

Global patterns of climate displacement and novel climate emergence

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Article

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Global patterns of climate displacement and novel climate emergence

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Abstract

Climate analogues link projected future conditions to present-day climates, but global patterns of climate displacement and novelty remain incompletely understood. Using a bias-adjusted CMIP6 ensemble under SSP1-2.6, SSP2-4.5, and SSP3-7.0, we identify the best historical analogue of each land cell's projected 2071–2100 climate among global climates from 1985–2014. Wasserstein distance compares full 30-year distributions of monthly temperature and precipitation, while a sigma-dissimilarity test evaluates matches against local historical interannual variability. Novel climates, lacking acceptable present-day analogues, cover approximately 1%, 11%, and 24% of analysed land across the three scenarios, respectively. They concentrate in tropical lowlands and are predominantly associated with warming. Most retain their present-day Köppen–Geiger classification, indicating intensification within existing climate types. Accepted analogues tend to lie equatorward and, for mountainous locations, downslope, with median geographic distances increasing from 174 to 348 and 547 km across the scenarios. A *k*-medoids approach summarizes the displacement field into an atlas of regional shifts and persistent intercontinental corridors.

The atlas identifies where present-day climates remain useful references for future conditions and where acceptable analogues are lost.

Keywords

climate analogues, CMIP6, novel climates, Wasserstein distance, Köppen–Geiger classification, k -medoids

Introduction

Climate change is reshaping local climates unevenly across the globe, creating place-specific risks for ecosystems and human systems, while global warming is projected to continue through much of the twenty-first century unless greenhouse gas emissions decline sufficiently and sustained net-negative emissions are achieved [1]. Beyond increases in global mean temperature, regional climates are being displaced: some locations come to resemble the present-day climate of somewhere else, while others move towards novel climates, defined as conditions with no present-day counterpart anywhere on Earth [2].

Climate analogue methods address this question by systematic search: they quantify the similarity between a location's projected future climate and the present-day climate of every candidate location and identify the best match [3]. They therefore serve not only as analytical instruments but also as tools of communication [4]. For one's home, a community where family members live, or a place tied to a livelihood, interest, or concern, an analogue replaces an abstract vector of projected temperature and precipitation with the contemporary climate of a named, mappable place. Presented in this form, a distant future becomes psychologically closer: it can be pictured, related to personal expertise, and reasoned about concretely [5]. Because the reference exists now, it can also be visited and studied: its seasonal regime can be observed alongside the ways people live, buildings are designed, crops are grown, water is managed, and ecosystems function, providing tangible reference points for anticipating and preparing for change [6]. A match does not, however, render the two locations socially or ecologically equivalent.

Drawing sector-specific lessons about housing, health, ecosystems, or agriculture requires variables and contextual information tailored to each question. The present study offers a general climatic analogue based on monthly temperature and precipitation, not a direct impact or adaptation prescription [6].

Applied from city to continental scales, analogue analysis consistently finds analogue distances of hundreds of kilometres within this century [5–8], together with a growing fraction of land whose future climate finds no acceptable match at all: from a few percent to approximately 40% of the domain by late century, depending on scenario, domain, and method [2, 9]. Two recent methodological advances have developed independently. The Wasserstein distance (WD) framework of Bulut et al. selects analogues by comparing entire 30-year multivariate distributions rather than climatological means but has been applied only to Europe [6]. The sigma dissimilarity of Mahony et al. provides a significance scale anchored in observed local interannual variability but matches climatological means and has been applied to North America [9].

The objective of this study is to establish, at a global scale, where projected late-century climates remain representable by acceptable present-day land analogues and where the present-day terrestrial climate catalogue ceases to provide such references. We further examine the geographic, latitudinal, and elevational displacement of surviving analogues and characterize the climatic differences associated with the loss of acceptable matches.

To achieve this objective, we combine these two strands: the WD locates each land cell’s best historical analogue by comparing full 30-year distributions of monthly temperature and precipitation features, and the sigma dissimilarity then evaluates the selected analogue against observed local interannual variability; cells beyond 2σ are deemed to have no acceptable analogue [2, 9]. The search runs over the global land surface, matching the projected 2071–2100 climate under the Shared Socioeconomic Pathways (SSP) scenarios SSP1-2.6, SSP2-4.5, and SSP3-7.0 [10] against the 1985–2014 climate. Retaining calendar months makes every accepted match a live analogue.

An exhaustive cell-level analogue field also poses a communication problem of its own. Each cell carries four spatial quantities (its latitude and longitude and its north–south and east–west displacement to its analogue), and tens of thousands of overlapping vectors cannot be rendered legibly on a world map. We therefore introduce a *k*-medoids mapping approach that translates this four-dimensional, location-specific field into two-dimensional maps while retaining an actual focal–analogue pair as the representative arrow of every mapped region. A global fit reveals planetary-scale displacement corridors, while independent fits within nine continental windows recover regional structure suppressed by the global summary. To our knowledge, this is the first use of *k*-medoids to map a climate-analogue displacement field. The maps offer a complementary perspective to anomaly and climate class maps.

Beyond measuring analogue distances, directions, and novelty on this basis, the analysis characterizes what it finds: the Köppen–Geiger identity of novel climates and per-feature attribution of the residual climatic difference establish what the no-analogue climates of the late century actually are, while the latitudinal and elevational structure of the analogue field shows where the analogues lie. We show that novel climates grow superlinearly with forcing, from 1% to 11% to 24% of searched land across the three scenarios, that they are overwhelmingly tropical, low-elevation, and temperature-driven, that analogues lie systematically equatorward and downslope of the locations they represent, and that late-century novelty is chiefly intensification within present-day climate types.

Results

We searched for the best historical analogue of the 2071–2100 climate at each of the 65,797 grid cells in the 0.5° land domain (Antarctica excluded; $142.8 \times 10^6 \text{ km}^2$) under SSP1-2.6, SSP2-4.5, and SSP3-7.0 [10]. Unless otherwise stated, three-value sequences below follow this scenario order, representing roughly low-, intermediate-, and high-forcing futures. Spatial shares, summary statistics, and correlations reported below are area-weighted by grid-cell area unless otherwise stated (Methods). SSP3-7.0, rather than SSP5-8.5, serves as the high-emission member in this study (Methods). The search used a four-member Coupled Model Intercomparison Project Phase 6 (CMIP6 [11]) ensemble, bias-adjusted within

phase 3b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b [12, 13]), with the 1985–2014 climate of every land cell as the historical candidate pool (Methods; Supplementary Table S1). The corresponding ensemble-mean warming of the searched land domain is 1.36 °C, 2.39 °C, and 3.50 °C relative to 1985–2014 (per-model values in Supplementary Table S2).

We used two complementary distances (Methods): the WD selects each future cell’s best historical analogue by comparing 30-year multivariate distributions of 36 monthly climate features [6], and a Mahalanobis distance expresses the residual climatic difference at the selected analogue in units of local interannual climate variability and determines whether that match is acceptable: cells beyond 2σ are classified as having novel climates without acceptable analogues [2, 9]. We report the statistic calculated from the across-model mean climatic difference as the ensemble sigma dissimilarity. Per-model verdicts and alternative aggregation rules are reported in the Robustness section below.

