

Supplementary Information

Global patterns of climate displacement and novel climate emergence

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This document is organized in eleven sections. Unless stated otherwise, every spatial share, distribution, and summary statistic in this document is weighted by the exact spherical grid-cell area (Section 11).

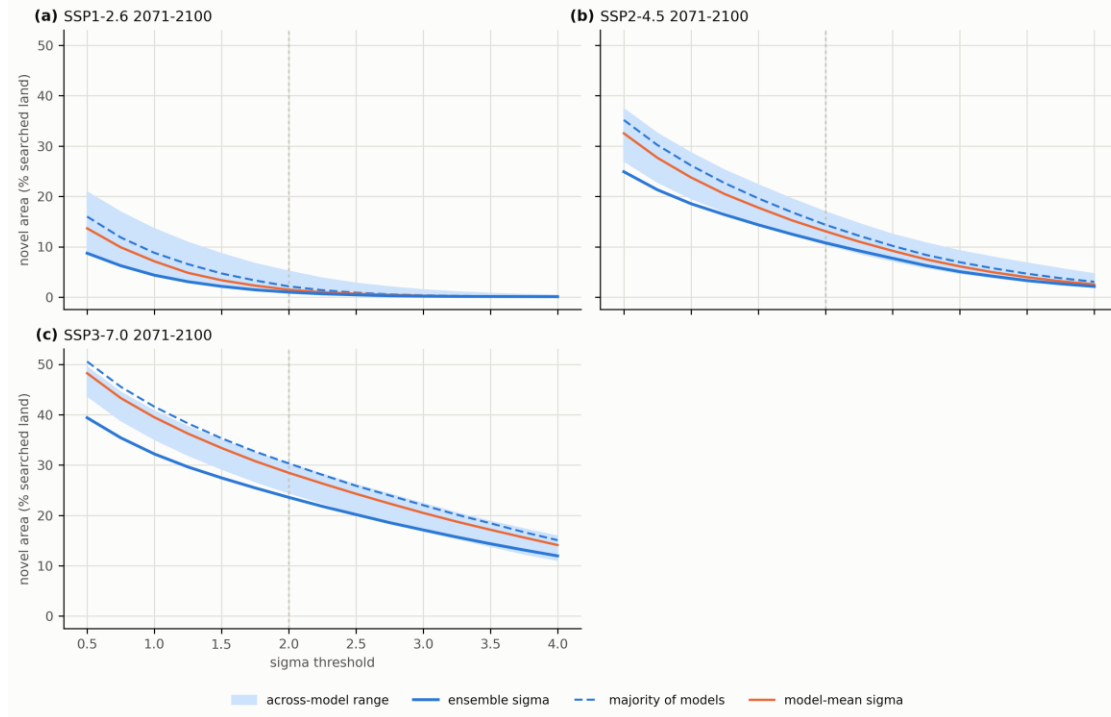
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Section 1. The novelty threshold and model agreement

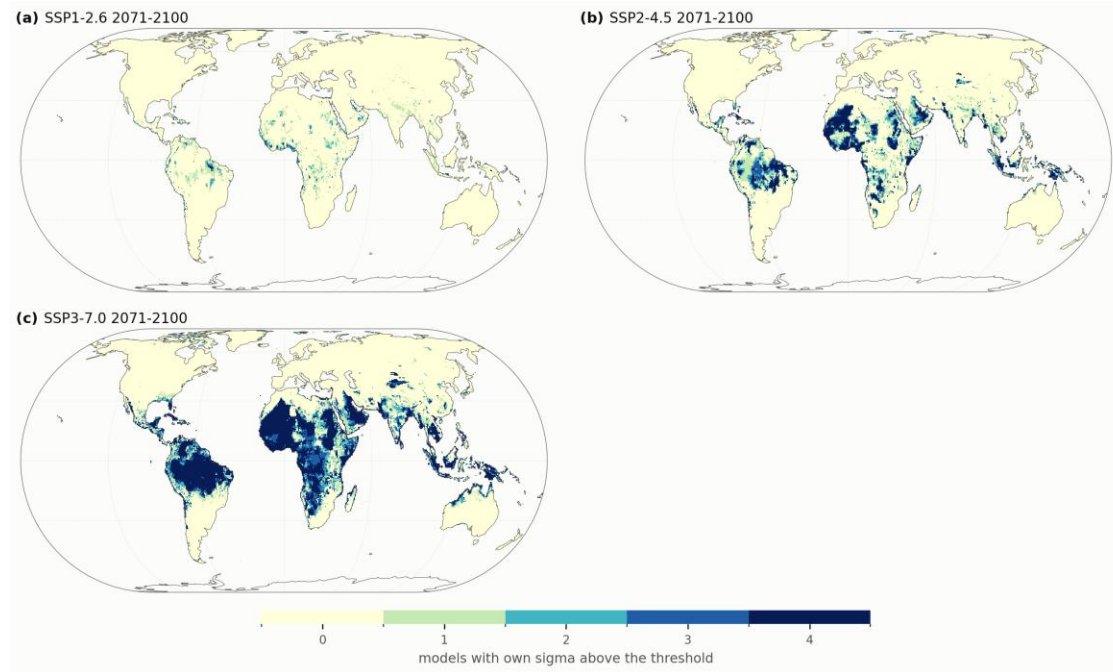
This section documents that neither the 2σ threshold nor the way the four models are combined drives the novelty verdict. Fig. S1 sweeps the threshold continuously under every ensemble definition. Fig. S2 counts, at each cell, the models individually exceeding the threshold, and Fig. S3 applies the top-50 candidate-set diagnostic of Bulut et al. [1] to the analogue locations: together they show the novelty maps to be conservative summaries of a verdict the ensemble largely agrees on.

Supplementary Figure S1. Novel climate area against the sigma threshold, under every ensemble definition.



Novel area (% of searched land, 2071–2100) as the sigma threshold sweeps continuously from 0.5σ to 4σ , per scenario. The solid blue line is the ensemble definition used in the main text. The orange line applies the test to the model-mean climatic difference (inter-model spread counted as dissimilarity), the dashed line declares a cell novel where a majority of models is novel, and the shaded band spans the most and least sensitive individual models. The curves are smooth through the 2σ choice (vertical dashed line), and the scenario ordering is preserved at every threshold. Selected values are listed in Supplementary Table S8.

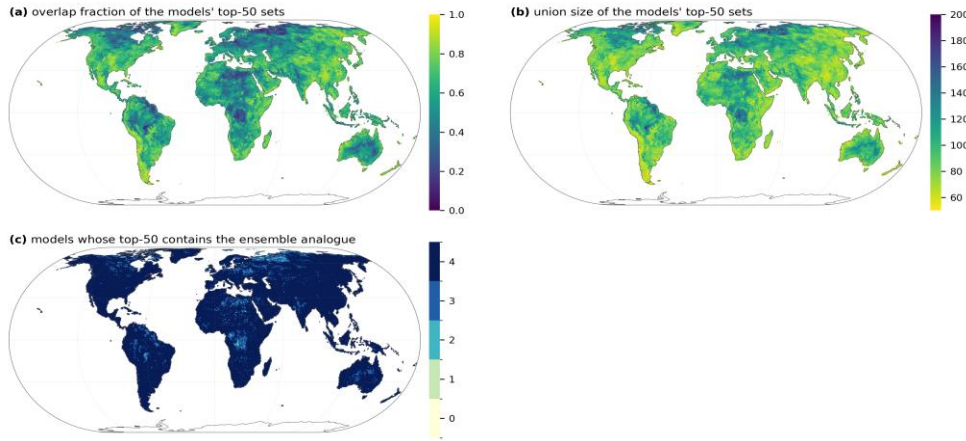
Supplementary Figure S2. The number of models calling each cell novel.



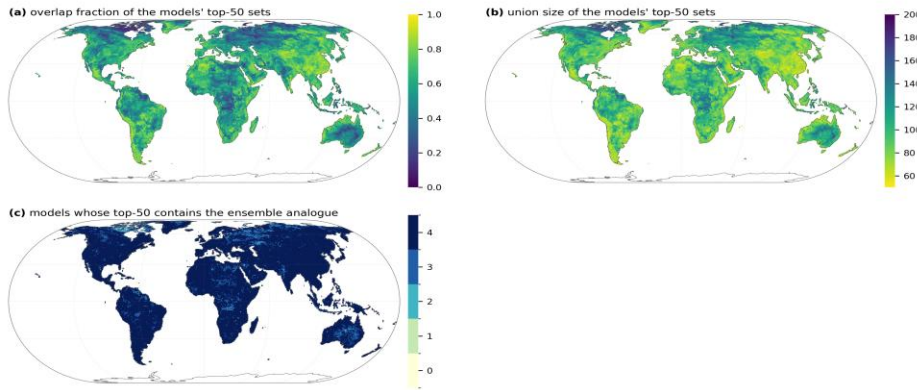
Count of models whose own sigma dissimilarity exceeds the 2σ threshold at the cell's analogue, for **(a)** SSP1-2.6, **(b)** SSP2-4.5, and **(c)** SSP3-7.0 (2071–2100). The discrete sequential colour scale counts the models, from pale yellow (none) to dark blue (all four). The share of searched land with unanimous agreement is 0.31%, 7.27%, and 19.75% across the scenarios. Of the ensemble novel area, the share supported by at least three of the four models is 74%, 91%, and 97% across the scenarios.

Supplementary Figure S3. Model agreement on analogue locations: the top-50 diagnostic.

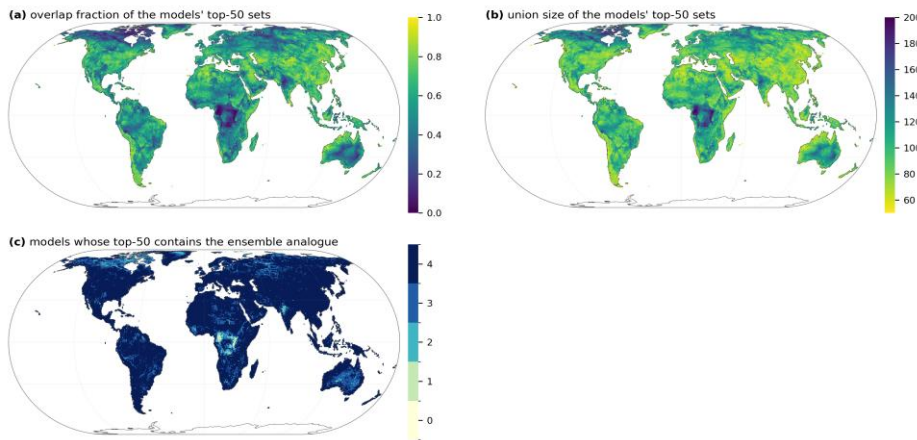
SSP1-2.6 2071-2100



SSP2-4.5 2071-2100



SSP3-7.0 2071-2100



One sheet per scenario, top to bottom: SSP1-2.6, SSP2-4.5, and SSP3-7.0 (2071–2100). Within each sheet, per-cell maps of the three top-50 agreement statistics of Bulut et al. [1], computed from each model's 50 lowest-distance candidate analogues: **(a)** the mean pairwise overlap fraction of the four models' top-50 sets (scenario means 0.60, 0.58, and 0.55), **(b)** the union size of the four sets (50 indicates identical sets and 200 disjoint sets), and **(c)** the number of models whose own top-50 contains the ensemble-selected analogue (all four models on 91.2%, 89.8%, and 84.6% of land and no model on at most 0.06%). Agreement erodes monotonically with forcing but stays high in absolute terms.

Section 2. The ensemble: selection, bias adjustment, and warming

Data. The data sources and domain are described in the main-text Methods. One property matters for this section: because every model’s daily output is mapped onto the W5E5 observational record upstream of this analysis, each model’s adjusted historical 1985–2014 record is observationally calibrated by construction and serves directly as its analogue candidate pool, and the historical and future samples entering the Wasserstein metric are drawn from the same, observation-anchored distribution family.

Members and selection (Table S1). The four selection criteria are given in the main-text Methods; Table S1 records the per-model details. GFDL-ESM4, MPI-ESM1-2-HR, and MRI-ESM2-0 are ISIMIP3b primary models, whereas MIROC6 is an ISIMIP3b second-tranche model that replaced a fourth-member candidate absent from the ISIMIP3b archive, and satisfies the same screening criteria.

Supplementary Table S1. CMIP6 models included in the four-member ensemble.

Model	Modelling centre (group)	Realization	Native atmospheric resolution	ECS (°C)	TCR (°C)	ISIMIP3b tranche	Model reference
GFDL-ESM4	NOAA Geophysical Fluid Dynamics Laboratory	r1i1p1f1	C96 cubed sphere, $\approx 1.0^\circ$ (archived $1.0^\circ \times 1.25^\circ$)	2.65	1.6	primary	Dunne et al. [2]
MIROC6	JAMSTEC/AORI/NIES/R-CCS consortium	r1i1p1f1	T85 spectral, $\approx 1.4^\circ$ (256×128)	2.60	1.6	secondary	Tatebe et al. [3]
MPI-ESM1-2-HR	Max Planck Institute for Meteorology	r1i1p1f1	T127 spectral, $\approx 0.9^\circ$ (384×192)	2.98	1.7	primary	Müller et al. [4]
MRI-ESM2-0	Meteorological Research Institute	r1i1p1f1	TL159 spectral, $\approx 1.1^\circ$ (320×160)	3.13	1.6	primary	Yukimoto et al. [5]

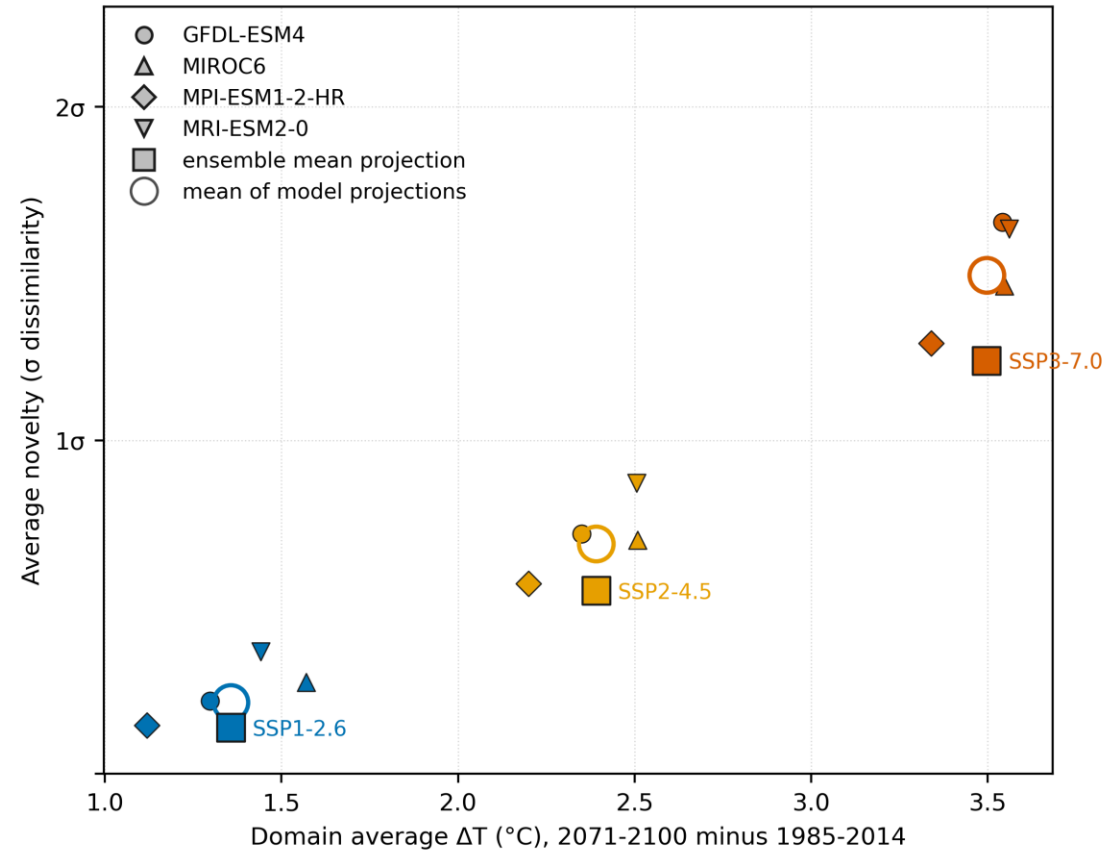
All members are used through their ISIMIP3b bias-adjusted daily and monthly output on the common ISIMIP 0.5° grid, and the native-resolution column describes the parent atmospheric model. ECS, equilibrium climate sensitivity; TCR, transient climate response. ECS values follow Zelinka et al. [6]; TCR values follow Meehl et al. [7]. Every member lies inside the AR6 assessed likely ranges (ECS 2.5–4.0 °C, TCR 1.4–2.2 °C) [8]. (After Table S2 in Appendix S5 of Mahony et al. [9], extended with the selection criteria of this study.)

Consequences of the screen. The exclusion of high-sensitivity models, and the resulting conditionality of every novelty share and analogue distance on AR6-consistent climate sensitivity, are discussed in the main text. One caveat runs the other way: because all four models share the ISIMIP3BASD calibration onto W5E5, their historical marginal distributions are strongly homogenized (the adjusted historical precipitation climatologies of different models correlate at ~ 0.999 in spatial pattern), which may flatter the inter-model agreement statistics relative to what raw-model ensembles would show.

Warming levels and the ensemble-averaging bias. Table S2(a) gives each member’s land warming per scenario: the inter-model spread is narrow, as the screen intends. Fig. S4 plots warming against domain-mean novelty per

model and shows why the sigma statistic is computed from the across-model mean climatic difference rather than from the ensemble-mean climate: the averaging bias demonstrated by Mahony et al. [9].

