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Climate-Stress Classification of Supply Network Strategies under Evidence-Layer Transition

Clinton Tyler Purtell

Clinical Assistant Professor of Supply Chain Management; Associate Director, Jim McNatt Institute for Logistics Research, University of North Texas

* Correspondence: clinton.purtell@unt.edu

Abstract
Climate responsive supply network strategy planning involves more than a ranking of alternative options in general circumstances. The occurrence of extreme weather events, political pressure, weak infrastructures, and uncertain recovery processes creates a decision environment in which a climate-responsive supply network strategy has to be robust when the focus of attention is shifted from balance of performance to continuity security, compound disruption, and adaptation expenditure. This paper will investigate four different supply network strategies through a 27-criteria decision matrix for environmental sustainability, climate resilience, and socio-economic performance. Entropy Regularized Regret-Concordance Fusion (ERCF) technique is applied to measure linguistic suitability, weighted criteria dominance, methodological agreement, perturbation-state mean stability, worst-state endurance, and regret resistance. A Climate Stress Transition Audit (CSTA) is used to analyze regime transition, adaptive option reserve, stress gate passage, downside pressure, and stability effectiveness. The Climate Stress Transition Panel includes 27 weighted criteria, four strategic alternatives, six normalized evidence matrices, four stress regimes, and perturbation state utility statistics. Ranking by ERCF technique is consistent, where the first is hybrid global-local sourcing and flexible logistics (S_4), second regional sourcing and resilience investment (S_3), third multiple global sourcing and moderate safety stock (S_2), and last single global sourcing and lean inventory (S_1). According to CSTA results, ranking is insufficient in evaluating strategies. S_4 strategy is the only dominant primary strategy with compound stress score of 1.0000 and a viable gap of 0.3500. S_3 strategy is the only non-hybrid strategy that can pass the stress gate with a compound stress score of 0.8367 and a positive viable gap of 0.0728. S_2 and S_1 failed due to inadequate criteria dominance, worst-state endurance, and regret resistance through diversification and lean efficiency.

Keywords: climate stress transition; supply network resilience; viability gate; adaptive optionality; regret-concordance fusion; climate-responsive sourcing.

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1. Introduction

Climate-responsive supply network design has been influenced by the realization that disruption is no longer an infrequent deviation from efficient performance, but a constitutive feature against whose background sourcing, logistics, inventory management, infrastructural and policy choices must be analyzed. Climate pressures on supply networks come from several sources: heat stress on labor and transportation capacity, flood risk at supplier and port facilities, electricity system disruptions, water shortages, emission regulations, infrastructural damage, and volatile market or community attitudes. They do not impact supply networks via a single channel. The same pressures can reduce production, delay shipment, alter input cost, disrupt services, and expose firms to reputational or regulatory penalties. Climate-responsive strategy choice thus cannot depend solely on a traditional multi-criteria ranking where the alternative gets rated highly due to its overall adequacy. An alternative that ranks well on such a balanced score may yet prove weak when the decision challenge shifts to issues of endurance, time to recovery, resilience investment, and regret prevention.

The supply chain risk and resilience literature lays out the grounds for this concern. Disruption research has started with the emphasis on disruption mitigation and flexible response to supply uncertainty [1]. The importance of contingency planning and flexible sourcing for disruption recovery has been demonstrated next [2]. The impact of network structure, density, and node criticality on disruption severity has been found as well [3]. Later research extended the problem to incorporate the idea that resilience entails absorbing and sustaining shock flows [4]. Reviews of the supply-chain resilience literature have further highlighted reconfiguration and recovery under uncertainty [5]. More recently, resilience has been viewed as an adaptive capability combining preparation, response, and renewal [6]. Resilience in supply chains should also be assessed jointly with operational disruption [7]. Supplier concentration and transport dependency become other sources of systemic vulnerability [8]. Robust network design research has also indicated that hazards cannot be analyzed separately [9]. Climate change complicates the problem even further since the hazard distribution is evolving [10]. Resilience, adaptation, and continuity, along with cost and performance, must thus be evaluated in combination [11].

Later resilience research has moreover emphasized that supply networks should be viewed as adaptive systems [12]. The adaptive perspective stresses transformation and reconfiguration rather than mere restoration [13]. Systematic resilience reviews have similarly identified adaptiveness as a key factor in network continuity [14]. The perspective is particularly relevant for the present problem as climate exposure makes visible options that may not be revealed in average performance scores: fallback capacity, alternative logistics, information visibility, extra recovery capacity, and the possibility of flow reorganization if a certain network component gets constrained. The use of digital twins improves understanding of disruption propagation [15]. The industry 4.0 risk analytics also enhances information visibility and coordination of the response [16]. However, the physical network must have a potential for responses to make these tools effective. That is why the ERCF evidence model is interpreted as a systematic decision record rather than just a score. The important issue is whether each alternative is able to display dominance, endurance, and regret-resistance needed under climate stress.

Thus, in climate-responsive network design the crucial problem is not only the ranking of alternatives according to the aggregated score, but the ability to survive when the weighting scheme of the decision changes. Viability is a more strict notion than preference. While the preferred strategy wins in a rank order because it scores well on a large number of criteria, a viable strategy has to stay away from unacceptable weaknesses on the criteria that become important under climate stress. Research on viable supply chains highlights survivability and continuity under severe disruption [17]. Related research extends this perspective to the adaptation capability [18]. Sustainable and resilient design of supply chains involves both economic and environmental objectives [19]. Digital resilience and sustainability also interact in non-compensatory ways [20]. Reviews of sustainable and resilient network design emphasize social and technological considerations as well [21]. More recent studies support the joint consideration of sustainability, resilience, and digital capability [22]. Low exposure to extreme weather events, recovery time, monitoring system, and backup resources may not fully compensate for a moderate superiority in cost efficiency.

Multi-criteria decision-making techniques are helpful in the analysis of the problem because they allow integrating expert evaluations, criterion weights, linguistic assessments, and relative performance of alternative strategies into a decision model. Recent climate-responsive supply network models have used fuzzy decision methods to deal with uncertain judgments [23]. More sophisticated fuzzy sets techniques add to this the possibility of dealing with incomplete or ambiguous evaluations [24]. Hybrid techniques are available to combine sustainability and resilience criteria as well [25]. Other recent decision models rank competing strategies under conditions of uncertainty and disruption [26]. While they increase transparency, the scores provided by these methods can obscure an important management issue – whether the selected alternative can remain robust when the interpretation focus moves from balanced performance to stress-specific performance. It is natural that such a transition occurs in the practice of strategy selection. Under normal circumstances, managers are primarily concerned about environmental impact, cost, resource efficiency, and policy compatibility. Under preparation for a disruption, they are primarily concerned about extreme-weather exposure, recovery time, backup resources, digital monitoring, and regret resistance. When preparing adaptation plans, they are primarily concerned about infrastructural flexibility, regional capacity, renewable energy integration, and scaling investments over time. A decision model which assumes the same interpretive context for all of these criteria overestimates the robustness of the alternative that ranks well in the balanced score.

The paper provides a stress transition viability interpretation of climate-responsive supply network strategy selection. The calculation involves four strategies: single global sourcing with lean inventory, multiple global suppliers with moderate safety stock, regional sourcing with high resilience investment, and hybrid global–local sourcing with flexible logistics [23]. The analysis starts with the Entropy-Regularized Regret–Concordance Fusion (ERCF) evidence model that combines linguistic adequacy, criterion dominance, method concordance, perturbation state mean stability, worst-state endurance, and regret resistance into a normalized evidence structure. Next, the ERCF evidence layer is subject to a Climate Stress Transition Audit (CSTA) analysis. CSTA is designed to address a tougher problem: which strategy survives when a multi-criteria decision problem transitions from balanced evidence to continuity protection, compound disruption, and adaptation investment? Adaptive optionality reserve, viability gate margin, downside compression, and stability efficiency are reported to distinguish a primary viable strategy from a viable fallback, a conditional strategy, and a fragile strategy without changing the underlying decision method.

