

Mapping Multi-Dimensional Climate Priority in Bangladesh's Garment Supply Network

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Abstract

The ready-made garment (RMG) production system in Bangladesh faces climate-related pressures at factories and nearby transport infrastructure. This study presents a framework for defining individual production areas where climate-related pressures overlap and prioritisation remains consistent across different weightings. There were 2,579 unique coordinate groups employed in the analysis of 4,784 factory records that were not marked closed. The four final components were direct river-flood exposure, positive extreme-rainfall intensification, ambient heat burden, and climate-logistics vulnerability. Hazard-specific measures were derived from JRC/CEMS GloFAS, CHIRPS, ERA5-Land, and OpenStreetMap-based road data, and harmonised to the common 0–100 relative-priority scale. Five alternative weighting scenarios were tested for sensitivity against the primary score, which was an equal-weight arithmetic mean. Four-component assessment was available for 2,576 coordinate groups, and three groups consisting of 13 factories remained non-assessable. In the primary specification, 2,299 factories (48.06%) belonged to priority groups (High or Very High). Spearman correlation with alternative weighting rankings was between 0.952 and 0.997, and overlap with the top one-tenth (decile) was between 70.93% and 94.96%. The intersection of the six top-decile sets yielded 128 weighting-robust groups containing 179 factories, with 125 of these groups containing at least two components scoring 75 or above. Among these robust groups, 91.41% of groups and 92.74% of represented factories were located in Dhaka, Gazipur, or Narayanganj. The framework is not a prediction of losses or disruptions, but rather a transparent screening tool for adaptation prioritisation.

Keywords: ambient heat, Bangladesh, climate priority, extreme rainfall, logistics vulnerability, ready-made garment, river flooding, spatial prioritisation

I Introduction

The ready-made garment industry in Bangladesh is structured through a dense production and logistics network in which environmental pressures can impact factories in several ways. A flooded production site can cause direct inundation of the factory site, a change in rainfall extremes can represent a different type of hydroclimatic pressure, high ambient temperature can cause greater thermal burden around industrial activities, and flooding of transport infrastructure around a factory site can cause accessibility issues without factory-site inundation. Thus, assessing climate impacts on supply chains is better served by maintaining the separation between physical hazards, production sites, and associated infrastructure instead of representing the system through a single hazard layer. The IPCC also identifies that climate effects can cascade through interconnected infrastructure systems and that transport infrastructure can be vulnerable to extreme events (Intergovernmental Panel on Climate Change, 2022).

This is especially important in the case of heat. Perceived heat-related health and productivity impacts have been directly investigated among production-line workers from two different RMG factories in Bangladesh, and experimental studies have been conducted to assess cooling strategies for heat environments relevant to garment production in Bangladesh (Smallcombe et al., 2025; Yeasmin et al., 2025). These findings not only show that heat is an important sectoral concern, but also demonstrate that regional ambient temperature cannot be considered a direct measure of workplace heat exposure because other factors listed above also influence experienced heat conditions.

Transport provides an additional pathway of exposure between climate hazards and industrial processes. Herrera Dappe et al. (2020) define Greater Dhaka as a key manufacturing hub and illustrate the significance of freight and logistics activities for the competitiveness of Bangladesh's industry. While this is not proof of climate disruption in individual factories, it supports the inclusion of surrounding facility accessibility and transport connectivity in discussions of industrial resilience, in addition to factory coordinates.

Interest in sustainability, logistics, vulnerability, and disruption also continues to grow within supply-chain scholarship focusing on Bangladesh. Recent studies have discussed green supply-chain transformation in the textile and apparel industry, environmental impacts of sustainable supply chains, logistics performance, external vulnerability assessment for food supply chains in Bangladesh, and disruption mitigation in poultry-feed supply chains (Ahmed et al., 2024; Fahim et al., 2024; Helal et al., 2024; Islam et al., 2025; Nahin et al., 2024). These studies demonstrate the practical relevance of environmental and resilience issues, but they differ from the present study in analytical scope and design. The framework developed here combines four climate-relevant dimensions across represented production locations in Bangladesh and explicitly examines the sensitivity of national rankings and upper-tail membership to alternative component weights.

The next methodological problem arises from aggregation. The choices made in constructing composite indicators, including normalisation, weighting, and aggregation, are critical to the resulting measure. The OECD/EU/JRC provides guidance on these decisions, emphasising that they should be transparent and subject to sensitivity analysis rather than treating a single composite specification as the sole measure of objectivity (OECD et al., 2008). This is especially significant when outputs are used for prioritisation, as relatively small variations in weights may not change national-level priorities but may change membership near fixed intervention thresholds.

The present study thus proposes a spatially explicit and decomposable climate-priority framework for the represented RMG production network in Bangladesh. It maintains four different final dimensions: direct river-flood exposure, positive extreme-rainfall intensification, ambient heat burden, and climate-logistics vulnerability. How do the four climate-priority dimensions vary across represented RMG production locations? To what extent are their spatial patterns distinct? How sensitive are the final rankings and upper-tail membership to alternative component weights? Lastly, which component profiles and geographic patterns characterise production locations that remain highly prioritised across the tested weighting scenarios?

The measure is deliberately defined as a climate priority and not as expected climate loss or absolute climate risk. It does not calculate economic losses, likelihood of factory failure, production losses, employee sickness, or likelihood of supply-chain disruption. It provides a set of rules for screening areas for further facility, occupational-heat, flood, infrastructure, and logistics evaluations.

2 Literature Background

Supply-chain climate-risk research increasingly goes beyond assessing individual hazards and aims to capture a more comprehensive view of supply-chain resilience, adaptation capacity, and vulnerability. Climate hazards affect industrial networks not only through direct exposure but also through secondary impacts on infrastructure, transport, workforce conditions, and continuity of production. As a result, climate adaptation solutions for supply chains need to consider both environmental stressors and the spatial organisation of supply-chain systems. The Intergovernmental Panel on Climate Change (2022) highlights that climate impacts can propagate through interconnected systems, including infrastructure and economic networks.

Flooding and other high-intensity events pose significant risks to industrial systems by affecting assets, access, and transportation systems. Traditional flood-exposure evaluations have often focused on hazard intensity or the extent of affected areas; however, for supply-chain applications, flood exposure information needs to be transformed into location-based implications for production networks. Likewise, higher temperatures pose specific challenges for labour-intensive manufacturing through impacts on worker comfort, productivity, and working conditions. Research on Bangladeshi RMG workers has examined perceived heat-related health and productivity impacts, while experimental studies have assessed cooling strategies relevant to garment-production environments (Smallcombe et al., 2025; Yeasmin et al., 2025).

The climate exposure of the apparel sector has also been studied directly in previous sector-level studies. Across major apparel production centres, including Dhaka, the Cornell ILR Global Labor Institute and Schroders study assessed exposure to extreme heat and flooding conditions and explored potential impacts on workers and the apparel industry (Judd et al., 2023). The present study is distinctive in its focus on a production-location network across Bangladesh and in its incorporation of direct river-flood exposure, positive extreme-rainfall intensification, ambient heat burden, and climate-logistics vulnerability within a decomposable prioritisation framework.