Supplementary Figure S4. Domain-mean warming against domain-mean novelty, per model and ensemble.



Each point is one model projection at (land-mean ΔT for 2071–2100 relative to the same model’s 1985–2014 bias-adjusted baseline, mean sigma dissimilarity). Scenario is encoded by colour and model by marker, with the ensemble-mean projection and the mean of the per-model novelty calculations marked alongside (after ref. [9], their Fig. 10). Novelty rises with warming across models and scenarios, and the ensemble-mean projection understates novelty by 35%, 20%, and 17% (SSP1-2.6, SSP2-4.5, and SSP3-7.0) relative to the mean of the per-model values, because averaging climate fields before measuring the climatic difference cancels model-specific excursions.

Supplementary Table S2. Warming level and climate-analogue statistics for each scenario (2071–2100 relative to 1985–2014).

(a) Land warming ΔT (°C) per ensemble member and for the ensemble mean:

Scenario	GFDL-ESM4	MIROC6	MPI-ESM1-2-HR	MRI-ESM2-0	Ensemble mean
SSP1-2.6	1.30	1.57	1.12	1.44	1.36
SSP2-4.5	2.35	2.51	2.20	2.51	2.39
SSP3-7.0	3.54	3.55	3.34	3.56	3.50

(b) Analogue statistics at the ensemble level:

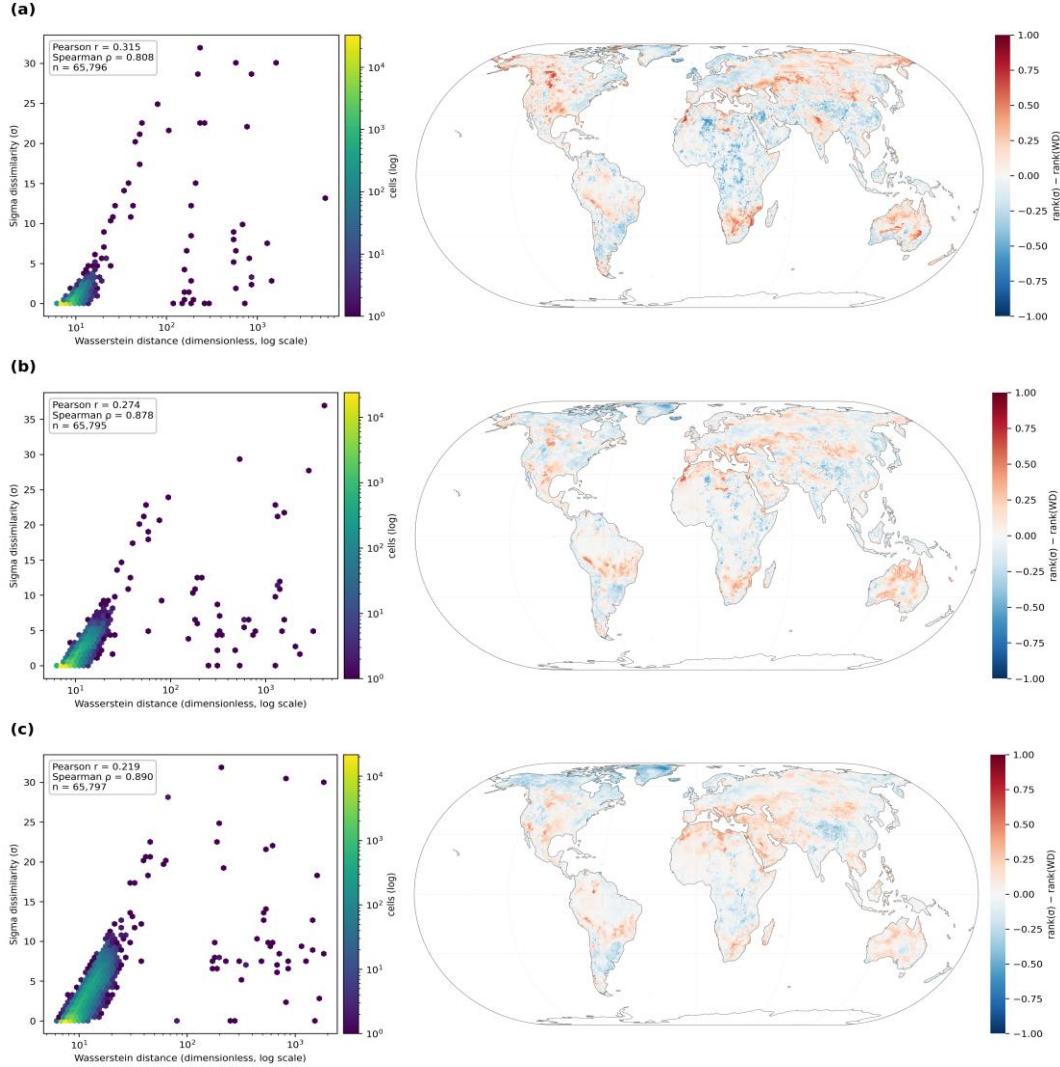
Scenario	Median WD	Analogue distance, median (km)	Analogue distance, IQR (km)	Analogue distance, p90 (km)	Analogue distance, mean (km)	Novel-cell analogue distance, median (km)	Self-analogues (% of analogue area)	Novel climate area (% of land)
SSP1-2.6	7.49	174	85–349	747	550	111	1.47	0.99
SSP2-4.5	7.91	348	172–714	2,311	1,233	543	0.06	10.78
SSP3-7.0	8.22	547	281–1,110	4,722	1,650	926	0.01	23.59

ΔT is the mean warming of the searched land domain, each model measured against its own bias-adjusted 1985–2014 baseline (the same per-model warming is plotted against per-model novelty in Supplementary Fig. S4). WD is the ensemble Wasserstein distance at the selected analogue (median over all searched land cells). Distance statistics are great-circle distances from each focal cell to its best analogue, computed over cells with an accepted analogue ($\sigma \leq 2$); IQR, interquartile range; p90, 90th percentile. The novel-cell column gives the same median for the cells without an acceptable analogue ($\sigma > 2$), whose nominal best match is poor by construction. Self-analogues are cells whose best analogue is the cell itself, and the column gives their share of the land area with an accepted analogue ($\sigma \leq 2$). Novel climate area is the share of searched land with ensemble sigma dissimilarity above 2σ .

Section 3. Agreement between the two distance metrics

Fig. S5 documents that the two distances of the analysis order the world consistently: the Wasserstein distance (WD), which selects each cell's best analogue, and the sigma dissimilarity, which judges it. The agreement is deliberately assessed on ranks, because the raw-scale correlation is destroyed by the hyper-arid outliers examined in Section 8. The rank agreement licenses the division of labour between the metrics, and the lack of raw-scale agreement rules out defining novelty by a WD threshold.

Supplementary Figure S5. Rank agreement between the Wasserstein distance and the sigma dissimilarity.



The joint distribution of the ensemble Wasserstein distance at the analogue (logarithmic axis) and the ensemble sigma dissimilarity, with the per-cell difference of their percentile ranks mapped alongside, for (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0. Spearman $\rho = 0.81, 0.88$, and 0.89 . The rank transform removes the leverage of the hyper-arid outlier cells of Supplementary Table S7 and Fig. S26.

Section 4. Geographic, elevational, and latitudinal structure of displacement

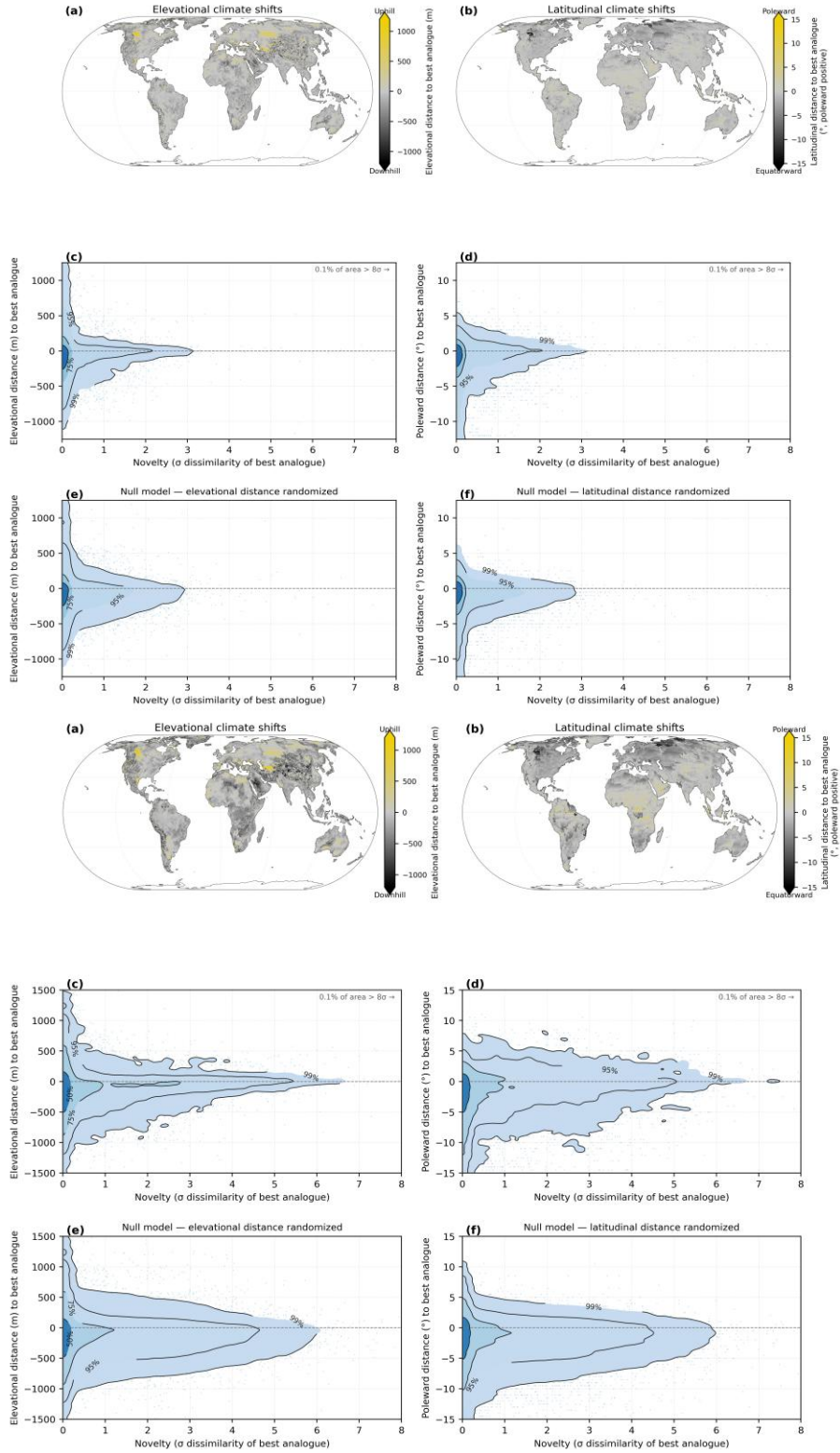
This section collects the material behind the main text’s finding that analogues lie equatorward and downslope and that novelty concentrates in the lowlands: the construction of the elevation–novelty null model (main-text Fig. 4g–l), the latitudinal statistics (Table S3), the per-cell displacement fields with their randomization nulls (Fig. S6), and the distribution of the great-circle analogue distance itself (Fig. S10, quantiles in Table S2).

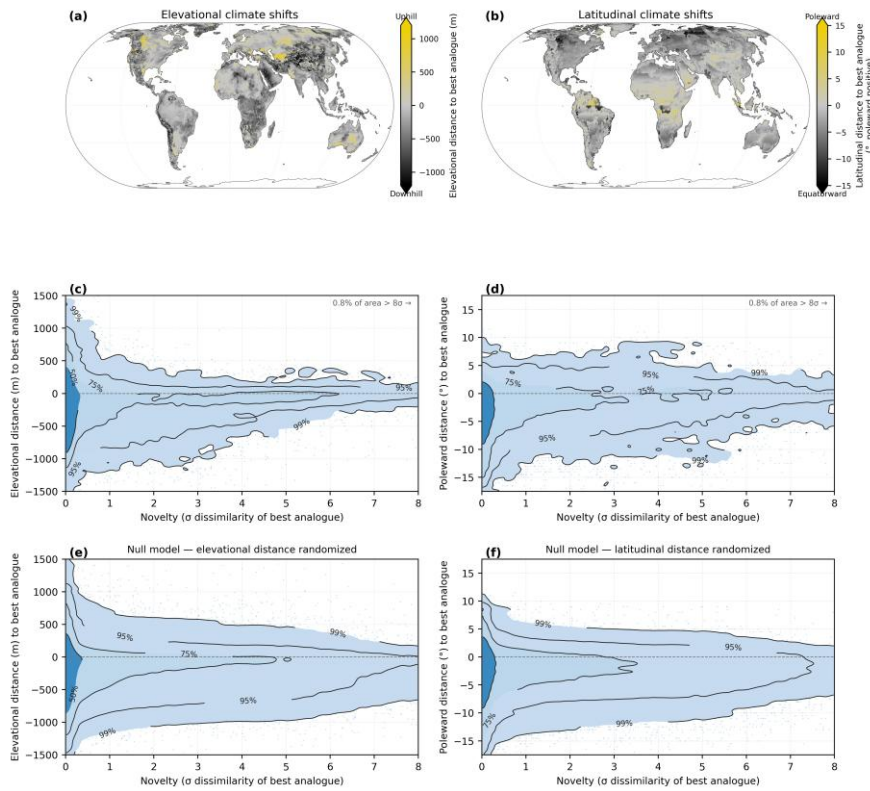
The elevation–novelty null model (main-text Fig. 4g–l, Table S3). Following Mahony et al. [9] (their Fig. 12), the null in which topographic position is randomized across cells is computed analytically, as the outer product of the two marginal histograms (the distribution an unlimited number of randomizations would converge to, free of the sampling noise of any single shuffle), with one seeded permutation drawn as the illustrative point cloud. By the symmetry of the product it is immaterial which of the two variables is treated as the randomized one. Because the null preserves both marginals, the piling of observed novelty onto low topographic positions cannot be explained by hypsometry alone. The association is quantified by a Spearman correlation with permutation significance (Table S3).

Equatorward displacement. In the extratropical shares quoted in the main text, ‘strictly equatorward’ means analogue $|\text{latitude}| < \text{focal } |\text{latitude}|$ by any margin, so it excludes only ties at the focal cell’s own grid latitude and implies no minimum displacement; the strictly poleward shares and the same-latitude-row category (self-analogues included: 14.3%, 6.9%, and 4.4% across the scenarios) complete the sum to 100%. Over all accepted cells, rather than the extratropics alone, the equatorward shares are 63.3%, 73.2%, and 81.2% (lower because tropical cells have no meaningful equatorward direction to move in).

The displacement fields and their nulls (Fig. S6). Fig. S6 documents both displacement components in full, one sheet per scenario: per-cell maps of the elevational and latitudinal displacement to the best analogue, the joint density of each component against the ensemble sigma dissimilarity, and null models built as the marginal product above.

Supplementary Figure S6. Elevational and latitudinal displacement to the best analogue: per-cell maps, joint densities with novelty, and null models.





One sheet per scenario, top to bottom: SSP1-2.6, SSP2-4.5, and SSP3-7.0 (2071–2100). Within each sheet: (a, b) maps of the elevational displacement (analogue minus focal elevation, m, with the W5E5 v2.0 orography sampled at both ends) and the latitudinal displacement ($^{\circ}$, poleward positive) to every searched cell's best analogue. (c, d) The density of each displacement component against the ensemble sigma dissimilarity, with contours enclosing 50%, 75%, 95%, and 99% of the probability mass and the annotation giving the land share beyond the 8σ display limit. (e, f) The corresponding null models, in which the displacement component is randomized across cells (the marginal-product construction of main-text Fig. 4j–l). The latitudinal maps are predominantly dark (equatorward) outside the tropics: 73.6%, 83.1%, and 87.9% of extratropical land finds its analogue strictly equatorward (analogue $|\text{latitude}| < \text{focal } |\text{latitude}|$, with no minimum margin), with a median shift of 1.0° , 2.0° , and 3.0° of latitude. The observed densities lean equatorward and downhill in a way the nulls do not.

Supplementary Table S3. Statistical evidence for the elevation–novelty association.

Scenario	Spearman ρ (σ versus elevation)	Permutation P	Novel area below 1,000 m (%)	All land below 1,000 m (%)	Median $\Delta\text{elev} < 500$ m	500–1,000 m	1,000–2,000 m	> 2,000 m
SSP1-2.6	−0.161	< 0.001	87.5	80.5	−33 m	−144 m	−169 m	−178 m
SSP2-4.5	−0.218	< 0.001	93.4	80.5	−59 m	−264 m	−307 m	−350 m
SSP3-7.0	−0.230	< 0.001	92.5	80.5	−60 m	−368 m	−476 m	−516 m

Spearman ρ is the rank correlation between ensemble sigma dissimilarity and focal elevation over all searched cells. P is a two-sided permutation test (999 permutations of elevation across cells). Median Δelev columns are the median elevational displacement (analogue minus focal elevation) of accepted analogues per focal elevation band (main-text Fig. 4a–c).