The research question is: *which climate-responsive supply network strategy remains viable when a multi-criteria decision problem transitions from balanced adequacy to compound climate-stress priorities?* The contribution of the paper is both methodological and interpretive. Methodologically, the paper interprets a traditional strategy ranking as a regime-sensitive viability classification without rejecting the multi-criteria decision information. Interpretively, it demonstrates that the same strategy ranking can have different managerial implications once stress gates are added. Climate adaptation decisions often require prior resilience investment [27]. Staged investment decisions under uncertainty are another important aspect of climate adaptation [28]. Additional challenges arise from implementation capacity and network redesign constraints [29]. Global reach and local responsiveness thus need explicit balancing [30]. The analysis provides a decision format suited to managers and policymakers interested not only in the best-ranked strategy but in the viable one.

2. Input data for the decision and analytical panel

2.1 Strategic options

The computation is based on a three-tier criterion hierarchy, Level-2 and Level-3 weightings at the end of these tiers, option assessment matrices, MCDM score comparisons, and expert-weight utility sensitivity for randomizing the climate-resilient supply chain strategy choice process [23]. The four evaluated strategies are denoted as

$$S_1 = \text{single global sourcing with lean inventory},$$

$$S_2 = \text{multiple global suppliers with moderate safety stock},$$

$$S_3 = \text{regional sourcing with high-resilience investment},$$

$$S_4 = \text{hybrid global–local sourcing with flexible logistics}.$$

There are 27 Level-3 criteria in the analytical data environment which are divided into environmental sustainability, climate resilience, and socioeconomic factors categories. Weights of the three Level-1 criteria are 0.362 for environmental sustainability, 0.342 for climate resilience, and 0.297 for socioeconomic factors. Such distribution suggests balanced but environmentally focused decision space where environmental and climate resilience issues combine to dominate the ordinary cost perception. The four alternatives have different operational logic. While S_1 is about focusing sourcing and tightening the slack, thus requiring continuity at great distances, S_2 diversifies supplier dependence but maintains global exposure. S_3 builds up the network towards greater regional capability and resilience investment, making less distance between disruption sensing, reaction, and recovery. Finally, S_4 combines global scope with regional backup and logistics flexibility. This differentiation is important since the results prove that diversification of suppliers does not equate to climate stress viability. The weight structure of criteria is visualized in Figure 1. The partitioned map includes three Level-1 dimensions and the most critical Level-2 and Level-3 criteria on a single plane where the weight structure is represented as a decision landscape rather than isolated rows of hierarchy.

The weight surface in Figure 1 proves that there is no domination of a single cost criterion in the decision panel. Environmental impact, resource efficiency, climate vulnerability, and climate adaptation investment comprise the biggest share of the hierarchy, and socioeconomic aspects retain their significance. This distribution explains why the classification at the end of the analysis cannot be interpreted as a mere sourcing cost criterion. The four alternatives are represented in Figure 2 in order to link mathematical notation with the operational forms of supply network. The panels divide lean global concentration, global supplier diversification, regional resilience investment, and global/local logistics hybrid into different network structures.

The operations comparison illustrated in Figure 2 sheds light on the following numerical findings. The least number of options is characteristic of the lean global sourcing, the multi-supplier global sourcing has larger supply reach and shared exposure, the regional sourcing has resilient investing concentrated near response points, and the hybrid global–local sourcing is characterized by the increased supply reach and backup capabilities.

2.2 Climate Stress Transition Panel

The Climate Stress Transition Panel includes the entire calculation structure applied for the stress transition test. It includes the complete information about the criterion weights, strategy scores, perturbation utilities and stress regime transformations used to identify alternatives. There are four interrelated blocks included in this panel.

The first one is criterion weight block including the 27 Level-3 weights along with their group membership at Level-2. The above-mentioned values determine the importance structure for both ERCF and CSTA procedure. The second one is the strategy performance block that includes weighted linguistic adequacy, weighted criterion dominance and evidence layer normalization for each strategy. The third one is the perturbation block, which includes mean state utility, standard deviation, worst-state utility, utility range, mean regret and maximum regret calculated in the current and randomized expert weight states. The last block is the stress regime block that translates six evidence layers of ERCF into four regime-specific scores (Table 1).

In the panel view, the ERCF layer vector is considered an intermediate variable, and the question asked is how each option transitions across different climate-stress regimes. The data set, in other words, is not only ranked but also configured in terms of a transition-sensitive decision panel where the weight of each evidence layer can be modified depending on the specific stress scenario being considered.

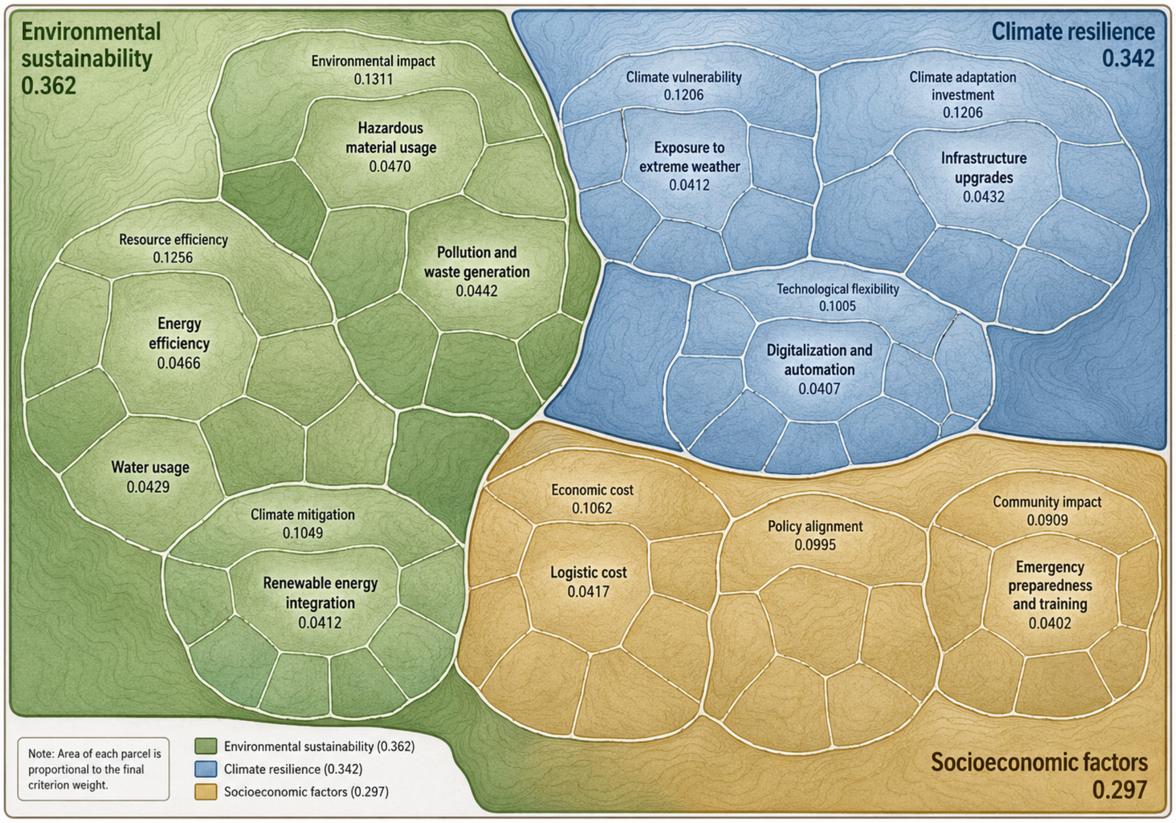


Figure 1. Criterion weight topography.

