

Heat-transport networks reveal life-cycle organization and a warm–cold asymmetry of marine temperature extremes

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Abstract

Marine heatwaves (MHWs) and cold spells (MCSs) are usually described as space–time objects, their internal heat pathways unresolved. Here we represent all 672 large offshore MHW and MCS objects of the East/Japan Sea in 1993–2022 as daily weighted directed networks whose nodes are the 0–50 m grid cells of an event and whose edges are anomaly heat fluxes across cell faces, closed by atmospheric and subsurface reservoirs. The mean net convergence of the network tracks the mean anomaly tendency of the members (median correlation 0.73). The inflow fraction from outside follows the perimeter-to-area ratio of the growing and shrinking object; per face, the boundary carries less flux than the interior, least near the peak, when recirculation, bottlenecks and hub persistence exceed early-growth values in 55–73% of events. Cold-spell networks recirculate more, carry more flux per boundary face and are less hierarchical than heatwave networks, with no detectable difference in the concentration of transport on dominant links; the recirculation and hierarchy contrasts are modest, robust to the object definition and associated with coherent anticyclonic flow through warm anomalies and rotational cyclonic flow around cold ones. The daily graphs describe how an extreme is organized and are candidate inputs for graph-based prediction.

Introduction

Marine heatwaves (MHWs) and marine cold spells (MCSs)—prolonged periods of anomalously warm or cold upper-ocean temperature^{1,2}—reorganize marine ecosystems and fisheries^{3,4}; MHWs are becoming more frequent and intense under climate change⁵, whereas MCSs are declining relative to a fixed baseline². Their physical drivers have been quantified with local heat budgets^{6–8}, which show that oceanic advection, and mesoscale eddies in particular, frequently controls event growth⁹, including in the East/Japan Sea¹⁰. Object-based analyses have since extended the description from grid points to coherent space–time objects with onset-to-peak and peak-to-decay phases^{9,11}. What these descriptions leave implicit is the *organization* of the transport: the budget is evaluated cell by cell or integrated over the object, so the routes, bottlenecks and loops along which anomalous heat is redistributed inside an event are not represented.

Network science provides a natural language for such organization. Climate networks have mostly been built from statistical similarity between distant time series^{12–15}; a less-explored class is the *flow network*, whose edges carry a conserved physical flux¹⁶. Power grids, river basins and vascular systems are classical flow networks, and their topology—degree distributions, tree-like versus looped structure, backbones of dominant links—encodes how they transport and how they fail^{17–19}. In the ocean, flow networks have been built in Lagrangian form, with regions as nodes and the probabilities of water transport between them as edges^{20,21}. The discretized heat budget of an ocean layer offers an Eulerian counterpart: every cell face carries a flux and every cell's tendency is the difference of its in- and out-fluxes. In a companion Letter we introduced the corresponding anomaly heat-transport network—an energy flux as edge weight, a node set that follows the event object, and reservoir nodes that close the

layer budget—for four large events²²; here we test, on the full population of events and with explicit controls for object geometry, which of its properties are general.

We construct daily anomaly heat-transport networks for every sufficiently large offshore MHW and MCS object detected in the East/Japan Sea in 1993–2022 and test three questions with population-level statistics: (i) Is there a common life cycle in network topology, and how much of it is set by the geometry of a growing and shrinking object? (ii) Do warm and cold extremes leave distinct topological fingerprints, and are they robust to the object definition, the definition of the peak, event size and season? (iii) With which properties of the flow are the fingerprints associated? We find that the course of external supply is geometric but that the flux per boundary face, recirculation and bottlenecks change consistently towards maturity in most events; a modest but robust warm–cold asymmetry in recirculation, flux per boundary face and hierarchy—but not in flux concentration—that is associated with the coherence and rotation of the flow carrying the anomaly; and a scaling of total internal transport with event size.

Results

Population and network construction

Events are the Tm50 (0–50 m mean temperature) objects of ref.¹⁰: cell-wise detrended anomalies exceed the 90th (MHW) or fall below the 10th (MCS) day-of-year percentile for ≥ 5 days¹, cell events are extended to the local extremum before and after the threshold crossings⁹, and eight-connected cells with overlapping exceedance intervals are joined into independent objects (4,377 MHW and 4,968 MCS objects). To exclude boundary effects and multi-year chains we analyze objects whose peak cell lies ≥ 50 km from the coast, whose exceedance duration is ≤ 200 days, whose life cycle lasts ≥ 15 days and whose daily membership reaches $N_{\text{peak}} \geq 50$ cells. This *main* set contains 375 MHW and 297 MCS objects (Fig. 1a), evenly distributed over seasons (DJF 103/80, MAM 85/64, JJA 101/79, SON 86/74) with similar sizes (median N_{peak} 98 versus 95 cells) and life cycles (56 versus 66 days; Supplementary Table 1). Networks were computed for a wider set of 1,633 objects (offshore ≥ 30 km, $N_{\text{peak}} \geq 20$) so that all filters could be varied in the sensitivity analysis.

For each day of an object we build a directed graph (Methods; Supplementary Fig. 1). Its nodes are the member cells, a one-cell ring of surrounding ocean cells, and two reservoir nodes representing the atmosphere (ATM) and the ocean below 50 m (SUB). Each edge carries the anomaly heat flux $\rho_0 c_p H \bar{u}_{\text{face}} q_{\text{face}} L$ across a cell face, where $q = sT$ is the signed anomaly ($s = +1$ for MHWs, -1 for MCSs), so that edges point in the direction of the anomaly heat flux, which is the direction in which the event anomaly is carried wherever $q > 0$ (Methods). The construction reproduces the four-event Letter²² to within int16 precision (peak-day networks of those four events are shown in Supplementary Fig. 2 and Supplementary Note 3). The net strength of a node, the difference between its in- and out-strengths, is the discretized heat-flux convergence of the cell. Accordingly, the mean net convergence of the member cells tracks their mean anomaly tendency with a median correlation of 0.73 across days (81% of objects

$r > 0.5$; Fig. 1e; this compares daily means over the member cells of the day, not the heat content of the moving object). Without any fitted coefficient the network reproduces a median of 36% of the tendency variance, with a median bias of + 0.01 K day⁻¹ and a root-mean-square residual of 0.10 K day⁻¹ against a tendency standard deviation of 0.11 K day⁻¹ (Supplementary Table 14); the diagnostic residual collects the budget of the background field, the transport by the covariance of vertical shear and temperature within the layer, which crosses faces but is not resolved by the layer-mean product, and mixing and assimilation increments (Methods; Supplementary Note 1, Supplementary Fig. 8). The network is thus a reduced-order diagnostic of the resolved layer transport rather than a closed model of the budget.

A common life cycle of network topology and its geometric part

Composited on the normalized life-cycle time τ (- 1 onset, 0 peak, + 1 end; peak = day of maximum area-integrated anomaly, P_i), the topology of MHW and MCS networks evolves along nearly the same mean path (Fig. 2). The fraction of the inflow to member cells that comes from outside the object (ring, SUB and ATM) is U-shaped: it is 0.74–0.77 in the first days, 0.28–0.30 during early growth, 0.15–0.17 near the peak, 0.28 in late decay and 0.73–0.75 at termination (medians; Supplementary Table 2). The near-peak value is below the early-growth value in 97% of MHWs and 97% of MCSs (paired Wilcoxon $p < 10^{-49}$; year-block bootstrap 95% CI of the median difference - 0.136 to - 0.113 and - 0.142 to - 0.119), below both the early-growth and the late-decay value in 94% and 91%, below both the onset and the end value in 98–99%, and the net convergence is larger in early growth (+ 0.06/+0.03 K day⁻¹) than in late decay (- 0.06/-0.08 K day⁻¹) in 93–95% of events, with an actual sign reversal in 71–72% (Supplementary Table 13). The U-shape itself, however, is geometric. Because interior faces scale with the area of an object and boundary faces with its perimeter, the ring-only external fraction expected if every face carried the same flux with a random direction, $\epsilon_{\text{geo}} = (B/2)/(E_{\text{geo}} + B/2)$, where B is the number of boundary faces and E_{geo} the number of interior faces, both counted from the daily mask (E_{geo} equals the number of active internal edges on 96.9% of object-days; Methods), follows the same course (medians 0.72–0.75, 0.28, 0.18–0.19, 0.30, 0.75; Fig. 2c, dotted) and explains the size dependence of the external fraction (Spearman $\rho = -0.60/-0.55$ with N_{peak} for the external fraction, - 0.58/-0.57 for the baseline; Supplementary Fig. 11). The ratio of the two fractions is not a measure of the flux per face (Supplementary Note 6); the boundary exchange itself is measured by the per-face ratios $r_{\text{in}} = (2I/B)/(\Phi/E_{\text{geo}})$, the ring inflow I per boundary face relative to the interior flux per face, and $r_{\text{ex}} = ((I + O)/B)/(\Phi/E_{\text{geo}})$, which adds the ring outflow O . Both are below one through most of the life cycle and lowest near the peak: r_{in} has medians of 0.97 (MHWs) and 0.96 (MCSs) in the first days, 0.84 and 0.89 in early growth, 0.67 and 0.77 near the peak, 0.74 and 0.80 in late decay and 0.89 and 0.90 in the last days (r_{ex} : 0.95/0.96, 0.80/0.86, 0.69/0.77, 0.83/0.88 and 0.96/0.93; Fig. 2l, Supplementary Fig. 11, Supplementary Table 15); near the peak r_{in} is below one in 94% and 91% of the objects and below its early-growth value in 80% and 77% (paired median differences - 0.15 and - 0.13, year-block intervals excluding zero). The inflow per boundary face is higher in early growth than in late decay (0.84 versus 0.74 and 0.89 versus 0.80), whereas the two-way exchange is nearly symmetric (0.80 versus 0.83 and