Bangladesh provides an important context in which to examine these issues because of its established ready-made garment (RMG) industry. This industry is highly concentrated in manufacturing clusters, where factories, suppliers, workers, and logistics systems are geographically interconnected. Previous studies have investigated sustainability issues, supply-chain challenges, and operational hazards affecting industrial sectors in Bangladesh. Studies focusing on Bangladesh supply chains have examined green supply-chain transformation in the textile and apparel industry, environmental impacts of sustainable supply-chain practices, logistics performance, external vulnerability assessment, and disruption mitigation (Ahmed et al., 2024; Fahim et al., 2024; Helal et al., 2024; Islam et al., 2025; Nahin et al., 2024). However, several existing studies analyse organisational practices or specific operational problems while providing limited evaluation of climate pressures across the spatial distribution of factories.

Another challenge for climate-priority assessment is the inclusion of multiple indicators. Data from different sources and spatial scales are required to represent flood exposure, extreme-rainfall change, ambient heat burden, and logistics accessibility. Transparent normalisation and aggregation procedures are therefore required to combine these dimensions. Without such procedures, prioritisation outcomes may depend substantially on methodological decisions rather than spatial patterns of climate and infrastructure exposure. The OECD/EU/JRC guidance on composite indicators emphasises the importance of transparent construction, weighting decisions, and sensitivity analysis when developing such measures (OECD et al., 2008).

The selection of weights is also an important source of uncertainty for composite indicators. Equal weighting provides a transparent baseline, but potential limitations arise because of the implicit assumption that all dimensions contribute equally. Alternative weighting approaches may produce different rankings when locations have uneven exposure across dimensions. Therefore, it is necessary to evaluate whether locations remain stable under different weighting schemes.

In this study, these research requirements are incorporated into a spatial prioritisation framework for the RMG production network in Bangladesh, considering multiple climate-relevant dimensions. The framework is not designed to estimate the probability of future disruptions; rather, it identifies locations experiencing multiple climate pressures and evaluates locations whose prioritisation remains stable under different weighting assumptions.

3 Materials and Methods

3.1 Study design and analytical sample

The study adopted an observational geospatial design based on secondary data, where production locations were linked with gridded environmental and infrastructure datasets.

The analysis integrated precipitation, flooding, temperature, and an OpenStreetMap-based road network to construct climate-relevant spatial indicators.

There were 4,811 records in the raw Bangladesh RMG facility file. Among these, 27 records had *is_closed* = *True* and were excluded, leaving 4,784 factory records with *is_closed* = *False*. This distinction is important because the field does not independently confirm that a facility was operational contemporaneously; it only indicates that the record was not marked as closed.

The facility export was sourced from Open Supply Hub (OS Hub). Since OS Hub contains contributions from multiple sources, the downloaded export includes multiple contributors, including substantial contributions from Mapped in Bangladesh. Therefore, the source is treated as a multi-contributor OS Hub export rather than a dataset representing Mapped in Bangladesh only (Open Supply Hub, 2026).

3.2 Coordinate groups and spatial quality

Latitude and longitude values were extracted from the facility records and paired exactly to create stable coordinate-group identifiers. This reduced the 4,784 factory records containing point locations into 2,579 unique coordinate groups, which were used as the spatial analytical units.

The number of factories represented by each coordinate group was calculated and used to classify groups according to their representation. A total of 1,817 coordinate groups represented a single factory, while 661 groups represented 2–5 factories.

Among the remaining shared-coordinate groups, 91 represented 6–20 factories and 10 represented more than 20 factories. The largest coordinate group represented 94 factories with the exact same coordinates.

Shared coordinates were not manually adjusted or relocated. Therefore, a coordinate group is interpreted as a representation of a production location rather than an assumption that every shared coordinate corresponds to a separate factory gate.

3.3 Administrative geography

Coordinate groups were linked with a Bangladesh ADM2 administrative boundary layer containing 64 polygons from geoBoundaries (Runfola et al., 2020). The primary approach was point-in-polygon assignment.

Seven factory records could not be resolved by strict point-in-polygon containment. For these records, assignment was made to the nearest ADM2 district polygon after confirming that the distance was below 500 m. The largest fallback distance was approximately 283.5 m.

All 4,784 factory records were assigned to a district. District geography was used only for reporting and aggregation purposes and was not used in the calculation of component scores.

3.4 Direct river-flood exposure

River-flood exposure was derived from the GloFAS Global River Flood Hazard Maps Version 2.1 provided by the Joint Research Centre (JRC) of the European Commission. The dataset provides modelled inundation depth values at approximately 90 m resolution for seven return periods (10, 20, 50, 75, 100, 200, and 500 years), together with diagnostic information on permanent water and spurious-depth conditions (Baugh et al., 2024).

The final flood component used the 100-year return-period inundation depth (d_{100}). Let:

$$X = \{d_{100,1}, d_{100,2}, \dots, d_{100,r}\} \quad (1)$$

where $r = 2,579$ is the number of coordinate groups and $d_{100,i}$ represents the modelled inundation depth, in metres, associated with coordinate group i under the RP100 flood-hazard scenario. The extracted value is a flood-depth measure rather than a probability assigned to the coordinate group.

A zero-preserving percentile transformation was applied to retain the distinction between locations with zero modelled flood depth and locations with positive flood exposure:

$$P^+(x_i) = \begin{cases} 0, & x_i \leq 0 \\ \text{average-rank percentile among positive observations,} & x_i > 0 \end{cases} \quad (2)$$

Throughout the analysis, percentile-rank operators are expressed on a 0–1 scale before any multiplication by 100. For P^+ , non-positive values are assigned zero, while positive observations receive average-rank percentiles calculated only among the positive observations.

This positive-only percentile transformation was first applied to the RP100 depth values to obtain the raw flood score:

$$F_i^{raw} = 100P^+(d_{100,i}) \quad (3)$$

The raw flood score was then transformed through the common final zero-preserving harmonisation:

$$F_i = 100P^+(F_i^{raw}) \quad (4)$$

where F_i represents the relative direct river-flood priority of coordinate group i .

The resulting flood component represents relative flood-priority conditions across locations. It does not represent the probability that a specific building will flood.

3.5 Positive extreme-rainfall intensification

Rainfall-related exposure was derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) Version 2.0 Final Daily dataset (Funk et al., 2015). The rainfall component was designed to capture positive changes in extreme rainfall characteristics rather than simply representing average rainfall conditions.

The analysis used 200 CHIRPS cells containing the 2,579 coordinate groups. A 35-year rainfall panel was constructed for 1991–2025, resulting in 7,000 cell-year observations. The baseline period was defined as 1991–2020, corresponding to the current WMO climatological standard-normal period, while 2021–2025 represented the recent comparison period (World Meteorological Organization, 2023).

Five rainfall indicators were initially evaluated:

- Rx1day: annual maximum one-day precipitation,
- Rx5day: annual maximum five-day precipitation,
- R20mm: annual number of days with precipitation ≥ 20 mm,
- R50mm: annual number of days with precipitation ≥ 50 mm,
- PRCPTOT: annual total wet-day precipitation.