Table 1. Climate Stress Transition Panel used for the analysis

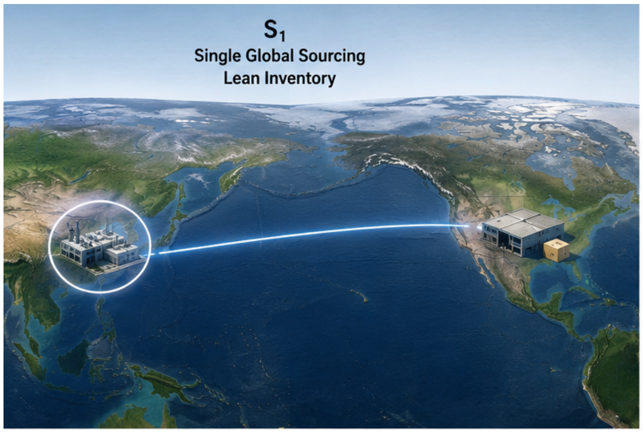
Panel block	Variables used or derived	Analytical use
Criterion-weight block	Final Level-3 weights, Level-2 grouping, criterion ranks, weight concentration.	Identifies which criteria govern adequacy and dominance.
Strategy-performance block	Weighted linguistic adequacy P_i, criterion dominance D_i, dominant-criterion count, normalized ERCF evidence layers.	Supplies the ERCF evidence matrix for CSTA.
Perturbation block	Mean utility, standard deviation, worst utility, range, mean regret, maximum regret across expert-weight states.	Measures downside endurance and expert-weight sensitivity.
Stress-regime block	Four stress-regime weight vectors applied to the six normalized ERCF layers.	Converts rank evidence into stress-transition viability scores.
Gate block	Adaptive optionality reserve, viability-gate margin, downside compression, stability efficiency.	Classifies alternatives as stress-viable, conditional, or fragile.

2.3 Criterion-weight profile

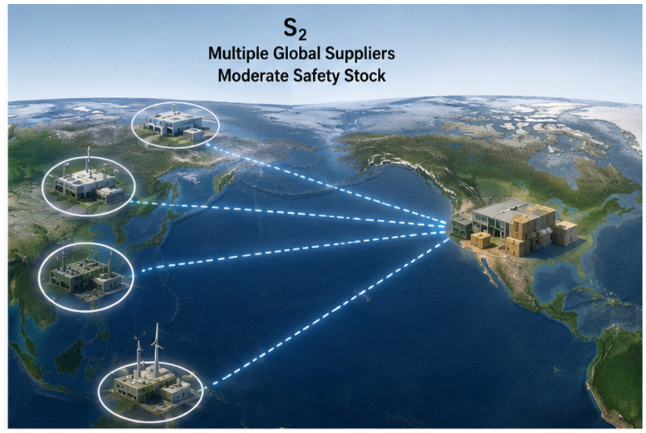
The Level-2 weights from Table 2 define the Level-2 hierarchy. Environmental impact is the most critical group, followed by resource efficiency, climate vulnerability, climate adaptation spending, economic cost, climate mitigation, technological flexibility, policy consistency, and community impact. The weights suggest that the decision task is not simply about minimizing costs. It is also about pressures for resources, climate exposure, adaptation, and environmental risks.

The combined weight of the first four Level-2 groups amounts to 0.4979 of the overall decision weight. Cost factors matter but are not dominant, with the hierarchy biased towards climate continuity, environmental impact, and adaptability.

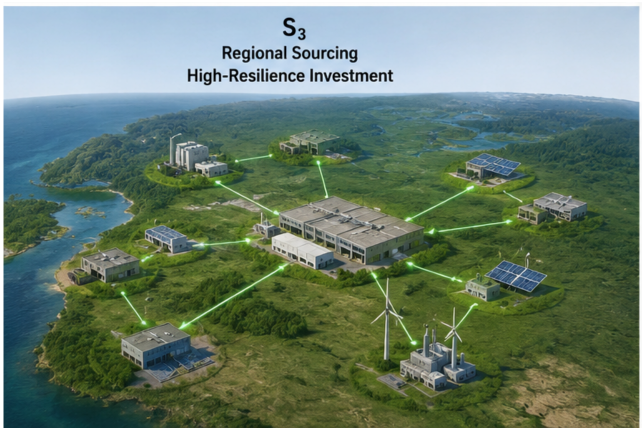
These weights of the Level-3 criteria are shown in Table 3. The concentration Herfindahl index for the set of 27 Level-3 weights amounts to 0.03796, which translates to roughly 26.35 criteria. The analysis is thus highly diversified across all criteria.



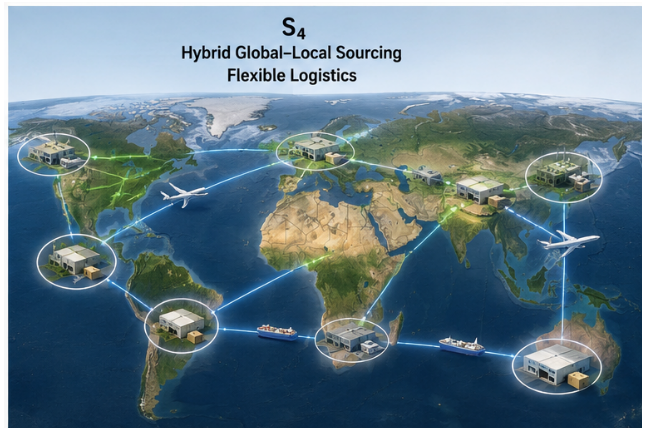
(a) S_1: single global sourcing



(b) S_2: multiple global suppliers



(c) S_3: regional resilience



(d) S_4: hybrid global–local logistics

Figure 2. Strategic network forms.

Table 2. Level-2 criterion weights used in the calculation

Level-2 criterion	Final weight	Rank
Environmental impact	0.1311	1
Resource efficiency	0.1256	2
Climate vulnerability	0.1206	3
Climate adaptation investment	0.1206	3
Economic cost	0.1062	5
Climate mitigation	0.1049	6
Technological flexibility	0.1005	7
Policy alignment	0.0995	8
Community impact	0.0909	9

On the other hand, the top 10 Level-3 criteria account for 42.89% of the total weight.

There are two major conclusions one can draw regarding the Level-3 profile. The 10 top-ranking criteria account for 42.89% of the total weight, meaning that the top criteria have quite a tangible impact. Simultaneously, the number of effective criteria is roughly 26.35, meaning that the ranking is not determined by just a single criterion.

Table 3. Level-3 criterion weights in the Climate Stress Transition Panel

Level-3 criterion	Final weight	Rank
Hazardous material usage	0.0470	1

Level-3 criterion	Final weight	Rank
Energy efficiency	0.0466	2
Pollution and waste generation	0.0442	3
Infrastructure upgrades	0.0432	4
Water usage	0.0429	5
Logistic cost	0.0417	6
Exposure to extreme weather	0.0412	7
Renewable energy integration	0.0412	8
Digitalization and automation	0.0407	9
Emergency preparedness and training	0.0402	10
Time to recover from disruptions	0.0400	11
Biodiversity and habitat preservation	0.0399	12
Backup resources	0.0393	13
Technology and monitoring systems	0.0372	14
Low-emission logistics	0.0369	15
Carbon policy compliance	0.0369	16
Material conservation	0.0361	17
Investment cost	0.0346	18
Local community welfare	0.0344	19
Job creation and fair labor practices	0.0318	20
Reporting and transparency	0.0314	21
Environmental standards and certifications	0.0313	22
Innovation capability	0.0299	23
Operational cost	0.0299	24
Flexibility of infrastructure	0.0299	25
Waste-to-energy practices	0.0268	26
Stakeholder engagement and acceptance	0.0246	27

3. Entropy-Regularized Regret–Concordance Fusion evidence model

The ERCF evidence framework is illustrated in Figure 3. As the figure demonstrates, the multi-layered structure of this profile makes it possible to visualize the logic of fusion before the components are evaluated.

