaic of the Xingu Integration Region (XIR), Pará, Brazil (250,792 km²), from the iGPP *Cartas da Terra* raster (reference year 2025) at 30 m, aggregated to the eight analytical tenure categories of this study (CAR-overlap variants merged into base categories; military, quilombola, urban and overlap areas grouped as Other), with the ten municipalities, the BR-230 and BR-163 federal highways and the municipal seats. Inset: location of the XIR in Pará, Brazil

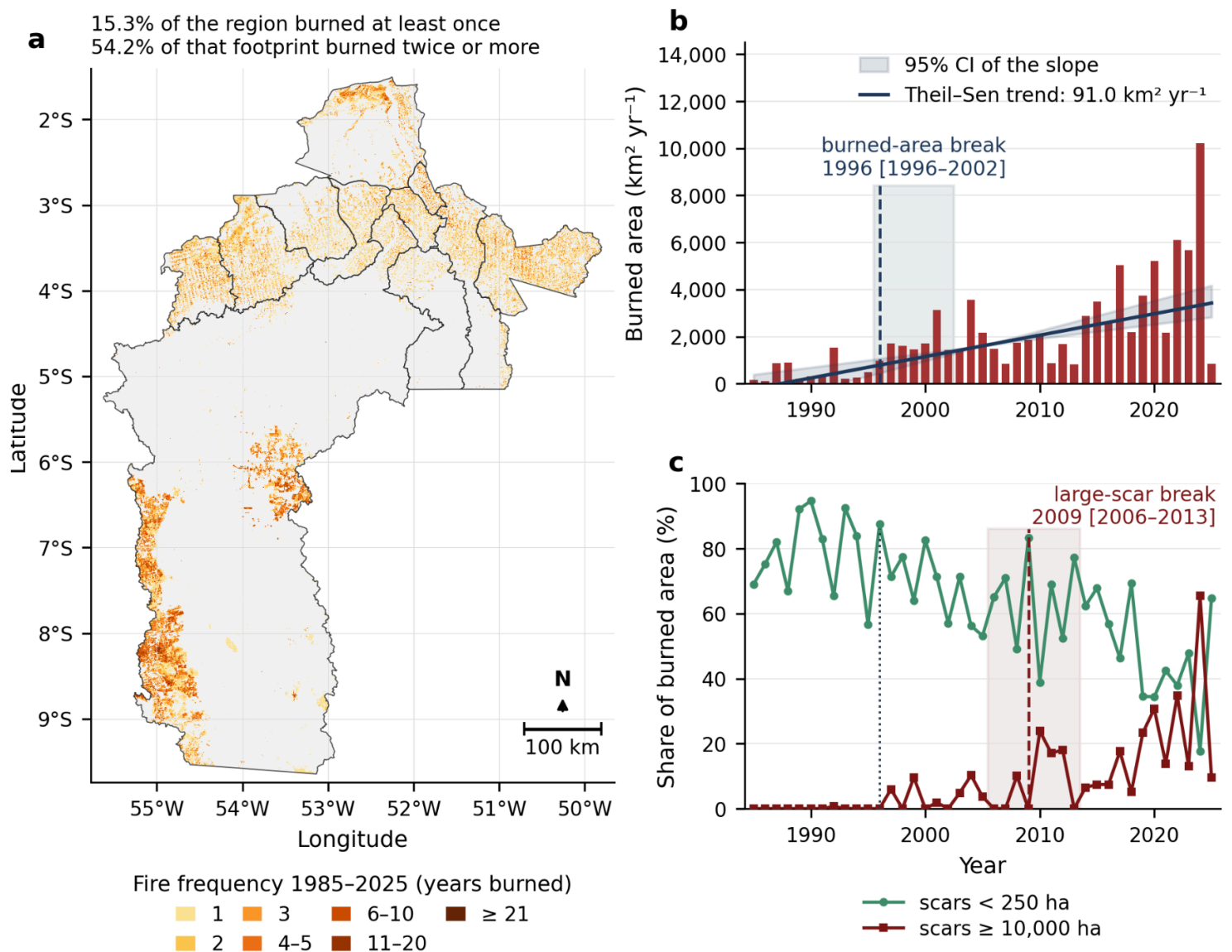


Figure 2

Staged reorganization of burned area, 1985– 2025. (a) Fire frequency per pixel (years burned) from the MapBiomas Fire Collection 5 public frequency product at 30 m. (b) Annual burned area with its Theil–Sen trend; the dashed line marks the Pettitt break in 1996 and the shaded band its bootstrap 95% CI. (c) Annual share of burned area in scars smaller than 250 ha and of 10,000 ha or more; the dashed line marks the large-scar break in 2009 and the shaded band its CI; the dotted line repeats the burned-area break for comparison. The two intervals do not overlap