For each rainfall indicator X , the percentage change between the recent and baseline periods was calculated as:

$$\Delta X_j = 100 \frac{\bar{X}_{j,2021-2025} - \bar{X}_{j,1991-2020}}{\bar{X}_{j,1991-2020}} \quad (5)$$

where j represents the CHIRPS cell.

Only positive changes were considered as indicators of increased rainfall-related pressure:

$$I_{X,j} = \max(0, \Delta X_j) \quad (6)$$

The initial assessment evaluated all five indicators. The final rainfall component retained Rx1day and R50mm to represent two complementary dimensions of extreme-rainfall change: the magnitude of annual maximum one-day rainfall and the frequency of days with rainfall of at least 50 mm. Rx5day, R20mm, and PRCPTOT were retained as diagnostic indicators but were not included as inputs to the final rainfall component.

The final raw rainfall component was calculated as:

$$R_i^{raw} = 50[P^+(I_{Rx1day,i}) + P^+(I_{R50mm,i})] \quad (7)$$

where P^+ represents the positive-only percentile transformation. The final rainfall component was then obtained through common zero-preserving harmonisation:

$$R_i = 100P^+(R_i^{raw}) \quad (8)$$

The resulting component represents relative extreme-rainfall intensification priority among production locations. It does not represent future rainfall prediction or direct flood probability.

3.6 Ambient heat burden

The ambient heat component was constructed using ERA5-Land reanalysis data (Muñoz-Sabater et al., 2021). ERA5-Land provides long-term land-surface climate variables at a native spatial resolution of approximately 9 km.

The 2,579 coordinate groups were associated with 111 distinct ERA5-Land cells, and a 35-year annual heat panel covering 1991–2025 was constructed. Of the coordinate groups, 2,578 received native ERA5-Land assignments, while one group was assigned to the nearest valid land pixel after spatial quality control. The heat component was designed to represent contemporary ambient thermal burden rather than occupational heat exposure inside factories.

Two temperature dimensions were considered:

- the 2021–2025 average of annual mean daily maximum temperature (TX_{mean}),
- the 2021–2025 average of annual mean daily minimum temperature (TN_{mean}).

For each ERA5-Land cell j , let TX_j^{recent} and TN_j^{recent} denote the 2021–2025 averages of annual mean daily maximum and minimum temperature, respectively. The raw heat burden score was calculated as:

$$H_j^{raw} = 100 [0.5P_c(TX_j^{recent}) + 0.5P_c(TN_j^{recent})] \quad (9)$$

where P_c represents the average-rank percentile, on a 0–1 scale, among the represented ERA5-Land cells.

The final heat component was assigned to each coordinate group through:

$$H_i = 100P_g(H_{j(i)}^{raw}) \quad (10)$$

where P_g represents the average-rank percentile, on a 0–1 scale, among valid coordinate-group observations and $j(i)$ identifies the ERA5-Land cell associated with coordinate group i .

The resulting heat component represents relative ambient heat burden across production locations. It does not measure workplace heat stress, worker health outcomes, or indoor factory conditions.

3.7 Strategic road network extraction

The logistics component incorporated transport accessibility and climate-related road vulnerability using OpenStreetMap road data from the Geofabrik Bangladesh extract, using the snapshot dated 16 August 2026 (Geofabrik GmbH and OpenStreetMap contributors, 2026).

The analysis focused on strategically important road classes:

- motorway,
- trunk,
- primary,
- secondary,
- tertiary.

The corresponding link classes (*motorway_link*, *trunk_link*, *primary_link*, *secondary_link*, and *tertiary_link*) were also retained and associated with the hierarchy of their parent road classes.

For the analysis, motorway, trunk, and primary roads and their corresponding link classes formed the core road network. The broader strategic-road network additionally included secondary and tertiary roads and their corresponding link classes.

After geometry and explicit motor-access screening, 35,289 usable strategic-road features remained from 35,321 initially retained features. The screening excluded 32 features carrying explicit motor-vehicle prohibitions.

Accessibility indicators and road-exposure measures relating to climate conditions were calculated using the extracted road network. The logistics component thus reflects transport accessibility and climate-related infrastructure vulnerability rather than transport performance in general.

The road-flood analysis was performed by sampling along road centrelines at approximately 90 m intervals within the usable strategic-road network. This resulted in 488,950 sample points across 35,289 retained road features. The length of the parent road feature was divided by the number of sample points created for that feature, and the resulting value was used as the length weight for each sample point. Road-length exposure was reconstructed from the centreline samples using this weighting.

Samples that were not clearly interpretable as ordinary road-surface exposure were not included in the primary road-flood exposure calculation. These comprised bridge or tunnel cases and samples affected by permanent-water or spurious-depth quality-control conditions.

The length-reconstruction validation compared sample-based road-length calculations with exact geometric calculations. The results were nearly identical across the audited local measures, with the lowest Spearman rank correlation being $\rho = 0.99997$. At the national level, the reconstructed road length had effectively zero difference from the exact total at the reported precision.

3.8 Climate-logistics vulnerability

The climate-logistics component was designed to represent the interaction between baseline road-access weakness and modelled flood exposure of surrounding strategic roads. Rather than treating logistics as a general infrastructure-performance measure, the component identifies production locations where weaker baseline road access coincides with greater flood exposure of the surrounding road network.

Two accessibility dimensions were considered:

- distance to the nearest core road network,
- strategic-road length within 2 km.

The accessibility component was calculated as:

$$A_i = 100[0.5P^\uparrow(D_{core,i}) + 0.5P^\downarrow(S_{2km,i})] \quad (11)$$

where $D_{core,i}$ represents distance to the core road network and $S_{2km,i}$ represents the total length of the strategic-road network within 2 km of coordinate group i . $P^\uparrow$ ranks larger raw values higher, whereas $P^\downarrow$ reverses the ranking so that smaller raw values receive higher scores. Thus, greater distance from the core network and lower surrounding strategic-road length both increase the accessibility-weakness score A_i .

Road segments were linked with the flood hazard dataset to identify climate-related road exposure. For coordinate group i , the primary road-flood exposure indicator was the share of interpretable strategic-road length within 5 km experiencing RP100 flood depth of at least 0.30 m:

$$E_i = \frac{\sum_{s \in \mathcal{S}_i(5 \text{ km})} w_s \mathbf{1}(d_{s,100} \geq 0.30)}{\sum_{s \in \mathcal{S}_i(5 \text{ km})} w_s} \quad (12)$$

where $\mathcal{S}_i(5 \text{ km})$ denotes the interpretable strategic-road samples within 5 km of coordinate group i , w_s represents the length weight assigned to road sample s , and $d_{s,100}$ represents its 100-year return-period flood depth.

The 0.30 m depth threshold and 5 km neighbourhood were used in the primary logistics specification. Alternative 0.10 m and 0.50 m depth thresholds, a 2 km neighbourhood, and core-road-only variants were examined as sensitivity specifications and were not used as inputs to the final climate-logistics component.

The accessibility and exposure dimensions were combined through:

$$L_i^{raw} = A_i E_i \quad (13)$$

The final climate-logistics component was obtained through common zero-preserving harmonisation:

$$L_i = 100P^+(L_i^{raw}) \quad (14)$$

Three coordinate groups lacked an assessable primary 5-km road-flood denominator; their logistics component values were left missing rather than imputed.