Extent and geography of novel climates

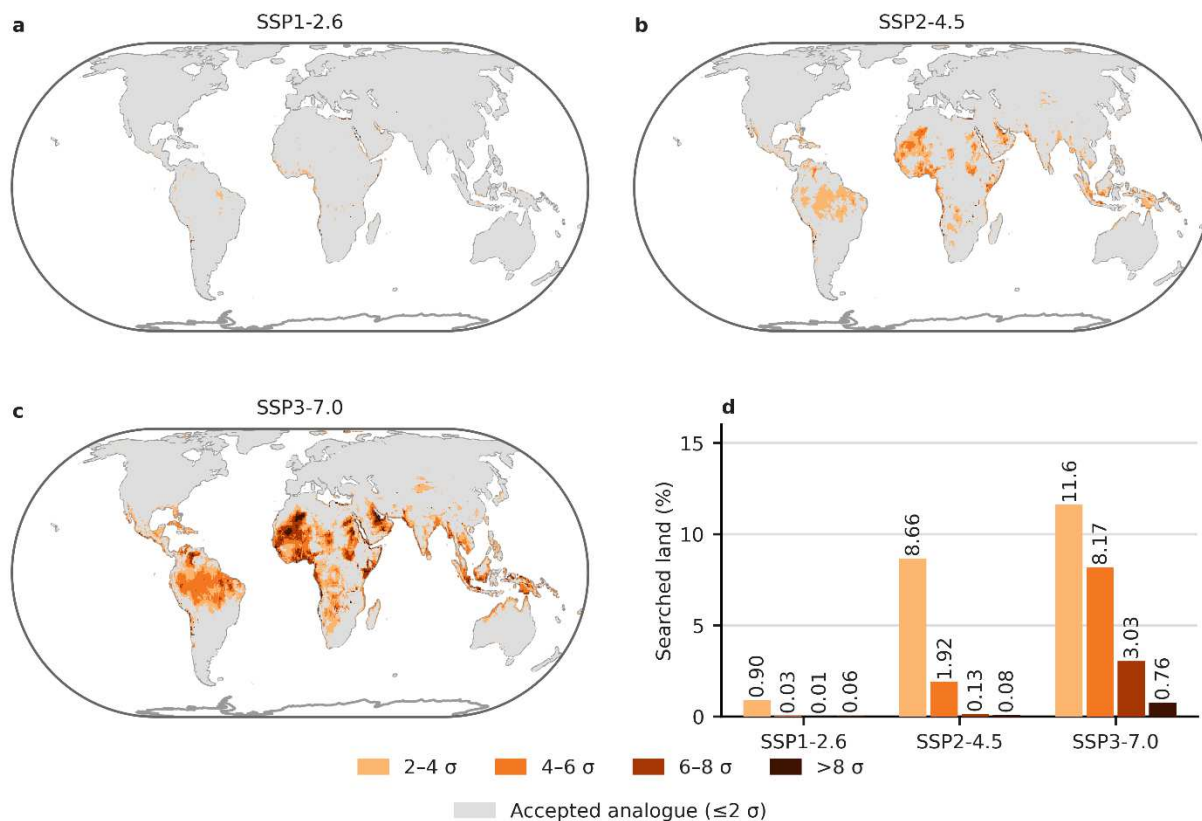
Novel climates cover 0.99%, 10.78%, and 23.59% of searched land; the growth with forcing is strongly superlinear (Fig. 1). Novelty also deepens: the area beyond 4σ (extreme novelty) rises to 0.10%, 2.12%, and 11.96% of land, so under SSP3-7.0 roughly half of all novel land lies beyond 4σ (Fig. 1, Supplementary Table S4).

Novelty is overwhelmingly a tropical, low-elevation phenomenon. Across the scenarios, 89.6%, 89.6%, and 86.6% of novel area lies within 23.5° of the equator, concentrated in Amazonia, the Sahel and central Africa, and the Maritime Continent (Fig. 1), the low-latitude concentration expected from the small interannual variability of the tropics [2, 14]. The deepest novelty shares this geography: of the land beyond 4σ under SSP3-7.0, 47.0% lies in Africa (the Sahel and the Congo Basin margins) and 25.9% in South America, almost all of it tropical, while the most extreme individual cells (locally up to 37σ , mapped on a full-range logarithmic colour scale in Supplementary Fig. S25) lie in hyper-arid coastal deserts along the Atacama–Peruvian coast, in the Namib, and in coastal Egypt, where the interannual

variability of precipitation is minute. A per-feature attribution of the ensemble climatic difference shows that the departure from the historical envelope is thermal: warming-dominated cells account for 87.2%, 91.3%, and 92.2% of novel land, whereas all precipitation-related categories combined stay below 5% in every scenario (Fig. 2).

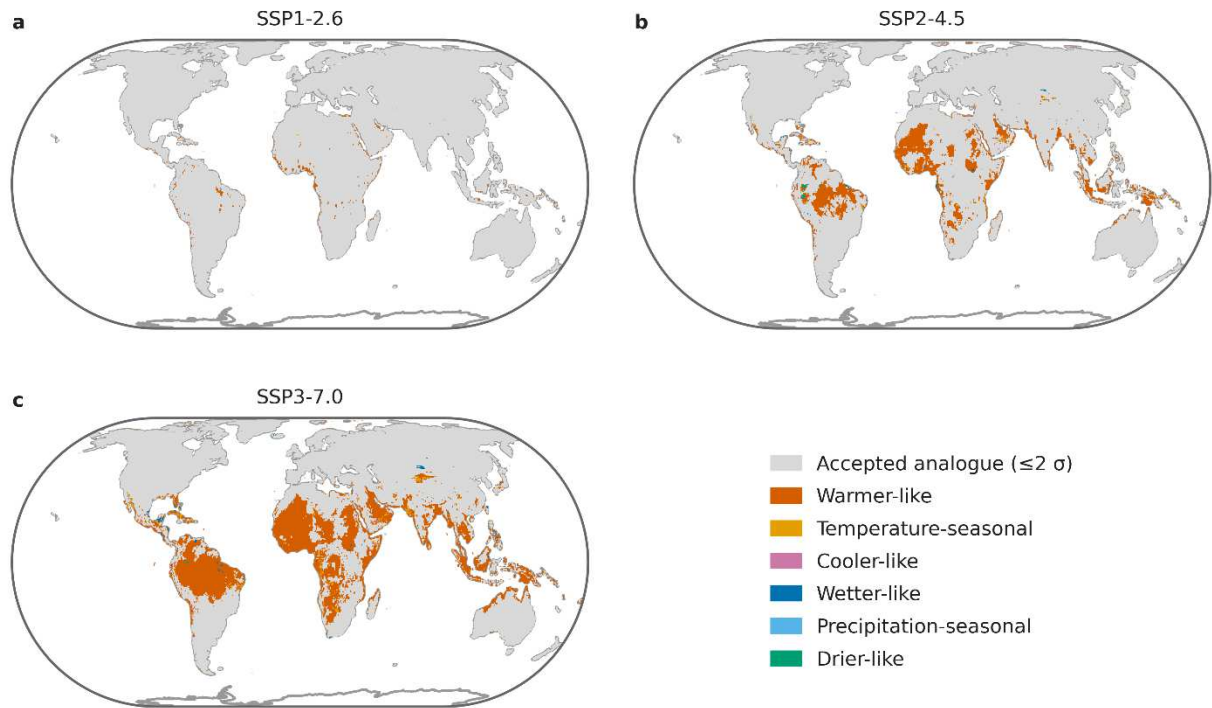
Classified by their future Köppen–Geiger type (thresholds of Peel et al. [15]; Methods), novel land is drawn almost entirely from the tropical and arid families. Under SSP3-7.0, savanna (Aw, 34.6%), desert (BW, 31.9%), steppe (BS, 11.9%), rainforest (Af, 10.3%), and monsoon (Am, 9.4%) together account for 98.1% of novel land while accounting for 55.2% of the searched land today (the composition is shown in Supplementary Fig. S8, and reference Köppen–Geiger maps are shown in Supplementary Fig. S7). Relative to their own present extents, the three tropical humid families are by far the most exposed: under SSP3-7.0, novel land classified by its future type equals 61% of savanna’s present area, 58% of monsoon’s, and 53% of rainforest’s, against 36% for desert, 23% for steppe, and below 4% for every temperate and continental family. Under SSP2-4.5, the same ratios are 25%, 33%, and 28%. The strong exposure of exactly these classes is consistent with constrained CMIP6 Köppen–Geiger projections, which expand the tropical and arid classes most strongly [16]. Novelty is chiefly intensification within a type rather than migration between types: 94.4%, 91.8%, and 86.5% of novel land retains its Köppen–Geiger classification, and more than 96% retains its main group, in every scenario (Supplementary Table S4). The same identity pattern can be read through the analogues themselves (Fig. 3; SSP1-2.6 and SSP2-4.5 in Supplementary Fig. S9): mapping each cell’s present Köppen family to the family of its closest analogue keeps the type on 82.5%, 67.8%, and 52.8% of searched land (novel area counted as changing type), and where the family does change, the flows follow the classic drying sequence, the tropical-to-arid direction of change shared by observed and projected Köppen–Geiger reclassifications [16, 17].