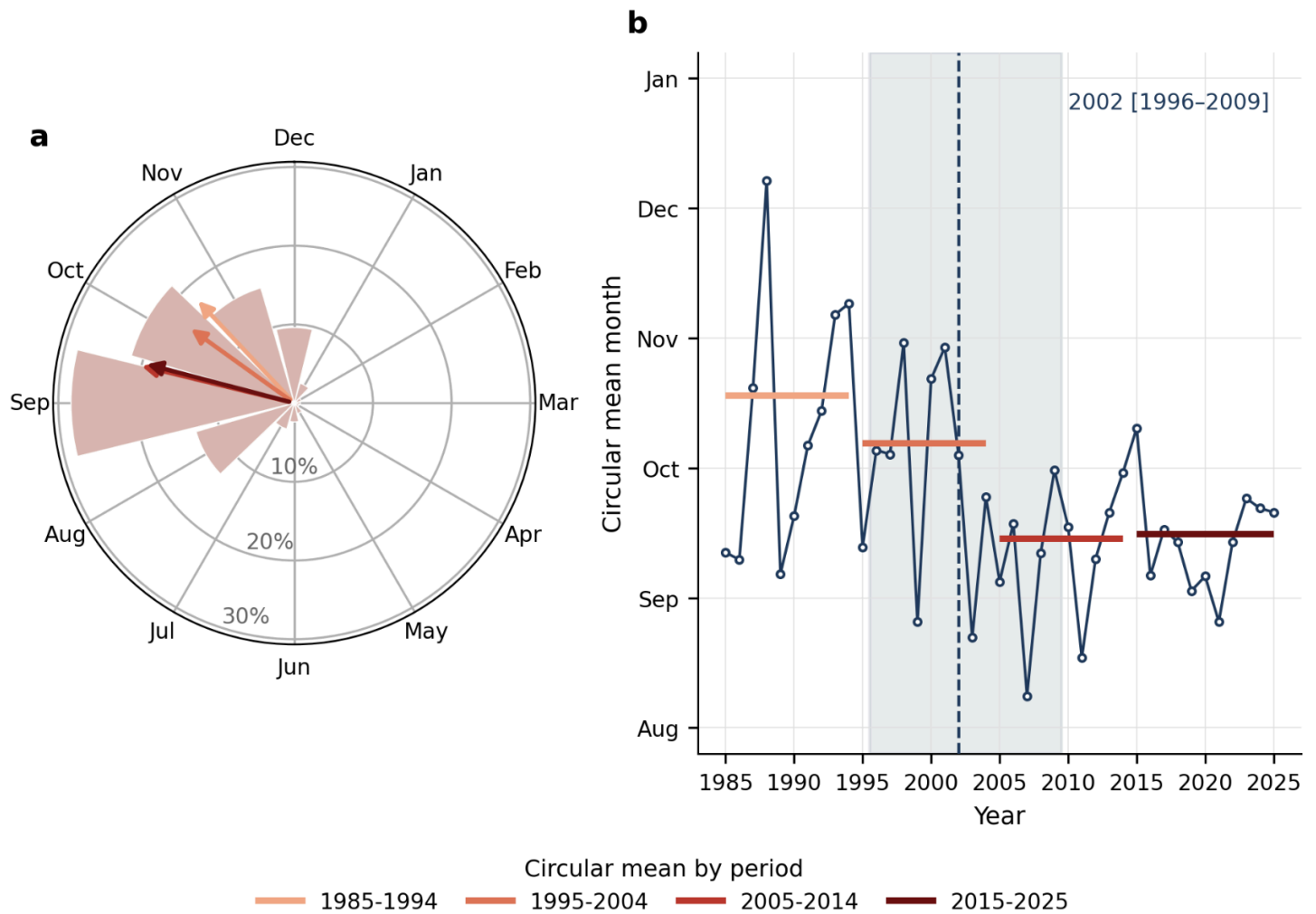


Figure 3

Seasonal displacement of burning. (a) Circular distribution of cumulative burned area by month (sectors, radial scale in % of the total) and period resultant vectors, whose length is proportional to the concentration R ; the seasonal mean migrates from November to September. (b) Annual area-weighted circular mean month on the unfolded axis (January above December), with period circular means (horizontal segments, 10.56 to 9.49); the dashed line marks the Pettitt break in 2002 (band 1996– 2009)