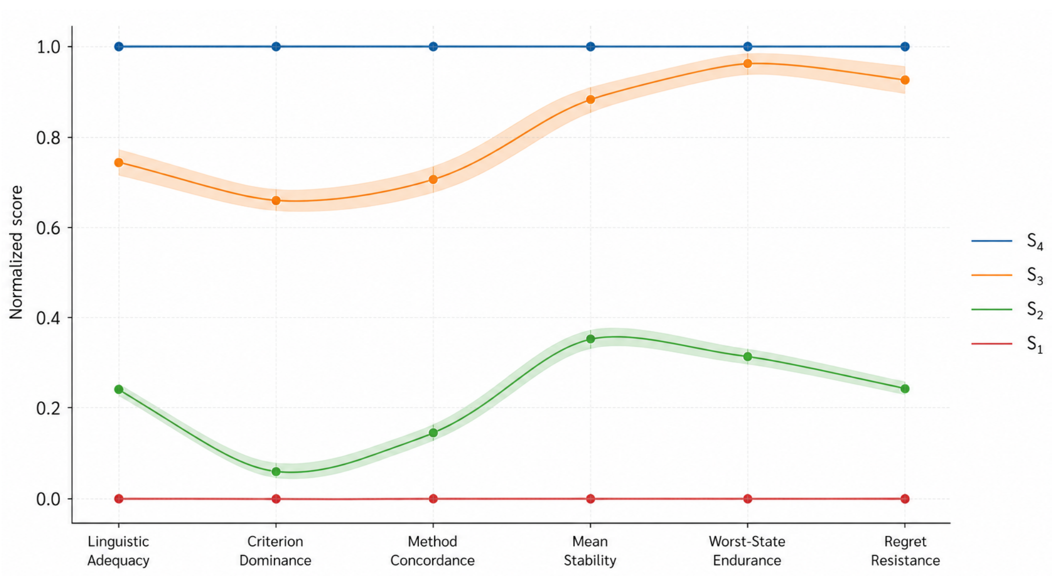


Figure 3. ERCF evidence weave.

As can be seen from Figure 3, the difference between the strength of a global rank and its strength in particular stress scenarios is clearly demonstrated through the evidence weave. The hybrid local–global approach occupies the top place in each evidence layer, whereas regional high resilience sourcing has higher ranks in stability, endurance and regret resistance, but much lower ones in criterion dominance.

3.1 Linguistic adequacy and weighted dominance

The ERCF method acts as the first analysis level. Linguistic expert ratings are transformed into numerical adequacy scores. Given a linguistic rating ℓ that is expressed in terms of the Fermatean fuzzy pair (μ_ℓ, ν_ℓ), the adequacy is

$$g(\ell) = \frac{1+\mu_\ell^3 - \nu_\ell^3}{2}. \tag{1}$$

The transformation in Eq. (1) converts each linguistic assessment into a scalar adequacy value while retaining the distinction between membership and non-membership information. Higher values indicate stronger criterion-level support. Let x_{ije} denote the linguistic rating of strategy i, criterion j, and expert e. The expert-averaged criterion performance is

$$p_{ij} = \frac{1}{E}\sum_{e=1}^{E} g(x_{ije}), \tag{2}$$

where $E = 10$. Weighted linguistic adequacy is then

$$P_i = \sum_{j=1}^{27} w_j p_{ij}. \tag{3}$$

Eq. (3) is compensatory because strong performance on one criterion can offset weakness on another. This makes the later dominance and gate calculations necessary for a stricter stress-viability reading. Weighted criterion dominance is defined as

$$D_i = \sum_{j=1}^{27} w_j I\left(p_{ij} = \max_r p_{rj}\right), \tag{4}$$

where $I(\cdot)$ equals one if the condition is true and zero otherwise. Dominance is less forgiving than adequacy because it records where a strategy is actually the best performer after weighting. Table 4 reports the adequacy and dominance results.

Table 4. ERCF adequacy and criterion dominance

Strategy	P_i	Normalized P_i	Dominant criteria	D_i
S_1	0.4656	0.0000	1	0.0346
S_2	0.5922	0.4607	2	0.0706
S_3	0.6938	0.8303	6	0.2360
S_4	0.7405	1.0000	18	0.6587

The dominance and adequacy indices demonstrate not only that S_4 is the most powerful in terms of overall adequacy, but also the most general criterion leader. It dominates 18 out of 27 criteria and possesses 65.87% of weighted dominance. Strategy S_3 can be considered as a powerful alternative with 23.60% of weighted dominance, while S_2 and S_1 have narrow domination bases.

The dominance mass in Figure 4 makes even stronger distinction between the four strategies due to conversion of the number of dominating criteria and weighted dominance into a compact visual scale. As one can see, superiority of S_4 is based on more general dominance, rather than one specific group of criteria.

It can be understood from the domination graph (Figure 4) that the first strategy is also the most important strategy. The reason for this is that the strategy S_4 is leading in 18 criteria and dominates with the 65.87% of weighted domination whereas S_3 is leading in six criteria and dominates with 23.60%. The distinction is not one of mere ranking; rather, it represents a quantifiable distinction in the scope of criterion leadership. The distinction is not one of mere ranking; rather, it represents a quantifiable distinction in the scope of criterion leadership.

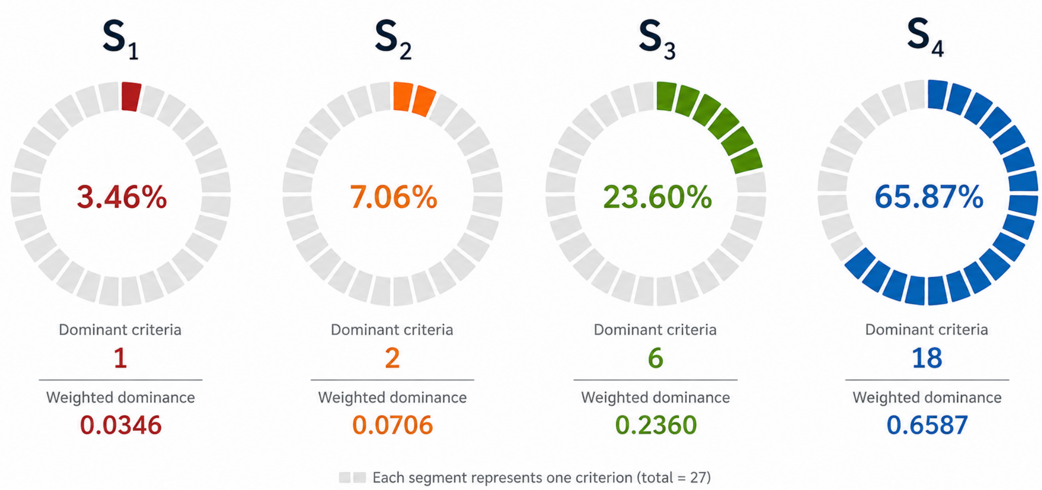


Figure 4. Weighted dominance mass.

3.2 Perturbation-state stability and regret

The stability layer uses expert-weight perturbation utilities. Let u_{ik} be the utility of strategy i under expert-weight state k. The mean utility, worst utility, and mean regret are

$$\bar{u}_i = \frac{1}{K}\sum_{k=1}^{K} u_{ik}, \tag{5}$$

$$\underline{u}_i = \min_k u_{ik}, \tag{6}$$

$$\rho_i = \frac{1}{K}\sum_{k=1}^{K}\left(\max_r u_{rk} - u_{ik}\right). \tag{7}$$

These expressions separate average support, downside support, and opportunity loss. A strategy with high mean utility may still be unattractive if its worst utility is low or its regret is large. The stability values are shown in Table 5.