Figure 1. Novel climate area and its depth beyond the threshold.



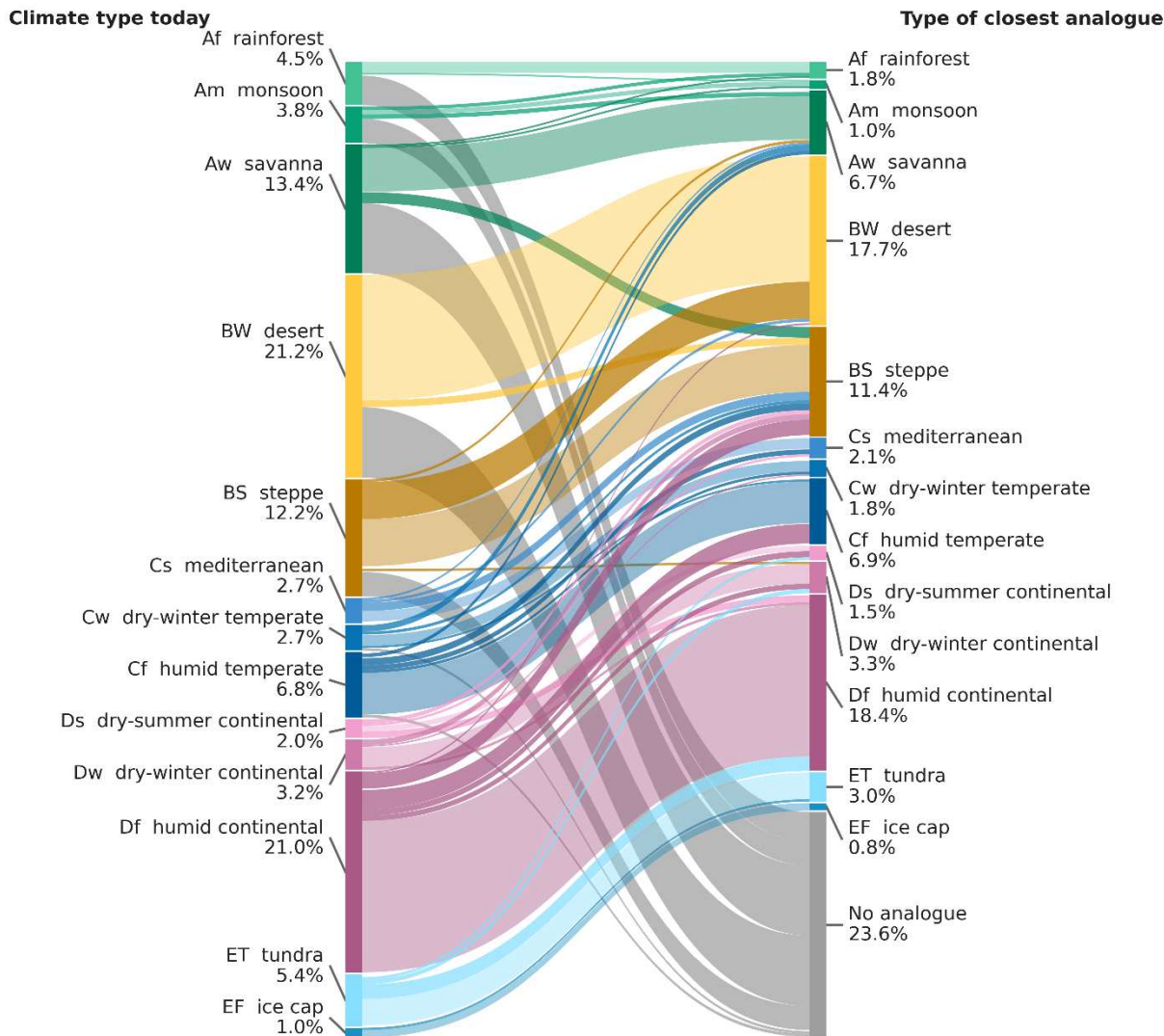
Ensemble sigma dissimilarity at the Wasserstein-selected analogue for 2071–2100 under (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0, banded at 2–4 σ , 4–6 σ , 6–8 σ , and beyond 8 σ on a sequential single-hue ramp (darker indicates a greater distance beyond any historical analogue). Light grey cells have an accepted analogue. (d) Percentages give the share of searched land inside each sigma band per scenario. The full-range (unbanded) sigma field is shown in Supplementary Fig. S25.

Figure 2. Attribution of the displacement behind novel climates.



Six-way classification of every novel cell by the dominant component of its residual climatic difference, for 2071–2100 under (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0. Light grey cells have an accepted analogue. Cells are classified as warmer-, cooler-, wetter-, or drier-like where a directional temperature or precipitation signal dominates the climatic difference, or as temperature- or precipitation-seasonal where the dominant signal varies in sign across the year. The classification rules are given in the Methods.

Figure 3. Köppen flow: where each climate type’s land area finds its analogue (SSP3-7.0).



Alluvial diagram [40] for SSP3-7.0, 2071–2100 (the SSP1-2.6 and SSP2-4.5 diagrams are shown in Supplementary Fig. S9). For every land cell, the left node is the Köppen–Geiger family of the cell’s own 1985–2014 reference normals and the right node is the family of those normals read at its closest analogue. Both endpoints classify one and the same historical climatology, so a shift reflects where the analogue lies. Novel cells flow into the separate ‘no analogue’ node (grey). Both columns are percentages of the same total searched land area. Ribbons carry the source family’s colour and flows below 0.15% of land area are not drawn. The reference Köppen–Geiger world maps behind this figure are shown in

Supplementary Fig. S7, and the composition of novel land by its future type is shown in Supplementary Fig. S8.