The resulting component represents relative climate-logistics vulnerability across production locations. It does not represent complete transport disruption probability or economic loss.

3.9 Common harmonisation and final climate-priority score

Because the four components were derived from different datasets and measurement scales, a common harmonisation procedure was applied before aggregation. Each component was transformed into a comparable 0–100 relative-priority scale while preserving meaningful zero values where no positive exposure or pressure was observed.

A coordinate group was considered assessable only when all four final components, F_i , R_i , H_i , and L_i , were available. This resulted in 2,576 assessable coordinate groups from the 2,579-group analytical universe, while three groups representing 13 factories remained non-assessable.

The final climate-priority score for coordinate group i was calculated using equal weighting across the four components:

$$C_i = 0.25F_i + 0.25R_i + 0.25H_i + 0.25L_i \quad (15)$$

where:

- F_i represents direct river-flood exposure,
- R_i represents positive extreme-rainfall intensification,
- H_i represents ambient heat burden,
- L_i represents climate-logistics vulnerability.

The equal-weight specification was selected as the primary model because no empirical loss function or externally elicited preference system was available to justify assigning consistently greater importance to one climate dimension than another. Equal weighting therefore provided a transparent primary specification, while alternative weights were used to test the sensitivity of the resulting rankings.

Among the 2,576 assessable coordinate groups, the final score percentile was calculated using average ranks:

$$Q_i = 100P_g(C_i) \quad (16)$$

where P_g represents the average-rank percentile of C_i , on a 0–1 scale, among all assessable coordinate groups.

The resulting classes were defined as:

$$Q_i \leq 25 : \text{Low}; \quad 25 < Q_i \leq 50 : \text{Moderate}; \quad 50 < Q_i \leq 75 : \text{High}; \quad Q_i > 75 : \text{Very High} \quad (17)$$

These classes are relative priority categories defined by quartile thresholds of the coordinate-group score distribution rather than absolute physical safety thresholds.

3.10 Weighting sensitivity and robust hotspots

Since composite indicators can be sensitive to weighting choices, five alternative weighting scenarios were evaluated alongside the equal-weight primary specification. These scenarios increased the emphasis on individual components while maintaining the same four-component structure. The equal-weight specification described above was retained as the primary scenario:

$$C_i^E = 0.25F_i + 0.25R_i + 0.25H_i + 0.25L_i \quad (18)$$

The alternative weighting scenarios were:

An earlier planned 30/25/25/20 specification was retained as an additional sensitivity scenario:

$$C_i^P = 0.30F_i + 0.25R_i + 0.25H_i + 0.20L_i \quad (19)$$

Flood-emphasised:

$$C_i^F = 0.40F_i + 0.20R_i + 0.20H_i + 0.20L_i \quad (20)$$

Rainfall-emphasised:

$$C_i^R = 0.20F_i + 0.40R_i + 0.20H_i + 0.20L_i \quad (21)$$

Heat-emphasised:

$$C_i^H = 0.20F_i + 0.20R_i + 0.40H_i + 0.20L_i \quad (22)$$

Logistics-emphasised:

$$C_i^L = 0.20F_i + 0.20R_i + 0.20H_i + 0.40L_i \quad (23)$$

Together with the equal-weight primary model, these formed the six-scenario weighting uncertainty envelope. The purpose of this sensitivity analysis was not to identify a single preferred weighting scheme, but to evaluate whether prioritised locations remained stable under reasonable changes in component importance.

For each weighting scenario, coordinate groups were ranked nationally. The primary robustness assessment focused on the upper decile of each ranking. With 2,576 coordinate groups having complete four-component scores, the number of coordinate groups in each top-decile set was:

$$N_{10} = \lceil 0.10 \times 2576 \rceil = 258 \quad (24)$$

For each scenario, the top-decile set therefore consisted of the 258 highest-ranked coordinate groups. A coordinate group was classified as a weighting-robust hotspot when it belonged to the top-decile set under all six weighting scenarios: the equal-weight primary specification and the five alternative specifications. The multidimensionality of robust hotspot groups was characterised using:

$$M_{75,i} = \sum_{k \in \{F, R, H, L\}} \mathbf{1}(k_i \geq 75) \quad (25)$$

where $\mathbf{1}(\cdot)$ is the indicator function and $M_{75,i}$ represents the number of component scores at or above 75 within coordinate group i .

An analogous measure was calculated at the stricter 90-point threshold:

$$M_{90,i} = \sum_{k \in \{F, R, H, L\}} \mathbf{1}(k_i \geq 90) \quad (26)$$

where $M_{90,i}$ represents the number of component scores at or above 90 within coordinate group i .

The resulting robust hotspots were subsequently examined through component profiles and geographic distribution to identify recurring combinations of climate pressures and spatial concentration patterns.

4 Results

4.1 Analytical coverage and final priority distribution

The final analytical universe comprised 2,579 coordinate groups representing 4,784 factory records. A complete four-component assessment was available for 2,576 coordinate groups, while three groups representing 13 factories remained non-assessable. Table 1 summarises the final analytical counts and primary findings.

Table 1: Final analytical counts and key findings

Finding	Value	Unit	Interpretation
Factory records not marked closed	4,784	factories	Factory analytical universe
Unique factory coordinate groups	2,579	coordinate groups	Spatial analytical units
Assessable coordinate groups	2,576	coordinate groups	Groups receiving complete four-component priority scores
Non-assessable coordinate groups	3	coordinate groups	Reported without imputation
Factories in non-assessable groups	13	factories	Factories reported without final-score imputation
Factories classified High or Very High priority	2,299	factories	48.06% of represented factories
Factories classified Very High priority	1,053	factories	22.01% of represented factories
Robust top-decile hotspot coordinate groups	128	coordinate groups	Remain in national top decile under all six tested weighting scenarios
Assessable-group share represented by	4.97%	–	Share of assessable coordinate groups

Finding	Value	Unit	Interpretation
robust hotspots			
Factories represented by robust top-decile hotspots	179	factories	3.74% of the represented national factory universe
Robust hotspot groups in Dhaka-Gazipur-Narayanganj	117	coordinate groups	91.41% of national robust hotspot groups
Robust-hotspot factories in Dhaka-Gazipur-Narayanganj	166	factories	92.74% of factories represented by robust hotspots

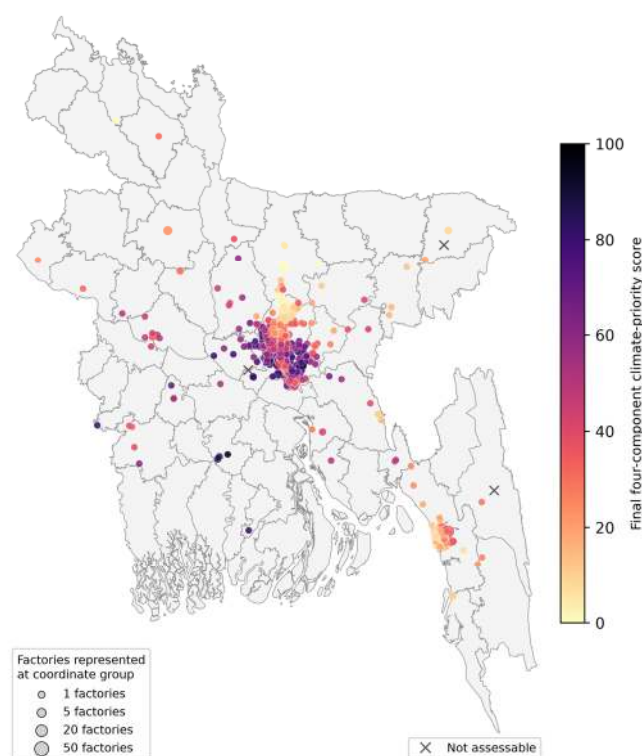
Note. “Factory records not marked closed” refers to records for which the source field is_closed was false; this does not independently verify contemporaneous operating status. Percentages use the represented factory or assessable coordinate-group population indicated in the corresponding interpretation.