Table 5. Perturbation-state stability and regret values

Strategy	$\bar{u}_i$	SD	$\underline{u}_i$	Range	ρ_i	Max regret
S_1	0.9246	0.0208	0.8970	0.0640	0.0754	0.1030
S_2	0.9435	0.0120	0.9270	0.0440	0.0565	0.0730
S_3	0.9946	0.0036	0.9880	0.0120	0.0054	0.0120
S_4	0.9987	0.0031	0.9900	0.0100	0.0013	0.0100

The stability layer shows the gap between the two adaptive strategies and the two globally concentrated strategies. The difference with S_1 and S_2 demonstrates that the gate result is indeed in line with the perturbation behavior. S_4 enjoys the largest mean utility and the smallest regret. S_3 is comparable with S_4 in terms of perturbation stability, even though its dominance breadth is smaller. S_1 and S_2 seem to be highly dependent on the expert weight change; the similar trend can be seen in the figures in Figure 5.

3.3 ERCF score

The calculation of ERCF includes six normalized layers of evidence, which are linguistic adequacy (LA), criterion dominance (CD), method concordance (MC), perturbation-state mean stability (SM), worst-state endurance (WS), and regret resistance (RR). The layer weights are

$$\omega = (0.1257, 0.2559, 0.1612, 0.1561, 0.1449, 0.1561).$$

The ERCF score is

$$\mathrm{ERCF}_i = \sum_{h=1}^{6} \omega_h y_{ih}, \tag{8}$$

where y_{ih} refers to the normalized value of strategy i in evidence layer h. The weights in the fusion process attach the highest weight to criterion dominance because the classification of climate-stress is based on both adequacy and breadth. Table 6 presents the ERCF evidence matrix and ranking.

The ERCF ranking is

$$S_4 \succ S_3 \succ S_2 \succ S_1.$$

This ranking is informative, but the final interpretation requires a stress-oriented reading. The CSTA procedure tests whether the ranked alternatives also satisfy climate-stress viability requirements.

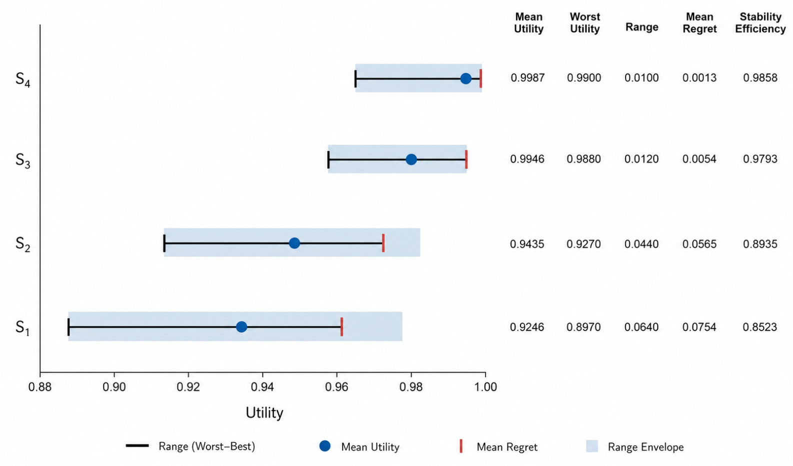


Figure 5. Perturbation stability fingerprints.

Table 6. ERCF evidence matrix and ranking

Strategy	LA	CD	MC	SM	WS	RR	ERCF
S_1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
S_2	0.4607	0.0577	0.2218	0.2552	0.3226	0.2552	0.2349
S_3	0.8303	0.3228	0.7676	0.9448	0.9785	0.9448	0.7475
S_4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

4. Climate Stress Transition Audit

4.1 Stress-regime scoring

The Climate Stress Transition Audit begins from the six normalized ERCF evidence layers. Let

$$\mathbf{y}_i = (LA_i, CD_i, MC_i, SM_i, WS_i, RR_i),$$

be the ERCF evidence vector for strategy i. Each stress regime r is represented by a non-negative layer-weight vector

$$\gamma_r = (\gamma_{r,LA}, \gamma_{r,CD}, \gamma_{r,MC}, \gamma_{r,SM}, \gamma_{r,WS}, \gamma_{r,RR}),$$

where $\sum_h \gamma_{rh} = 1$. The CSTA score is

$$T_{ir} = \sum_{h=1}^{6} \gamma_{rh} y_{ih}. \tag{9}$$

Application of the six layers of ERCF evidence under stresses is done through Eq. (9) such that balanced preference can be distinguished from viability under climate stress conditions. There are four regimes considered. Balanced regime is equal to ERCF entropy weighted regime. Continuity protection regime makes perturbation-state mean stability, worst-state endurance, and regret resistance more dominant. Compound disruption regime puts highest emphasis on worst-state endurance and regret resistance. Adaptation investment regime gives higher importance to criterion dominance due to credibility of implementation depending on cross-criteria support.

The regimes are not meant to predict an actual occurrence. Rather, they are decision-stress regimes that seek to ascertain whether the alternative is still a viable decision when the focus shifts from adequacy to climate-continuity protection.

Table 7. Stress-regime layer weights used in CSTA

Regime	LA	CD	MC	SM	WS	RR
Balanced evidence	0.1257	0.2559	0.1612	0.1561	0.1449	0.1561
Continuity protection	0.0800	0.1400	0.0800	0.2400	0.2200	0.2400
Compound disruption	0.0500	0.1700	0.0400	0.1600	0.3100	0.2700
Adaptation investment	0.1500	0.2800	0.0500	0.1300	0.1600	0.2300

4.2 Adaptive optionality reserve

Ranking may obscure how a strategy incorporates scope, durability, and minimal regret. Thus, CSTA offers adaptive optionality reserve:

$$AOR_i = \frac{CD_i + WS_i + RR_i}{3}. \tag{10}$$

This value is computed using the normalized scale of the ERCF evidence measure. It determines whether a particular strategy displays a combination of three kinds of strength related to the climate: criterion dominance, worst state performance, and regret minimization. Its scope is deliberately more limited than that of the ERCF evidence measure because linguistic adequacy, method agreement, and mean stability are excluded.

4.3 Viability-gate margin

The CSTA method also entails a non-compensatory gate. A strategy qualifies as being stress viable if it meets minimum criteria in terms of criterion dominance, worst state endurance, and regret avoidance:

$$CD_i \geq \theta_{CD}, \qquad WS_i \geq \theta_{WS}, \qquad RR_i \geq \theta_{RR}.$$

The thresholds used here are

$$\theta_{CD} = 0.25, \qquad \theta_{WS} = 0.65, \qquad \theta_{RR} = 0.65.$$

The gate margin is

$$VG_i = \min\left(CD_i - \theta_{CD}, WS_i - \theta_{WS}, RR_i - \theta_{RR}\right). \tag{11}$$

Positive values indicate that the strategy meets all three conditions. Negative values reveal the weakest non-meet condition. This gate serves to ensure that the strategy cannot be considered a viable one just because of outstanding performance on one side and poor performance on another.

4.4 Downside compression and stability efficiency

The last two CSTA tests employ the original values of the perturbations. Downside compression is

$$K_i = \frac{u_i}{\bar{u}_i}. \tag{12}$$

A value closer to one means that the worst observed utility is close to the average utility. Stability efficiency is

$$E_i = \frac{\bar{u}_i}{1 + \sigma_i + R_i}, \tag{13}$$

where σ_i is the standard deviation of perturbation states and R_i is the range of utility values. This measure punishes strategies in which large deviation accompanies their mean utility values.

5. Results

5.1 Stress-regime scores

Table 8 contains CSTA regime scores, which reflect the regime-level analysis. First of all, one must note that the ranking of regimes is consistent in all four stress types: S_4 retains its position at the top, S_3 maintains its second place, S_2 holds third place and S_1 keeps fourth place. This fact cannot be seen as evidence of the equal managerial meaning of all four strategies under climate stress conditions. Regime scores help us see the differences in distances between the alternatives when we move from balanced evidence to continuity protection, compound disruption and adaptation investments. The rise of S_3 in continuity and compound-stress regimes is very important since it explains why the second ranked strategy can serve as an alternative. The normalized leader in all six ERCF evidence layers has a score of 1.0000 in all regimes, making it the benchmark for the other three.