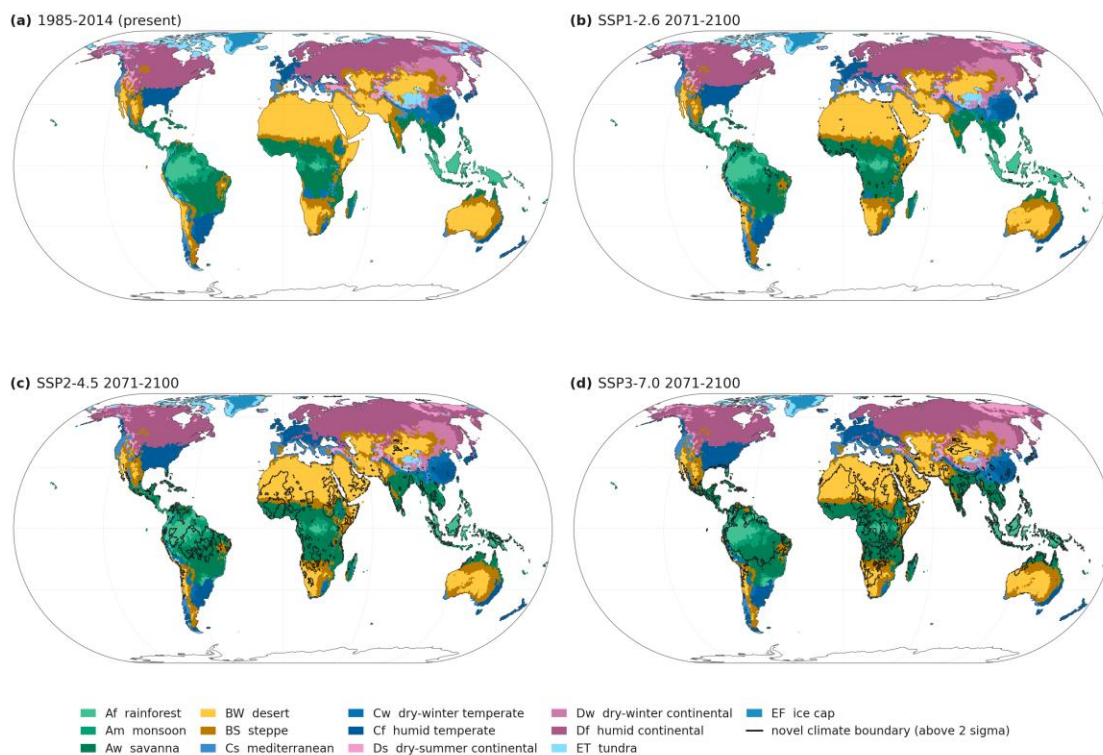
Section 5. Köppen–Geiger identity

Every cell is given a Köppen–Geiger class as specified in the main-text Methods. Two views result.

The maps (Fig. S7) give the reference frame for every Köppen statement in the main text: where each family lies today, and where the ensemble puts it at the end of the century.

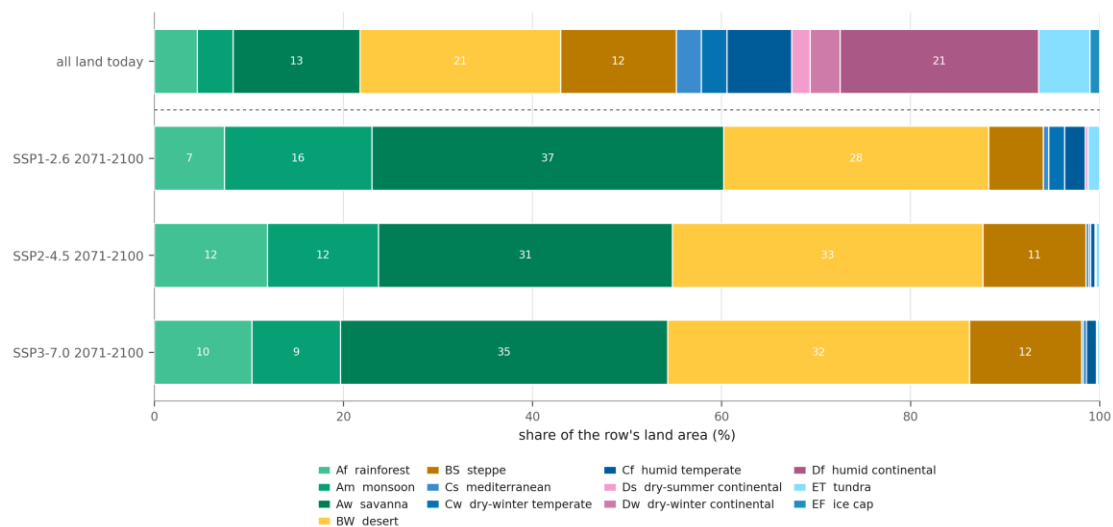
The composition (Fig. S8, Table S4) quantifies the identity of novel land by its future type and the exposure of each family relative to its own present extent. Main-text Fig. 3 and Fig. S9 read the same identity through the analogues instead (present type against the type of the closest analogue), which involves no classification of projected climate at all (main-text Methods).

Supplementary Figure S7. Köppen–Geiger world maps, today and at the end of the century.



Two-letter Köppen–Geiger families (thresholds of Peel et al. [10]) of (a) the 1985–2014 reference normals (the ensemble mean) and (b–d) the ensemble-mean 2071–2100 climatology under SSP1-2.6, SSP2-4.5, and SSP3-7.0. On the future panels, dark contour lines enclose the novel area (ensemble sigma dissimilarity $> 2\sigma$): inside those lines the mapped type is an extrapolated label (the climate has no acceptable historical analogue), which is why the boundary is drawn rather than the cells masked. Monthly mean temperature is approximated by the mean of daily maximum and minimum, the only temperature moments in the feature space.

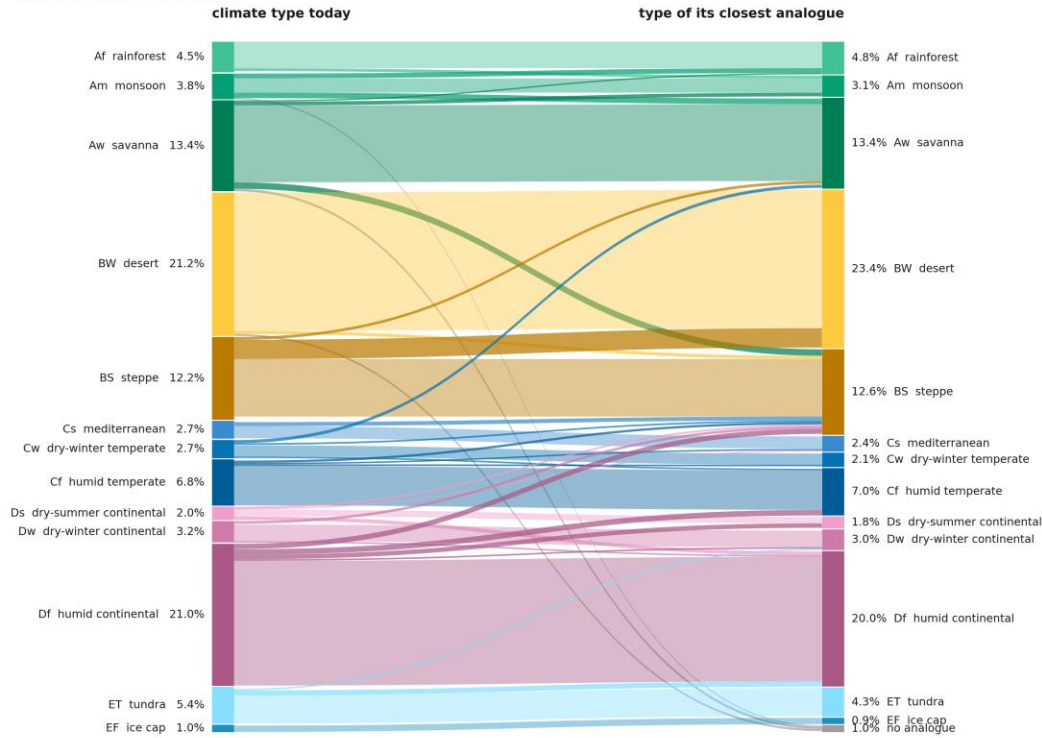
Supplementary Figure S8. Köppen–Geiger composition of novel land.



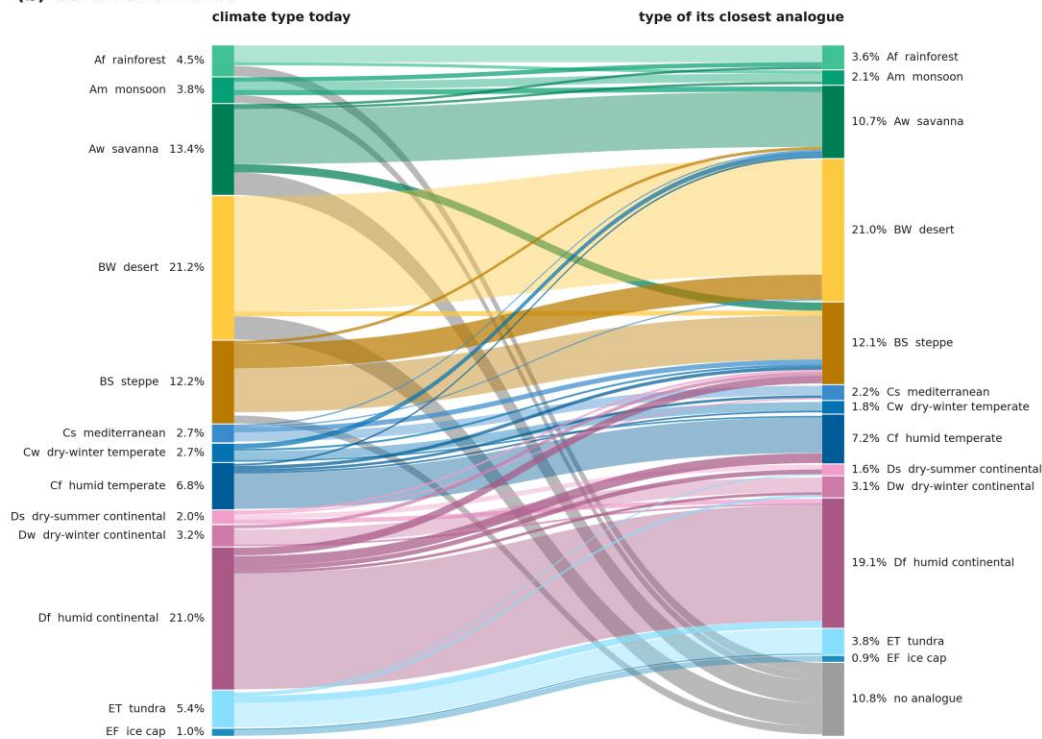
The top bar shows the composition of all searched land today by Köppen–Geiger family. Each lower bar shows the composition of one scenario’s novel land (2071–2100) by the future type of those same cells. Numbers are percentages of each row’s land area, and families contributing less than ~5% are left unlabelled.

Supplementary Figure S9. Köppen flow at lower forcing: SSP1-2.6 and SSP2-4.5.

(a) SSP1-2.6 2071-2100



(b) SSP2-4.5 2071-2100



As in main-text Fig. 3 (alluvial diagrams) [11], but for **(a) SSP1-2.6** and **(b) SSP2-4.5** (2071–2100). Mapping each cell's present family to its analogue's family keeps the type on 82.5% (SSP1-2.6) and 67.8% (SSP2-4.5) of searched land, against 52.8% under SSP3-7.0 (main-text Fig. 3).

Supplementary Table S4. Novel climate area by scenario: extent, depth, identity, and per-family exposure.

Scenario	Novel area (10 ⁶ km ²)	> 2 σ (% of land)	> 3 σ (% of land)	> 4 σ (% of land)	Tropical share of novel area (%)	Köppen name retained (% of novel area)
SSP1-2.6	1.42	0.99	0.19	0.10	89.6	94.4
SSP2-4.5	15.40	10.78	5.06	2.12	89.6	91.8
SSP3-7.0	33.69	23.59	17.11	11.96	86.6	86.5

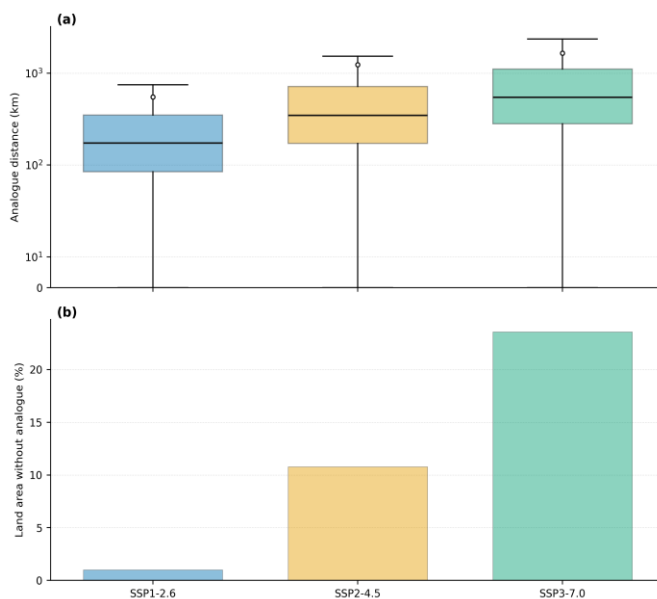
Novel area is evaluated at the ensemble sigma dissimilarity. Threshold columns are cumulative shares of searched land (a cell beyond 4 σ also counts at 2 σ and 3 σ). Tropical share is the fraction of each scenario's novel area lying within 23.5° of the equator. Köppen name retained is the fraction of novel land whose future Köppen–Geiger type keeps its present name.

Novel area relative to each Köppen family's present extent (% , novel land classified by its future type divided by the family's present area):

Köppen family	Present area (10 ⁶ km ²)	SSP1-2.6	SSP2-4.5	SSP3-7.0
Aw savanna	19.18	2.8	25.0	60.8
Am monsoon	5.42	4.1	33.4	58.3
Af rainforest	6.49	1.6	28.4	53.5
BW desert	30.30	1.3	16.7	35.5
BS steppe	17.46	0.5	9.6	22.9
Cf humid temperate	9.76	0.3	0.7	3.7

(Families below Cf contribute under 3% in every scenario.)

Supplementary Figure S10. Analogue distance and land without analogues by scenario



Discussed in Section 4. **(a)** Distribution of the great-circle distance from every land cell to its best Wasserstein analogue (2071–2100 climate matched against 1985–2014), restricted to cells with an accepted analogue ($\sigma \leq 2$).

Boxes span the interquartile range with the median as the black line, and open circles are means. Whiskers extend to the most extreme values within $1.5 \times$ the interquartile range beyond the quartiles (values beyond the whiskers are not drawn), and the distance axis is logarithmic above 10 km. **(b)** Percentage of searched land area without any acceptable analogue (ensemble sigma dissimilarity $> 2\sigma$). $n = 65,797$ land cells (0.5° grid, Antarctica excluded). The quantiles drawn in **(a)** are tabulated in Table S2.

Section 6. The clustering: choice of K , initialization, and the regional windows

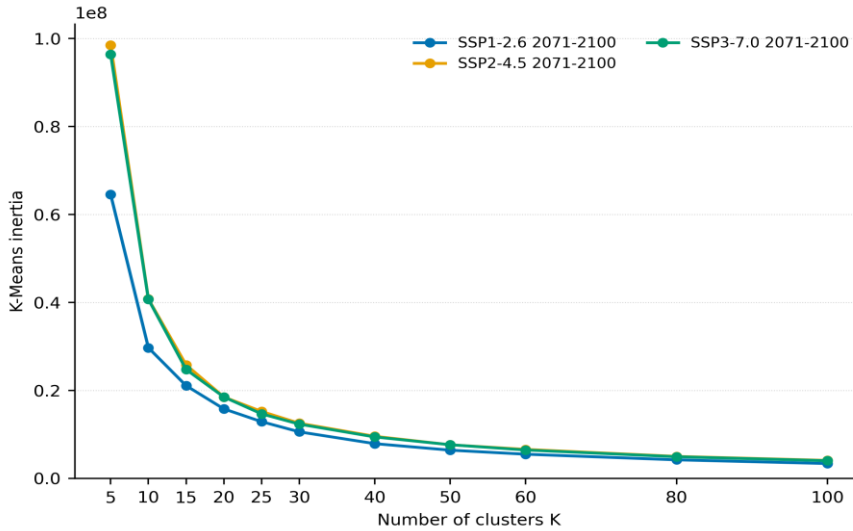
Because a clustering always returns some partition, this section documents that nothing mapped by the k -medoids summary (main-text Figs. 5 and 6) depends on its two arbitrary inputs, K and the random initialization, and defines the regional windows used by the refits.

Choice of K (Figs. S11–S12). The within-cluster inertia falls smoothly with K and never plateaus (Fig. S11), so the objective alone cannot fix K . It is fixed instead on the structural criterion of Fig. S12 (corridor-area saturation), whose legend also documents the rendering effect (more faithful arrows at generous K) behind the production choice of $K = 30$.

Initialization (Fig. S13, Table S5). The production estimator was re-run at restart levels 1 to 10,000 with independent seeds. The corridor set stays intact in every run, and the production maps use 10,000 restarts globally and 5,000 per regional window.