Analogue distances and directions

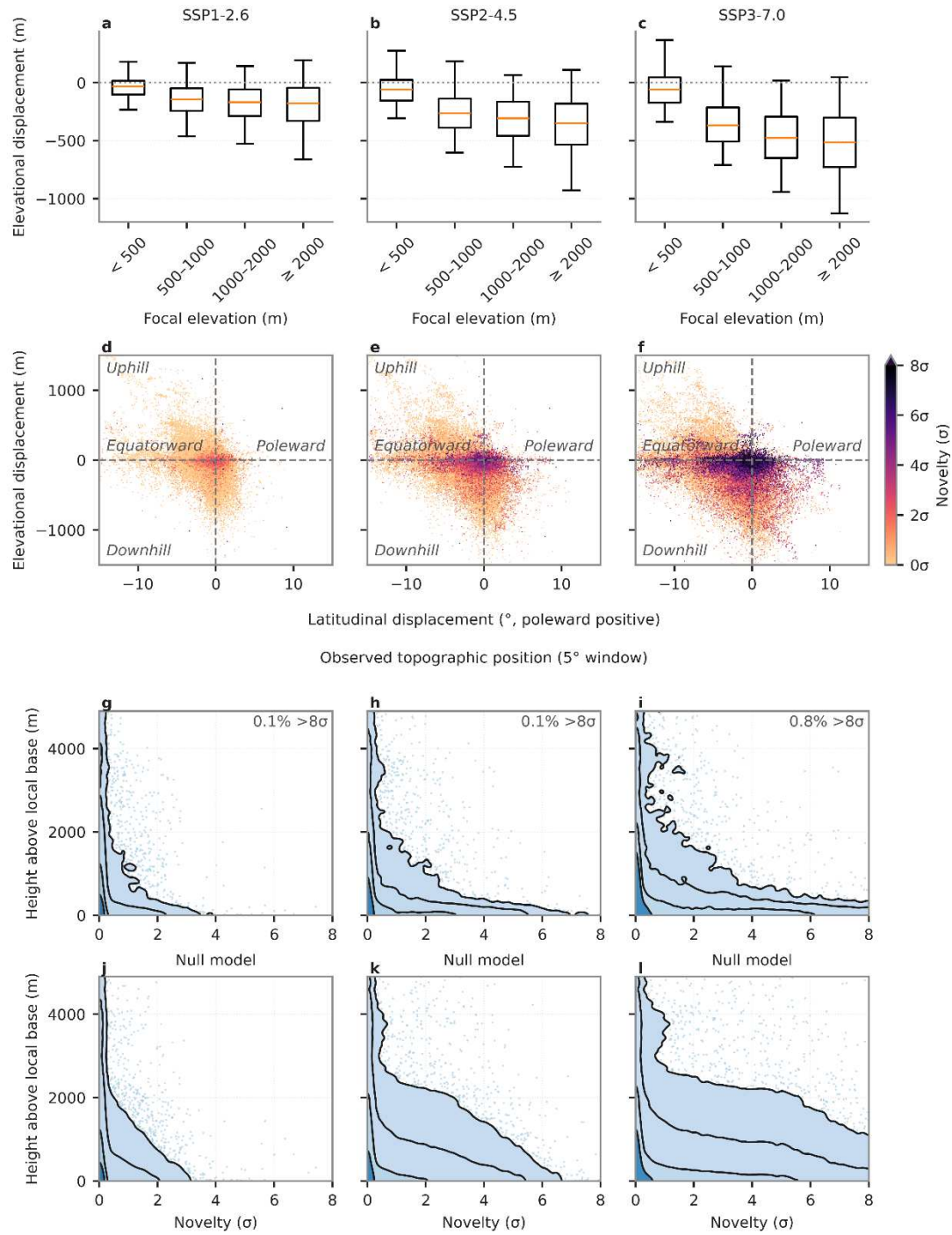
The median great-circle distance to the best analogue increases across the scenarios: 174 km (interquartile range 85–349 km), 348 km (172–714 km), and 547 km (281–1,110 km) after masking novel land (Supplementary Fig. S10a and Table S2). The upper tail grows faster than the median, and the mean (550, 1,233, and 1,650 km) sits far above the median throughout, because a growing minority of cells finds its best climatic match on another continent. Self-analogues (cells whose best analogue is the cell itself) become vanishingly rare under forcing: 1.47%, 0.06%, and 0.01% of the area with an accepted analogue. Where novel cells are nonetheless assigned a nominal best match, that match grows increasingly remote with forcing: the median nominal analogue distance across the novel area is 111, 543, and 926 km (Supplementary Table S2).

Accepted analogues lie systematically equatorward: outside the tropics, the share of land whose best analogue lies strictly closer to the equator than the focal cell is 73.6%, 83.1%, and 87.9%, against 12.2%, 10.0%, and 7.6% strictly poleward, with a median equatorward shift of 1.0°, 2.0°, and 3.0° of latitude (Fig. 4d–f; Supplementary Fig. S6). A location’s future climate is found on its equatorward side, and this tendency strengthens with forcing.

Elevation acts the same way: mountain cells find their future climate a few hundred metres downslope. The median vertical offset of accepted analogues is –169, –307, and –476 m for cells at 1,000–2,000 m, and –178, –350, and –516 m for cells above 2,000 m, whereas cells below 500 m show almost no vertical displacement (–33 to –60 m across the scenarios; Fig. 4a–c). Accordingly, land below 1,000 m in elevation becomes novel far more often (1.08%, 12.51%, and 27.10% of the band) than land at 1,000–2,000 m (0.52%, 4.35%, and 11.36%) or above 2,000 m (0.91%, 2.01%, and 3.77%). The association is

191 statistically robust in the sense of Mahony et al. [9]: the Spearman correlation between sigma dissimilarity
192 and focal elevation is -0.16 , -0.22 , and -0.23 , and novel land is over-represented below 1,000 m: 87.5%,
193 93.4%, and 92.5% of novel area lies in that band, against 80.5% of all searched land (Fig. 4g–l,
194 Supplementary Table S3).

Figure 4. Elevational and latitudinal displacement of analogues and the topographic structure of novelty.



(a–c) Distribution of the elevational displacement to the best analogue (analogue elevation minus focal elevation, m) of cells with an accepted analogue, grouped by focal elevation band, for (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0. Boxes span the interquartile range with the median as the centre line, and whiskers reach the 5th and 95th percentiles (band medians in Supplementary Table S3). (d–f) Joint latitudinal–elevational displacement: every searched cell is one point at its latitudinal ($^{\circ}$, poleward positive) and elevational (m) displacement to its best analogue, coloured by the ensemble sigma dissimilarity at that analogue on a sequential 0– 8σ scale. (g–i) Density of novelty (sigma dissimilarity of the best analogue) against topographic position (metres above the lowest land elevation within a 5° moving window) for the three scenarios. Contours enclose 50%, 75%, 95%, and 99% of the probability mass, and the annotation gives the land share beyond the 8σ display limit. (j–l) The corresponding null model, in which topographic position is randomized across cells: computed exactly as the product of the two marginal distributions, so it retains the decline of land area with height above the local base. The point cloud is a single seeded permutation, drawn for illustration (statistics in Supplementary Table S3).

Mapping analogue displacement

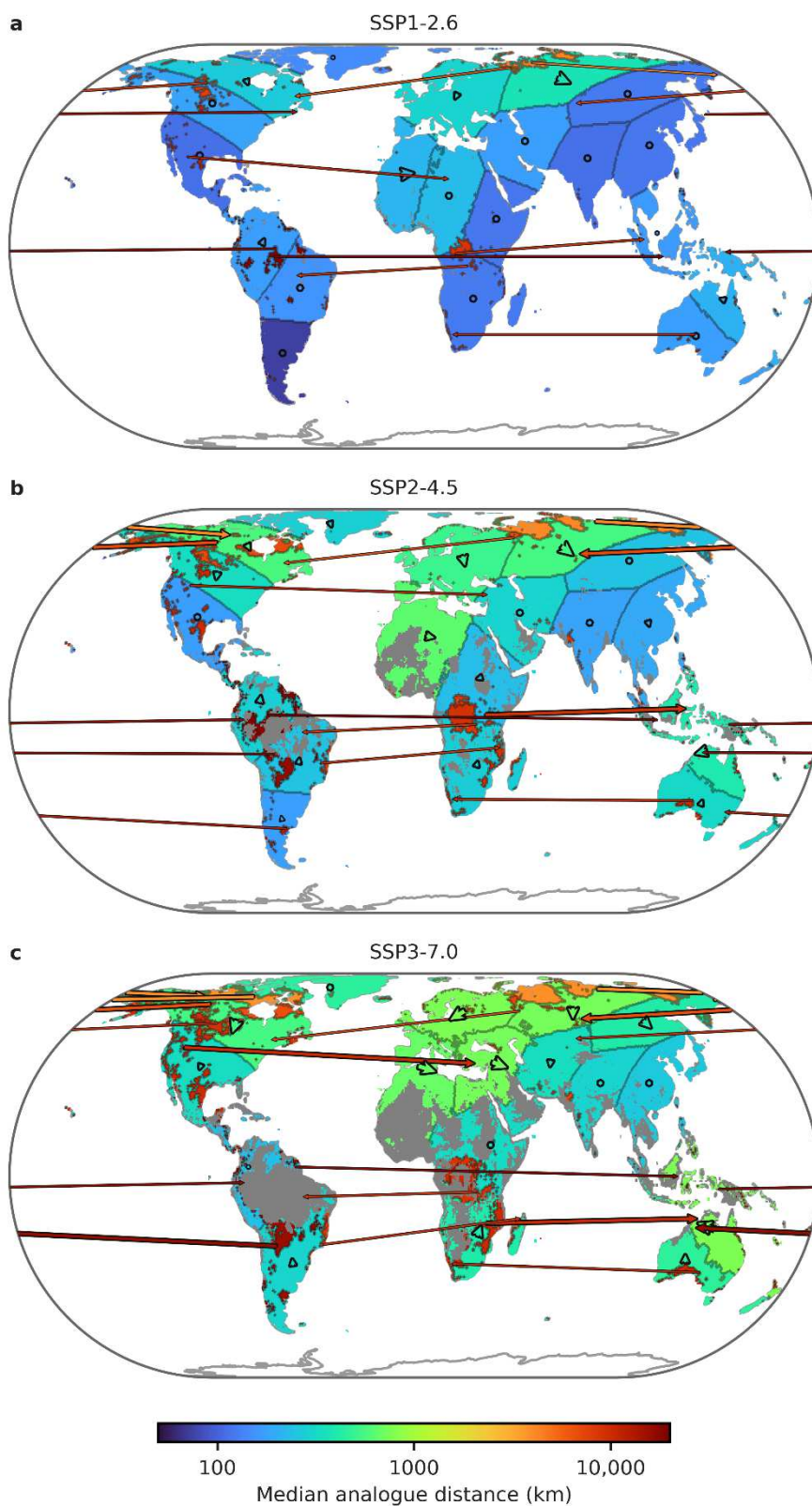
To summarize the ~65,000 focal-to-analogue displacement vectors, we clustered them with a k -medoids partition on each cell’s position and vector components, with novel cells held out as a separate class (Methods). The production configuration is $K = 30$ for the global fit and $K = 20$ independently within each of nine continental windows (Methods). Its sensitivity to K and to the random initialization is examined in the Robustness section below. Every cluster core is a real member cell, so each mapped arrow is an actual focal–analogue pair, and each cluster is coloured according to its median analogue distance (Fig. 5).