However, the greatest movement happens for S_3. The regional sourcing with high-resilience investment receives a balanced-evidence score of 0.7475, but its score grows to 0.8418 in continuity protection and 0.8367 in compound disruption. This is no minor detail. It demonstrates the increased performance of S_3 due to the higher weighting of perturbation-state mean stability, worst-state endurance and regret resistance in the decision model. Hence, S_3 is no ordinary second-ranking option. It is not just inferior to S_4 in aggregated orderings. It is the only option that approaches the hybrid strategy as the decision context gets more challenging.

Table 8. CSTA regime scores for four supply network strategies

Strategy	Balanced	Continuity	Compound	Adaptation
S_1	0.0000	0.0000	0.0000	0.0000
S_2	0.2349	0.2561	0.2515	0.2398
S_3	0.7475	0.8418	0.8367	0.7500
S_4	1.0000	1.0000	1.0000	1.0000

The movement of S_2 is significantly less noticeable. Multiple global suppliers with moderate safety stocks grow from 0.2349 in balanced evidence to 0.2561 in continuity protection and 0.2515 in compound disruption. These scores indicate some value added by diversification, but it is insufficient to provide stress viability. This alternative still lags behind both the regional and hybrid strategies because of low normalized criterion dominance, worst-state endurance and regret resistance. S_1 retains 0.0000 in all regimes since it is the least viable option among the normalized ERCF layers. Consequently, the lean global sourcing fails to produce any stress transition reserve in case of climate continuity being decisive in the decision. As disruption studies demonstrate, normal efficiency cannot be substituted with recovery capacity in presence of structural risks [31]. In addition, risk management research reveals the inefficiency of efficiency-based reactions to severe disruptions [7]. Finally, resilience modeling demonstrates that redundancy and recovery capability become key when the disruption travels throughout the network [32].

Thus, the stress-regime movement is presented in Figure 6. The graph presents that the ordinal ranking does not change, but the difference between strategies becomes different as the decision emphasis shifts towards continuity protection and compound disruption.

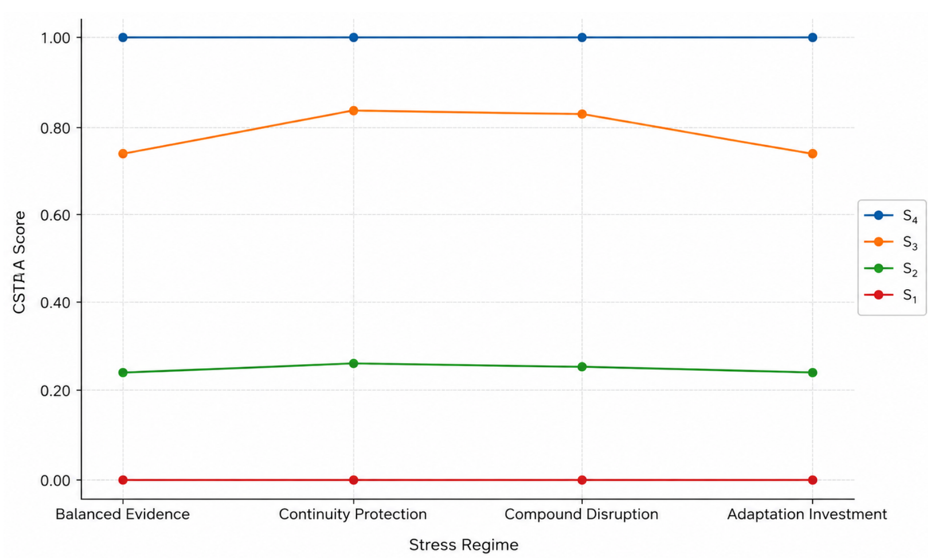


Figure 6. CSTA stress-regime drift.

5.2 Optionality adaptation and viability gate margin

Secondly, there is the non-compensatory viability gate. In Table 9, you can find the adaptive optionality buffer and the margin of the viability gate. This gate is more stringent than the regime score, as it is concerned about whether the alternative meets the minimum conditions for dominance on criteria, worst state robustness, and regret immunity. Those thresholds are $\theta_{CD} = 0.25$,

$\theta_{WS} = 0.65$, and $\theta_{RR} = 0.65$. This way, a strategy will not pass the viability test simply by showing good results in criteria that are easy to compensate. In a climate-stress scenario, the strategy could be considered non-defensible because of lack of dominance in critical criteria, low robustness in worst state, and too much regret regardless of the regime score. In line with the risk analysis framework, the downside risk cannot overshadow the average score [33]. Similarly, robust network design literature argues for consideration of the worst state [34].

Table 9. Adaptive optionality reserve and stress-viability gate

Strategy	AOR	VG	Status	Limiting condition
S_1	0.0000	-0.6500	Fails	Worst-state and regret resistance
S_2	0.2118	-0.3948	Fails	Regret resistance and dominance
S_3	0.7487	0.0728	Passes	Criterion dominance is the narrowest margin
S_4	1.0000	0.3500	Passes	No binding gate condition

The four strategies are divided into two viable and two unviable through the gate criteria. Strategy S_4 passes through the gate with an adaptive optionality reserve of 1.0000 and gate margin of 0.3500. It has no gate condition, thus the least of the three gate components satisfies the required threshold by a margin. Strategy S_3 passes with an adaptive optionality reserve of 0.7487 and viability margin of 0.0728. The critical gate is criterion dominance and not worst-state endurance or regret resistance. This is relevant practically since it will enable us identify what can improve the strategy in order for it to be converted from a fall-back to a primary strategy. Further investments in supplier capability, monitoring mechanism, or adaptation will increase the dominance reserve.

Strategy S_2 and strategy S_1 fail the gate test. Strategy S_2 has an adaptive optionality reserve of 0.2118 which is inadequate to pass the gate. Its viability margin is -0.3948 and the limiting condition is regret resistance and dominance. This implies that diversified sourcing from various global suppliers enhances normal risk spreading but does not provide adequate stress-specific information to meet the climate disruption requirements. Strategy S_1 has an adaptive optionality reserve of 0.0000 and viability margin of -0.6500. The limiting conditions are worst-state and regret resistance, implying that lean global sourcing strategy is structurally inappropriate when designing the strategy for climate disruption.

In Figure 7, the gate cross-section puts the three requirement thresholds on the same scale. Such an interpretation of the figure shows why S_3 succeeds by a small positive amount and why S_2 falls short of the viability requirement, despite being superior to S_1.

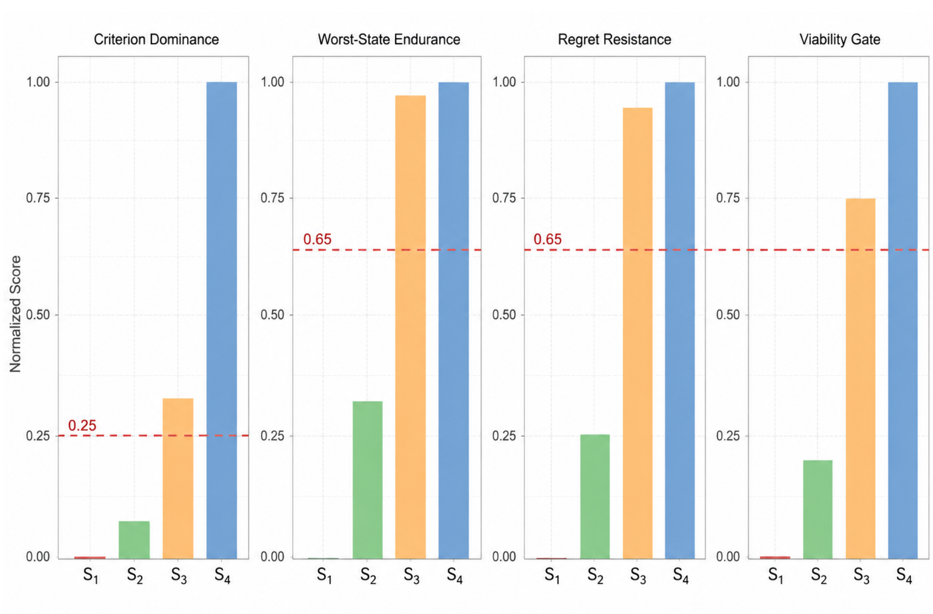


Figure 7. Viability cross-section.