0.86 versus 0.88), consistent with net inflow during growth. A synthetic object with a constant flux per face reproduces the U-shape of the external fraction with $r_{\text{in}} = r_{\text{ex}} = 1$ at every step (Supplementary Fig. 11c). Growth is therefore accompanied by a weakening of the flux per boundary face relative to the interior, and decay reverses it; in the four events of the companion Letter an exact decomposition of the active-face fluxes associates the deficit with weaker anomalies at the rim in all four events and with a weaker rim flow in one of them, neither factor being uniquely responsible²²; the decomposition was not computed for the population. The large onset and termination values of the external fraction itself reflect the small size of the object on those days.

The internal structure changes together with the supply. Near the peak, the largest strongly connected component (SCC; the set of nodes that can all reach each other along directed edges, i.e. the recirculating core of the daily graph) is larger than in early growth in 58% of MHWs and 66% of MCSs (median increase + 0.019 and + 0.058; $p < 10^{-10}$). The flow hierarchy, the fraction of edges that lie on no directed cycle²³, is correspondingly lower (− 0.040 and − 0.084; 64% and 73% of events). The normalized betweenness of the most central node is higher (+ 0.030 and + 0.034; 70% and 71% of events), indicating sharper bottlenecks, and the day-to-day persistence of the top-5% hubs is higher (+ 0.021 and + 0.034; 55% and 56%). These are population-level tendencies: they hold for a majority of objects, not for all, and the fraction of objects in which the near-peak value exceeds both the early-growth and the late-decay value is 39–56% (Supplementary Table 13). The flux concentration barely changes (top-10% edge share + 0.012) and the Gini coefficient of node strength decreases slightly (− 0.012). Maturity is therefore characterized, on average, not by a few dominant links but by a more evenly loaded, more looped and more persistent network with well-defined bottlenecks. Across the 432 combinations of three peak definitions, four offshore distances, four size thresholds, three duration thresholds and three chain cut-offs, the decrease of the external fraction and the increase of betweenness are significant ($p < 0.05$) with the expected sign of the median difference in 100% of settings for both phenomena; the SCC, SCC-excess and hierarchy effects in 100% of settings for MCSs and in 75%, 78% and 84% for MHWs, and the hub-persistence effect in 85% (MCSs) and 99% (MHWs) (Fig. 7b, Supplementary Table 7). Every MHW setting in which the recirculation or hierarchy effect is lost includes objects as small as 20 cells ($N_{\text{peak}} \geq 20$), for which the member subgraph is too small for a meaningful strongly connected component; among the settings with $N_{\text{peak}} \geq 50$ these three MHW effects are significant with the expected sign in 100% of settings and hub persistence in 98% (MHWs) and 81% (MCSs).

Warm–cold asymmetry: cold spells recirculate, heatwaves flow through

Warm and cold events differ modestly but consistently in how their transport is organized (Fig. 3, Supplementary Table 3). Near the peak, MCS networks have a larger recirculating core than MHW networks (median SCC fraction 0.19 versus 0.11; Cliff's $\delta = -0.19$, Mann–Whitney $p_{\text{FDR}} = 7 \times 10^{-5}$, within-year permutation $p = 0.001$). They carry a larger share of their flux on directed cycles (0.19 versus 0.09, δ

= -0.20) and have a lower flow hierarchy (0.78 versus 0.90, $\delta = +0.20$). They also draw a larger fraction of their inflow from outside the object (0.17 versus 0.15, $\delta = -0.21$, $p_{\text{FDR}} = 5 \times 10^{-5}$), a contrast that is larger per face (r_{in} 0.77 versus 0.67, $\delta = -0.35$, Mann–Whitney $p = 10^{-14}$, within-year permutation $p = 5 \times 10^{-4}$, size- and season-adjusted $p = 2 \times 10^{-9}$; r_{ex} 0.77 versus 0.69, $\delta = -0.28$, adjusted $p = 5 \times 10^{-7}$) because the geometric baselines of the two phenomena are nearly equal ($\delta = -0.08$, $p = 0.06$); the r_{in} contrast has the same sign in every season ($\delta = -0.18$ to -0.46 ; $p \leq 6 \times 10^{-5}$ except in autumn, $\delta = -0.18$, $p = 0.051$) and in every size quartile ($\delta = -0.21$ to -0.45 ; $p \leq 0.026$), whereas the r_{ex} contrast is not significant in autumn ($\delta = -0.10$, $p = 0.27$) and in the smallest quartile ($\delta = -0.14$, $p = 0.13$); both ratios are tested separately from the 14-feature family of Supplementary Table 3 (Supplementary Fig. 11, Supplementary Table 15). A Cliff's δ of ± 0.2 corresponds to a probability of about 0.6 that a randomly chosen object of one phenomenon exceeds one of the other: the distributions overlap substantially, and the contrast is a shift of the population, not a separation of events. These contrasts are not size artifacts. They persist after adjusting for $\log N_{\text{peak}}$ and season in a year-clustered regression ($p = 0.0005$, 0.0004 , 0.0002 and 0.0002), they have the same sign in the three smallest size quartiles ($\delta = -0.21$ to -0.28 for the SCC fraction), and they are strongest in summer ($\delta = -0.30$ in JJA, -0.23 in SON, -0.13 in DJF, -0.06 in MAM; Fig. 3, Supplementary Tables 3 and 10).

The concentration of transport does not differ: the top-10% edge-flux share (0.256 versus 0.259, $\delta = -0.01$, $p = 0.88$) and the Gini coefficient of node strength (0.314 versus 0.313, $p = 0.81$) are indistinguishable, and both increase with event size in the same way for the two phenomena (Fig. 4). The only distributional difference is a slightly broader edge-flux distribution in MHWs (σ of $\log$ flux 1.32 versus 1.29, $\delta = +0.10$), which is not significant after false-discovery-rate control ($p_{\text{FDR}} = 0.053$) but is after size and season adjustment ($p = 0.034$), and which becomes clearer for large events ($\delta = +0.28$ in the largest size quartile). The hub-dominated fingerprint of the four events²² is therefore not a population property, not even within the largest quartile (top-10% share $\delta = +0.11$, Gini $\delta = +0.15$, $p_{\text{FDR}} \geq 0.28$); the population fingerprint is a difference in *circulation* and in the flux per boundary face, not in concentration.

To separate recirculation in the flux pattern from the lattice geometry, we compared each daily network with a null model in which the direction of every edge is randomized while the weights and the lattice are kept (Methods). Near the peak, MHW networks recirculate *less* than random (median SCC excess -0.057 , year-block 95% CI -0.078 to -0.032 ; 39% of objects positive; Fig. 5), whereas the MCS excess is positive on average but its year-block interval includes zero ($+0.028$, CI -0.010 to $+0.060$; 54% positive; object-level Wilcoxon $p < 10^{-4}$, a test that assumes independent objects; Supplementary Table 5). The MCS excess is clearly positive in summer ($+0.068$, CI $+0.020$ to $+0.135$) and small in autumn ($+0.029$) and winter ($+0.030$), whereas the MHW excess is negative in all seasons (-0.045 to -0.075). Both phenomena are more hierarchical than random (the flow hierarchy exceeds the null by 0.16 in MHWs and 0.07 in MCSs). Heatwave transport is therefore organized as through-flow that is more directional than random, whereas cold-spell transport is closer to, and in summer beyond, the random expectation of recirculation. The asymmetry is unrelated to how well the budget closes (Spearman ρ between closure r and SCC excess -0.04 and -0.09 , not significant; among objects with $r > 0.7$ the medians are -0.068

versus $+0.031$, $p = 8 \times 10^{-4}$), so that no significant monotonic association between closure and the excess is detected across objects; their independence was not tested, and the result does not show that the unresolved transport would leave the graph unchanged. The null preserves the lattice and the weights only; it does not preserve continuity or the spatial correlation of the flow. The Monte Carlo error of the 20-realization null mean is 0.02 per day, small against the per-day excess (median $|\text{excess}|$ 0.14) and averaged down further in the window means.