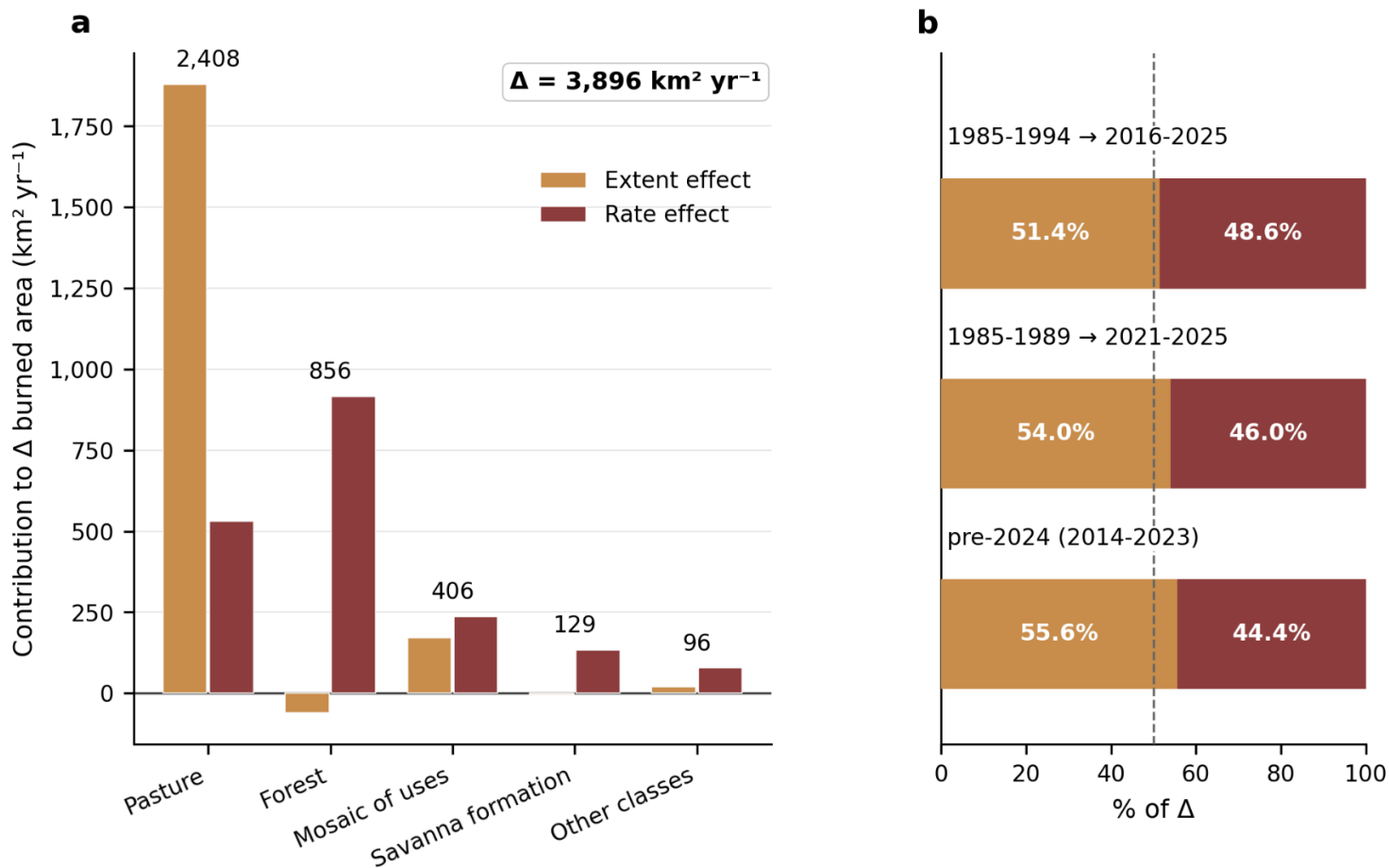


Figure 4

LMDI decomposition of the change in mean annual burned area. (a) Extent and rate effects by land-cover class (bars from zero; class totals above the bars), first to last decade ($\Delta = 3,896 \text{ km}^2 \text{ yr}^{-1}$); forest contributes 22.0% almost entirely through rate, from a contracting extent. (b) Extent/rate split under three window choices, including the pre-2024 window (2014–2023); the near-parity is insensitive to the window