5.3 Compression of downside and stability efficiency

The downside compression and stability efficiency metrics presented in Table 10 measure stability based on perturbation analysis. These measures leverage the perturbation-utility information to highlight how well the strategies are able to control their downside variability. K_i measures the extent to which the downside is compressed compared to the upper limit of performance, whereas E_i punishes for mean regret and range. The values show that all strategies have relatively high compression scores, but the differences in stability efficiency are more revealing.

The highest stability efficiency is achieved for S_4, where $\bar{R}_{S_4} = 0.0013$ and $R_{S_4} = 0.0100$. Therefore, the highest evidence of robustness in both layers is achieved for the hybrid strategy, and the highest stability efficiency is 0.9858. The next alternative, S_3 achieves stability efficiency of 0.9793 with mean regret 0.0054 and $R_{S_3} = 0.0120$. So, despite the superiority of the hybrid strategy in both layers, the differences between stability efficiencies of S_3 and S_4 in the perturbation-stability layer are minimal. Less efficient alternatives are S_2 and S_1; the stability efficiencies for them equal 0.8935 and 0.8523 respectively. Also, their mean regrets are an order of magnitude larger than that of S_3 and S_4. Therefore, this example confirms that stress gate is not controlled by arbitrary threshold. It is also seen that the alternatives that failed the gate are characterized by poor regret control and perturbation response.

Table 10. Downside compression and stability efficiency from perturbation utilities

Strategy	K_i	E_i	Mean regret	Utility range
S_1	0.9701	0.8523	0.0754	0.0640
S_2	0.9825	0.8935	0.0565	0.0440
S_3	0.9934	0.9793	0.0054	0.0120
S_4	0.9913	0.9858	0.0013	0.0100

The perturbation fingerprint of each alternative in Figure 5 represents the stability profile based on utility, regret and range values. The narrow utility envelopes of S_3 and S_4 indicate that good performance of these alternatives is combined with the high stability.

From the stability fingerprints presented in Figure 5, one can deduce that the gate result is congruent with the perturbation result. S_3 and S_4 have thin utility regions and low regret values, whereas S_1 and S_2 have lower stability efficiencies and bigger downside moves.

5.4 Stress-transition classification

Table 11 summarizes the decision classification based on the quantified findings. S_4 is the main viable strategy as it satisfies full dominance by the ERCF, top-performing compound-stress strategies, full adaptive optionality reserve, and the biggest gate margin. S_3 is a viable fallback strategy. This is no trivial conclusion. What it means is that regional sourcing along with highly resilient investments is resilient enough to be employed in scenarios where hybrid global–regional sourcing cannot be applied due to restrictions related to suppliers, finance, logistics, or regulations. S_2 is a conditional strategy since it has some level of diversification but does not pass the viability gate. S_1 is a fragile strategy due to lack of stress evidence in the layers.

Table 11. Stress-transition classification of the four strategies

Strategy	Compound	Gate	Class	Interpretation
S_1	0.0000	Fail	Fragile	Low normalized support in all ERCF layers; unsuitable where climate disturbance is central.
S_2	0.2515	Fail	Conditional	Provides diversification, but not enough dominance or regret resistance for stress viability.
S_3	0.8367	Pass	Viable fallback	Strong endurance and regret control; useful where regional capacity is feasible.
S_4	1.0000	Pass	Primary viable	Broadest dominance, best stress-regime support, and no binding gate weakness.

Classification provides a more accurate answer to the research question than the traditional ranking. In case of balanced preference, S_4 wins hands down and S_3 takes the second place. In case of climate-stress viability as a decision objective, S_4 still wins, but S_3 gets strategically important as the only backup option. S_2 cannot be considered climate-viable without supplementary local responses, recovery investments or climate stress monitoring. And S_1 should not be selected if climate disruptions are assumed at the core of the planning process. The real-world takeaway from these results is that climate-responsible supply chain planning requires ranking as a preliminary stage and viability as the decision criterion.

The stress-viability spectrum in Figure 8 collapses the classification into a single axis: horizontal placement shows the gate margin and marker size shows compound stress viability; zero shows the borderline between viable and conditional / fragile strategies.

The stress-viability spectrum in Figure 8 gives the last visual answer to the research question. S_4 is distinguished from the gate by the largest positive margin, S_3 stays above the gate as the only viable fallback, and S_2 and S_1 stay below zero despite the difference in the logic of operation.

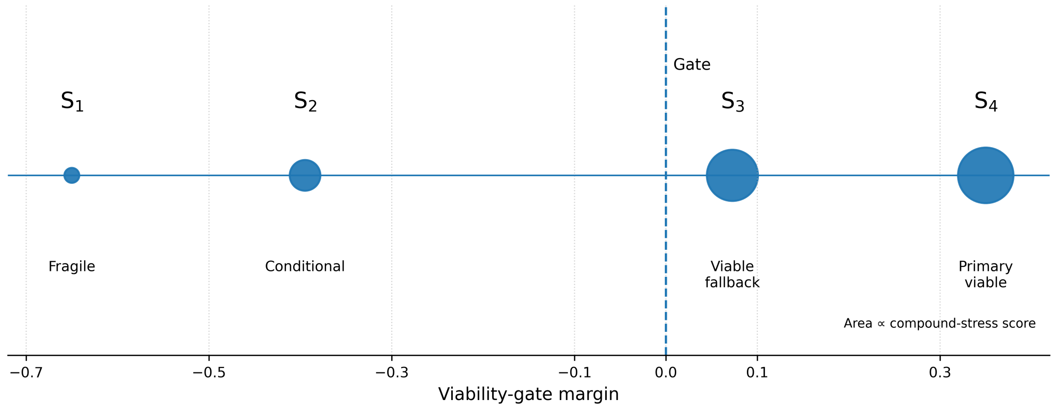


Figure 8. Stress-viability spectrum.

6. Discussion

The findings illustrate why climate-aware supply network strategy selection should not stop at a single aggregate ranking. The ranking by ERCF suggests a clear preference order, but the CSTA interpretation points out where this order includes a strategy's strategic relevance in the climate regime. First and foremost, S_4 emerges as a rank leader and a viable supply chain strategy for climate disruption. It leads all six ERCF evidence layers, obtains a compound stress score of 1.0000, passes the gate with a margin of 0.3500, and shows the highest stability efficiency. This is crucial because climate disruption usually works through interacting failures, and the hybrid network can sustain global sourcing while retaining regional response capacity, routing flexibility, and optionality for adaptation investments. Viability supply chains research stresses flexibility and the ability to survive catastrophic disruption [17]. Studies related to the subject emphasize network reconfiguration and continuity [18]. Digital and organizational flexibility can improve resilience in a dynamic environment [30]. More recent studies highlight the importance of response capacity and not only of inventory buffers [35].