Factory counts associated with the final coordinate-group priority classes were distributed as follows: 1,096 factories were classified as Low priority (22.91%), 1,376 as Moderate priority (28.76%), 1,246 as High priority (26.05%), and 1,053 as Very High priority (22.01%). The 13 non-assessable factories represented 0.27% of the total analytical universe.

Together, High- and Very High-priority groups represented 2,299 factories, corresponding to 48.06% of all represented factories. These classes were defined using coordinate-group percentiles rather than factory-level quartiles. Therefore, factory counts were not expected to be evenly distributed among the four priority categories because larger coordinate groups represent multiple factories.

The national distribution of final climate-priority scores is presented in Figure 1.

Climate Priority Across Bangladesh's RMG Supply Network
Flood exposure, extreme rainfall, ambient heat burden, and climate-logistics vulnerability



Points represent unique factory-coordinate groups. Point size reflects represented factory concentration. Scores are relative prioritisation measures, not probabilities of loss or expected economic damage.

Figure 1: National distribution of final climate-priority scores among assessed RMG coordinate groups.

Note. Colour denotes the equal-weight four-component climate-priority score on a 0–100 scale. Symbol size reflects the number of factory records represented by each coordinate group. “X” denotes

non-assessable locations. Scores represent relative screening priorities rather than probabilities of loss or disruption.

4.2 *Four-component structure*

Among the 2,576 assessable coordinate groups, the mean component scores were 15.38 for direct river-flood priority, 50.01 for extreme-rainfall intensification priority, 50.05 for ambient heat burden, and 48.93 for climate-logistics vulnerability.

The comparatively lower mean flood score resulted from the large proportion of zero flood-exposure values rather than from reduced weighting in the final composite score.

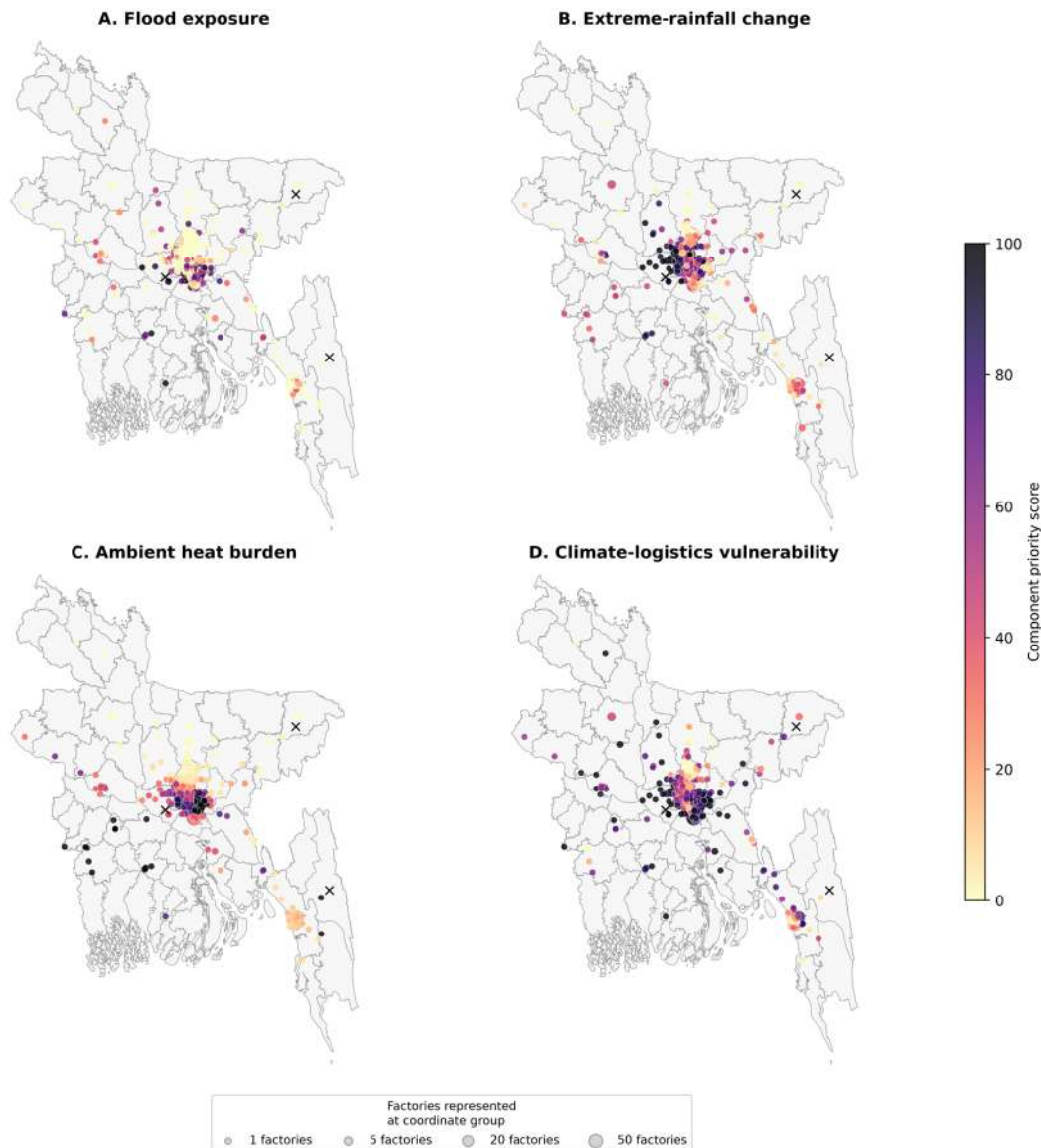
The four components demonstrated distinct spatial characteristics and were not redundant. Pairwise Spearman rank correlations were -0.093 between rainfall and flood, 0.280 between heat and flood, 0.607 between logistics and flood, 0.245 between rainfall and heat, 0.107 between rainfall and logistics, and 0.339 between heat and logistics.

The strongest association occurred between flood and logistics components, which is expected because the climate-logistics component incorporates exposure of surrounding road infrastructure to flood conditions.