Most clusters describe short-range analogue offsets of one to a few hundred kilometres, directed predominantly equatorward or downslope: at the global map scale these short arrows appear as small

marks. Under SSP2-4.5, the five largest clusters, each holding 5.7–6.4% of land, displace by short-to-moderate distances: the Baltic–East European plain (6.4% of land, median member analogue distance 510 km, with the analogue lying to the south-south-west), the Transbaikal–Amur margin (6.2%, 243 km, southward), the central Sahara (5.9%, 630 km, east-south-east), the central Siberian plateau (5.7%, 548 km, south-south-east), and the Iranian highlands (5.7%, 290 km, southward). Superimposed on this local picture, a stable set of intercontinental corridors is already apparent under SSP1-2.6 and persists under stronger forcing. Under SSP2-4.5, these corridors include central Amazonia → Borneo (median member analogue distance 18,726 km; 0.58% of land), the southern Amazon → northern Australia (16,532 km; 0.72%), the south-western United States and northern Mexico → Anatolia and Arabia (10,070 km; 0.77%), the Congo Basin → Sumatra (9,237 km; 1.06%), boreal western Canada → Central Asia and the Russian Far East (6,860 km; 1.25%), the reverse pairing New Guinea → north-western South America (15,306 km), and further pairings (central Australia → Namibia, the central Congo → the Amazon margins, the Brazilian cerrado → east Africa, the northern Urals → eastern Canada, northern Patagonia → south-east Australia). Together, the eleven corridor clusters account for 5.9% of land. Every cluster of the production portfolio is listed in Supplementary Table S6. With increasing forcing the cluster fill colours shift towards longer distances, and the novel class spreads over Amazonia, the Sahara and Sahel, and central Africa (Fig. 5b, c).

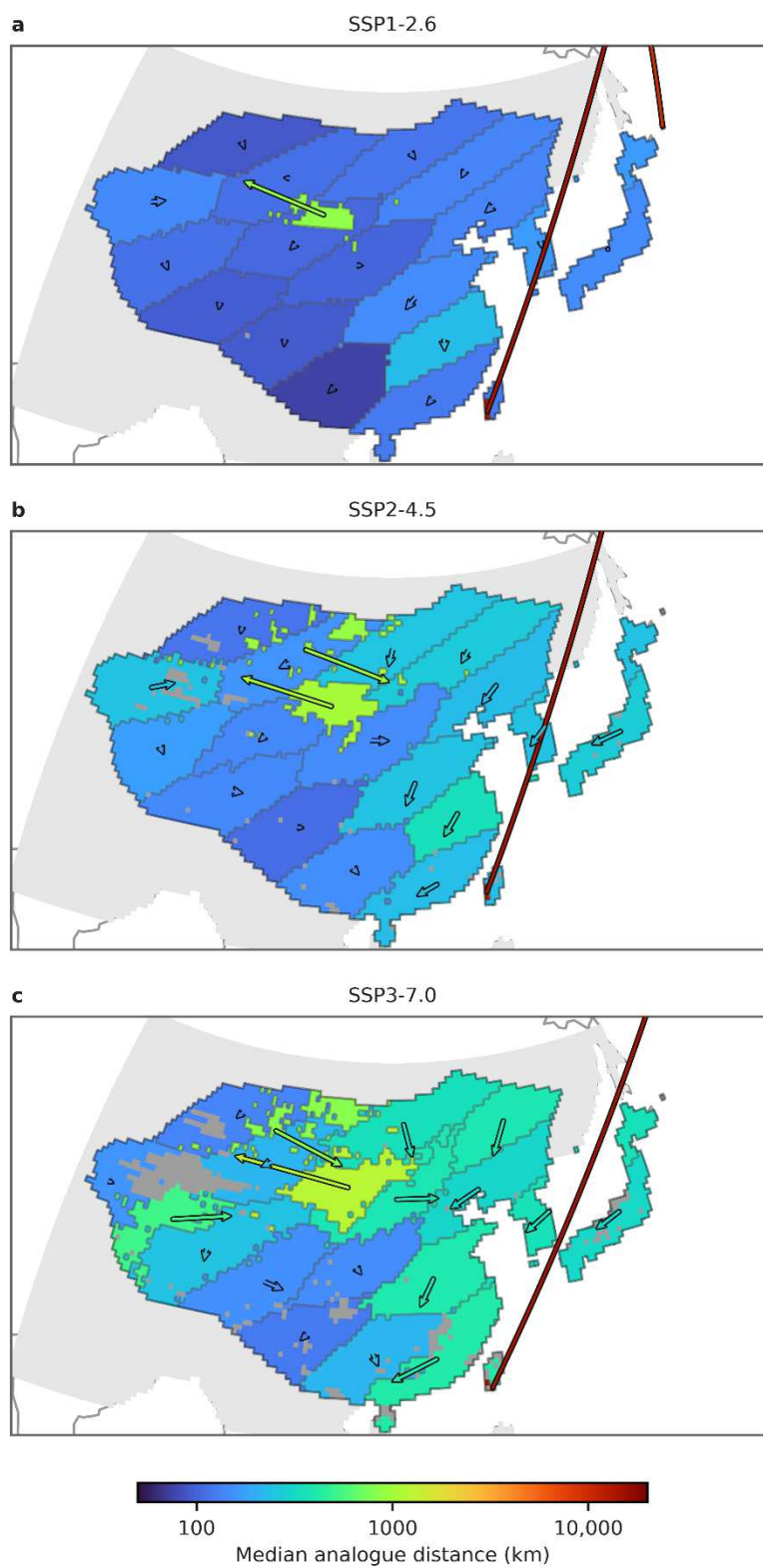
Refitting the clustering independently inside nine continental windows (window definitions in Supplementary Fig. S14; $K = 20$ per region; Figs. S15–S23) resolves analogue-offset structure that the global fit necessarily averages into a few large clusters. East Asia is shown as an example across the three scenarios (Fig. 6). At the global level the region is covered essentially by three large clusters (median analogue distances of roughly 180–240 km). The regional refit resolves twenty, of which seventeen are short-range (median 109–342 km) and directed overwhelmingly equatorward or towards the coast: the lower Yangtze basin shifting south-west by a median 342 km, the North China Plain south by 243 km, Japan south-west along the archipelago (273 km), Korea south-west (240 km), the Tibetan Plateau interior