Second, S_3 demonstrates a notable feature. High resilience investment in regional network sourcing does not beat S_4 in the ranking but becomes more effective as the regime gets more stressful. Its continuity protection score of 0.8418 and compound disruption score of 0.8367 prove that the strategy fits the dimensions that matter most for climate survival. Positive viability margin of 0.0728 proves that the result is not a compensatory one. This is important for implementation because the leading strategy in the ranking is not always the implementable one. Companies may not have access to proper regional suppliers, get locked into contract relationships, or lack the necessary capital to build hybrid network sourcing. In such cases, the regional high-resilience strategy will serve as a well-defended alternative, especially in case when the goal is reduction of vulnerability to global transport disruption, shortened recovery routes, and focused adaptation investments in fewer but strong nodes. The research on network design proves that resilience investments must be measured against disruption severity [27]. Sustainable resilient network designs emphasize the importance of recovery speed [36]. Critical flows preservation is another key condition for disruption preparedness [37].

The conditional classification of S_2 strategy is equally important. Multiple global suppliers with moderate safety stock is often considered a good risk spreading strategy, and results indicate that it outperforms lean sourcing. Nevertheless, CSTA shows that diversification is not sufficient for climate viability. S_2 cannot pass the gate since its domination and regret resistance measures are still too low. Practically speaking, increasing the number of global suppliers will decrease dependence on a single source but also will preserve the same vulnerability to common transport corridors, synchronization of climate risks, energy system disruption, port congestion, and geopolitical and regulatory restrictions. Moderate safety stock will provide buffer for short disruptions but will not increase recovery capability, monitoring quality, emergency preparedness, and infrastructure flexibility. This means that the strategy should be regarded as conditional one that might be strengthened by regional response capacity, digital monitoring, supplier development program, and climate contingency contracts. Without such improvements, it should be seen as a risk-spreading strategy rather than a viable one.

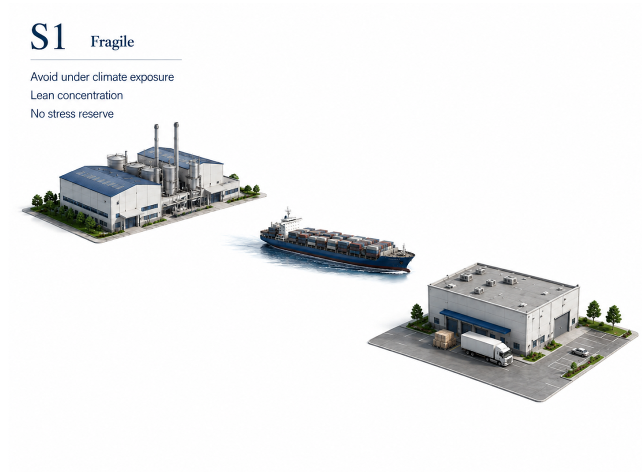
Finally, weak performance of S_1 illustrates the limits of lean global sourcing in climate disruptive regime. The lean inventory and single global sourcing may produce cost and coordination advantages in stable environment, but CSTA results prove that they do not guarantee stress viability. Strategy S_1 gets a score of 0.0000 in all regimes and fails the gate by the biggest margin. This is not to say that there are no benefits of the lean approach, but lean global concentration is not sufficient when the problem statement explicitly takes climate disruption into account. Convergent network structure can amplify disruption severity [3]. Limited contingency flexibility can lengthen recovery [2]. Low slack can reduce responsiveness to structural risks [1]. Climate aspect makes the problem even more difficult since hazards can be synchronized across infrastructure systems and adaptation might require proactive investment before disruption occurs.

The management translation presented in Figure 9 summarizes the quantitative classification in the form of implementation guidance. The visual panel keeps the four classes separate to distinguish adoption, fallback, conditional strengthening, and avoidance of a strategy under climate exposure.

(a) Primary viable: S_4

(b) Viable fallback: S_3

(c) Conditional: S_2



(d) Fragile: S_1

Figure 9. Managerial translation.

The managerial translation of Figure 9 connects the numerical classifications with implementation choices. The practical recommendation is not just to increase the number of suppliers; it is to maintain global reach while developing local responsiveness, monitoring, resilience, and logistics.

Methodologically, the paper demonstrates the transformation of a multi-criteria evidence model into a decision-making format of stress transition. ERCF delivers an interpretable combination of adequacy, dominance, concordance, stability, endurance, and regret. CSTA provides a second interpretation, inquiring about the behavior of the evidence under change of the managerial regime. The adaptive optionality reserve considers the minimum of dominance, worst-state endurance, and regret resistance. The viability-gate margin introduces explicit non-compensatoriness into the decision process. Downside compression and stability efficiency tie the classification to perturbation behavior rather than to numerical scores alone. This set of indicators reduces the risk of choosing a strategy that is well-scored but weak in terms of the most vulnerable climate-stress aspects. The robust supply-network design literature focuses on the protection from disruption in the adverse climate conditions [9]. The related literature on network design is also oriented towards avoidance of unacceptable losses in case of extreme climate disruption [34]. The risk analysis literature warns about the perils of relying on expected performance alone [33].

There are also implications for climate governance and sustainable supply chain management. Environmental sustainability, resilience, cost, technological flexibility, alignment with policies, and community impacts are typically evaluated separately. Within the criterion profile, environmental sustainability and climate resilience are the top two Level-1 factors, whereas the upper end of the weight profile includes Level-3 preferences such as hazardous material usage, energy efficiency, pollution and waste production, infrastructure, water usage, logistics cost, exposure to extreme weather, renewable energy, digitalization, and emergency preparedness. Thus, the viable climate-responsive strategy needs to combine the performance on environmental dimensions with continuity capability. The best alternatives are not those optimizing any one sustainability dimension, but those combining mitigation, resource efficiency, monitoring, flexibility, and recovery capability. Climate-resilient digital research stresses the joint design of resilience and sustainability [20]. The recent decision models also combine the sustainable and resilient supply-chain priorities [25]. Contemporary general studies call for joint development of digital capabilities, resilience, and sustainability rather than sequential [22].

The interpretation of the findings is limited by the particular 27-criterion decision matrix, four strategies, comparative MCDM scores, and expert weights randomized within their intervals. The analysis evaluates the internal decision logic of this particular climate-responsive supply network case rather than providing the estimates of universal empirical effects across industries. The gate threshold choices are transparent and can be adjusted according to the safety demands, ability to substitute among suppliers, or the nature of the public service. The regime weights represent explicit transitions of the manager from the balanced evaluation to continuity protection, compound disruption, and investment in adaptation. The sector-specific applications can include stricter gate thresholds, known records of disruptions, or climate hazards represented by the stochastic state variables. The main result remains valid within the 27-criterion criterion profile considered here: hybrid global–local sourcing is the primary viable strategy, regional high-resilience sourcing is the only defensible fallback, multi-supplier global sourcing is conditional, and lean single global sourcing is fragile.

7. Conclusion

The research question was whether hybrid global-local sourcing remained viable when the decision evidence is reinterpreted in terms of climate stresses. The answer is straightforward: hybrid global–local sourcing with flexible logistics, S_4, is the primary viable strategy. It is the leader in ERCF, dominates 18 out of 27 criteria, gets 65.87% of total weighted dominance, maximizes the compound-stress score (1.0000), surpasses the viability gate by 0.3500, and wins in stability efficiency. Thus, the advantage of this strategy is not grounded in any particular criterion; it consists in breadth, endurance, and regret resistance.

The regional high-resilience sourcing with S_3 is the only defensible fallback. It is not better than S_4, but it passes the gate by 0.0728 margin and becomes stronger under continuity protection and compound disruption. The limitation of this strategy is dominance of the criteria, which means that it is necessary to improve its broad capabilities to make it a primary choice. Multi-supplier global sourcing with moderate safety stock, S_2, is conditional because diversification does not create enough dominance or regret resistance. Single global sourcing with lean inventory, S_1, is fragile and should not be selected in case of climate disruption.

Thus, the conclusion is not any particular preference ordering. It separates the top-ranked strategy from those that are able to resist the climate-stress gate. The climate-responsive supply network should focus on hybrid global–local flexibility where implementation conditions allow, use regional high-resilience sourcing as a fallback, strengthen global diversification before treating it as climate-ready, and avoid lean global sourcing in climate-disruptive conditions.

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