However, the final climate-priority score should not be interpreted as a single latent hazard measure. The four dimensions represent different spatial mechanisms, and their incomplete correlations demonstrate the value of maintaining component-level decomposition. The national spatial patterns of the four components are presented separately in Figure 2.

Four Dimensions of Climate Priority Across Bangladesh's RMG Supply Network

Frozen component scores shown on a common 0–100 scale



Points represent unique factory-coordinate groups. Only final-framework assessable locations are coloured; x denotes non-assessable locations. Point size reflects represented factory concentration. All four panels use the identical 0–100 colour scale.

Figure 2: Spatial decomposition of the four climate-priority components: flood, rainfall, heat, and climate-logistics vulnerability.

Note. Panels show (A) direct river-flood exposure, (B) positive extreme-rainfall intensification, (C) ambient heat burden, and (D) climate-logistics vulnerability. All four components are shown on the same 0–100 relative-priority scale. Symbol size reflects the number of factory records represented by each coordinate group, while x denotes non-assessable locations where applicable.

4.3 Weighting sensitivity

The final rankings showed high consistency across the six weighting scenarios, including the equal-weight primary specification and five alternative weighting schemes (Table 2).

The earlier planned 30/25/25/20 weighting specification produced a Spearman rank correlation of $\rho = 0.9973$ and a top-decile overlap of 94.96% with the equal-weight model. Flood-emphasised weighting produced $\rho = 0.9870$ with 87.21% top-decile overlap. Rainfall-emphasised weighting produced $\rho = 0.9522$ with 70.93% overlap, heat-emphasised weighting produced $\rho = 0.9659$ with 91.47% overlap, and logistics-emphasised weighting produced $\rho = 0.9724$ with 93.80% overlap.

Rainfall-emphasised weighting produced the largest change in upper-tail membership despite maintaining a rank correlation above 0.95. This demonstrates the distinction between national ranking stability and membership stability near a fixed intervention threshold.

Table 2: Weighting sensitivity of the final climate-priority ranking

Scenario	ρ with primary	Top-decile n	Overlap n	Overlap
Equal weights (25/25/25/25)	1.0000	258	258	100.00%
Earlier planned (30/25/25/20)	0.9973	258	245	94.96%
Flood-heavy (40/20/20/20)	0.9870	258	225	87.21%
Rainfall-heavy (20/40/20/20)	0.9522	258	183	70.93%
Heat-heavy (20/20/40/20)	0.9659	258	236	91.47%
Logistics-heavy (20/20/20/40)	0.9724	258	242	93.80%

Note. ρ denotes Spearman rank correlation with the equal-weight primary specification. Top-decile overlap is the share of the 258 primary top-decile coordinate groups retained under each alternative weighting scenario. The weighting-robust hotspot definition uses only these six arithmetic weighting scenarios.

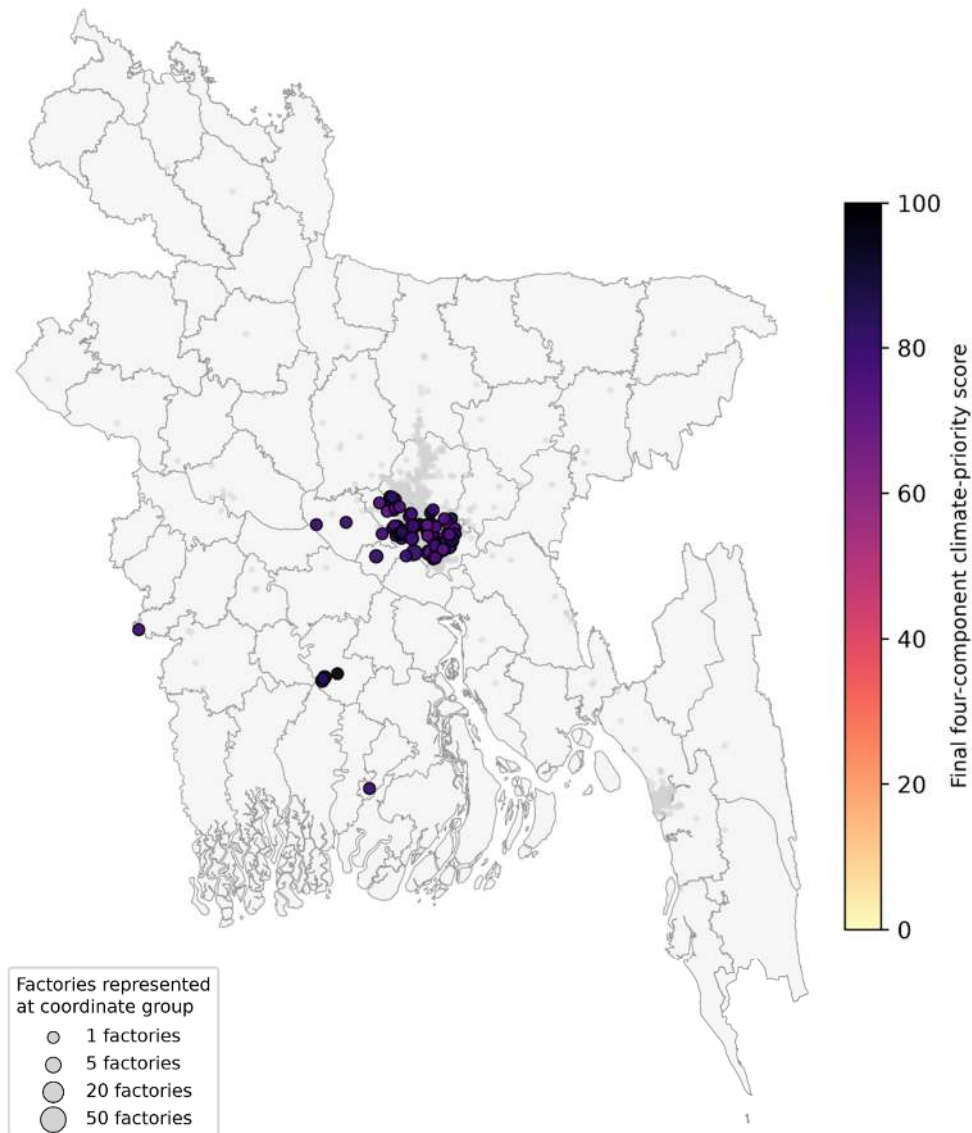
4.4 Weighting-robust hotspots

The intersection of the six top-decile sets, each containing 258 coordinate groups, identified 128 weighting-robust coordinate groups representing 179 factories. These groups accounted for 4.97% of assessable coordinate groups and 3.74% of the represented national factory universe.

The weighting-robust set therefore represents a substantially narrower prioritisation group than either the High/Very High priority classes or the top decile under any individual weighting specification. The spatial distribution of the 128-group intersection is presented in Figure 3.

Robust Multi-Dimensional Climate-Priority Hotspots

Coordinate groups remaining in the national top decile under all six weighting scenarios



Robust hotspot set: 128 coordinate groups representing 179 factories. Grey points show other assessable RMG locations.

Figure 3: Weighting-robust climate-priority hotspots identified through intersection of six top-decile rankings.