247 barely moving at all (109–175 km). Two Gobi-margin clusters instead displace by roughly 900–1,000 km,
248 one westward into the Xinjiang basins (1,031 km), one south-eastward into Inner Mongolia (897 km).
249 The regional fit also identifies one intercontinental connection that the global fit does not resolve: part of
250 Taiwan finds its analogue on the Florida–Caribbean coast (14,095 km). Reading the window across the
251 scenarios (Fig. 6) shows this structure intensifying: the median analogue distance of East Asia’s non-
252 novel land increases from 120 km to 202 km and 281 km; the novel share grows to 0.02%, 1.62%, and
253 6.59% of the window, and the Taiwan connection persists in every scenario (median 14,096, 14,095, and
254 14,326 km). Throughout, the region remains almost self-sufficient. Every regional cluster whose analogue
255 lies beyond its own window is mapped in Supplementary Fig. S24.



k-medoids clustering ($K = 30$) of the focal-to-analogue displacement field for 2071–2100 under (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0. Each cluster is coloured according to its median analogue distance on a fixed 50–20,000 km logarithmic colour scale (shared with Fig. 6), and thin dark lines mark cluster boundaries. Each arrow is the actual focal-to-analogue displacement of the cluster’s core member cell, drawn at one of three widths according to the cluster’s share of the clustered land area (thin below 1%, intermediate from 1% to 3%, and thick at 3% or more). Clusters with very short core displacements appear as small marks. Grey cells are novel and are excluded from the clustering. Every cluster of the production partition is named, located, and quantified in Supplementary Table S6, and the sensitivity of the partition to K and to the random initialization is examined in Supplementary Figs. S11–S13.

268 **Figure 6. Regional clusters of analogue displacement: East Asia across the three scenarios.**



269

As in Fig. 5, but for the clustering ($K = 20$) refitted independently inside the East Asian window, for 2071–2100 under (a) SSP1-2.6, (b) SSP2-4.5, and (c) SSP3-7.0. Cluster fills, the colour scale, and the three arrow-width tiers follow Fig. 5, with the width breaks at 1.5% and 4.5% of the region’s clustered land area. Arrows clipped at the frame (drawn without arrowheads) lead to analogues outside the mapped region, and pale grey shading marks land outside the region, shown for context. The window definitions are shown in Supplementary Fig. S14, all nine regional windows are shown in Supplementary Figs. S15–S23, and every regional cluster whose analogue lies beyond its own window is mapped in Supplementary Fig. S24.

Robustness and sensitivity

The four models agree closely on the warming level of each scenario (Supplementary Table S2), and novelty is relatively consistent between models: per-model novel areas span 0.91–5.15% of land under SSP1-2.6 and 24.53–30.25% under SSP3-7.0 (Supplementary Fig. S28, Table S8). The share of the ensemble novel area supported by at least three of the four models rises to 74%, 91%, and 97%, and the land on which all four models individually agree the climate is novel grows to 0.31%, 7.27%, and 19.75% (per-cell agreement maps in Supplementary Fig. S2). Model agreement was highest where novelty was temperature-dominated, and per-model warming covaried with novel area (Supplementary Fig. S4). The models also agree on the location of the analogues: applying the top 50 candidate-set diagnostic of Bulut et al. [6] globally, the mean pairwise overlap of the models’ 50 best candidates is 0.55–0.60, and on 84.6–91.2% of land the ensemble-selected analogue lies inside every single model’s own top 50 list (Supplementary Fig. S3 and Section 1).

The two metrics rank the world consistently: the Spearman rank correlation between the ensemble WD and the sigma dissimilarity is $\rho = 0.81, 0.88, \text{ and } 0.89$ (Supplementary Fig. S5). The raw-scale (Pearson) correlation is far lower (0.22–0.32), chiefly because a few dozen hyper-arid cells, 0.08–0.10% of the

searched domain, on the Atacama–Peruvian coast, the Namib, the Sahara, and the Arabian Peninsula, carry extreme WD values: the WD standardizes each feature by the focal cell’s own projected interannual variability (Methods), which collapses wherever a projected month is effectively rainless. Excluding these cells restores the Pearson correlation to 0.80–0.93 (Supplementary Figs. S26–S27 and Table S7).

Sweeping the threshold continuously from 0.5σ to 4σ changes the novel areas smoothly, with no discontinuity at the 2σ choice, and preserves the scenario ordering at every threshold (Supplementary Fig. S1, Table S8). The verdict is equally insensitive to the precipitation normalization of the sigma null itself (Methods; Supplementary Section 10, Table S9).

Repeating the entire search on 1.0° and 2.0° aggregations of the same data inflates novelty monotonically: 1.99%, 14.40%, and 27.54% of land at 1.0° and 4.97%, 21.79%, and 33.22% at 2.0° , against 0.99%, 10.78%, and 23.59% at 0.5° . Coarser resolution also lengthens analogue distances overall, while increasing the frequency of self-analogues (Supplementary Fig. S28, Table S8 and Section 9).

The k -medoids summary is a visualization device rather than an inference (Supplementary Section 6, Figs. S11–S13, Table S5). Because the within-cluster objective improves smoothly with K , K is chosen using a structural criterion. The land area occupied by intercontinental corridor clusters (mean member analogue distance $> 5,000$ km) saturates for every K from 15 to 100 (higher K merely subdivides corridors that are already resolved). Across 69 independently seeded refits using 1 to 10,000 random restarts, the initialization is effectively converged at the production setting: single-start fits end up to 25.4% above the best objective found, every seed comes within 3.3% at 1,000 restarts, and all come within 0.7% at 10,000. The mean pairwise adjusted Rand index between independent seeds rises to 0.89–0.94 at 10,000 restarts, with the remaining disagreement confined to boundaries between neighbouring short-range clusters.

Discussion

This study set out to map, at a global scale and with distribution-aware metrics, where the climates of 2071–2100 can still be found on the present-day Earth, and where they cannot. Three regularities organize

the answer. First, the emergence of novel climates is strongly superlinear in forcing and overwhelmingly a tropical, low-elevation phenomenon. In every scenario roughly nine-tenths of novel land lies within the tropics, where interannual variability is smallest and even a moderate absolute change amounts to many local standard deviations [2, 14]. Second, where analogues survive, they lie equatorward and downslope, and both pulls strengthen monotonically with forcing. Highlands remain matchable because a reservoir of warmer climates persists below them, whereas lowlands have no such reservoir and become novel first. This is the topographic mechanism identified by Mahony et al. [9] in western North America, reproduced here at the global scale. Third, novelty is intensification rather than reorganization: warming dominates the residual climatic difference on 87–92% of novel land, and the large majority of novel cells keep their Köppen–Geiger name. That novel cells so rarely change name is partly a property of the classification itself: the Köppen–Geiger thresholds leave the tropical and arid families open-ended (neither has an upper temperature boundary that further warming could cross), so their climates can warm indefinitely and retain their names. The future tropics that emerge from this analysis are not so much a new kind of climate as hotter versions of themselves, pushed beyond the historical envelope from within. Because novelty is primarily temperature-driven, the model agreement likely reflects the comparatively constrained thermal signal rather than the noisier precipitation response.

These regularities bear directly on the purpose of the analogue method. Climate analogues are valued as translation devices, allowing one location to reason about its future from the present of another [5–7]. Our results define the limits of that translation. It fails soonest, and most completely, exactly where change is largest: under SSP3-7.0, nearly a quarter of searched land, including more than half of the present extent of the savanna, monsoon, and rainforest zones, has no acceptable present-day reference anywhere on land. Where the translation still works, it is usually regional: most land finds its analogue within a few hundred kilometres, and windows such as East Asia remain almost climatically self-sufficient in every scenario. However, a stable minority of land depends on intercontinental counterparts, so analogue-informed

adaptation there would have to transfer experience across continents, institutions, and biogeographic realms.

The study makes four contributions to this literature. First, it joins two recent strands of analogue methodology: Wasserstein selection of the analogue from full 30-year distributions [6] and sigma-dissimilarity judgement of that analogue against an observation-anchored variability null [9]. To our knowledge, this is the first time the two have been combined. Second, the feature space remains monthly rather than seasonal, so the match is time-resolved (a shift in the timing of the seasonal cycle counts against a candidate), and every accepted analogue is live in the month-for-month sense introduced above (Methods). Third, the *k*-medoids cartography renders the cell-level analogue field readable at a glance: the global map and the nine regional windows (Fig. 5 and Supplementary Figs. S15–S23) form an atlas giving the approximate present-day location of the late-century climate of any land location of interest. Fourth, the novel class is characterized: its Köppen–Geiger identity and the per-feature attribution establish what the no-analogue climates actually are (Figs. 2 and 3; Supplementary Fig. S8).