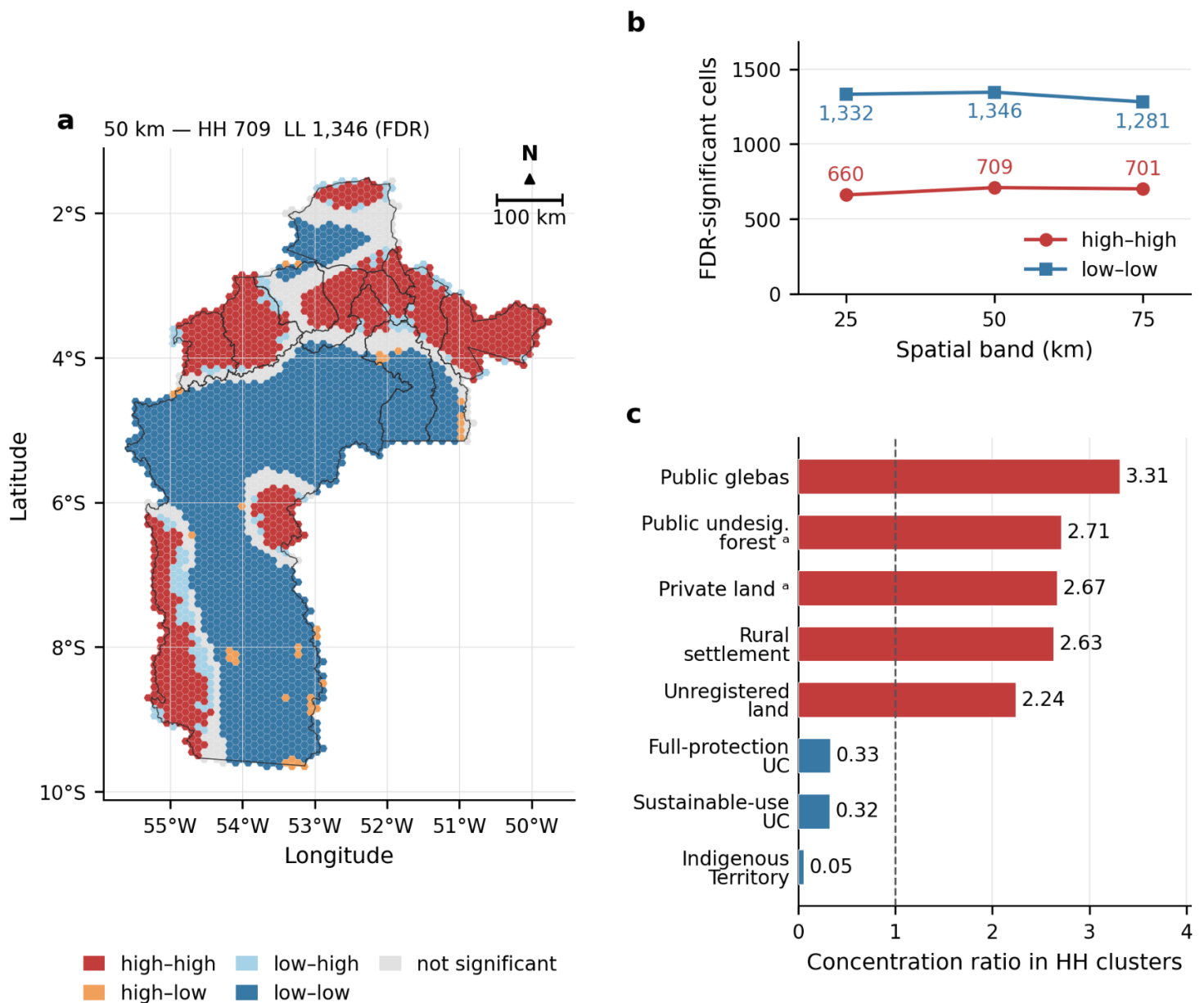


Figure 5

Spatial clustering of cumulative burned area per unit of within-region cell area and its tenure context. (a) Local Moran's I on the 2,554-cell hexagonal grid at the 50 km band after false-discovery-rate correction. (b) FDR-significant high-high and low-low counts at the 25, 50 and 75 km bands. (c) Concentration ratio of each tenure category within high-high clusters at 50 km — share of the category among HH cells divided by its share among all cells; red bars mark ratios above 1 and blue below 1. ^a Categories with dominant-cell capture below 50%