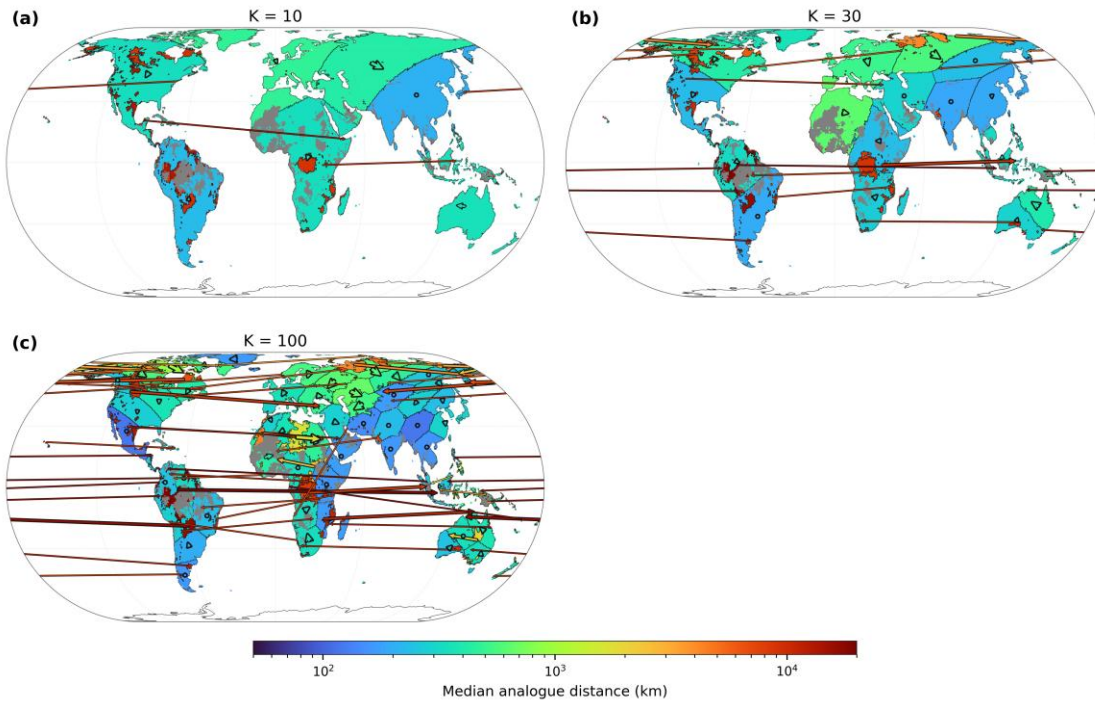
Regional windows and their exits (Figs. S14–S24, Table S6). The nine continental windows (Fig. S14) partition the searched land. The nine regional sheets (Figs. S15–S23, one per window with all three scenarios) show the within-window structure the global fit averages away, the exit maps (Fig. S24) complete their out-of-window arrows, and Table S6 closes the section by naming every cluster of the production global partition, with its core pair, area share, and distances, so each arrow of main-text Fig. 5 can be looked up.

Supplementary Figure S11. Within-cluster inertia against the number of clusters K .



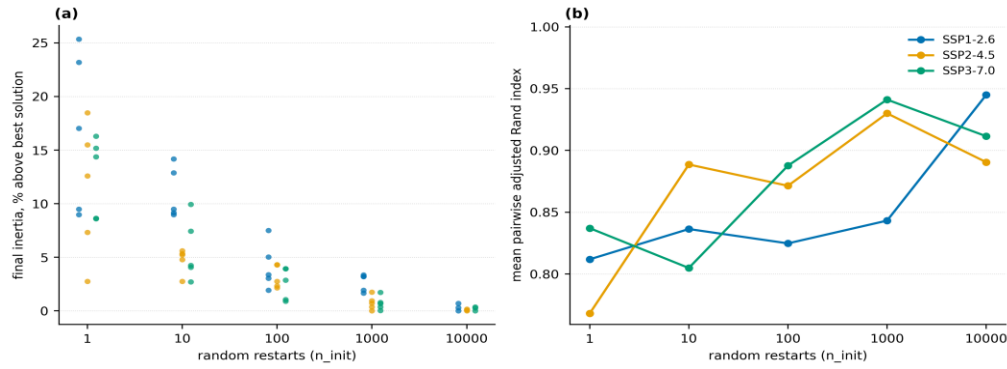
k -medoids inertia of the global displacement clustering for $K = 5$ to 100, one line per scenario (each scenario's inertia is comparable only within its own line). The decay is smooth with its strongest curvature below $K \approx 20$: the reduction per step of five falls from 54–59% ($K = 5 \rightarrow 10$) to 16–18% ($K = 25 \rightarrow 30$). Inertia necessarily keeps falling at higher K (a further 67–68% from $K = 30$ to $K = 100$).

Supplementary Figure S12. Global cluster maps at $K = 10, 30$, and 100 (SSP2-4.5).



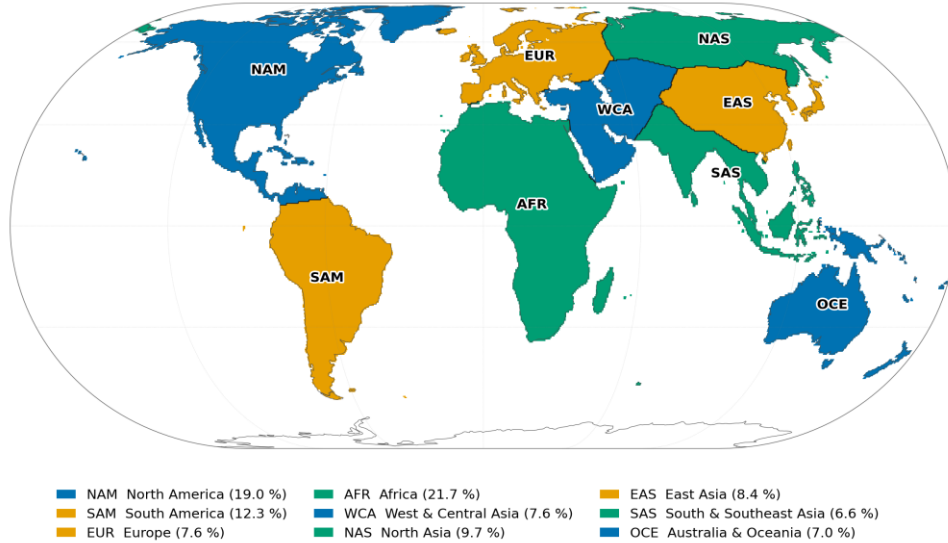
The clustering of main-text Fig. 5b recomputed at **(a)** $K = 10$, **(b)** $K = 30$, and **(c)** $K = 100$ (100 random restarts each). The single colour bar applies to all three panels (the fixed 50–20,000 km logarithmic scale shared by every displacement figure). The intercontinental corridors (Amazonia → Maritime Continent, south-western North America → west Asia and north Africa, Congo → Maritime Continent, boreal Canada → Siberia) are present at every K from 10 upward, and the land area they occupy is fixed: clusters with mean member analogue distance beyond 5,000 km carry 5.8–6.1% of land under SSP2-4.5 (1.9–2.1% under SSP1-2.6, 7.1–7.7% under SSP3-7.0) at every K from 15 to 100, while their count merely subdivides (8 corridor clusters at $K = 20$, 12 at $K = 30$, 34 at $K = 100$). Only $K = 5$ merges the corridors into one (SSP2-4.5) or none (SSP1-2.6). What higher K buys is arrow fidelity rather than new geography. At low K , large clusters pool members whose displacement directions disagree. The core (the real member cell that minimizes the weighted distance to all members in the position–displacement space) then sits near the centre of a broad, direction-mixed distribution, so its own displacement is short, and the drawn arrow understates the cluster’s median and mean analogue distance (the fill colour carries the median instead). At higher K the same land splits into directionally coherent clusters whose cores displace with their members, so arrows lengthen toward the member statistics and the displacement field is rendered in more faithful detail. This is the reason the production map ($K = 30$) sits above the elbow of Supplementary Fig. S11. Higher K therefore refines boundaries and arrow fidelity within a stable corridor geography rather than discovering new structure.

Supplementary Figure S13. Sensitivity of the production clustering to random initialization.



The full production estimator (weighted k -means fit + Lloyd refinement to real-member cores, $K = 30$) re-run at 1, 10, 100, 1,000, and 10,000 random restarts with five independent seeds per level (three at 10,000), per scenario: 69 fits in total. **(a)** Final (post-refinement) inertia of every run, as the percentage above the best solution found for that scenario (the convergence figures are quoted in the main text). **(b)** Mean pairwise adjusted Rand index (ARI) between the seeds' partitions at each restart level. Reproducibility rises from single starts to 0.82–0.94 at 100 or more restarts, without ever reaching 1: independent runs keep finding equally good but not identical partitions (near-degenerate optima that more restarts cannot remove). The count of intercontinental corridor clusters (mean member analogue distance > 5,000 km) stays within 9–16 in all 69 runs, narrows to 9–12 at 1,000 restarts and to 9–11 at 10,000, matching the production maps (9, 11, and 11), so the corridor structure of main-text Fig. 5 does not depend on the initialization.

Supplementary Figure S14. The nine continental windows of the regional clustering.



The land partition used by the regional refits of main-text Fig. 6 and Supplementary Figs. S15–S24: NAM North America (19.0% of searched land), SAM South America (12.3%), EUR Europe (7.6%), AFR Africa (21.7%), WCA West & Central Asia (7.6%), NAS North Asia (9.7%), EAS East Asia (8.4%), SAS South & Southeast Asia (6.6%), and OCE Australia & Oceania (7.0%). Every searched cell belongs to exactly one window. The clustering is refitted independently inside each, and analogues are still searched globally, so a cluster may point out of its own window (Supplementary Fig. S24).

Supplementary Figures S15–S23. Regional k -medoids clustering: one sheet per continental window, all three scenarios.

Figure S15 (North America):

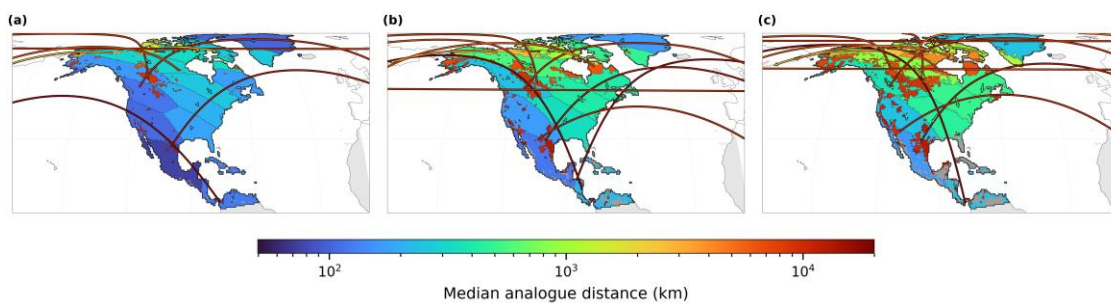


Figure S16 (South America):

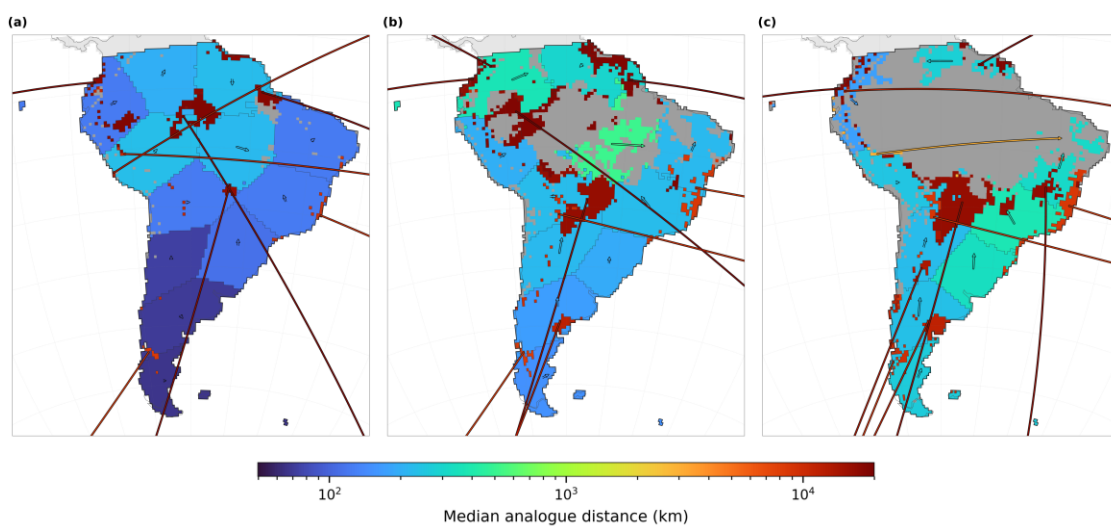


Figure S17 (Europe):

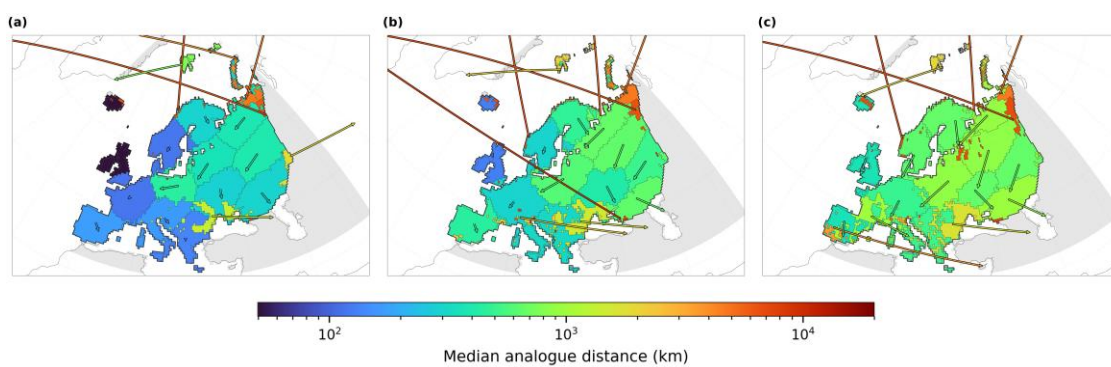


Figure S18 (Africa):

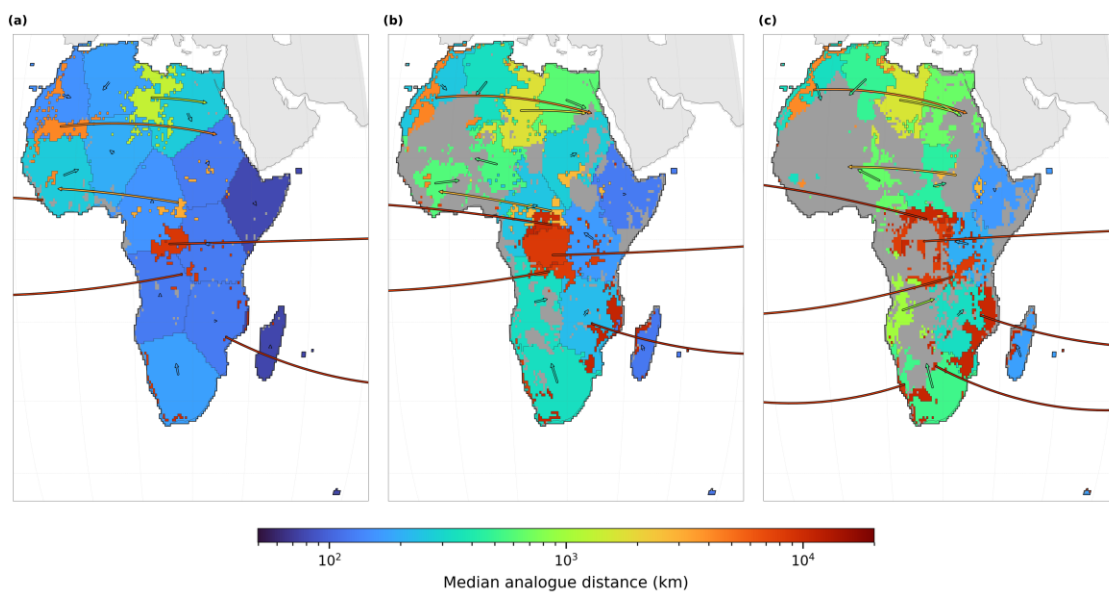


Figure S19 (West & Central Asia):

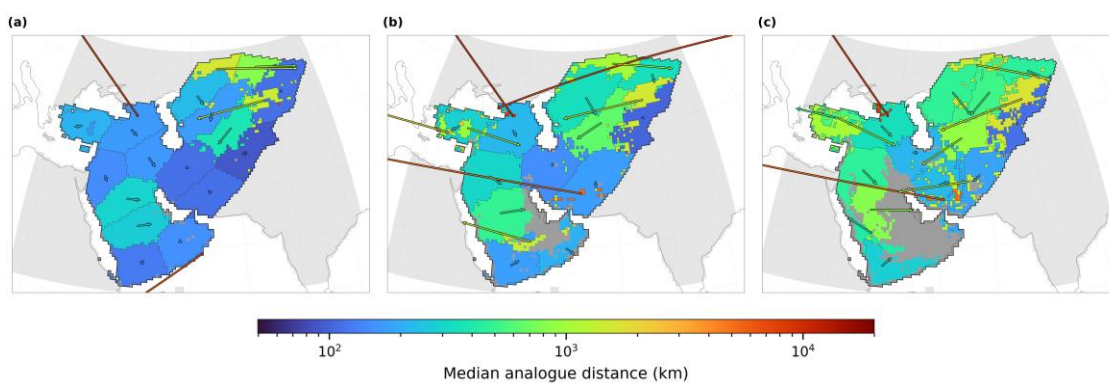


Figure S20 (North Asia):