Robustness to peak definition, object size and filters

Three definitions of the peak give the same results (Supplementary Fig. 5): the day of maximum membership (P_n , "largest single object"), the day of maximum area-integrated anomaly (P_i , "maximum day $\times$ temperature") and the day of maximum cell amplitude (P_a). P_n precedes P_i by a median of one day (74% of MHWs and 70% of MCSs within ± 5 days; Supplementary Fig. 9). The warm–cold contrasts agree to within 0.05 in Cliff's δ for the three definitions (SCC fraction $\delta = -0.19, -0.19, -0.20$; hierarchy $+0.20, +0.20, +0.20$; external fraction $-0.18, -0.21, -0.23$ for P_n, P_i, P_a ; Supplementary Table 8, Supplementary Note 5). Across the 432 filter $\times$ peak-definition settings, the external-fraction contrast is significant in 100% of settings (90% after size adjustment). The SCC and hierarchy contrasts keep their sign in 89–96% of settings and are significant in 69% (Fig. 7a), and the lognormal-width contrast keeps its sign in 100% and is significant in 79%. The settings in which the recirculation contrast is lost are those restricted to the largest events ($N_{\text{peak}} \geq 200$, $n = 138$), for which MHWs and MCSs recirculate alike ($\delta = -0.02$; Supplementary Fig. 7, Supplementary Note 4) and for which the SCC excess of both phenomena is positive (medians $+0.11$). The contrast is thus a property of events up to a few hundred cells ($\approx 10^4$ km²), that is, of the mesoscale. Restricting events to ≥ 100 km from the coast leaves all contrasts unchanged. The 432 settings are nested subsets of one catalogue, not independent replications; they test the sensitivity to the object definition, not the reproducibility of the result. The per-face ratios r_{in} and r_{ex} were computed for the main set only, with the season and size strata above as their sensitivity check.

Kinematic associations of the asymmetry

The asymmetry is associated with the flow in which the anomaly is embedded (Fig. 8); because the network and the kinematic diagnostics are computed from the same velocity field, the association is descriptive and does not by itself establish causation. On the peak day, MHW objects sit in anticyclonic flow (median $\zeta/f = -0.057$; 24% of member cells cyclonic) and MCS objects in cyclonic flow ($+0.058$; 79% cyclonic), with almost complete separation ($\delta = -0.94$), as expected from the thermal-wind balance of warm and cold cores. More importantly for the topology, the flow through MHW objects is faster (median layer speed 0.18 versus 0.13 m s⁻¹, $\delta = +0.31$) and more coherent (flow coherence $|\langle u \rangle|/|\langle u \rangle| = 0.69$ versus 0.59 , $\delta = +0.18$, $p = 10^{-4}$). Flow coherence is by far the strongest single correlate of network recirculation in both phenomena (Supplementary Table 9) (Spearman $\rho = -0.64$ for MHWs and -0.65 for MCSs between coherence and the SCC excess; $\rho = +0.64/+0.64$ with flow hierarchy), followed by the

magnitude of relative vorticity ($\rho = +0.25$ and $+0.44$ with the SCC excess). Recirculating networks are thus the graph signature of rotational, low-coherence flow on the day of the graph; they do not measure the residence time of water or a persistent trapping of the anomaly, which would require Lagrangian or time-respecting analysis. A consistent interpretation is that warm anomalies in the East/Japan Sea are carried by the coherent north-eastward branches of the Tsushima Warm Current and the frontal jets of the northern basin^{24–26}, whereas cold anomalies sit in slower cyclonic circulations of the basin interiors²⁴; this correspondence with the known circulation is an interpretation, not a result of the present analysis. Consistently, the persistent backbones of MHW networks are directionally coherent (mean resultant length 0.50; 71% of backbone edge-days point east or north) whereas those of MCS networks are less so (0.41; 40% east, 24% south; Fig. 6, Supplementary Table 11).

Seasonality and scaling

Within each phenomenon the life-cycle shape is season-independent (Supplementary Fig. 4) but the levels are modulated. MHWs are most self-contained in summer (external fraction near the peak 0.14 in JJA versus 0.17 in DJF; Kruskal–Wallis $p_{\text{FDR}} = 0.004$) and their hubs are more persistent in summer (Jaccard 0.59 versus 0.54, $p = 0.01$). MCSs have the most pronounced bottlenecks and the most persistent hubs in summer and autumn (betweenness 0.16 versus 0.13, hub persistence 0.61 versus 0.50 relative to winter; $p_{\text{FDR}} = 0.008$), and their external supply decreases from winter to autumn (0.18 to 0.15, $p_{\text{FDR}} = 0.01$; Supplementary Table 4). The warm–cold recirculation asymmetry is a summer–autumn phenomenon (above), consistent with the seasonal strengthening of the stratified mesoscale field.

Finally, the total internal transport scales with event size: on the peak day, $\Phi \propto N^{1.19}$ for MHWs (year-block 95% CI 1.11–1.29) and $N^{1.18}$ (1.07–1.28) for MCSs ($r = 0.79$ – 0.81), and the run maxima give the same exponents (1.17 and 1.16; Supplementary Fig. 6, Supplementary Table 16). The superlinear exponent arises partly because the number of edges grows almost linearly with N and partly because the mean edge flux Φ/E itself increases weakly with size ($\propto N^{0.14}$ and $N^{0.12}$, CI 0.05–0.23 and 0.02–0.22): larger events carry somewhat more heat per link, not only more links. Flux concentration, Gini coefficient and the width of the log-flux distribution increase with size as well (Spearman $\rho = 0.5$ – 0.6 for concentration and Gini; Supplementary Table 6), as expected for weight distributions without a heavy tail on a lattice.

Discussion

Three results emerge from 672 events. First, the topology of the anomaly heat-transport network follows a common mean course through the life cycle of an event. The U-shaped external inflow fraction, whose near-peak value lies below the early-growth value in 97% of events, is a consequence of the perimeter-to-area ratio of a growing and shrinking object; the physical signal is a flux per boundary face that is lower than the flux per interior face, lowest near the peak (below one in 91–94% of events and below its early-

growth value in 77–80%), accompanied by more recirculation, sharper bottlenecks and more persistent hubs in a majority of events and by a more even distribution of node strength. The consistency of the mean course across two phenomena, four seasons, two orders of magnitude in size and three decades is notable, but individual events scatter widely around it. Whether the trajectory of the boundary exchange has predictive value is an open question: the objects, their peaks and the normalized time are defined a posteriori, so that any forecast application would have to detect events from past information only and be tested out of sample against a persistence baseline.

Second, warm and cold extremes are topologically asymmetric in a specific, modest and robust way: cold-spell networks recirculate more, carry more flux per boundary face and are less hierarchical than heatwave networks, which recirculate less than random-direction networks, while no difference in the concentration of flux on dominant links is detected. The effect sizes are small ($|\delta| \approx 0.2\text{--}0.35$) and the distributions overlap; the asymmetry is a population shift, not a classifier of individual events. It is associated with kinematics—coherent, fast, anticyclonic flow through warm anomalies versus rotational, slow, cyclonic flow around cold anomalies—which in the East/Japan Sea is consistent with the contrast between warm-current branches and basin-interior cyclonic recirculations. This qualifies the picture drawn from four events²², in which the heatwaves appeared hub-dominated: with population statistics the hub-dominance vanishes, also among the largest events, and the circulation contrast remains. The asymmetry is strongest in summer and disappears for the largest events, which span several circulation features and recirculate alike; it is therefore a mesoscale property, in line with the mesoscale-eddy control of event growth identified by heat-budget analyses^{9,10}.

Third, the network quantities obey simple scaling: total internal transport grows superlinearly with size, with a weak increase of the mean edge flux, and among the candidate forms the edge-weight distributions have an exponential or lognormal rather than a power-law tail²⁷ (Supplementary Fig. 3, Supplementary Note 2), as in other spatially embedded flow networks^{16,17}. In these respects heat-transport networks resemble power grids and river networks, but they differ from river networks in carrying loops that wax and wane with the life cycle and from power grids in having a direction field set by the circulation. The direction-randomized null model, which preserves lattice and weights but not continuity, isolates this directional information and is a benchmark, with that limitation, for future comparisons across basins.

The construction has known limitations. The layer-mean product $\bar{u}q$ omits the transport by the covariance of vertical shear and temperature within 0–50 m, which crosses faces and is therefore absent from the graph; the vertical velocity is inferred from the divergence of the layer flow; and the budget of the background field is collected in the residual. Together these limit the closure: the mean net convergence correlates with the mean anomaly tendency of the member cells at a median $r = 0.73$ but, without any fitted coefficient, reproduces a median of 36% of its variance (Supplementary Tables 1 and 14); which of the unresolved terms dominates the residual was not determined; a level-wise construction would resolve the vertical-covariance transport but would not necessarily reduce the residual, and that comparison remains to be done. The graph is therefore a reduced-order diagnostic of the resolved layer

transport. Within that scope the topology is relatively stable: no significant monotonic association between closure and topology is detected across events (Supplementary Note 1), and the one background perturbation we tested, subtracting only the seasonal climatology so that the 30-year trend stays in the anomaly, on a fixed catalogue, changes most near-peak features by a median of less than 0.01 (up to 0.03 for the Gini coefficient and 0.11 for the rank-based hub persistence and log-flux width at the 90th percentile of objects; Supplementary Methods 5, Supplementary Fig. 10, Supplementary Table 12). The strength-based metrics use the incident horizontal strength, which includes faces shared with ring cells; an internal-only definition raises the Gini coefficient by 0.01–0.05 and changes hub identities but not the aggregate statistics in the four events of the companion Letter (Supplementary Note 7, Supplementary Fig. 12, Supplementary Table 17), and was not recomputed for the population. The events are those of a single reanalysis and basin; the kinematic association suggests that the asymmetry may generalize wherever warm anomalies are advected by boundary currents and cold anomalies form in cyclonic interiors, a hypothesis that can be tested with the same pipeline in other regions. A level-wise construction would allow vertically stacked voxels of subsurface-reaching events¹¹ to be linked by vertical advection edges, and the daily graphs—whose node features and edge weights are of the kind aggregated by message-passing graph neural networks^{28–30}—are candidate inputs for data-driven prediction of ocean extremes, pending the out-of-sample tests described above.