Note. Highlighted coordinate groups remained within the national top decile under all six arithmetic weighting scenarios. Grey points represent other assessable RMG coordinate groups. The robust set contains 128 coordinate groups representing 179 factories.

4.5 *Multidimensionality and dominant components*

The weighting-robust groups demonstrated substantial multidimensionality. Among the 128 groups, no group had all four component scores below 75. A total of 125 groups (97.66%) had at least two components with scores of 75 or higher, 72 groups (56.25%) had at least three components at or above this threshold, and nine groups (7.03%) had all four components at or above 75 (Table 3).

Table 3: Multidimensionality of the 128 weighting-robust hotspots

Minimum components	Groups ≥ 75	Factories ≥ 75	Groups ≥ 90	Factories ≥ 90
1	128	179	114	159
2	125	176	65	88
3	72	101	13	19
4	9	13	0	0

Note. Thresholds of 75 and 90 were applied only after robust-hotspot membership had been determined and did not affect score construction or hotspot selection.

Using a stricter threshold of 90, 114 groups had at least one component at or above 90, 65 groups had at least two components at or above this level, 13 groups had at least three components at or above 90, and no group had all four components at or above this threshold.

Heat represented the largest component among the weighting-robust groups, being the dominant component in 57 groups (44.53%). Flood was dominant in 29 groups (22.66%), logistics in 25 groups (19.53%), and rainfall in 17 groups (13.28%). Therefore, no single climate dimension consistently dominated the robust hotspot set.

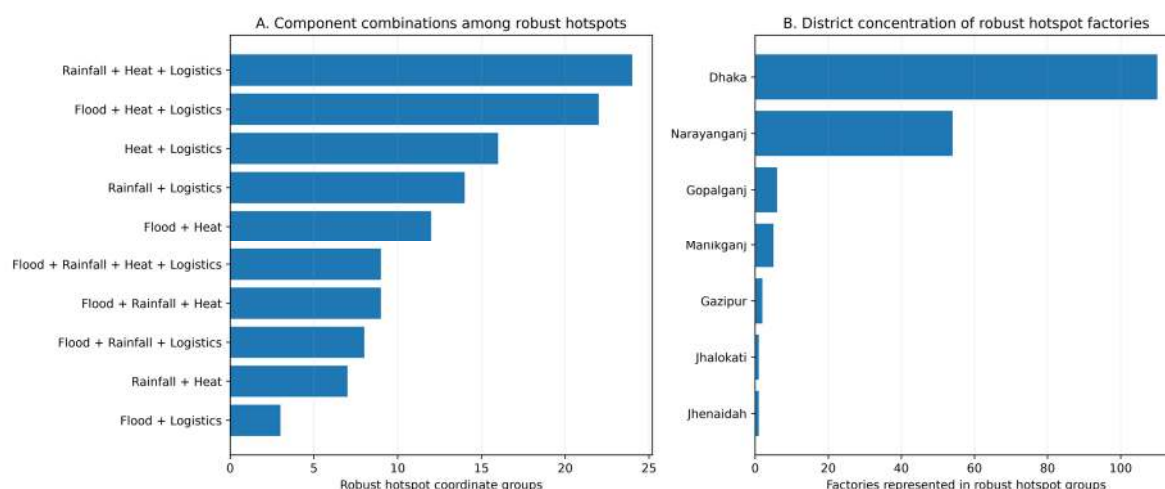
The most frequent exact component combinations at the 75-point threshold were Rainfall + Heat + Logistics (24 groups representing 35 factories), Flood + Heat + Logistics (22 groups representing 27 factories), Heat + Logistics (16 groups representing 25 factories), Rainfall + Logistics (14 groups representing 18 factories), and Flood + Heat (12 groups representing 15 factories). All exact component combinations are presented in Table 4, while the summarised component typology and district concentration patterns are shown in Figure 4.

Table 4: Exact component combinations at the 75-point threshold among weighting-robust hotspots

Component combination	Groups	Factories	Mean priority	Group share	Factory share
Rainfall + Heat + Logistics	24	35	78.06	18.75%	19.55%
Flood + Heat + Logistics	22	27	78.79	17.19%	15.08%
Heat + Logistics	16	25	75.19	12.50%	13.97%
Rainfall + Logistics	14	18	76.37	10.94%	10.06%
Flood + Heat	12	15	75.78	9.38%	8.38%
Flood + Rainfall + Heat	9	13	81.62	7.03%	7.26%
Flood + Rainfall + Heat + Logistics	9	13	88.09	7.03%	7.26%
Flood + Rainfall + Logistics	8	13	83.94	6.25%	7.26%
Rainfall + Heat	7	9	74.31	5.47%	5.03%
Flood + Logistics	3	7	79.14	2.34%	3.91%
Flood	1	1	75.53	0.78%	0.56%
Flood + Rainfall	1	1	74.40	0.78%	0.56%
Heat	1	1	69.49	0.78%	0.56%
Rainfall	1	1	70.86	0.78%	0.56%

Note. Component combinations describe final harmonised component scores of at least 75 among the already-identified weighting-robust hotspots. The 75-point threshold is descriptive only and was not used to construct the final score or determine robust-hotspot membership.

Typology and Geographic Concentration of Robust RMG Climate-Priority Hotspots



Robust hotspots are coordinate groups remaining in the national top decile under all six tested weighting scenarios. Component combinations identify frozen component scores ≥ 75 ; no final scores are recalculated.

Figure 4: Component typology and geographic concentration of weighting-robust hotspots.

Note. The left panel shows exact combinations of final component scores at or above 75 among the 128 weighting-robust coordinate groups, while the right panel shows the number of factory records represented by robust groups in each district. The 75-point threshold is descriptive only and was not used to construct the final score or determine robust-hotspot membership.

4.6 Geographic concentration

The weighting-robust hotspot population was geographically concentrated in Dhaka and neighbouring industrial districts (Table 5). Dhaka contained 79 robust groups representing 110 factories, while Narayanganj contained 36 groups representing 54 factories. Additional robust groups were identified in Gopalganj (four groups, six factories), Manikganj (five groups, five factories), Gazipur (two groups, two factories), Jhalokati (one group, one factory), and Jhenaidah (one group, one factory).

Dhaka, Narayanganj, and Gazipur together represented 117 robust groups and 166 factories, corresponding to 92.74% of the national weighting-robust factory population.

The within-district shares should be interpreted relative to the number of represented factories within each district and not as the proportion of the district's entire industrial sector affected by climate risk. For example, Dhaka contained 110 robust factories among 1,911 represented factories (5.76%), Narayanganj contained 54 among 716 (7.54%), and Gazipur contained two among 1,530 (0.13%).

Districts with smaller represented factory populations require careful interpretation. For example, Gopalganj showed a 100% within-area share because all six represented factories belonged to robust groups, but this percentage reflects a small denominator and should not be compared directly with larger industrial districts such as Dhaka or Narayanganj.