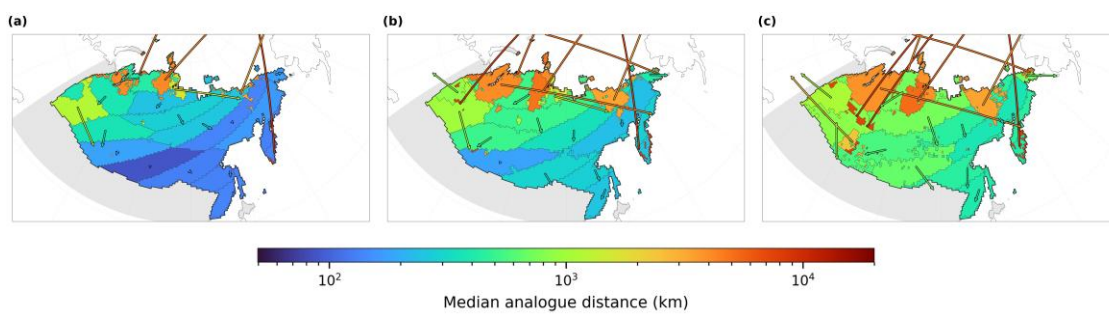


Figure S21 (East Asia):

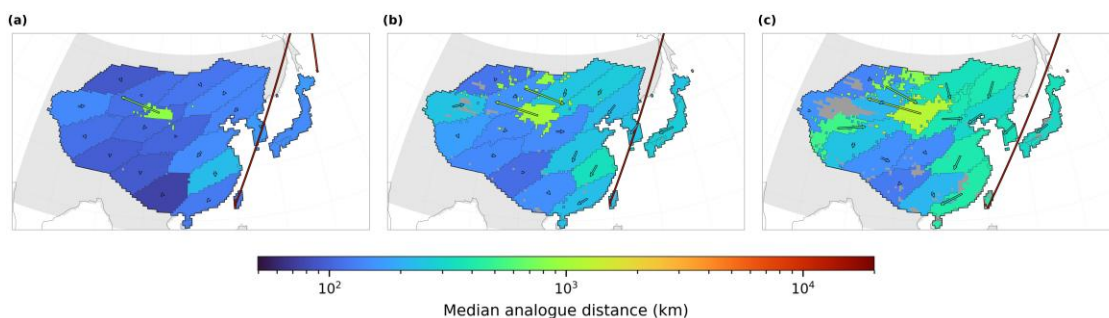


Figure S22 (South & Southeast Asia):

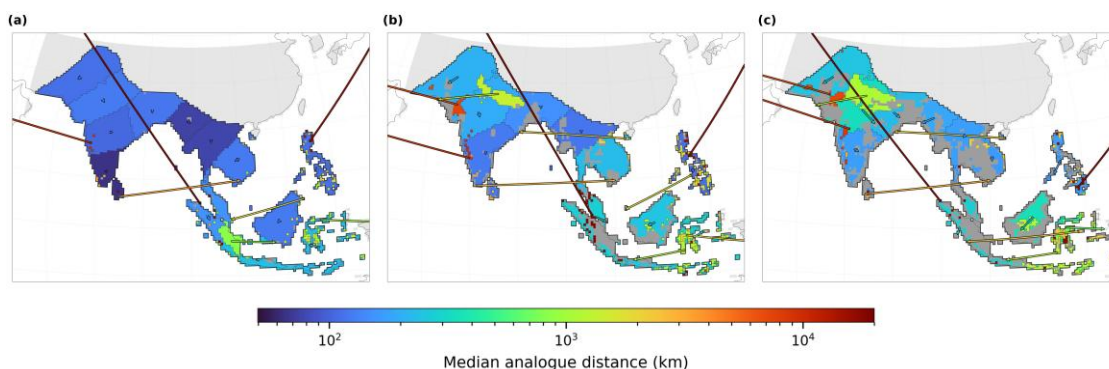
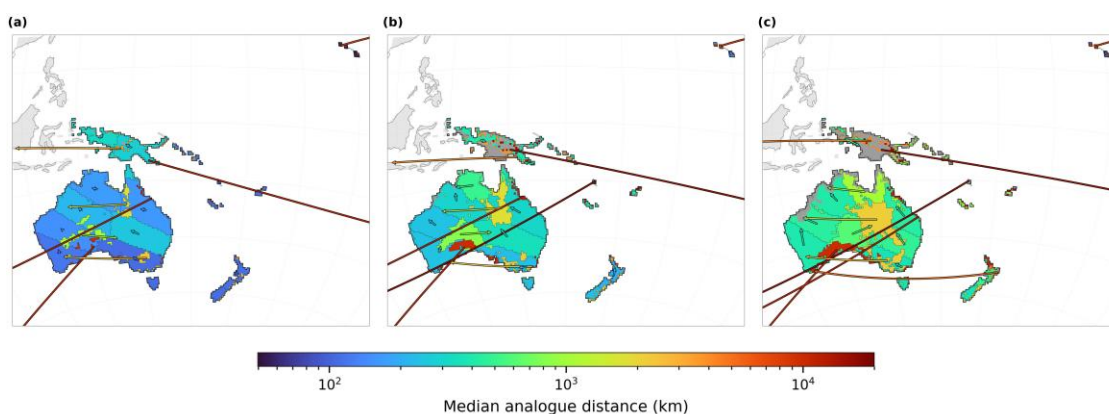


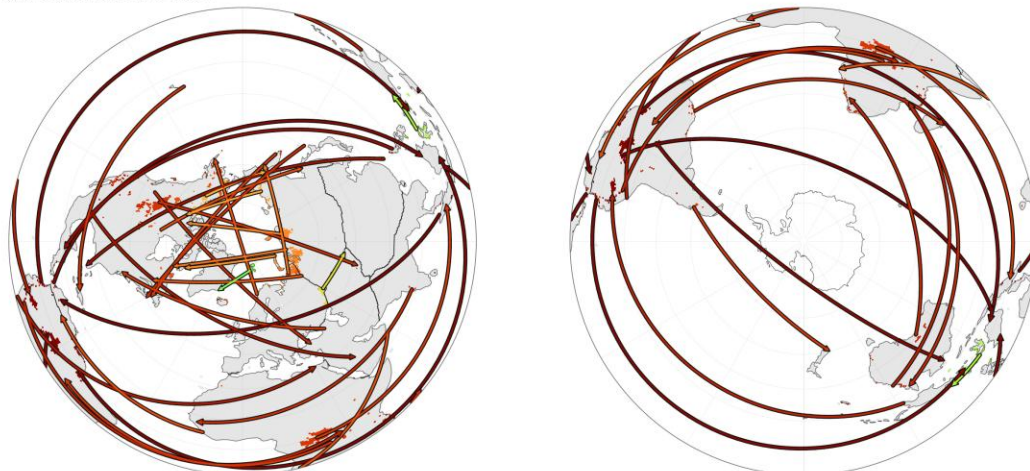
Figure S23 (Australia & Oceania):



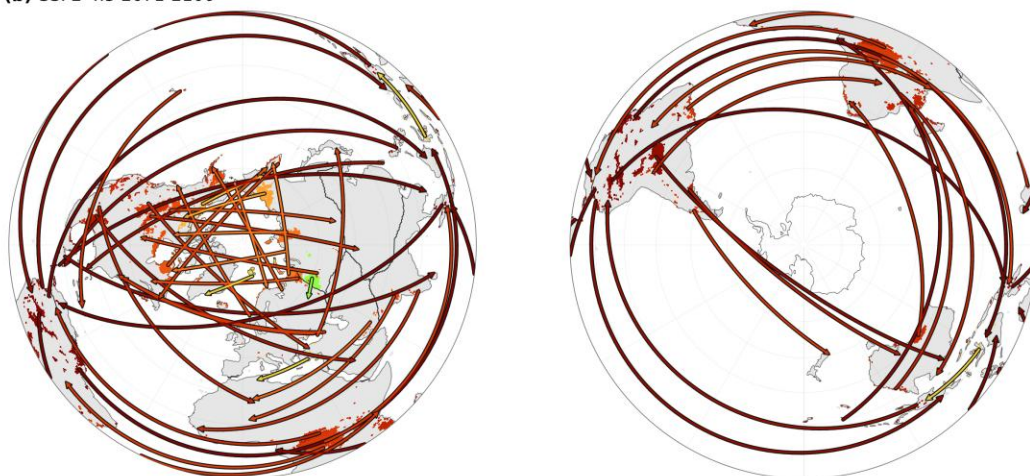
As in main-text Fig. 6, but one sheet per continental window of Supplementary Fig. S14, with the three scenarios side by side: Fig. S15 North America, Fig. S16 South America, Fig. S17 Europe, Fig. S18 Africa, Fig. S19 West & Central Asia, Fig. S20 North Asia, Fig. S21 East Asia, Fig. S22 South & Southeast Asia, Fig. S23 Australia & Oceania. Each sheet shows one window under (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0 (2071–2100), and the single colour bar below applies to all three panels. Arrows clipped at the frame connect to analogues outside the window (completed in Supplementary Fig. S24).

Supplementary Figure S24. Regional clusters whose analogues lie outside their own window.

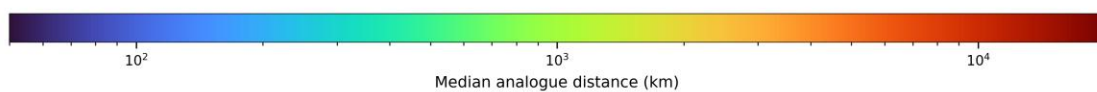
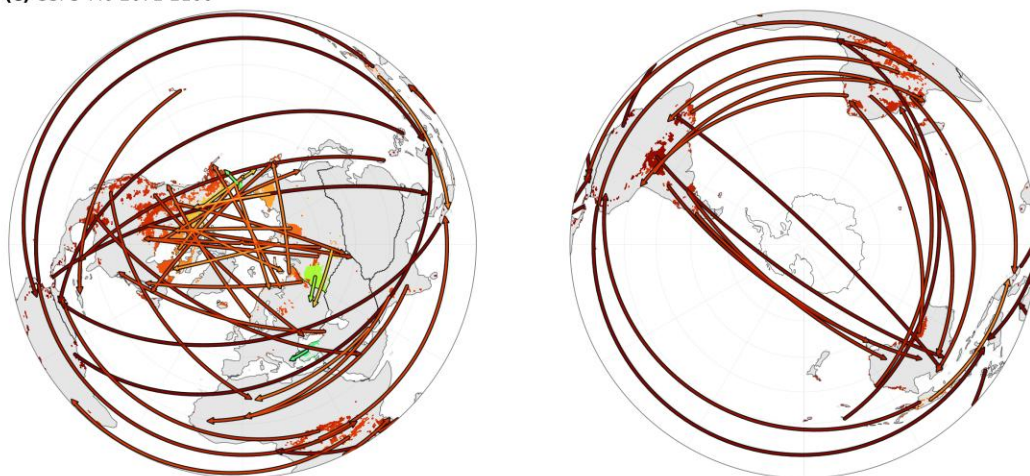
(a) SSP1-2.6 2071-2100



(b) SSP2-4.5 2071-2100



(c) SSP3-7.0 2071-2100



For (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0, every cluster of the nine regional refits (Supplementary Figs. S15–S23) whose core analogue lies beyond its own continental window, drawn on northern- and southern-hemisphere views: the cluster’s member cells are filled, and the arrow is the core cell’s real focal–analogue pair, both coloured by the cluster’s median analogue distance on the fixed 50–20,000 km logarithmic scale of every displacement figure. These are the arrows that the regional clip maps can only show clipped at the frame: under SSP2-4.5, 57 of the 180 regional clusters exit their window, including the Taiwan → Florida–Caribbean exit quoted in the main text. The web of shorter (orange) arrows across the Arctic reflects neighbouring high-latitude windows exchanging analogues across their shared boundaries, and the longest, darkest arcs are the same intercontinental corridors the global fit resolves (main-text Fig. 5, Supplementary Table S6).

Supplementary Table S5. Sensitivity of the k -medoids partition to random restarts ($K = 30$, five seeds per level, three at 10,000).

Scenario	Restarts	Mean pairwise ARI	Min pairwise ARI	Max inertia excess (%)	Mean ARI versus production	Corridor clusters (min–max)
SSP1-2.6	1	0.81	0.72	25.4	0.79	10–14
SSP1-2.6	10	0.84	0.76	14.2	0.82	10–12
SSP1-2.6	100	0.82	0.72	7.5	0.85	9–11
SSP1-2.6	1,000	0.84	0.72	3.3	0.86	9–10
SSP1-2.6	10,000	0.94	0.92	0.7	0.90	9–9
SSP2-4.5	1	0.77	0.66	18.5	0.76	12–16
SSP2-4.5	10	0.89	0.78	5.6	0.87	12–13
SSP2-4.5	100	0.87	0.70	4.3	0.90	11–12
SSP2-4.5	1,000	0.93	0.86	1.7	0.93	11–11
SSP2-4.5	10,000	0.89	0.84	0.1	0.89	10–11
SSP3-7.0	1	0.84	0.72	16.3	0.78	13–15
SSP3-7.0	10	0.80	0.68	9.9	0.82	11–13
SSP3-7.0	100	0.89	0.76	3.9	0.90	10–12
SSP3-7.0	1,000	0.94	0.90	1.7	0.95	11–12
SSP3-7.0	10,000	0.91	0.89	0.4	0.95	11–11

ARI, adjusted Rand index [12] between the partitions of independent seeds at the same restart level (pairwise over that level’s seeds). Inertia excess is relative to the best solution observed for that scenario across all levels and seeds. ‘ARI versus production’ compares each run against the production partition ($K = 30$, 10,000 restarts, seed 0). Corridor clusters follow the corridor criterion of the main text and are counted out of $K = 30$.

Supplementary Table S6. The production global k -medoids partition ($K = 30$, 10,000 restarts): every cluster, named.

(a) SSP1-2.6 (2071–2100):

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
Baltic–east European plain	53.25° N, 23.25° E	51.25° N, 21.75° E	6.44	294	348
Transbaikal–Amur margin	53.25° N, 114.75° E	52.25° N, 114.25° E	6.21	123	192
Iranian highlands	34.75° N, 53.25° E	34.25° N, 53.25° E	6.07	173	264

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
Zambezian plateau	16.75° S, 26.75° E	16.25° S, 27.25° E	5.99	124	211
Central Siberian plateau	60.75° N, 82.75° E	58.25° N, 87.25° E	5.97	370	526
Central Sahel	16.25° N, 15.75° E	16.25° N, 16.75° E	5.86	228	422
East-central China	33.25° N, 112.25° E	32.75° N, 111.75° E	5.60	120	165
Northern Great Plains	49.25° N, 105.25° W	47.75° N, 104.75° W	5.40	184	242
Himalayan front	28.75° N, 81.25° E	28.25° N, 81.75° E	4.99	111	180
Western Sahara (Mali–Algeria)	23.25° N, 5.75° W	23.75° N, 0.25° W	4.99	215	736
Brazilian cerrado	13.25° S, 51.25° W	12.75° S, 50.75° W	4.89	157	217
Boreal Canada (Hudson Bay)	59.75° N, 95.25° W	57.75° N, 92.75° W	4.87	265	427
Sudanian savanna belt	8.75° N, 36.75° E	8.75° N, 35.75° E	4.73	121	252
Chihuahuan Desert	29.75° N, 100.75° W	29.25° N, 100.75° W	4.60	111	144
Central Amazonia	0.75° N, 67.75° W	2.25° N, 66.75° W	4.41	176	238
Central Australia	29.25° S, 132.25° E	28.75° S, 133.25° E	3.75	174	309
North Australian savanna	17.25° S, 140.75° E	16.75° S, 138.75° E	3.23	207	405
Pampas	35.25° S, 63.25° W	34.75° S, 63.75° W	3.07	74	131
West Greenland coast	72.75° N, 53.25° W	71.75° N, 51.25° W	2.85	146	307
Maritime Continent (Borneo)	4.25° N, 108.25° E	3.75° N, 108.25° E	2.55	167	349
North Siberian coast → Russian Far East and Arctic Canada	69.25° N, 74.25° E	62.25° N, 176.25° E	0.53	4,283	4,290
Boreal Alberta → Central Asian steppe	58.25° N, 116.25° W	49.25° N, 84.75° E	0.43	7,732	7,662
Central Amazonia → Borneo	3.25° S, 62.25° W	3.25° S, 110.75° E	0.40	18,912	18,654
Congo Basin → Sumatra	2.25° S, 18.25° E	2.25° N, 102.25° E	0.39	8,894	9,203
South-western United States → Anatolia–Arabia	29.25° N, 106.25° W	21.75° N, 15.75° E	0.27	10,178	10,585
Tropical South America → New	0.75° S, 62.25° W	1.75° S, 138.75° E	0.13	16,958	16,743

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
Guinea–northern Australia					
Central Congo → Amazon margins	6.25° S, 23.75° E	9.25° S, 52.25° W	0.13	8,667	8,750
Northern Urals → eastern Canada	66.25° N, 58.75° E	52.25° N, 63.25° W	0.12	6,033	5,675
Central Australia → Namibia	28.75° S, 131.75° E	28.75° S, 18.25° E	0.09	10,430	11,874
North-west Pacific islands → western North Atlantic	44.75° N, 147.25° E	45.75° N, 59.75° W	0.04	13,774	11,933

(b) *SSP2-4.5 (2071–2100)*:

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
Baltic–east European plain	54.25° N, 26.25° E	50.25° N, 26.75° E	6.41	510	566
Transbaikal–Amur margin	52.25° N, 114.75° E	50.75° N, 114.25° E	6.15	243	347
Central Sahara	24.25° N, 5.75° E	23.75° N, 9.25° E	5.94	630	1,010
Central Siberian plateau	58.75° N, 83.25° E	54.75° N, 86.25° E	5.73	548	639
Iranian highlands	32.25° N, 50.25° E	31.25° N, 50.25° E	5.69	290	415
East-central China	29.25° N, 109.75° E	27.75° N, 109.75° E	5.60	191	277
Sudanian savanna belt	10.75° N, 30.25° E	10.25° N, 28.25° E	5.09	233	478
Northern Great Plains	47.25° N, 101.25° W	44.75° N, 100.25° W	4.94	332	388
Zambeian plateau	17.75° S, 28.25° E	16.25° S, 28.75° E	4.65	270	361
Himalayan front	28.75° N, 82.25° E	28.25° N, 82.75° E	4.64	182	320
Boreal Canada (Hudson Bay)	59.75° N, 94.75° W	57.25° N, 91.25° W	4.39	569	838
Chihuahuan Desert	30.75° N, 102.25° W	29.75° N, 101.75° W	3.76	174	225
Central Australia	30.75° S, 135.25° E	29.25° S, 135.25° E	3.73	314	454
North Australian savanna	12.75° S, 131.25° E	13.75° S, 126.75° E	3.52	400	762
Brazilian cerrado	16.75° S, 52.25° W	15.25° S, 51.75° W	3.52	244	323
West Greenland coast	72.75° N, 55.25° W	69.75° N, 52.25° W	2.82	277	519
North-west Amazonia	2.75° N, 68.75° W	4.75° N, 68.25° W	2.76	279	366

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
Pampas	36.25° S, 63.75° W	34.75° S, 63.75° W	2.54	174	210
North Siberian coast → Russian Far East and Arctic Canada	73.25° N, 120.25° E	64.75° N, 110.25° W	1.44	4,139	4,228
Boreal western Canada → Central Asia and the Russian Far East	60.75° N, 113.25° W	55.25° N, 90.75° E	1.25	6,860	7,141
Congo Basin → Sumatra	1.25° S, 31.75° E	0.75° N, 120.75° E	1.06	9,237	9,536
South-western United States → Anatolia–Arabia	42.25° N, 111.75° W	38.75° N, 35.75° E	0.77	10,070	10,296
Southern Amazon → northern Australia	13.75° S, 62.75° W	13.25° S, 129.75° E	0.72	16,532	16,738
Central Congo → Amazon margins	4.25° S, 27.75° E	6.75° S, 49.75° W	0.59	8,600	8,878
Central Amazonia → Borneo	1.25° S, 64.75° W	2.75° S, 108.25° E	0.58	18,726	18,551
Central Australia → Namibia	29.25° S, 130.75° E	28.75° S, 18.25° E	0.30	10,345	12,347
Northern Urals → eastern Canada	63.25° N, 58.75° E	51.25° N, 68.75° W	0.25	6,389	6,122
Brazilian cerrado → east Africa	16.75° S, 42.25° W	11.75° S, 38.25° E	0.19	8,657	8,873
Northern Patagonia → south-east Australia	39.25° S, 62.75° W	33.25° S, 148.25° E	0.09	11,433	10,724
New Guinea → north-western South America	4.25° S, 140.25° E	2.75° S, 75.75° W	0.07	15,306	15,492

(c) SSP3-7.0 (2071–2100):

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
Boreal Canada (Hudson Bay)	54.25° N, 96.25° W	49.25° N, 94.75° W	5.61	551	691
Transbaikal–Amur margin	54.25° N, 124.25° E	51.25° N, 125.25° E	4.87	414	506
Southern Great Plains	36.75° N, 103.25° W	35.25° N, 103.25° W	4.80	327	352
Baltic–east European plain	58.75° N, 28.25° E	54.75° N, 19.75° E	4.60	758	776
East-central	30.25° N,	29.75° N,	4.55	263	354

Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
China	110.75° E	109.25° E			
Central Siberian plateau	60.25° N, 90.75° E	55.25° N, 86.75° E	4.49	736	803
Gran Chaco–Paraná	29.25° S, 56.75° W	27.25° S, 56.75° W	4.22	297	345
Eastern Anatolia	37.75° N, 38.25° E	35.75° N, 44.75° E	4.18	723	813
Northern Sahara (Algeria)	36.25° N, 2.25° E	34.25° N, 10.25° E	4.11	682	1,124
Pamir–Hindu Kush margin	38.25° N, 66.75° E	36.25° N, 65.75° E	4.08	334	527
Himalayan front	30.25° N, 87.75° E	29.25° N, 87.25° E	3.93	292	467
Sudanian savanna belt	9.75° N, 34.25° E	9.75° N, 32.75° E	3.71	324	503
North Australian savanna	17.25° S, 136.25° E	15.25° S, 128.25° E	3.25	773	1,179
Central Australia	28.25° S, 126.75° E	25.75° S, 125.75° E	2.94	468	623
West Greenland coast	72.25° N, 54.75° W	69.75° N, 52.25° W	2.78	461	720
Zambezian plateau	19.25° S, 28.75° E	16.25° S, 30.25° E	2.78	404	528
North Siberian coast → Russian Far East and Arctic Canada	71.25° N, 118.25° E	66.75° N, 127.75° W	1.84	3,917	4,175
North-west Amazonia	2.75° N, 73.75° W	2.25° N, 73.25° W	1.53	235	476
Great Basin → Anatolia–Arabia	43.25° N, 115.25° W	37.25° N, 29.25° E	1.34	10,112	10,300
Boreal western Canada → Russian Far East	62.25° N, 118.75° W	55.25° N, 91.75° E	1.18	6,555	6,727
Zambezi–Katanga plateau → northern Australia and Sumatra	15.25° S, 32.75° E	13.75° S, 127.25° E	1.09	10,232	9,916
Arctic Canada → Chukotka	66.25° N, 97.25° W	64.75° N, 179.75° E	1.01	3,852	3,583
Chiquitania–Pantanal → north-western Australia	22.75° S, 63.25° W	16.75° S, 127.75° E	0.94	16,068	15,246
Central Congo → Amazon margins	5.25° S, 28.25° E	6.75° S, 49.25° W	0.71	8,966	9,445
Boreal western Canada → Kazakh–Altai steppe	53.25° N, 105.75° W	46.75° N, 83.25° E	0.54	9,093	8,953
Southern Urals	58.75° N, 59.25°	46.25° N, 72.75°	0.42	7,086	7,050

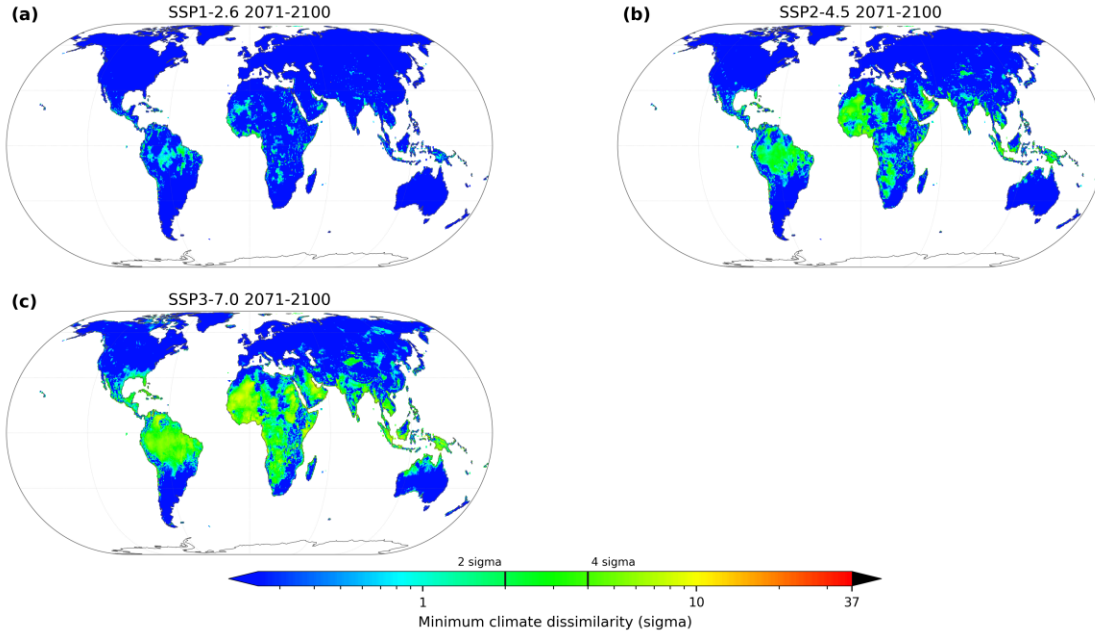
Cluster	Core cell	Core analogue	Area (% of land)	Median distance (km)	Mean distance (km)
→ eastern Canada	E	W			
Central Australia → Namibia	31.75° S, 135.25° E	28.75° S, 17.75° E	0.37	10,242	10,852
Brazilian cerrado → east Africa	22.25° S, 41.75° W	13.75° S, 47.75° E	0.25	8,690	9,034
Eastern Brazil–Guianas → northern Australia	2.75° N, 52.75° W	0.25° S, 117.25° E	0.21	16,990	17,598
New Guinea → north-western South America	4.25° S, 135.75° E	2.25° S, 75.75° W	0.08	15,996	16,192

Clusters of the production global partition (main-text Fig. 5), one sub-table per scenario, sorted by land-area share. The core is the cluster's real member cell that minimizes the weighted distance to all members in the position–displacement feature space, and 'core analogue' is that cell's actual best-analogue location, that is, the arrow drawn in main-text Fig. 5. Clusters whose displacement links two distinct regions are written focal region → analogue region, and those meeting the main-text corridor criterion are the corridor clusters. Names describe the cluster's member geography, whereas the core columns give one real member pair, which can sit toward the cluster's edge. Median and mean are member analogue distances, and the novel class ($\sigma > 2$) is excluded.

Section 7. The extreme tail: hyper-sigma cells and attribution

The banded maps of main-text Fig. 1 clip the sigma scale at 8σ ; Fig. S25 shows the unclipped field, whose local maxima sit on the hyper-arid coastal deserts, the same cells that dominate Section 8. The attribution analysis of main-text Fig. 2 rests on the exact additive per-feature decomposition of the ensemble climatic difference (z_k^2 over the 36 features; Section 11). Beyond the warmer-dominated shares quoted in the main text, novel land is temperature-seasonal on a further 6.1%, 4.2%, and 4.9% across the scenarios.

Supplementary Figure S25. Full-range sigma dissimilarity, logarithmic scale.



As in main-text Fig. 1a–c, but unbanded: the ensemble sigma dissimilarity is drawn on a logarithmic colour scale. Dark lines on the colour bar mark the 2σ novelty threshold and the 4σ ‘extreme novelty’ level of Mahony et al. [9].

Section 8. The hyper-arid outliers and the two standardization scales

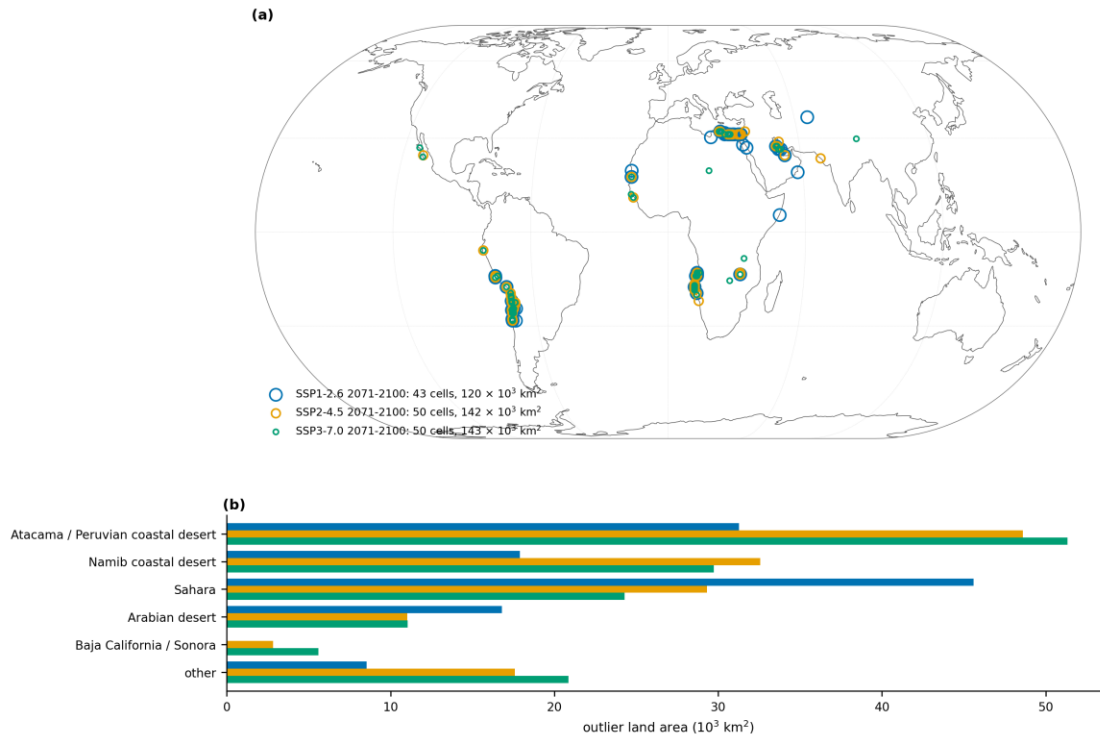
A handful of cells (43 to 50 per scenario, 0.08–0.10% of the searched domain) carry ensemble Wasserstein distances of roughly 50–5,600 against a bulk 99th percentile of 12–18. This section documents where they are, why they arise, and why they motivate placing the novelty threshold on the historical-variability sigma scale rather than on the WD.

Mechanism. The Wasserstein metric standardizes each of the 36 features by the standard deviation of the focal cell’s projected 2071–2100 sample, floored at 10^{-6} (ref. [1], their eq. 6). Where a projection is effectively rainless, that scale collapses to the floor and any finite absolute precipitation change is divided by an almost-zero number: the metric explodes for reasons unrelated to climate displacement. The floor genuinely engages in the production run: 936 (model, cell, feature) entries across the twelve model–scenario combinations (between 52 and 123 per combination) have a sample standard deviation of exactly zero, every one a log-precipitation feature whose projected 30-year month is identically rainless (96, 104, and 112 distinct cells under SSP1-2.6, SSP2-4.5, and SSP3-7.0, union over models). The activation is binary rather than marginal: the smallest standard deviation above the floor is 5.9×10^{-4} , three orders of magnitude clear of it, and no temperature feature falls below 0.07 K. The affected cells are real, identifiable, and few: most sit in five hyper-arid deserts, with a small monsoonal residual (Fig. S26). Excluding the outliers restores the raw-scale agreement between the metrics (Table S7).

Relative versus absolute variability (Fig. S27). The coefficient of variation (CV) of precipitation makes the degeneracy visible as geography; Fig. S27 maps it, historical and projected, with the outlier cells overlaid.

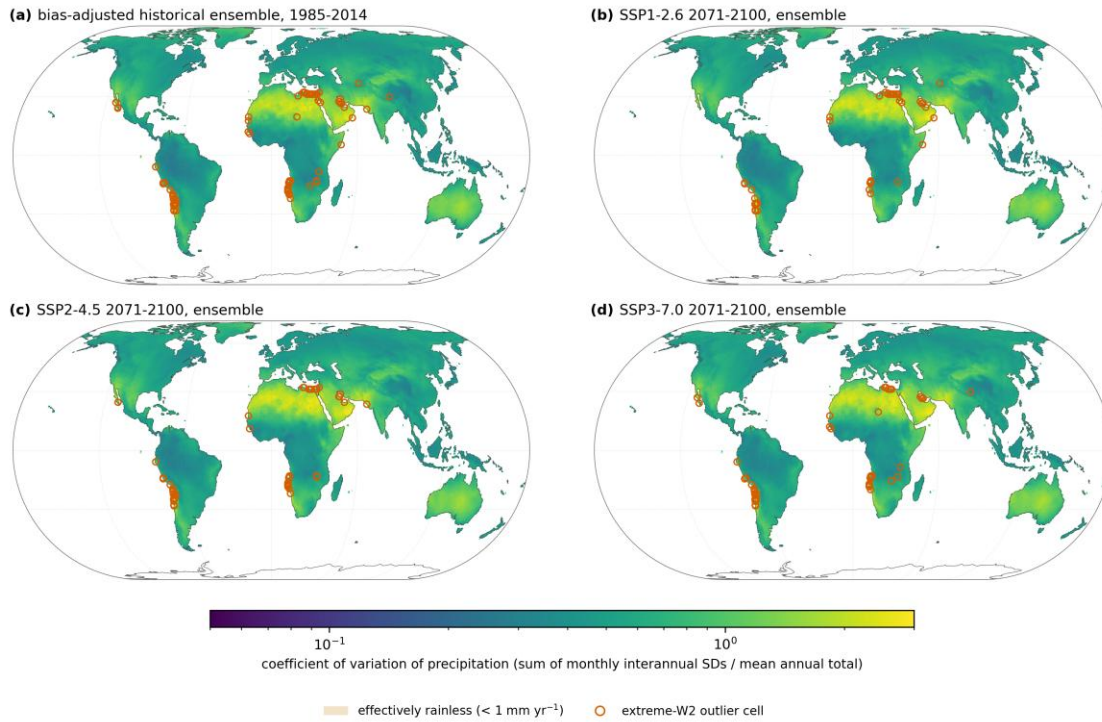
Why the novelty threshold stands on historical variability. The sigma dissimilarity normalizes the ensemble climatic difference against the pooled historical interannual variability of the four bias-adjusted models (Section 10 and main-text Methods). Three properties follow. First, the null is anchored in the observed record: the 2σ test asks whether the projected climatic difference is improbable against the variability a place has actually exhibited, not against a model’s own projected variability. Second, the yardstick is common to all scenarios and models, so differences in novel area measure climatic difference, not rescaled variability. Third, the test does not inherit the projected-standard-deviation degeneracy documented above, which is exactly the failure mode a WD threshold would import into the headline novel-area numbers. The hyper-arid cells still register extreme sigma values (up to 37σ , Fig. S25), but those are finite, rank-consistent with the rest of the field, and carry the correct qualitative message: in a place with almost no interannual variability, a small absolute change is a large climatic event.