Methods

Data and events

We use daily GLORYS12V1 (1/12°) temperature and velocity³¹ and ERA5 surface heat fluxes³² (regridded to the GLORYS12 grid by bilinear interpolation) for 1993–2022 over 34–45°N, 127–144°E. Tm50, the thickness-weighted 0–50 m mean temperature (cells with less than 90% layer coverage are excluded), is detrended cell-wise (mean-preserving linear trend over 1993–2022), and events are detected with the threshold definition of Hobday et al.¹ (90th/10th day-of-year percentile from a ± 5 -day window smoothed over 31 days, 29 February averaged from adjacent days, minimum duration 5 days, gaps ≤ 2 days merged). Each cell event is extended backward and forward to the nearest local extremum of the anomaly within 20 days⁹; cell events in eight-connected cells whose threshold-exceedance (standard) intervals overlap or are adjacent are united into objects¹⁰, and the daily membership of a cell in an object is its extended interval. The East/Japan Sea basin mask of ref.¹⁰ excludes the Pacific side of the straits. The surface-flux anomaly Q' is the departure from the day-of-year climatology of the retained flux and is not detrended.

Object catalogue, filters and peak definitions

For every object we record footprint, daily membership $N(t)$, peak-cell coast distance, exceedance duration and life-cycle length. The main filter (offshore ≥ 50 km, $N_{\text{peak}} \geq 50$, life cycle ≥ 15 days, exceedance ≤ 200 days) was chosen so that each phenomenon $\times$ season class contains ≥ 60 objects; the processing set (≥ 30 km, ≥ 20 cells, ≥ 10 days, ≤ 365 days) contains 1,633 objects. Three peak days are

defined per object: P_n , the day of maximum $N(t)$; P_i , the day of maximum area-integrated anomaly of exceeding cells $\sum q A$; and P_a , the day of maximum cell anomaly (the peak node of ref.¹⁰). Phases are onset-to-peak and peak-to-end, and τ is the time normalized separately within each phase. Season is assigned by the month of the peak day.

Network construction

Full definitions, the derivation of the layer anomaly budget in flux form and the discretization are given in Supplementary Methods 5–6 and Supplementary Fig. 1; the sensitivity of the topology to the one background perturbation tested (climatology with the linear trend retained, on a fixed catalogue) is documented in Supplementary Methods 5, Supplementary Fig. 10 and Supplementary Table 12. For day t the nodes are the member cells, the eight-connected ring of surrounding ocean cells, and two reservoir nodes ATM and SUB. With $q = sT'$ ($s = \pm 1$), the horizontal edge between adjacent cells is $F = \rho_0 c_p H \bar{u}_{\text{face}} q_{\text{face}} L_{\text{face}}$ ($\rho_0 = 1,026 \text{ kg m}^{-3}$, $c_p = 4,000 \text{ J kg}^{-1} \text{ K}^{-1}$, $H = 50 \text{ m}$; face values are cell averages, L the spherical face length). The vertical edge is $F_{\text{SUB}} = \rho_0 c_p w_b q_b A$, with $w_b = H \nabla \cdot \bar{u}_{50}$ from continuity and $q_b = sT'(-50 \text{ m})$. The atmospheric edge is $F_{\text{ATM}} = s Q' A$, where Q' is the anomaly of the net surface heat flux retained in the layer after removing the 4.8% of shortwave radiation penetrating below 50 m (Paulson–Simpson Jerlov-I³³). Edges point in the direction of positive F with weight $|F|$; faces with $|F| < 1 \text{ kW}$ are dropped. Because membership extends to the local extremum of the anomaly, a member cell can carry $q < 0$ on part of its days (4–22% of member cell-days in the four Letter events; Supplementary Table 17); on such faces the edge points in the direction of the anomaly heat flux, which is opposite to the flow. Land is a wall; the basin mask is applied only after the divergence is computed so that the straits are not artificial walls. The net strength of a node then equals the discretized heat-flux convergence, $\rho_0 c_p H A dq/dt = s_{\text{in}} - s_{\text{out}} + R$, where the residual R is defined diagnostically as the difference between the observed tendency and the net strength and collects the budget of the background field (including the advection of its gradient), the horizontal divergence of the vertical shear–temperature covariance within the layer, and mixing and assimilation increments (Supplementary Methods 5); closure is quantified by the correlation, bias and root-mean-square residual between the mean tendency and the mean net convergence of the member cells across days (Supplementary Note 1, Supplementary Table 14). For MCSs, $q = -T'$, so that a positive net convergence in K day^{-1} denotes a strengthening of the cold anomaly.

Metrics

Mathematical definitions of all metrics are given in Supplementary Methods 7–8. Four groups of metrics are computed. Size and transport: the number of member nodes N and member–member edges E , the total internal flux Φ (the sum of the member–member edge weights, which counts heat each time it crosses a face), and the external fraction ε , the share of the gross inflow to members that comes from ring, SUB and ATM edges. Because interior faces scale with the area of an object and boundary faces with its perimeter, the ring-only fraction $\varepsilon_{\text{ring}} = I/(\Phi + I)$ is compared with a geometric baseline $\varepsilon_{\text{geo}} = (B/2)/(E_{\text{geo}} + B/2)$, its value if every face carried the same flux with a random direction, where B is the number of boundary faces (faces between a member cell and an ocean cell outside the object) and E_{geo}

the number of interior faces (faces between two member cells), both counted directly from the daily mask. E_{geo} equals the number of active member–member edges E on 96.9% of the 46,650 object-days; where they differ, the 1 kW threshold removes a median of 0.4% and at most 8.3% of the interior faces (objects with ≥ 10 cells), and E_{geo} is used in all geometric quantities so that the denominators are defined on the same support for both phenomena. The number of ring cells, used as a proxy for B in an earlier version, differs from B by more than 4% on 77% of the object-days. The ratio $\varepsilon_{\text{ring}}/\varepsilon_{\text{geo}}$ is not a per-face quantity (Supplementary Note 6); the flux per boundary face relative to the flux per interior face is the odds ratio $r_{\text{in}} = [\varepsilon_{\text{ring}}/(1 - \varepsilon_{\text{ring}})]/[\varepsilon_{\text{geo}}/(1 - \varepsilon_{\text{geo}})] = (2I/B)/(\Phi/E_{\text{geo}})$, which assumes that half of the boundary faces carry inflow, and the two-way exchange ratio $r_{\text{ex}} = ((I + O)/B)/(\Phi/E_{\text{geo}})$, which makes no such assumption. Both are defined on days with $\Phi > 0$, $E_{\text{geo}} > 0$ and $B > 0$ and summarized within a window by the median over valid days; the number of objects with a valid value is reported for every window (Supplementary Methods 7, Supplementary Note 6). Heterogeneity: the share of Φ on the strongest 10% of member–member edges, the Gini coefficient of node strength, and the width σ of the log-flux distribution (pooled over the object). Here and for the hubs, the strength of a member cell is its incident horizontal strength $s_{\text{in},h} + s_{\text{out},h}$, including the faces it shares with ring cells; the sensitivity to an internal-only definition is given in Supplementary Fig. 12 and Supplementary Table 17. Flow structure, computed on the subgraph of member cells and member–member edges only: the largest-SCC fraction³⁴, the flow hierarchy²³ and the flux fraction on directed cycles, the maximum normalized weighted betweenness (distance $1/w$)³⁵, the disparity-filter backbone³⁶ ($\alpha = 0.3$) and its flux share, and Louvain modularity³⁷. Persistence: the Jaccard similarity of the top-5% strength hubs between consecutive days. Metrics requiring a graph are evaluated on days with ≥ 10 member cells. For the null model, the direction of every member–member edge is flipped with probability $\frac{1}{2}$ (20 realizations per day; Monte Carlo standard error of the daily null mean 0.02) and the SCC fraction and hierarchy are averaged; the excess is observed minus null. The null preserves the lattice and the edge weights but not continuity or the spatial correlation of the flow. Per-object features are window means over early growth ($\tau < -0.25$), near-peak ($|\tau| \leq 0.25$) and late decay ($\tau > 0.25$), and the first/last three days; the per-face ratios use the median within a window.