The resolution experiments indicate that part of the spread among published novelty estimates is methodological rather than climatic. Repeating the entire search on coarser grids inflates novel area monotonically, to 33% of land at 2.0° under SSP3-7.0, because aggregation reduces the candidate pool to one-sixteenth of its size at 0.5° and averages away the mountain and coastal climates that supply marginal matches. Read in the other direction, the same monotonic trend implies that a search finer than 0.5° would be likely to lower the estimates further, as a larger and more climatically diverse candidate pool resolves matches this grid still smooths over. Novel-climate area is therefore not a scale-free quantity, and cross-study comparisons should control for search resolution as deliberately as for scenario, domain, and threshold.

Several conditions bound these results. They are conditional on AR6-consistent climate sensitivity: the four-model ensemble excludes high-sensitivity models by design, so the principal area estimates are conservative relative to unscreened ensembles, and per-model verdicts bracket them (Supplementary

Table S8). The 2σ threshold is a convention retained for comparability with the sigma-dissimilarity literature [9]. Sweeping it moves absolute areas smoothly but never reorders the scenarios. The feature space comprises monthly means of daily maximum/minimum temperature and daily precipitation (pr), so an analogue here is a seasonal-climate analogue: daily extremes, humidity, and wind, and the transient path by which a place reaches its late-century climate, lie outside the match, as do the non-climatic attributes of place, from soils and photoperiod to land use, that shape how the same climate is experienced at the analogue location. Furthermore, the bias adjustment anchors every field to a single historical reference, so uncertainty in W5E5 propagates into both the candidate pool and the variability null. That uncertainty is largest for precipitation in the data-sparse tropics, where W5E5 relies on gauge-based Global Precipitation Climatology Centre (GPCC) adjustment [18, 19], and both the gauge network and the agreement among precipitation products are weakest, particularly in Amazonia and central Africa, where novelty is concentrated [20, 21].

Two further limitations follow from deliberate design choices. The calendar-month convention that keeps the metric single-valued across the equator also means that a hemisphere-crossing candidate must match the focal cell's seasonal cycle in anti-phase. Permitting a six-month seasonal realignment for cross-equatorial candidates would enlarge the effective analogue pool and would be expected to lower the novel-area estimates, at the price of the live-analogue property and of a displacement field that is continuous across the equator. Because the sigma scale expresses climatic difference in units of local interannual variability, it is most severe precisely where that variability nearly vanishes. The most extreme values occur in hyper-arid coastal deserts where interannual variability, particularly in precipitation, is minute. These same cells destabilize the Wasserstein scale (Supplementary Figs. S25 and S26). Their novelty is real on the metric's own terms, but a score of many tens of sigma expresses an improbability measured against a near-zero reference, not a proportionally large physical change, and may overstate how different these climates will in fact be; a dissimilarity measure suited to hyper-arid climates remains an open methodological question.

Methods

Climate data and study domain

All model data are the ISIMIP3b bias-adjusted CMIP6 simulations [13], adjusted and statistically downscaled with the trend-preserving ISIMIP3BASD method (v2.5) [12, 22] against the W5E5 v2.0 observational reference [18, 19]. Two 30-year windows are used: 1985–2014 from the bias-adjusted historical runs (the analogue candidate pool) and 2071–2100 under SSP1-2.6, SSP2-4.5, and SSP3-7.0 [10, 11]. SSP5-8.5 is not used because emission pathways reaching 8.5 W m^{-2} by 2100 are no longer considered plausible and are not carried forward in the CMIP7 scenario design [23]. Monthly precipitation comes from the ISIMIP3b monthly archive. Monthly means of daily maximum and minimum temperature are aggregated from the daily files for this study. The search domain is the ISIMIP land–sea mask without Antarctica (north of 60° S): 65,797 cells at 0.5° , $142.8 \times 10^6 \text{ km}^2$. For the resolution experiments, the entire pipeline is repeated on 1.0° and 2.0° area-weighted aggregations (cells kept where at least half the block is land). Every plotted or tabulated share is area-weighted with exact spherical cell areas.

The ensemble comprises four CMIP6 models (GFDL-ESM4 [24], MIROC6 [25], MPI-ESM1-2-HR [26], and MRI-ESM2-0 [27], all realization r1i1p1f1) selected before the analysis using four criteria: (i) equilibrium climate sensitivity (ECS) and transient climate response (TCR) inside the IPCC AR6 assessed likely ranges (ECS $2.5\text{--}4.0^\circ \text{ C}$, TCR $1.4\text{--}2.2^\circ \text{ C}$) [28]; (ii) inter-model independence, with four modelling centres with distinct atmosphere and ocean components; (iii) complete ISIMIP3b coverage for all three scenarios; and (iv) comparatively high native resolution, with all four parent atmospheres running near 1° ($0.9\text{--}1.4^\circ$; Supplementary Table S1), so the fields entering the common 0.5° grid carry as much genuine spatial detail as the screened pool offers. Per-model details, including ECS [29] and TCR [30], are given in Supplementary Table S1. The AR6 screen deliberately departs from the ISIMIP standard five, which contains two models now regarded as excessively sensitive (UKESM1-0-LL, ECS 5.34° C ; IPSL-CM6A-LR, 4.56° C) [31]: retaining them would inflate every novelty and analogue-distance figure through a

sensitivity that the assessed evidence does not support. All results are therefore conditional on AR6-consistent climate sensitivity, and single-model results (Supplementary Table S8) bound the effect of the ensemble choice.

Climate feature space

Each cell and period is represented by its 30-year cloud of 36 annual features: 12 calendar months $\times$ $\{\ln(1 + \text{precipitation})$, maximum temperature, minimum temperature $\}$. This is the variable set of the sigma-dissimilarity literature, kept at monthly resolution: Mahony et al. [9] and Fitzpatrick & Dunn [5] use the same three variables as four-season averages, while the seasonal feature space of Bulut et al. [6] describes each season by its mean temperature, its within-season extremes of daily temperature, and its precipitation total for four seasons. The monthly feature space is retained for three reasons. First, monthly features preserve shifts in the timing of the seasonal cycle that seasonal averaging may obscure. Second, calendar months provide a globally consistent feature definition, avoiding arbitrary hemisphere-specific seasons and discontinuities at the equator. Cross-equatorial analogues must therefore match the actual anti-phase seasonal cycle rather than rely on seasonal relabelling. Third, the analogue is live: because both windows are described by the same calendar months, the analogue’s present-day annual cycle is the focal cell’s projected future month for month. The projected climate can be experienced today by travelling to the analogue location, with no seasonal translation or time lag between the two.

Wasserstein analogue search

Following Bulut et al. [6], the dissimilarity between a focal future cell j and a candidate historical cell i is the exact WD between the two 30-point clouds, computed per model. Throughout this work, the WD is the quadratic member of the Wasserstein family [32]. Both clouds are standardized per feature by the standard deviation of the focal cell’s future sample (computed with denominator $n - 1$ and floored at 10^{-6} ; their eq. 6), and the empirical WD reduces to a 30×30 linear assignment problem over squared-Euclidean costs, solved exactly with a Jonker–Volgenant solver [33]. The distance $D_m(j, i)$ is the square root of the mean matched cost for model m . Per-model distance fields are averaged cell-wise, the

analogue of j is the cell minimizing the ensemble distance, and each model’s own 50 best candidates are stored for the agreement diagnostics. All $\approx 4.3 \times 10^9$ cell pairs per model and scenario are solved exhaustively on a GPU (custom CUDA kernel, one exact solver per warp; validated against SciPy’s reference implementation, with a float64 audit of winner pairs; Supplementary Section 11). Because an empirical 30-sample WD in 36 dimensions has a positive sampling floor even for identical climates, the WD value is reported as a distance, and never converted to a significance statement.