Supplementary Figure S26. The hyper-arid cells with extreme Wasserstein distances: locations and land area.



(a) Every cell whose ensemble Wasserstein distance exceeds 50 (the bulk 99th percentile is 12–18), marked per scenario with concentric open rings where the same cell recurs. The legend gives the cell count and total land area per scenario. (b) The same land area split by desert region. The cells concentrate in five hyper-arid regions where the near-zero interannual variability of precipitation collapses the Wasserstein standardization scale (Supplementary Table S7): the Atacama–Peruvian coastal desert (46 scenario-cells), the Sahara (37), the Namib (27), the Arabian Peninsula (14), and Baja California/Sonora (3). The residual 16 ‘other’ scenario-cells (Guinea coast, Zambezi highlands, Tibetan Plateau, lower Indus) are monsoonal rather than arid: their annual totals reach 130–2,100 mm, but their bone-dry dry-season months have the same near-zero variability, so the same per-feature floor bites there through individual months.

Supplementary Figure S27. Coefficient of variation (CV) of precipitation, historical and projected, and the cells where the absolute scale collapses.



Relative interannual variability of precipitation (the sum over calendar months of the interannual standard deviation of monthly precipitation totals, divided by the mean annual total) for (a) the bias-adjusted historical ensemble (1985–2014) and (b–d) the ensemble projection for 2071–2100 under each scenario (mean of the four per-model values, logarithmic colour scale). Cells whose mean annual total falls below 1 mm are drawn in a separate ‘effectively rainless’ shade, because a ratio of two near-zero numbers has no meaning there. Orange rings mark the extreme-WD cells of Supplementary Fig. S26 (all scenarios’ cells on panel a, each scenario’s own on b–d). The two quantities are two sides of one degeneracy: the outlier cells sit on the high-CV desert belts (median CV 1.36 at the outlier cells against a land median of 0.57 in the historical ensemble, and 1.07–1.45 against 0.57–0.58 in the projections) precisely because their absolute variability (the Wasserstein standardization scale of Section 8) is collapsing toward zero.

Supplementary Table S7. Hyper-arid cells with extreme Wasserstein distances, and their effect on the metric-agreement statistics.

Scenario	Outlier cells (WD > 50)	Outlier area (10 ³ km ² , % of land)	Median annual precipitation (mm)	Max WD	Bulk p99 WD	Pearson <i>r</i> (all cells)	Pearson <i>r</i> (without outliers)	Spearman ρ (all cells)
SSP1- 2.6	43	120 (0.08)	79	5,636	12.3	0.32	0.80	0.81
SSP2- 4.5	50	142 (0.10)	65	4,163	15.9	0.27	0.91	0.88
SSP3- 7.0	50	143 (0.10)	85	1,843	18.4	0.22	0.93	0.89

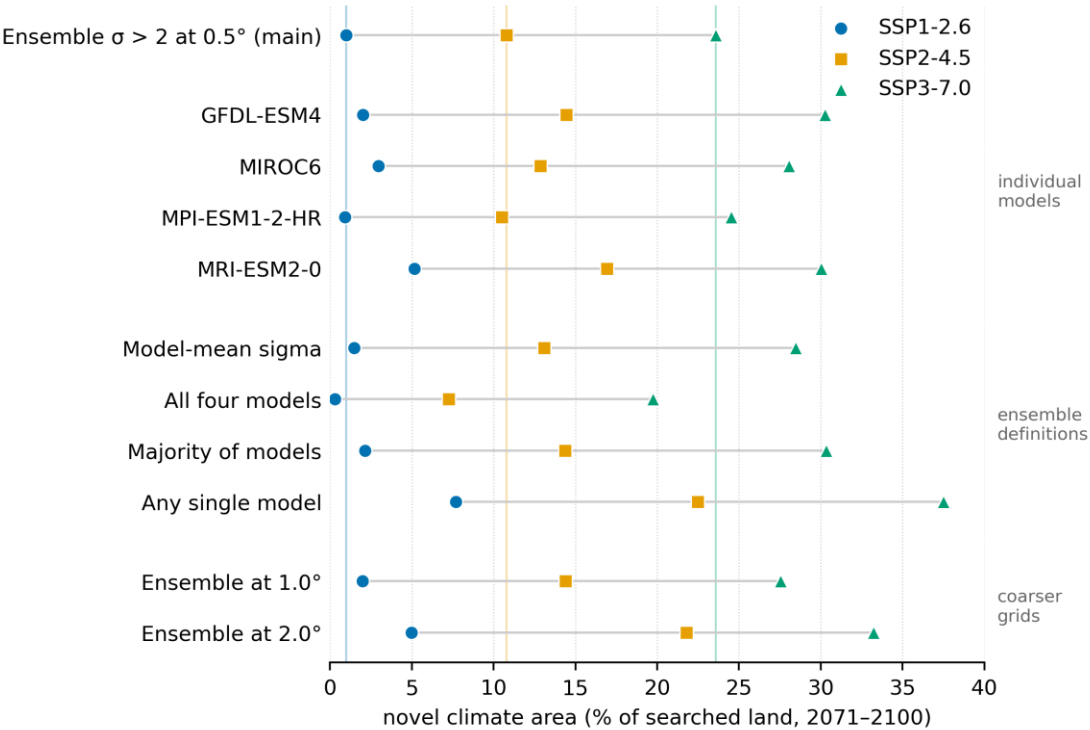
The outlier regions, their scenario-cell counts, and the 16 monsoonal residual cells are mapped and quantified in Supplementary Fig. S26. Median annual precipitation is that of the W5E5-anchored 1985–2014 reference normals at the outlier cells, and the accompanying coefficient-of-variation maps are Supplementary Fig. S27. The most

extreme cells across the scenarios: 26.75° N, 35.75° E (Arabian desert, WD 5,636 under SSP1-2.6); 14.25° S, 76.25° W (Peruvian coast, 4,163, SSP2-4.5); 25.75° S, 70.75° W (Atacama, 3,053); 24.25° S, 69.75° W (Atacama, 2,965); 32.25° N, 24.25° E (Sahara, 2,333); and 27.75° S, 71.25° W (Atacama, 1,843, SSP3-7.0). WD, Wasserstein distance; p99, 99th percentile.

Section 9. Novel area under alternative definitions, models, and grids

The headline novel areas are one member of a family of defensible definitions, and Fig. S28 and Table S8 place them inside that family: per-model verdicts, vote-based and model-mean aggregations, and the full search repeated on 1.0° and 2.0° aggregations of the same data. The ensemble definition of the main text sits at the conservative end throughout, and every definition preserves the scenario ordering. In the resolution rows, novelty inflates monotonically with coarsening, the aggregation mechanism discussed in the main text. The analogue statistics degrade in parallel: the median analogue distance under SSP1-2.6 lengthens from 174 km at 0.5° to 221 km at 1.0° and 264 km at 2.0°, and the self-analogue share of the area with an accepted analogue at low forcing grows from 1.47% at 0.5° to 12.80% at 2.0°.

Supplementary Figure S28. Novel climate area under alternative definitions, individual models, and coarser grids.



Novel area (% of searched land, 2071–2100) for each scenario (colour and marker) under the study’s main definition (ensemble sigma dissimilarity $> 2\sigma$ at 0.5°, top row, thin vertical lines), for each ensemble member’s own climatic-difference field, for the alternative ensemble aggregations, and for the full search repeated on 1.0° and 2.0° aggregations of the same data. Grey bars connect the three scenarios of one row. Row definitions and numeric values are given in Supplementary Table S8.

Supplementary Table S8. Novel climate area (% of searched land) under alternative novelty definitions, individual models, and coarser grids.

Definition	SSP1-2.6	SSP2-4.5	SSP3-7.0
Ensemble $\sigma > 2$ at 0.5° (main result)	0.99	10.78	23.59
GFDL-ESM4	2.01	14.45	30.25

Definition	SSP1-2.6	SSP2-4.5	SSP3-7.0
MIROC6	2.97	12.85	28.07
MPI-ESM1-2-HR	0.91	10.51	24.53
MRI-ESM2-0	5.15	16.94	30.04
Model-mean sigma	1.48	13.08	28.46
Majority of models	2.14	14.37	30.33
Any model	7.69	22.48	37.49
All models	0.31	7.27	19.75
Ensemble at 1.0°	1.99	14.40	27.54
Ensemble at 2.0°	4.97	21.79	33.22

Model rows apply the same $\sigma > 2$ test to each model's own climatic-difference field. Model-mean sigma applies the test to the model-mean climatic difference with inter-model spread counted as dissimilarity (an upper bound). Vote rows declare a cell novel where at least one, a majority, or all four models are individually novel. Resolution rows repeat the entire analogue search on 1.0° and 2.0° aggregations of the same data. This table is drawn as Supplementary Fig. S28.

Ensemble novel area (%) at selected thresholds of the continuous sweep (Supplementary Fig. S1):

Threshold	SSP1-2.6	SSP2-4.5	SSP3-7.0
1.0 σ	4.36	18.56	32.21
1.5 σ	2.14	14.36	27.45
2.0 σ (main)	0.99	10.78	23.59
3.0 σ	0.19	5.06	17.11
4.0 σ	0.10	2.12	11.96

Section 10. The precipitation normalization of the sigma null: quantile matching and its sensitivity

The sigma null asks how improbable the ensemble climatic difference is against a place’s own interannual climatic variability (ICV), which requires expressing every feature’s ICV on a common standard-normal scale. Temperature ICV is close enough to Gaussian for a linear z-score. Monthly precipitation ICV is not, and, as Mahony et al. [9] discuss in their Appendix S8, a log transformation is only a partial remedy. Fig. S29 measures the violation on this pipeline’s own ICV sample (the pooled detrended 4×30 -year historical features of the sigma null, 120 samples per cell): the median |skewness| of the log-transformed monthly precipitation residuals is 0.41–0.52 depending on calendar month, where pure sampling noise at $n = 120$ would sit near 0.15. In any given month, 22–29% of land shows |skewness| above 1, and a Jarque–Bera screen rejects normality at the 1% level over 35–43% of the searched area. The temperature features (worst of 24 per cell) show no comparable violation.

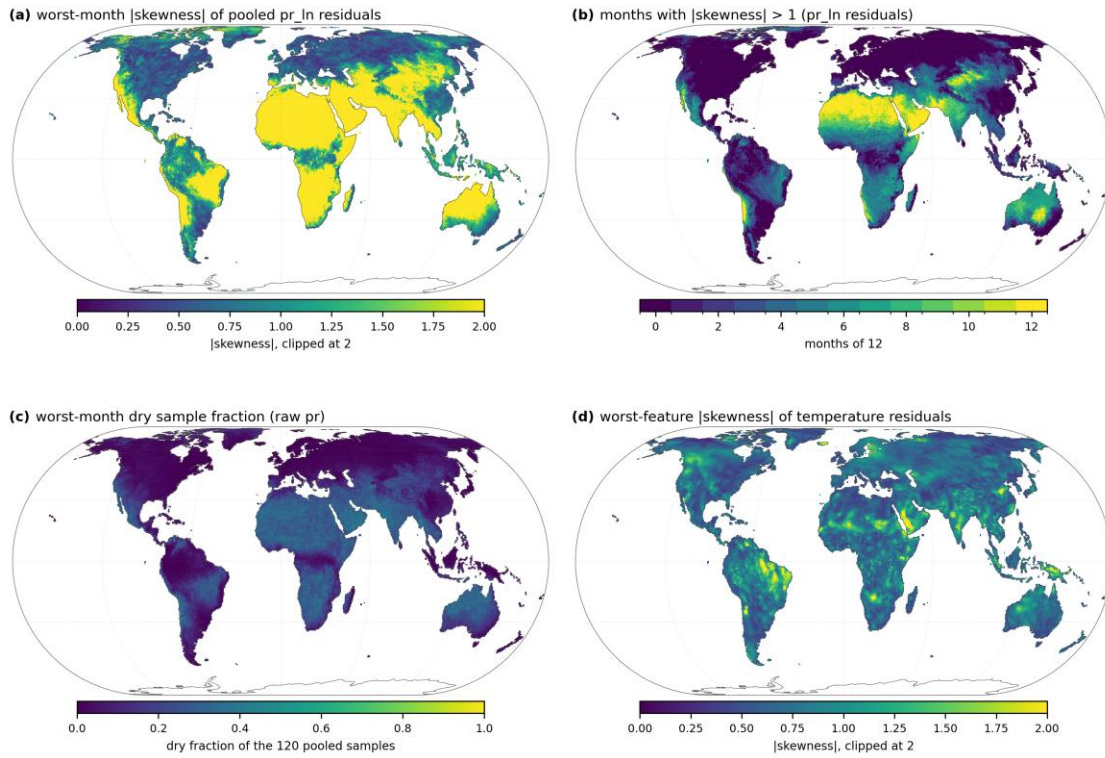
The production null therefore normalizes precipitation ICV by quantile matching, the alternative Mahony et al. [9] recommend for exactly this situation (their S8, and the construction of the standardized precipitation index (SPI)) [13]: per cell and calendar month, a dry-mass + gamma mixture $H(x) = q + (1 - q)G(x; \alpha, \beta)$ is fitted to the 120 pooled raw-precipitation samples, where x is monthly precipitation, q is the dry fraction ($\leq 10^{-4}$ mm day $^{-1}$), and G is a gamma cumulative distribution function with shape α and scale β fitted to the wet samples by the Thom estimator [14], and values become z-scores through $z = \Phi^{-1}(H(x))$, with the SPI convention $H = q/2$ for dry values, the far tail evaluated on the survival side (no precision horizon appears before the $\sim 8.2\sigma$ detection ceiling), and $|z|$ capped at 8.21. Mahony et al. could not apply this recipe because their ICV proxies were weather stations: grid cells far from the station fall beyond the decimal precision of the fitted cumulative distribution function (CDF). They note, however, that the limitation vanishes when ‘the transformation was calculated at the cell level’. The fits are usable for 99.998% of the 789,564 cell-months (65,797 cells $\times$ 12 calendar months), and the exceptions, and how they are handled, are documented in the next paragraph and in Table S10. The transformed features then enter the sigma null exactly as specified in the main-text Methods and Section 11, with standard-normal marginals by construction, so the assumption the machinery rests on holds exactly rather than approximately. After the transform, the median |skewness| of the normalized precipitation samples falls to 0.30 (95th percentile 1.07; a two-parameter gamma cannot normalize every bimodal or heavy-tailed sample).

The 14 hyper-arid cells whose fit is borrowed (Table S10). A gamma distribution can only be estimated from wet samples, and we require at least 15 of the 120 pooled values above the 10^{-4} mm day $^{-1}$ dry threshold for a usable fit: below that, two parameters would be read from a handful of points and the novelty z-score from the noise of their far tail. Sixteen cell-months in 14 cells fail this requirement, in two distinct regimes. The first is the perennially rainless coastal deserts: eight cells along the Atacama–Peruvian coast (annual precipitation 1.7–56 mm) and two on the Namib coast of Angola (39–41 mm), whose driest calendar months contain between 0 and 13 wet values among all 120 model-years. The second is dry-season absolutism in otherwise wetter climates: three cells on the Libyan–Egyptian Mediterranean coast and one on the Karakum margin receive 144–212 mm per year, but their July or August is rainless in essentially every year of every model, the same month-wise degeneracy that produces the ‘monsoonal’ Wasserstein outliers of Section 8. For these cell-months the mixture of the nearest cell whose same-calendar-month fit is usable is borrowed in full (α , β , and the dry mass q together, so the transform remains a proper distribution): in all sixteen cases the donor is the immediately adjacent 0.5° grid cell, 44–53 km away, typically the first cell inland of the coastal fog desert, where the same month holds 59–106 wet samples (Table S10). The borrowed transform then serves as T_{jk} everywhere the focal cell’s own fit would have: it normalizes the focal cell’s pooled ICV samples entering the null correlation, and it maps both ends of the climatic difference (the future and the analogue-historical 30-year means), with dry values taking $z = \Phi^{-1}(q/2)$ under the

donor's dry mass. The construction reads the focal cell's precipitation against the closest estimable wet-day distribution, a regional-representativeness assumption we consider preferable to either alternative: fitting on fewer than 15 points, or falling back to the linearly standardized log-precipitation z-score, which in exactly these cells divides by a near-zero standard deviation (the degeneracy of Section 8). The assumption touches 0.002% of all cell-months and roughly 0.02% of searched land. Its possible influence on the verdict is bounded by where the 14 cells stand: under SSP2-4.5 all fourteen, and under SSP3-7.0 thirteen, are novel with a median ensemble sigma of 4.4 and 7.3 (verdicts carried by the thermal climatic difference, which the borrowing does not touch), while under SSP1-2.6 they straddle the threshold (five of fourteen novel, median 1.86σ), so at most a few of these individual cells could plausibly read differently under a different dry-cell rule. No borrowing is needed at all on the 1.0° and 2.0° grids, where aggregation pools enough wet samples everywhere.