Statistics

All procedures are specified in Supplementary Methods 9; the object is the sample unit throughout. Life-cycle effects are tested per object with paired Wilcoxon signed-rank tests between windows (one-sided in the direction expected from the four-event Letter for the external fraction, SCC, SCC excess, hierarchy, betweenness and hub persistence; two-sided for the concentration metrics), reported with the fraction of objects showing the effect (Supplementary Table 13) and a 95% confidence interval of the median difference from a year-block bootstrap (2,000 resamples of calendar years, which respects the dependence of events within a year); the year-block interval is the primary measure of uncertainty where it and the object-level test disagree. Warm–cold contrasts use two-sided Mann–Whitney U tests with Cliff's δ ³⁸ as effect size, Benjamini–Hochberg³⁹ control of the false-discovery rate across the family of 14 near-peak features (Supplementary Table 3; Fig. 3 displays ten of them), a within-year label-

permutation test (1,000 permutations), and an ordinary-least-squares model of each feature on phenomenon, $\log N_{\text{peak}}$ and season with year-clustered standard errors. Contrasts are repeated within size quartiles and seasons. The per-face ratios r_{in} and r_{ex} , introduced after the family was fixed, are tested with the same procedures (2,000 permutations; year-block bootstrap with 500 resamples for the composites and 1,000 for the window summaries) but reported separately with raw p values and year-block confidence intervals (Supplementary Table 15); they are not included in the 432-setting sensitivity analysis. Seasonal differences within a phenomenon use Kruskal–Wallis tests (FDR-controlled) and JJA-versus-DJF Mann–Whitney tests. Sensitivity is assessed by repeating the key tests for all 432 combinations of peak definition (P_n, P_i, P_a), offshore distance (30, 50, 75, 100 km), size threshold (20, 50, 100, 200 cells), life-cycle threshold (10, 15, 30 days) and chain cut-off (120, 200, 365 days); for each test we report the fraction of settings with $p < 0.05$, the fraction in which the median effect has the expected sign, and the fraction satisfying both (Supplementary Table 7). Composites on τ use 20 bins with year-block bootstrap 95% confidence bands of the mean. Scaling exponents are ordinary least-squares slopes in log–log space with year-block bootstrap confidence intervals, for both run-maximum and same-day (peak-day) quantities (Supplementary Table 16).

Kinematic diagnostics

On the P_i peak day we compute for the member cells the relative vorticity $\zeta = \partial v / \partial x - \partial u / \partial y$ of the layer flow normalized by the Coriolis parameter f , the fraction of cyclonic cells, the mean speed and the flow coherence $|\langle u \rangle| / \langle |u| \rangle$ (1 for parallel flow, 0 for purely rotational or disordered flow), and relate them to the network features with Spearman correlations. These diagnostics are computed from the same velocity field as the network, so that the correlations describe associations within one data set rather than independent evidence.

Declarations

Data availability

GLORYS12V1 (GLOBAL_MULTIYEAR_PHY_001_030, accessed 2026) is distributed by the Copernicus Marine Service and ERA5 (ref.³²) by the Copernicus Climate Data Store. The object catalogue follows ref.¹⁰. The object catalogue, the per-object daily network metrics and features, the 432-setting sensitivity results (Supplementary Data 1) and the source data of all figures are deposited at [Zenodo DOI to be assigned before submission; a private reviewer link will be provided].

Code availability

The MATLAB code that builds the layer caches and the Python pipeline (network_analysis_full/, f00–f19: layer cache, catalogue, network construction, statistics, figures, tables, kinematics, supplementary analyses, the boundary-face count and the checks added after review), together with the environment file and the run order, are deposited with the data at [Zenodo DOI to be assigned before submission].

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Author contributions

G.L.: conceptualization, methodology, software, formal analysis, visualization, writing – original draft, writing – review and editing; J.-J.P.: conceptualization, supervision, writing – review and editing.

Competing interests

The authors declare no competing interests.

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Figures

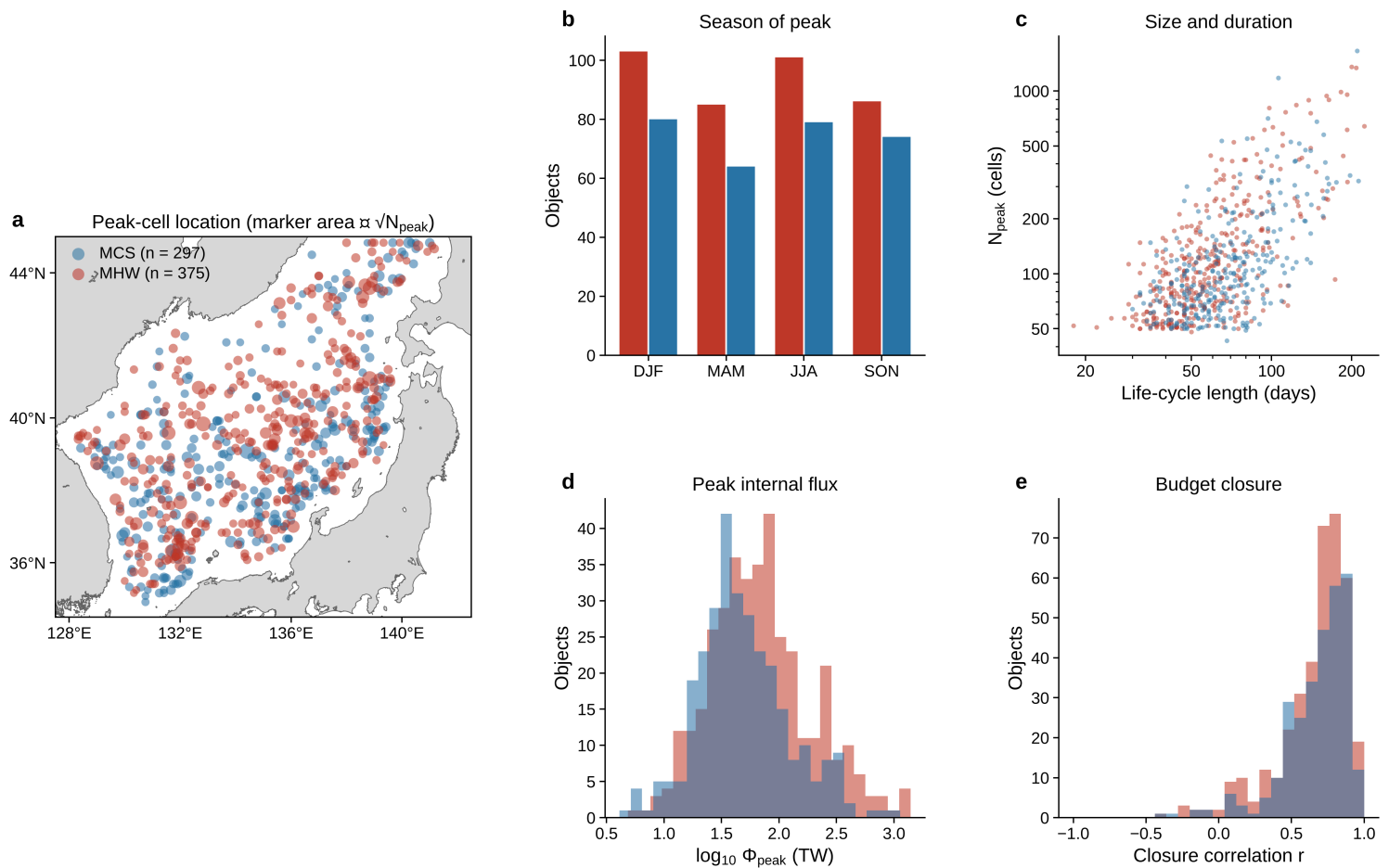


Figure 1

Analyzed events. **a**, Peak-cell locations of the 375 MHW (red) and 297 MCS (blue) objects of the main set; marker area proportional to $\sqrt{N_{\text{peak}}}$ (run maximum of the daily membership). **b**, Number of objects by season of the peak. **c**, Peak membership versus life-cycle length. **d**, Distribution of peak internal flux Φ_{peak} . **e**, Distribution of the closure correlation between the mean net network convergence of the member cells and their mean anomaly tendency dq/dt across the days of each object.