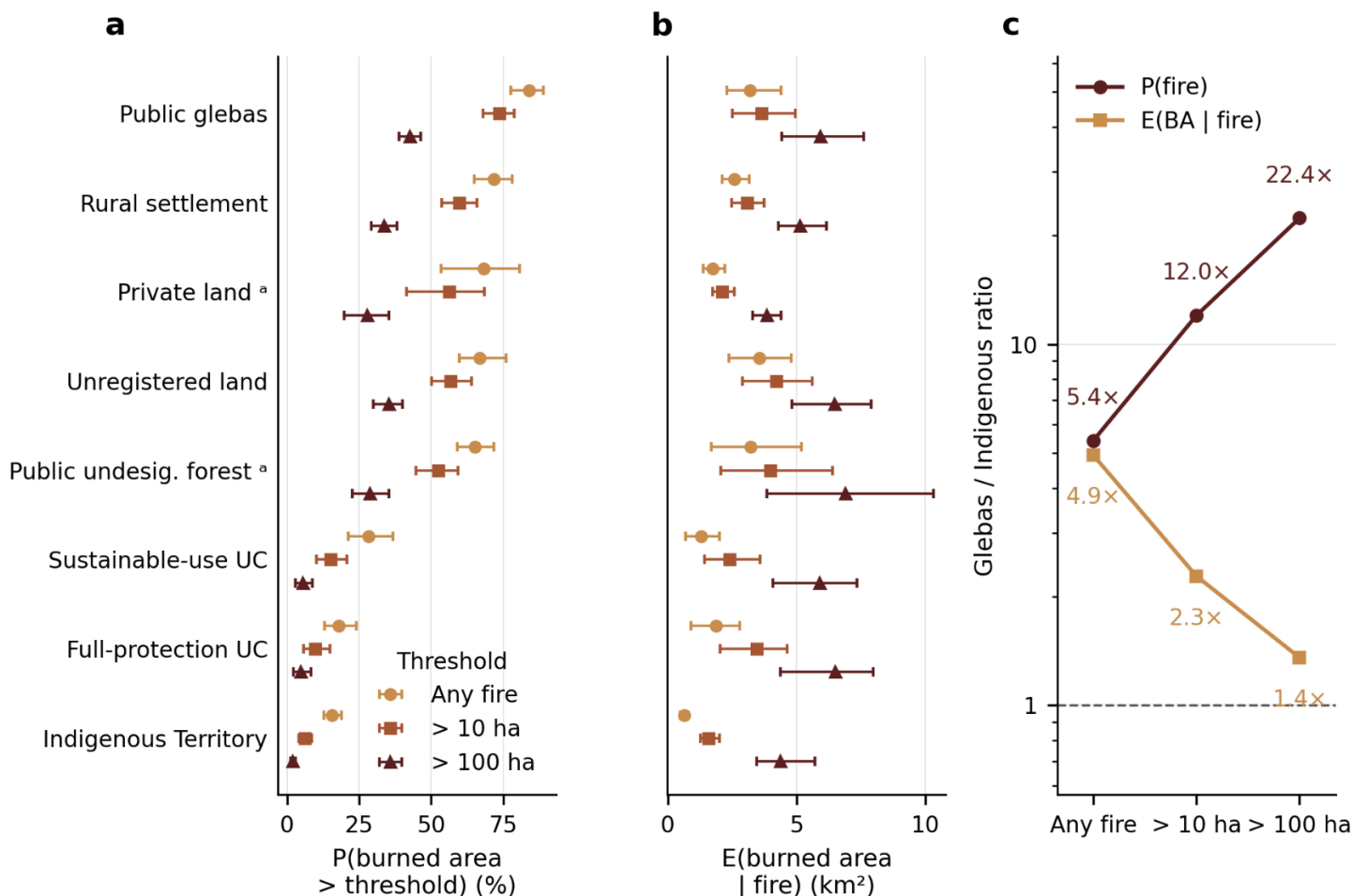


Figure 6

Occurrence and conditional magnitude of fire by tenure category. (a) Probability that annual burned area exceeds each threshold, by dominant tenure category, with 95% intervals from a spatial block bootstrap (50 km blocks, 1,000 replicates). (b) Mean burned area given fire, same design. (c) On a logarithmic scale with the dashed line at parity, the glebas-to-Indigenous ratio across thresholds: widening for occurrence and collapsing for conditional magnitude. ^a Categories with dominant-cell capture below 50%, whose hexagon-based values partly describe the neighbourhood