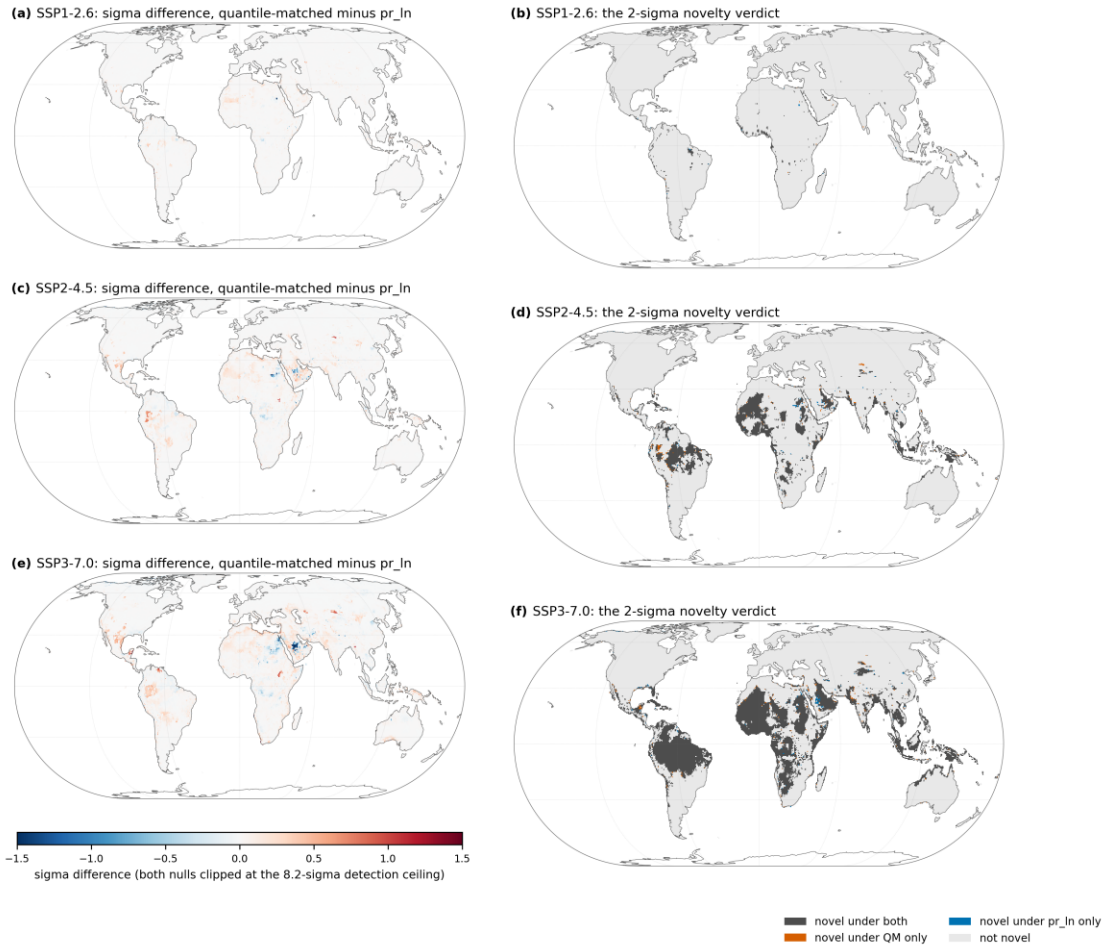
Sensitivity: the verdict does not depend on the choice. Every sigma was recomputed under the log-transformation alternative: the identical machinery with the linearly standardized log-precipitation ICV in place of the quantile matching, at the same Wasserstein-selected analogues. Table S9 and Figs. S30–S31 summarize the comparison. The three headline novel areas move by -0.01 , $+0.19$, and $+0.15$ percentage points of land (quantile matching minus log transformation), the 2σ verdict flips on at most 0.68% of searched land (0.06%, 0.54%, and 0.68% across the scenarios), and over the 99.96% of the domain outside the hyper-arid regime the cell-wise sigma difference sits between -0.07σ and $+0.15\sigma$ (5th–95th percentile, worst scenario) with a median of 0.00σ . The two nulls disagree materially only in the hyper-arid regime (worst-month dry fraction above 0.5, 0.04% of searched land), where the log-transformed null divides by a near-zero standard deviation and can misstate sigma by several σ , the same degeneracy family as the Wasserstein outliers of Section 8, which the explicit dry mass of the mixture absorbs. This mirrors the sensitivity bookend of Mahony et al. [9] (their S8, Fig. S16): the assumed distribution of precipitation ICV ‘is not of overriding importance’ to the novelty verdict. The quantile-matched null, however, makes the distributional assumption true by construction and handles rainless months explicitly, which is why it is the production choice.

Supplementary Figure S29. Residual non-normality of the sigma-null ICV under the log transformation.



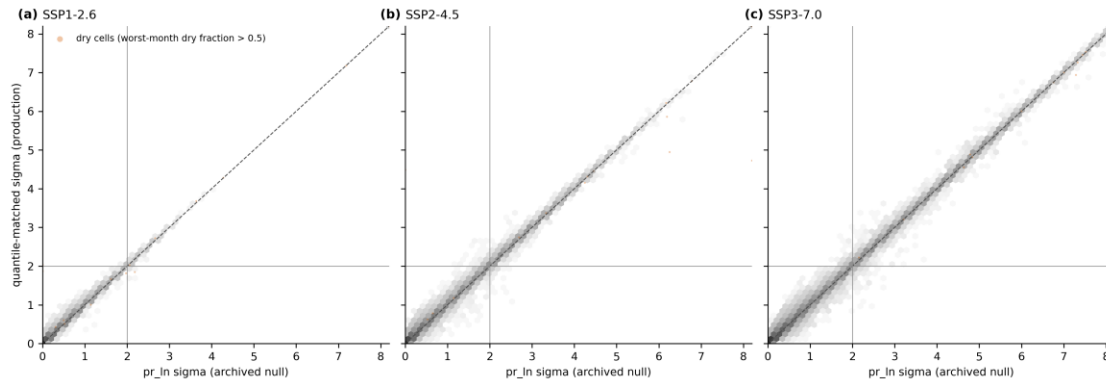
(a) Worst-calendar-month |skewness| of the pooled detrended log-precipitation residuals (120 samples per cell), clipped at 2. (b) Number of calendar months (of 12) with |skewness| > 1. (c) Worst-month dry (zero-precipitation) fraction of the pooled raw-precipitation sample: the point mass no value transformation can remove and the quantity the mixture's dry mass q absorbs. (d) Worst-feature |skewness| of the 24 temperature residuals, the scale reference: temperature ICV supports the linear z-score, precipitation ICV does not.

Supplementary Figure S30. The novelty verdict under the two precipitation normalizations.



Left column: cell-wise sigma difference, quantile-matched minus log-transformed null, both clipped at the $\sim 8.2\sigma$ detection ceiling so mutually saturated cells read as agreement, for **(a)** SSP1-2.6, **(c)** SSP2-4.5, **(e)** SSP3-7.0. Right column **(b, d, f)**: the 2σ novelty verdict (novel under both nulls, under only one, or under neither). Slight increases (warm hues) spread across the semi-arid belts, the same direction as the raw-versus-log bookend of Mahony et al. [9] (their Fig. S16), and decreases concentrate in the hyper-arid cores.

Supplementary Figure S31. Cell-by-cell sigma under the two nulls.



Ensemble sigma under the log-transformed null (horizontal) against the production quantile-matched null (vertical), per scenario. The grey hexagonal density covers all searched cells (logarithmic counts), and the orange

points are the hyper-arid cells (worst-month dry fraction > 0.5 , 0.04% of land). The dashed line is equality, and thin lines mark the 2σ threshold. The mass hugs the identity line, and the visible departures are the hyper-arid cells below it.

Supplementary Table S9. Novel climate area under the two precipitation normalizations of the sigma null.

Scenario	Threshold	Quantile-matched (production, %)	Log-transformed (%)	Difference (pp)	Flips to novel (pp)	Flips to analogue (pp)
SSP1-2.6	2σ	0.99	1.00	-0.01	+0.03	-0.03
SSP1-2.6	3σ	0.19	0.19	-0.00	+0.01	-0.01
SSP1-2.6	4σ	0.10	0.10	-0.00	+0.00	-0.00
SSP2-4.5	2σ	10.78	10.59	+0.19	+0.37	-0.17
SSP2-4.5	3σ	5.06	4.94	+0.12	+0.20	-0.09
SSP2-4.5	4σ	2.12	2.06	+0.07	+0.10	-0.03
SSP3-7.0	2σ	23.59	23.43	+0.15	+0.42	-0.26
SSP3-7.0	3σ	17.11	17.04	+0.07	+0.30	-0.22
SSP3-7.0	4σ	11.96	11.92	+0.04	+0.18	-0.14

Shares of searched land beyond each threshold under the production quantile-matched null and under the log-transformation alternative, evaluated at the identical Wasserstein-selected analogues. Flip columns split the net difference into land newly beyond and newly within the threshold; pp, percentage points. The verification tolerances behind the comparison are given in Section 11.

Supplementary Table S10. The 16 hyper-arid cell-months whose precipitation mixture is borrowed from the adjacent cell.

Cell (lat, lon)	Region	Annual precip. (mm)	Month	Wet samples (of 120)	Donor cell (lat, lon)	Donor wet samples	Distance (km)
19.25° S, 70.25° W	Atacama–Peruvian coast	18.9	May	0	19.25° S, 69.75° W	100	52
19.75° S, 70.25° W	Atacama–Peruvian coast	18.6	Oct	0	19.75° S, 69.75° W	74	52
20.25° S, 70.25° W	Atacama–Peruvian coast	3.5	Sep	9	20.25° S, 69.75° W	99	52
20.25° S, 70.25° W	Atacama–Peruvian coast	3.5	Oct	0	20.25° S, 69.75° W	95	52
20.75° S, 70.25° W	Atacama–Peruvian coast	2.4	Sep	9	20.75° S, 69.75° W	97	52
21.25° S, 70.25° W	Atacama–Peruvian coast	1.7	Sep	5	21.25° S, 69.75° W	104	52
21.75° S, 70.25° W	Atacama–Peruvian coast	2.2	Sep	0	21.75° S, 69.75° W	106	52
25.75° S, 70.25° W	Atacama–Peruvian coast	16.5	Nov	7	25.75° S, 70.75° W	67	50

Cell (lat, lon)	Region	Annual precip. (mm)	Month	Wet samples (of 120)	Donor cell (lat, lon)	Donor wet samples	Distance (km)
28.25° S, 69.75° W	Atacama–Peruvian coast	56.3	Nov	13	28.25° S, 69.25° W	85	49
16.75° S, 11.75° E	Namib coast (Angola)	40.9	May	0	16.75° S, 12.25° E	97	53
16.75° S, 11.75° E	Namib coast (Angola)	40.9	Jul	5	16.75° S, 12.25° E	103	53
17.75° S, 11.75° E	Namib coast (Angola)	39.3	May	0	17.75° S, 12.25° E	102	53
30.25° N, 19.75° E	Libyan Mediterranean coast	144.2	Jul	1	30.25° N, 19.25° E	59	48
30.75° N, 19.75° E	Libyan Mediterranean coast	147.8	Jul	0	30.75° N, 20.25° E	96	48
31.25° N, 29.75° E	Egyptian Mediterranean coast	153.5	Jul	0	31.25° N, 30.25° E	95	48
37.25° N, 66.25° E	Karakum margin (Turkmen–Afghan border)	211.6	Aug	10	37.25° N, 65.75° E	99	44

Every cell-month (of 789,564) whose dry-mass + gamma fit is unusable (Section 10), with the donor cell whose same-calendar-month mixture it borrows. Annual precipitation is that of the W5E5-anchored 1985–2014 reference normals at the focal cell. Wet-sample counts refer to the calendar month listed, and the same cells' other eleven months carry their own usable fits.

Section 11. Supplementary Methods

This section collects the technical detail behind the Methods of the main text.

Data acquisition and monthly aggregation. The ISIMIP3b archive was mirrored locally (124 files, ≈ 232 GB, size-verified manifest): monthly precipitation from the ISIMIP3b monthly aggregation, daily tasmax/tasmin from files.isimip.org in year chunks overlapping the two analysis windows. Daily files were aggregated to calendar-month means (the CMIP Amon semantics: the monthly mean of the daily maximum/minimum) because no monthly tasmax/tasmin product exists in the ISIMIP3b distribution, with tripwires refusing implausible values (temperatures outside 150–350 K, precipitation outside 0–864 mm day⁻¹) and incomplete months. A further tripwire refuses any model-scenario whose land-mean annual precipitation falls outside 1–4 mm day⁻¹, and all 16 model-scenario combinations passed (2.27–2.49 mm day⁻¹). Monthly tasmin > tasmax anywhere aborts the build.

Domain, area weighting, and coarse grids. The domain is the ISIMIP landseamask_no-ant land mask north of 60° S on the native 0.5° grid: 65,797 cells, 142.8×10^6 km². Every share reported anywhere in the paper is weighted by the exact spherical cell area $R^2 \Delta\lambda (\sin(\varphi + \Delta\varphi/2) - \sin(\varphi - \Delta\varphi/2))$, where R is the Earth’s radius, φ the cell-centre latitude, and $\Delta\varphi$ and $\Delta\lambda$ the grid spacings. The 1.0° and 2.0° repeats aggregate the monthly series by area-weighted block means in physical space (blocks kept where at least half their area is land: 16,630 and 4,120 cells) and re-run the identical pipeline end to end.

The analysis space. Monthly precipitation enters as $\ln(1 + \text{pr mm day}^{-1})$ and temperatures in kelvin. A cell-period is the 30×36 matrix of its yearly features (12 months $\times$ three variables, month-major). The Wasserstein clouds, the climatologies, the reference normals (the ensemble mean of the four bias-adjusted historical climatologies, which ISIMIP3BASD anchors to the W5E5 record), and the sigma-null variability statistics are all derived from these series, so every figure is consistent with the search inputs.

The exact Wasserstein solver. Each 30×30 assignment problem of the Wasserstein search (main-text Methods) is solved by a custom CUDA kernel running one exact Jonker–Volgenant shortest-augmenting-path solver per warp with the cost matrix in shared memory, with candidate clouds staged per block and reused across focal cells. Validation: the solver is checked against SciPy’s reference linear-assignment routine on more than 12,000 assignment problems and the pair kernel against an independent CPU reference implementation (agreement $< 10^{-4}$), and a float64 audit of 510 sampled winner pairs shows a maximum relative deviation of 1.04×10^{-6} (recorded in the product attributes).

The sigma null, in full. Per cell j and feature k , the normalizing transform T_{jk} is linear for the 24 temperature features ($z = (x - x_{\text{ref}})/s_{\text{hist}}$, where x is the feature value, x_{ref} the reference-normal value, and s_{hist} the pooled per-model-detrended historical standard deviation) and is the quantile-matching transform of Section 10 for the 12 precipitation features. The per-feature climatic difference z_k is the across-model mean of the difference between the transformed 30-year means at the focal cell and its selected analogue, and $D^2 = \sum_k z_k^2$. Under the null, D^2 is distributed as $\sum_k \lambda_k \chi^2_1$, with λ_k the eigenvalues (kept above 10^{-3}) of the correlation matrix of the transformed pooled ICV samples. The pooled sample supports a full-rank 36×36 correlation everywhere (smallest sampled eigenvalue 5.3×10^{-3}). The CDF is evaluated by Imhof [15] numerical inversion with a leading-eigenvalue tail expansion below survival probability 10^{-8} , and σ follows from D^2 by main-text eq. (1). Because the climatic difference is normalized but never whitened, it decomposes exactly into per-feature contributions z_k^2 , which is what the attribution of main-text Fig. 2 uses (identity verified cell by cell to 6×10^{-8} over all 65,797 cells and three scenarios). Pooling per-model-detrended samples keeps inter-model spread out of the null (the pooled

variance equals the mean of the per-model variances exactly), and the pooled standard deviation tracks an independent observed detrended reference within $\sim 5\text{--}13\%$ in the median across the three variables.

***k*-medoids clustering.** Cells with an accepted analogue are embedded, with exact-area weights, as $(\varphi, \lambda \cos \bar{\varphi}, \Delta\varphi, \Delta\lambda \cos \bar{\varphi})$: latitude, cosine-scaled longitude, and the two displacement components; the estimator itself (the weighted *k*-means++ fit, the Lloyd refinement to real-member cores, and the production *K* and restart counts) is specified in the main-text Methods. Partition agreement across seeds is measured with the adjusted Rand index on the common non-novel cell set.

Top-50 agreement diagnostic. Each model’s 50 lowest-distance candidate analogues per focal cell are stored during the search; the three statistics computed from them follow Bulut et al. [1] and are defined in the legend of Fig. S3.

Correlations and permutation tests. The area-weighted Pearson and Spearman constructions of the main-text Methods apply to every correlation in this document, including the WD–sigma agreement statistics (Section 3, Table S7) and the elevation–novelty association. For the latter, the two-sided *P* value is the fraction of permuted $|\rho| \geq \text{observed } |\rho|$ over the 999 elevation permutations (area weights kept with the cells), and the marginal histograms entering the topographic-position null of Section 4 are the area-weighted ones.

Verification chain. Independent rebuilds reproduce the stored products at every stage where an identity exists: the attribution identity (6×10^{-8}), the pooled-standard-deviation reconstruction (4.5×10^{-7}), the log-null climatic difference and its sigma against the archived log-transformation products (6.3×10^{-5} and 5.8×10^{-4}), and the solver audits above. All tolerances are recorded in the product attributes.

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