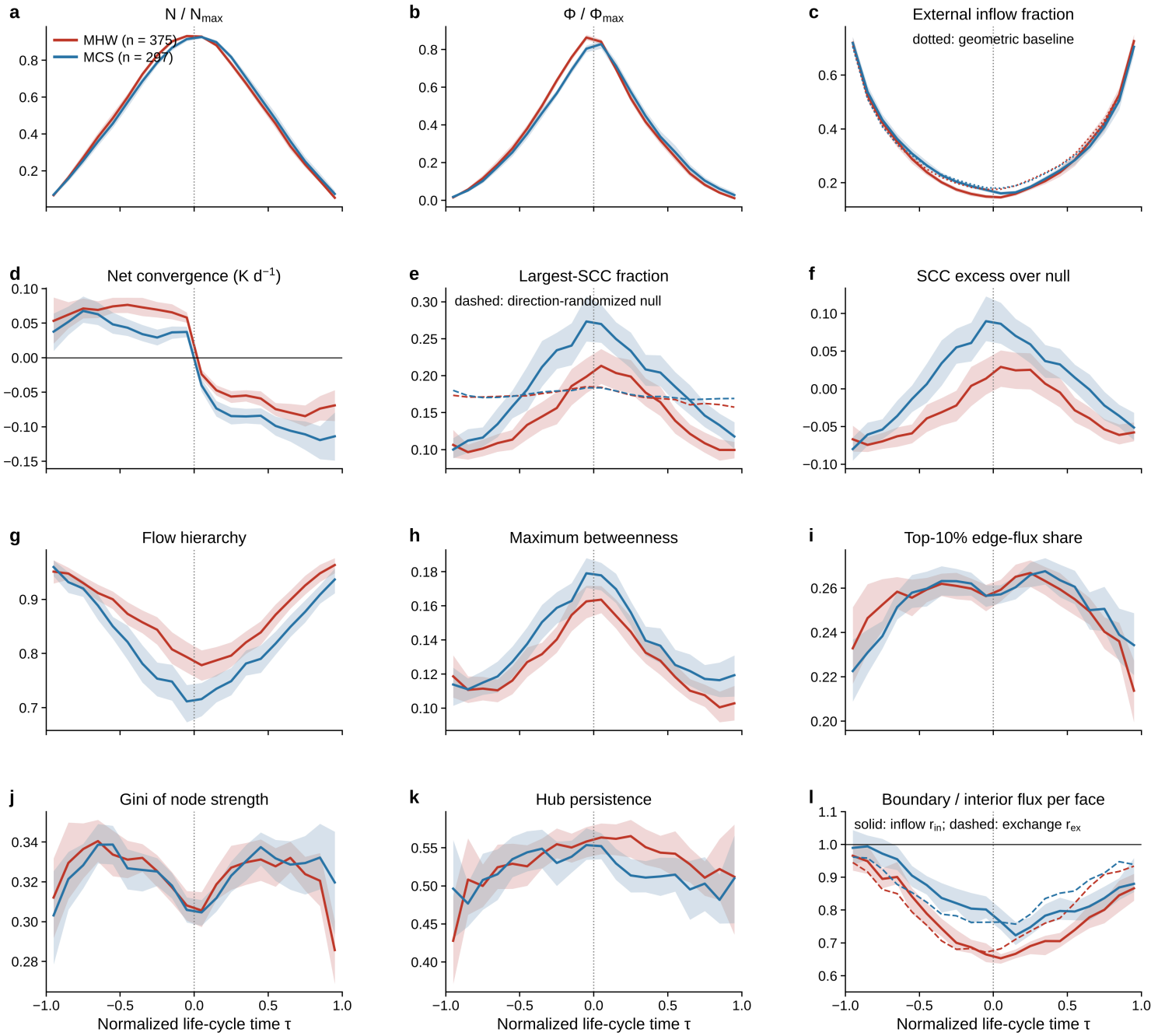


Figure 2

Common life cycle of network topology. Composites on normalized life-cycle time τ (-1 onset, 0 peak, $+1$ end; 20 bins) for MHWs (red, $n = 375$) and MCSs (blue, $n = 297$); shading, year-block bootstrap 95% confidence bands of the mean, which describe the uncertainty of the mean and not the spread between objects (event-level frequencies are given in Supplementary Table 13). **a**, Membership $N/N_{\max}$. **b**, Internal flux $\Phi/\Phi_{\max}$. **c**, External inflow fraction; dotted, the geometric baseline $\varepsilon_{\text{geo}} = (B/2)/(E_{\text{geo}} + B/2)$ expected from the numbers of interior and boundary faces alone. **d**, Mean net convergence of the member cells. **e**, Largest-SCC fraction (dashed: direction-randomized null). **f**, SCC excess over the null. **g**, Flow hierarchy. **h**, Maximum betweenness. **i**, Top-10% edge-flux share. **j**, Gini coefficient of node strength. **k**, Hub persistence. **l**, Flux per boundary face relative to the flux per interior face: inflow ratio r_{in} (solid, median

with year-block 95% band, 500 resamples) and two-way exchange ratio r_{ex} (dashed, median); the horizontal line marks 1. Topological metrics (**e–k**) use days with at least 10 member cells; **i** uses days with $\Phi > 0$, $E_{\text{geo}} > 0$ and $B > 0$.

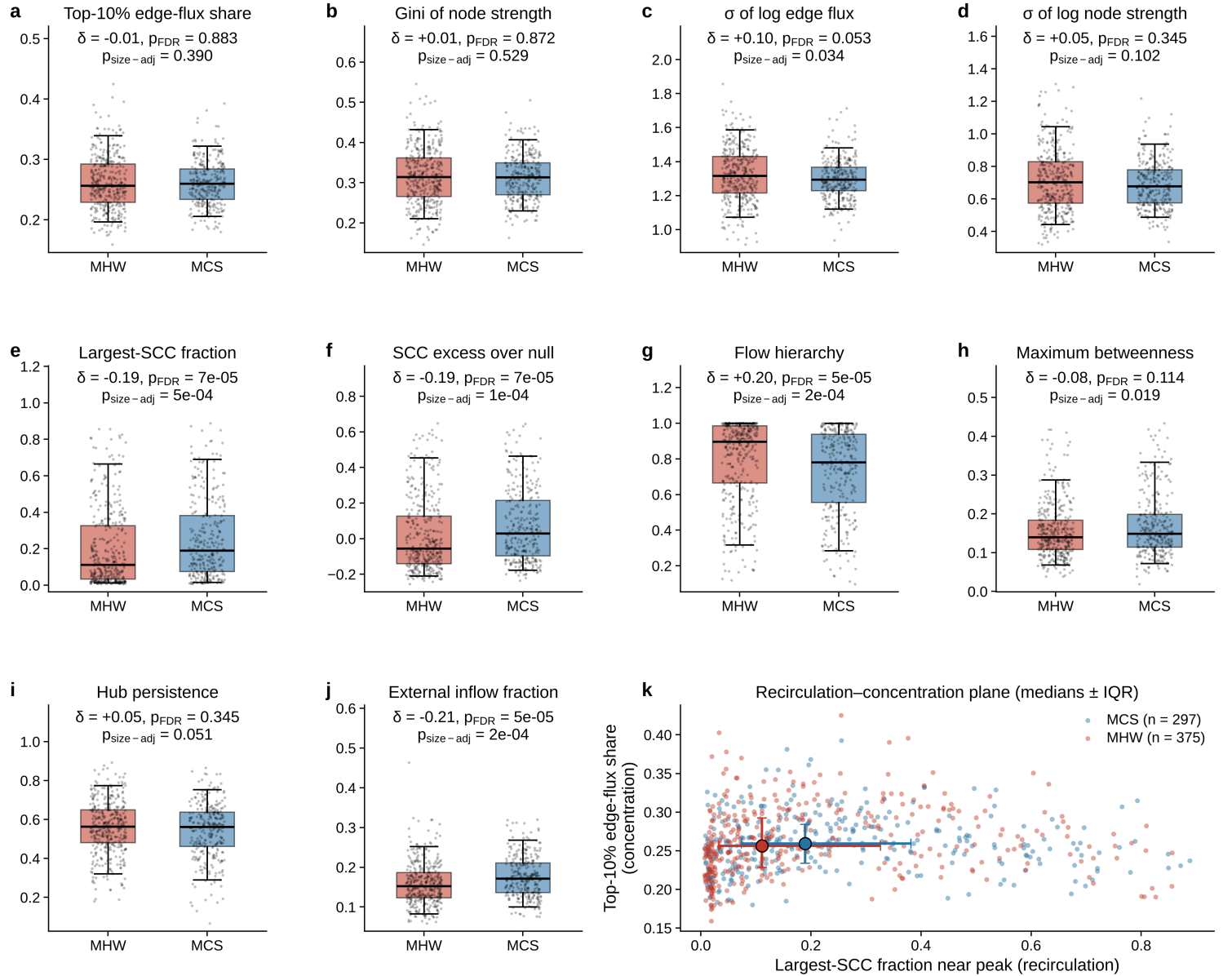


Figure 3

Warm-cold fingerprints near the peak. a–j, Box plots (median, quartiles; whiskers, 5th–95th percentiles) and individual objects for the near-peak features of MHWs (red) and MCSs (blue): top-10% edge-flux share (**a**), Gini coefficient of node strength (**b**), σ of log edge flux (**c**), σ of log node strength (**d**), largest-SCC fraction (**e**), SCC excess over the null (**f**), flow hierarchy (**g**), maximum betweenness (**h**), hub persistence (**i**) and external inflow fraction (**j**), with Cliff's δ (MHW – MCS), the FDR-adjusted Mann–Whitney p (family: the 14 near-peak features of Supplementary Table 3, of which ten are shown) and the size- and season-adjusted year-clustered regression p ; the sample unit is the object (375 MHWs, 297 MCSs). **k**, Recirculation–concentration plane; large symbols are medians with interquartile ranges.