Sigma dissimilarity and the novelty threshold

The sigma dissimilarity applies the interannual-climatic-variability (ICV) null of Mahony et al. [9] at the Wasserstein-selected analogue. Per feature k , the climatic difference is the across-model mean difference between the future and analogue-historical 30-year means, both transformed by T_{jk} , the normalizing transform of feature k at focal cell j ; the squared differences sum to the ensemble distance D^2 . The null distribution of D^2 is a generalized chi-square over the eigenvalues of the correlation matrix of the normalized ICV samples, evaluated by Imhof inversion [34], and the sigma dissimilarity is

$$\sigma = \Phi^{-1} \left(\frac{1+F(D^2)}{2} \right) \quad (1)$$

where F is the cumulative distribution function of the null distribution of D^2 and Φ^{-1} is the standard-normal quantile function. Novel climate is declared beyond 2σ , the ‘novel climate’ convention of the sigma-dissimilarity framework [9], retained here for comparability. The ICV sample pools the linearly detrended historical yearly features of the four models ($4 \times 30 = 120$ samples, 112 residual degrees of freedom), sufficient to support the full 36×36 feature correlation.

The temperature features are standardized linearly. Monthly precipitation ICV is strongly non-normal even after the log transformation (Supplementary Fig. S29), so the twelve precipitation features enter the null through quantile matching: per cell and calendar month, a dry-mass + gamma mixture is fitted to the 120 pooled samples (Thom’s estimator [35]),

$$H(x) = q + (1 - q)G(x; \alpha, \beta) \quad (2)$$

where x is monthly precipitation, q is the fitted dry-month (zero-precipitation) probability, and $G(x; \alpha, \beta)$ is the gamma cumulative distribution function with shape α and scale β . Values map onto standard-normal z-scores as $z = \Phi^{-1}(H(x))$, the construction of the standardized precipitation index [36] and the alternative Mahony et al. [9] recommend for exactly this purpose but could not apply with their station-based ICV proxies (their Appendix S8). After the transform, the null's normal-marginal assumption holds by construction. Sixteen hyper-arid cell-months (in 14 of 65,797 cells) have too few wet samples for fitting and therefore borrow the nearest usable neighbour's mixture (Supplementary Table S10). Replacing the quantile matching by the log-transformed alternative moves the principal novel-area estimates by at most 0.19 percentage points and flips the verdict on at most 0.7% of land (Supplementary Section 10, Figs. S30–S31, Table S9). Full formulas, fit diagnostics, and the borrowed-fit rule are in Supplementary Sections 10 and 11.

Per-feature attribution of the climatic difference

We characterized climatic novelty at each grid cell using six mutually exclusive categories that capture (i) whether air temperature or precipitation dominates the novelty signal and (ii) whether the dominant element shows a predominantly positive, negative, or mixed seasonal tendency. To diagnose the direction of change in the dominant element, we decomposed the monthly ensemble distance D^2 into contributions from positive and negative anomalies and summed them separately over the year. If positive-anomaly contributions exceeded two thirds of the annual ensemble distance, the cell was classified as warmer-like (temperature) or wetter-like (precipitation). If negative-anomaly contributions exceeded two thirds, it was classified as cooler-like (temperature) or drier-like (precipitation). Cells meeting neither criterion were classified as temperature-seasonal or precipitation-seasonal, indicating substantial intra-annual variability without a consistent directional shift. The scheme therefore identifies whether novelty at a site is governed primarily by temperature or precipitation and whether the dominant signal reflects

warming/wetting, cooling/drying, or increased seasonal variability relative to the closest historical analogue.

Köppen–Geiger classification

Köppen–Geiger types follow the thresholds of Peel et al. [15], applied identically to the 1985–2014 reference normals (the ensemble mean of the four historical climatologies) and to the ensemble-mean 2071–2100 climatology. Monthly mean temperature is approximated by the mean of daily maximum and minimum temperatures. Main-text Fig. 3 (the Köppen flow) classifies only the historical reference normals, once at the focal cell and once at its analogue, so no threshold rule is ever applied to projected climate there. The world maps (Supplementary Fig. S7) do classify the projected climatology, with the novel area overlaid as a contour because inside it the mapped label is an extrapolation.

Analogue-distance statistics

Here, analogue distance denotes the great-circle distance between cell centres; feature-space residuals are described as climatic differences. Elevations at both ends are sampled from the W5E5 v2.0 orography [18], the reference surface of the bias adjustment. Distribution statistics (median, quartiles, and 90th percentile) are area-weighted over cells with an accepted analogue ($\sigma \leq 2$). All correlations are likewise area-weighted: Pearson correlations are weighted product-moment correlations, and Spearman correlations are weighted Pearson correlations of area-weighted fractional ranks. This applies both to the agreement statistics between the two metrics (Supplementary Section 3) and to the elevation–novelty association, whose significance comes from 999 permutations of elevation across cells (area weights kept with the cells; two-sided). The topographic-position null in Fig. 4j–l is the exact product of the area-weighted marginals (Supplementary Section 4). The per-cell maps of both displacement components, their joint densities against novelty, and the corresponding randomization nulls are collected in Supplementary Fig. S6. Fig. 4d–f overlays the two components in one scatter plot per scenario, coloured by novelty.

Analogue-vector clustering

The focal–analogue field is summarized by area-weighted k -medoids in the four-dimensional feature space (latitude, cos-latitude-scaled longitude, and the two displacement components, the longitudinal one wrapped at the antimeridian and scaled by the same cosine). Area weighting runs through the estimator end to end, acting both on the coordinates and on the sizes: every cell carries its exact spherical cell area as weight (normalized to mean one within each fit), the objective is the area-weighted within-cluster sum of squared feature distances, every centre update is the area-weighted mean of the member cells' feature vectors, and all reported cluster statistics, the land-area shares, and the median member analogue distance that fills the maps, are area-weighted as well, so a cluster's position, boundary, and summary numbers reflect the land area it covers rather than its cell count (0.5° cell areas fall with the cosine of latitude, and an unweighted fit would overweight the high latitudes accordingly). A weighted k -means fit [37, 38] (k -means++ seeding, the best of many random restarts) provides the initial partition, and a Lloyd refinement then constrains every cluster core to a real member cell: each core snaps to the member cell nearest its cluster's area-weighted feature mean (for squared distances that member is the cluster's optimal real core), memberships are reassigned to the nearest core, and the loop repeats until the assignment is stable, so that each mapped arrow is an actual focal–analogue pair. Novel cells ($\sigma > 2$) are held out as their own class. The production fits use $K = 30$ with 10,000 random restarts globally and $K = 20$ with 5,000 restarts within each of nine continental windows. K is chosen to provide a visually interpretable summary of the displacement field. Initialization stability is quantified with the adjusted Rand index [39] over 69 independently seeded fits, and both analyses are reported in Supplementary Section 6. The clustering compresses the focal-to-analogue vector field for display. The underlying analogue and novelty results do not depend on the partition.

Code availability

The analysis code that produced all results and figures of this study is available at <https://github.com/Harrington-Tsunogai/Global-Climate-Analogs/tree/main/climate-displacement-novelty>.

Data availability

The ISIMIP3b bias-adjusted CMIP6 climate input data analysed in this study are publicly available from the ISIMIP Repository at <https://doi.org/10.48364/ISIMIP.842396.1>, and the W5E5 v2.0 observational reference dataset is available at <https://doi.org/10.48364/ISIMIP.342217>. The derived data products of this study are available at <https://github.com/Harrington-Tsunogai/Global-Climate-Analogs/tree/main/climate-displacement-novelty>.

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Author contributions

J.H.-T. conceived the study, developed the clustering-based climate analogue framework and novelty classification methodology, performed all data processing and computational analyses, produced all figures, and drafted the manuscript. Q.-V.D. provided scientific supervision and guidance and revised the manuscript.

664 **Additional Information**

665 **Competing interests**

666 The authors declare no competing interests.

667 **Supplementary information**

668 Supplementary material accompanies this paper (Supplementary Figs. S1–S31, Supplementary Tables
669 S1–S10, and Supplementary Sections 1–11).

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