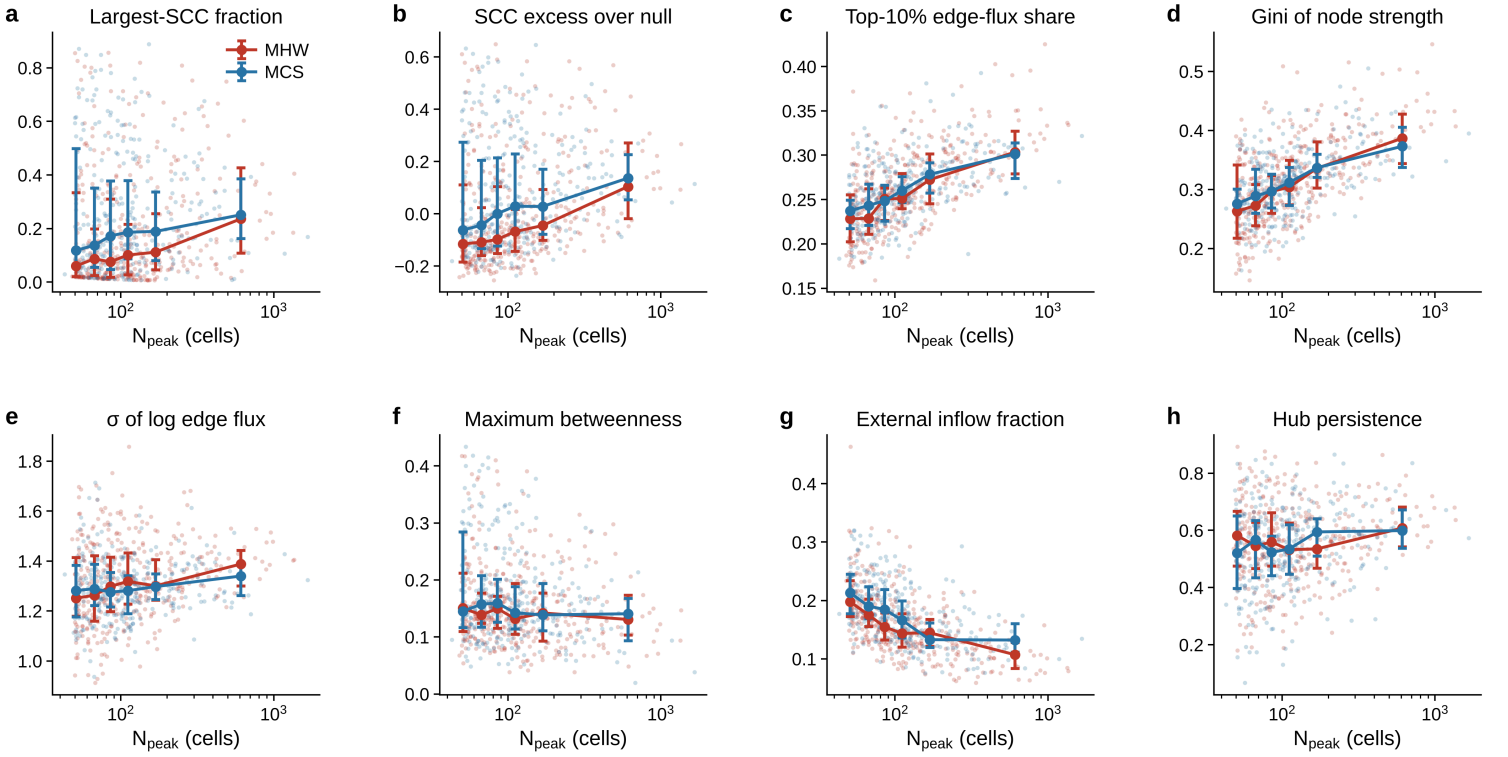


Figure 4

Size dependence. Near-peak largest-SCC fraction (**a**), SCC excess over the null (**b**), top-10% edge-flux share (**c**), Gini coefficient of node strength (**d**), σ of log edge flux (**e**), maximum betweenness (**f**), external inflow fraction (**g**) and hub persistence (**h**) versus N_{peak} (run maximum of the daily membership), with medians and interquartile ranges in six size bins for MHWs (red) and MCSs (blue); the bins partition the same 672 objects as Fig. 3.

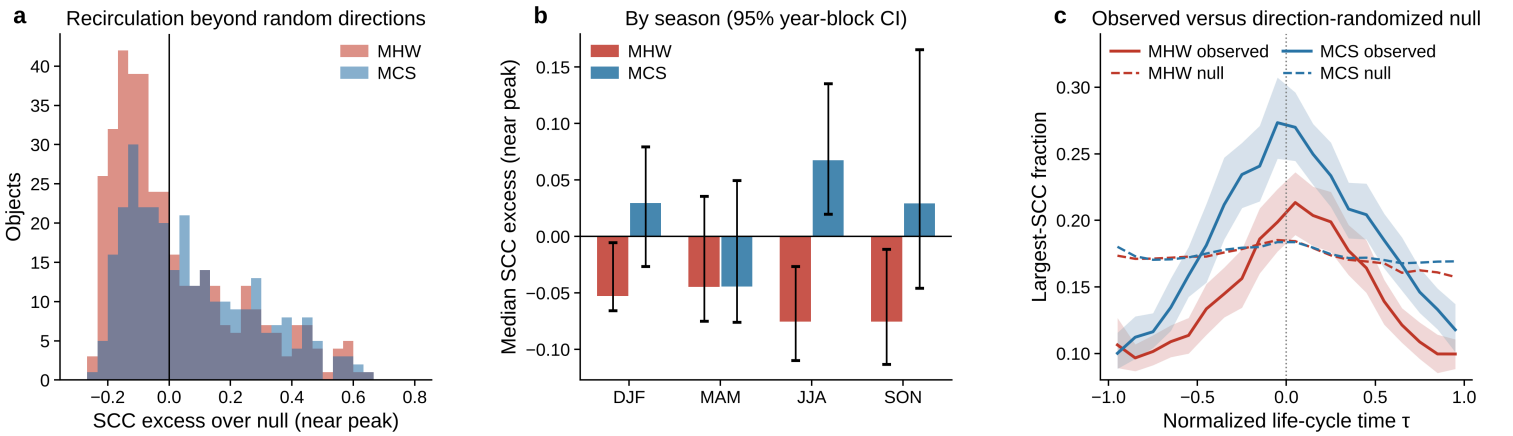


Figure 5

Recirculation against a direction-randomized null. **a**, Distribution of the near-peak SCC excess (observed minus null) over objects. **b**, Median excess by season with year-block 95% confidence intervals; intervals that include zero (all MCS seasons except summer, and MCSs overall) indicate that the excess is not distinguishable from zero at the population level, although the object-level Wilcoxon

test is significant. **c**, Composite observed (solid, with year-block 95% bands of the mean) and null (dashed) SCC fraction along τ .

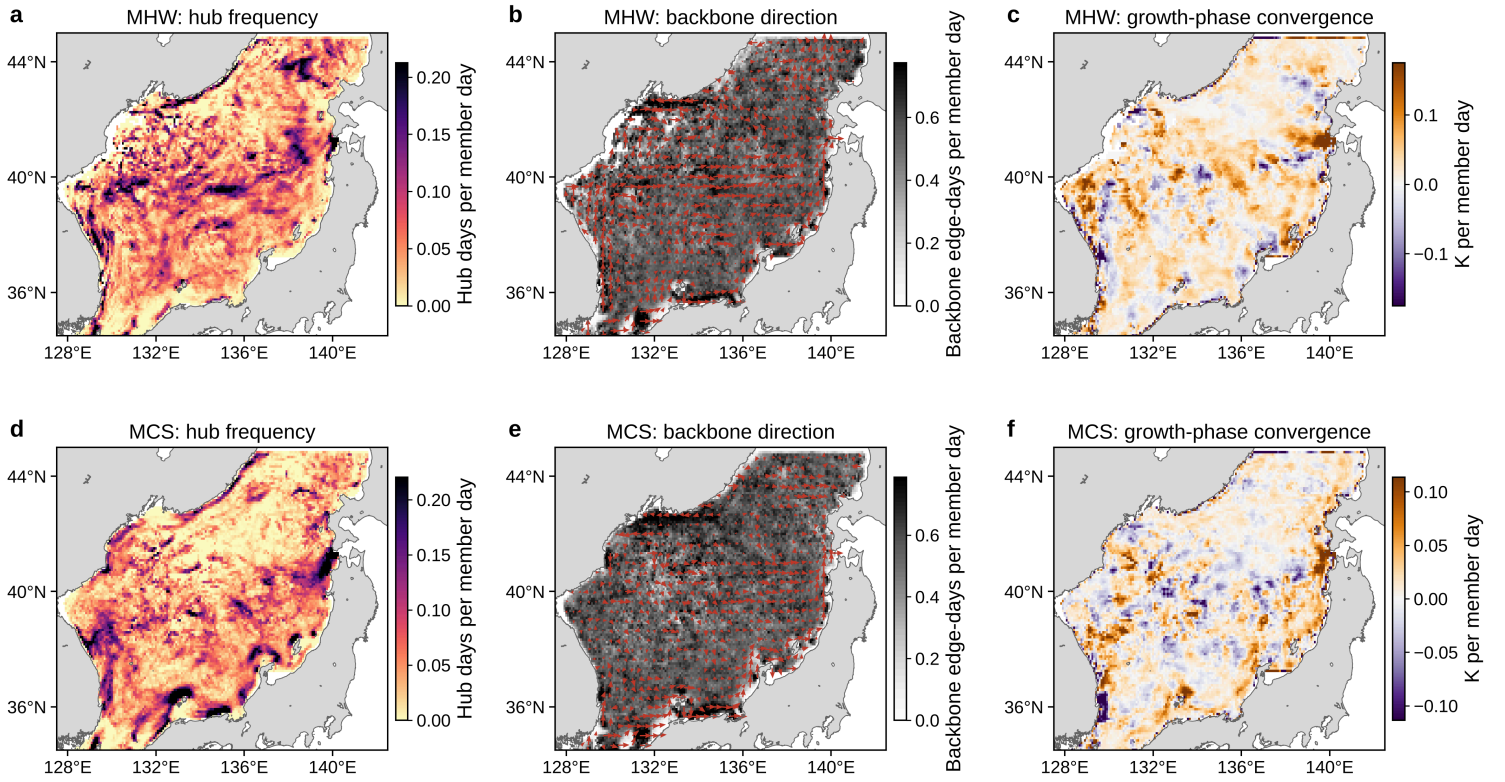


Figure 6

Spatial organization. Hub frequency (hub days per member day; **a, d**), dominant direction of persistent backbone edges (arrows; shading, backbone edge-days per member day, i.e. normalized by the exposure of each cell; **b, e**) and growth-phase net convergence per member day (**c, f**), accumulated over all main-set MHWs (**a–c**) and MCSs (**d–f**); cells with at least 20 member-days are shown. Overlapping objects contribute repeatedly to a cell; the maps describe where the population's hubs, backbones and convergence concentrate, not independent events.

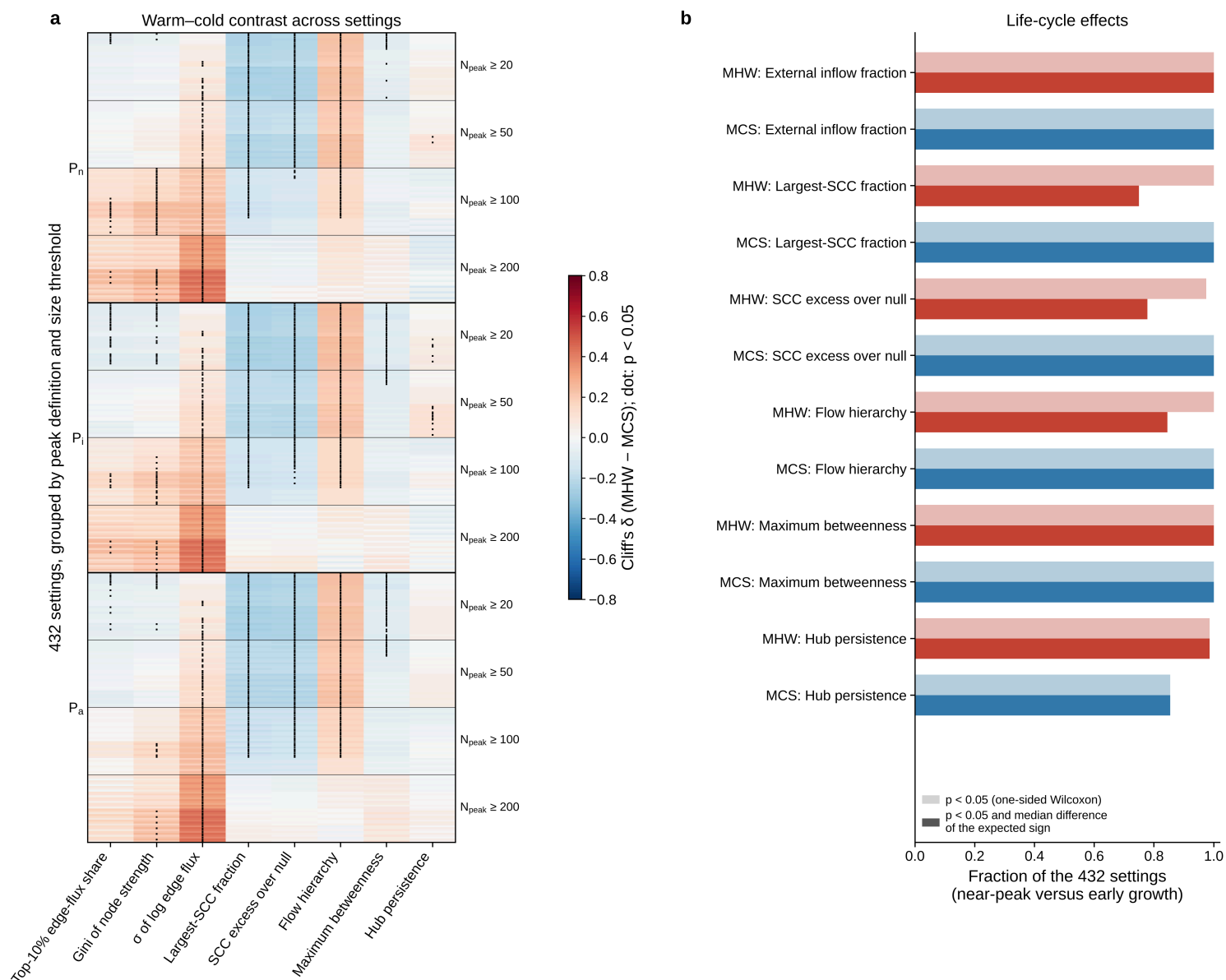


Figure 7

Sensitivity to the object definition. **a**, Cliff's δ of the warm-cold contrast for eight near-peak features across the 432 combinations of peak definition and filter thresholds (nested subsets of one catalogue, not independent replications), grouped by peak definition and size threshold (dots: $p < 0.05$). **b**, Fraction of settings in which each life-cycle effect (near-peak versus early growth) is significant (light bars, one-sided Wilcoxon $p < 0.05$) and significant with the expected sign of the median difference (dark bars).

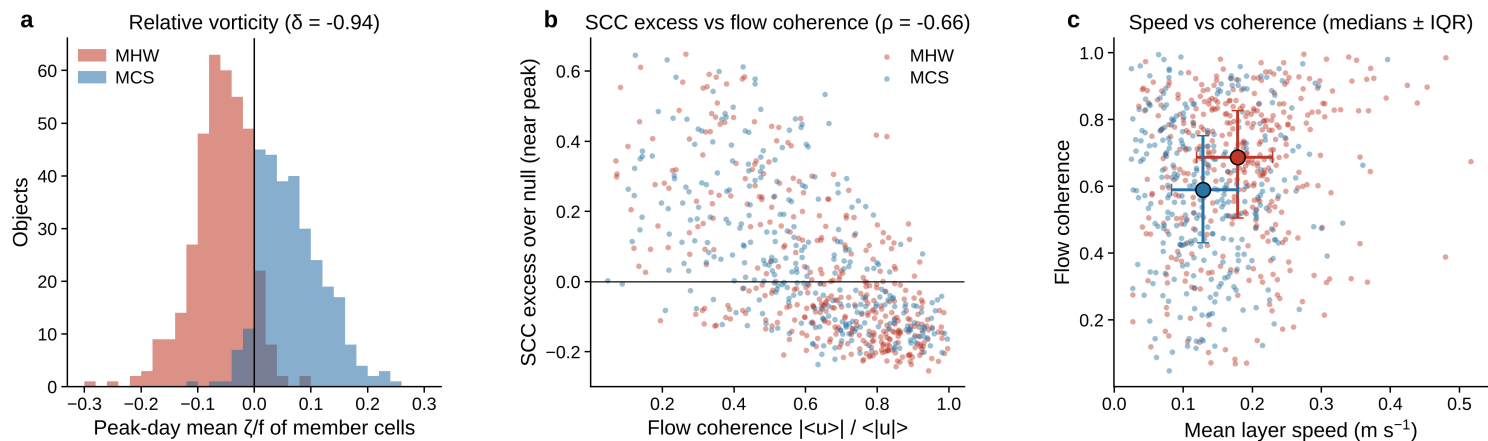


Figure 8

Kinematic associations. **a**, Peak-day mean relative vorticity ζ/f of member cells. **b**, Near-peak SCC excess versus flow coherence of the member cells on the peak day (Spearman ρ pooled over both phenomena). **c**, Mean layer speed versus flow coherence with medians $\pm$ interquartile ranges. The kinematic diagnostics and the network are computed from the same velocity field.

Supplementary Files

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