Table 5: Geographic concentration of weighting-robust hotspots

Geography	All factories	Robust groups	Robust factories	Within-area share	National share	robust-factory
Dhaka	1,911	79	110	5.76%	61.45%	
Narayanganj	716	36	54	7.54%	30.17%	
Gopalganj	6	4	6	100.00%	3.35%	
Manikganj	9	5	5	55.56%	2.79%	
Gazipur	1,530	2	2	0.13%	1.12%	
Jhalokati	1	1	1	100.00%	0.56%	
Jhenaidah	1	1	1	100.00%	0.56%	
Dhaka-Gazipur-Narayanganj	–	117	166	–	92.74%	

Note. District rows include locations with at least one factory represented by a weighting-robust hotspot. The final row aggregates Dhaka, Gazipur, and Narayanganj. Within-area share uses all represented factories in the corresponding district as the denominator; national

robust-factory share uses the 179 factories represented by the national robust-hotspot set as the denominator. A detailed view of the Dhaka–Gazipur–Narayanganj industrial belt is provided in Figure A1.

5 Discussion

5.1 *Climate priority is predominantly multi-dimensional*

The clearest substantive result is that weighting-robust hotspots were generally characterised by elevated scores across multiple dimensions rather than by a single dominant climate pressure. Among the 128 weighting-robust coordinate groups, 72 groups (56.25%) had at least three components with scores of 75 or higher, while only three groups had fewer than two components at or above this threshold.

The term multi-dimensional requires careful interpretation. The framework does not simulate the physical interaction, causal relationship, or temporal co-occurrence of all four climate-related processes. Therefore, it should not be interpreted as a compound-event model. Instead, it identifies production locations that demonstrate high relative priority across multiple climate-relevant dimensions. This interpretation is consistent with broader understanding of cascading climate impacts through interconnected infrastructure and economic systems, while recognising that the present framework does not jointly model these processes (Intergovernmental Panel on Climate Change, 2022).

Component decomposition also provides operational value. A high final priority score may arise from different combinations of underlying pressures, such as ambient heat burden, climate-logistics vulnerability, direct river-flood exposure, or extreme-rainfall intensification. Maintaining these component profiles prevents the composite index from becoming an opaque ranking and allows adaptation strategies to be matched with the dominant contributing factors.

5.2 *Robustness strengthens rather than eliminates uncertainty*

The sensitivity analysis indicates that the overall ranking structure was highly stable, while uncertainty remained more substantial near the upper-tail selection threshold. All alternative weighting scenarios produced Spearman correlations above 0.95 with the primary model, indicating that broad national ordering was not dependent on a single weighting specification.

However, top-decile overlap showed greater variation, particularly under rainfall-emphasised weighting. This demonstrates that ranking stability and threshold membership stability are different concepts. Locations near a fixed intervention threshold may move into or outside the selected group even when their overall relative ordering remains highly similar.

The weighting-robust intersection provides a conservative prioritisation rule. Rather than identifying locations selected under only one weighting assumption, it identifies the smaller set of locations that remain consistently prioritised across all tested weighting scenarios. This follows composite-indicator guidance that methodological sensitivity should be assessed and reported rather than hidden within a single specification (OECD et al., 2008).

The robustness analysis does not remove uncertainty from the framework. It only evaluates uncertainty associated with the tested weighting assumptions. Other uncertainties, including source-data limitations, coordinate accuracy, hazard-model uncertainty, road-network completeness, and future climate conditions, remain outside the scope of the analysis.

5.3 *Heat is important but is not measured occupational heat stress*

Although heat was the most frequent dominant component among weighting-robust groups, it represented the dominant component in fewer than half of these locations. Therefore, the results should not be interpreted as a heat-only assessment or as evidence that the identified factories are necessarily the hottest workplaces in Bangladesh.

Previous research on Bangladesh's RMG sector has demonstrated that workplace heat exposure can affect worker conditions and productivity, and that cooling interventions can reduce physiological strain under extreme-heat conditions (Smallcombe et al., 2025; Yeasmin et al., 2025). However, these studies involve workplace-level exposure measurements or experimental assessments, whereas the present heat component uses outdoor climate reanalysis data.

Accordingly, the appropriate interpretation of the heat component is as a screening indicator for locations where detailed occupational heat assessments may be warranted. Such assessments may include indoor temperature and humidity monitoring, evaluation of ventilation and building conditions, cooling interventions, hydration practices,

work-rest arrangements, and worker health investigations. The component should not be considered a substitute for workplace-level occupational heat measurements.

5.4 *Flood and logistics are related but not redundant*

The strongest pairwise correlation among the final components was observed between flood and logistics (0.607). This relationship is methodologically understandable because the climate-logistics component explicitly incorporates surrounding road exposure to flood conditions. However, the two dimensions represent different exposure pathways.

The flood component (F_i) represents modelled inundation exposure at the production coordinate, whereas the logistics component (L_i) represents surrounding transport accessibility vulnerability based on road-network exposure, including the proportion of strategic-road length within 5 km exposed to RP100 flood depth at or above 0.30 m. Therefore, a factory may have relatively low direct modelled flood exposure while still receiving a high logistics vulnerability score because surrounding access routes are exposed.

This distinction is important for adaptation planning. Site-level flood protection, drainage improvement, equipment elevation, and emergency procedures address different mechanisms from transport-focused measures such as route redundancy, bridge assessment, access-corridor drainage, and transport contingency planning.

5.5 *Geographic concentration creates a supply-network concern*

A notable finding from the supply-chain perspective is the geographic concentration of weighting-robust hotspots within Dhaka, Narayanganj, and Gazipur. These three districts together contained 92.74% of the national weighting-robust factory population. This concentration does not imply that all identified locations will experience simultaneous failure during a climate event. Rather, it indicates that a relatively small geographic region contains a substantial share of locations consistently prioritised under alternative weighting assumptions.

The importance of the Greater Dhaka manufacturing and transport system in Bangladesh has also been recognised in previous logistics research (Herrera Dappe et al., 2020). The concentration of robust hotspots therefore has implications beyond individual factories. Shared infrastructure, including roads, drainage systems, bridges, worker commuting routes, electricity networks, and industrial-service infrastructure, may create common dependencies across multiple production locations.

The results therefore support analysis at both facility and industrial-cluster levels. However, geographic interpretation requires careful consideration of denominators. District contribution to the national robust-hotspot population and within-district robust shares represent different measures. For example, Gazipur contributed only two robust factories despite having a large represented factory population, while smaller districts such as Gopalganj showed high within-area percentages because of smaller denominators. Therefore, district-level percentages should be interpreted together with represented factory counts.

5.6 *Managerial and policy implications*

The framework supports a sequential approach of “First Screen, Second Diagnosis, Third Investment.” A heat-dominated hotspot may warrant detailed occupational-heat assessment, while a flood-dominated hotspot may require site-level investigation of flooding, drainage, elevation, and emergency access conditions. Similarly, logistics-dominated hotspots may require assessment of route redundancy, bridge dependencies, corridor drainage, and transport contingency planning.

Locations characterised by multiple elevated dimensions may require coordinated interventions rather than single-hazard responses.

For brands and buyers, the results may support supplier-resilience engagement, geographic portfolio assessment, and targeted discussions regarding adaptation priorities. However, the framework should not be used as a standalone mechanism for supplier penalty or exclusion. The model does not include management quality, existing adaptation capacity, buyer dependence, production value, or facility-level resilience measures. A highly prioritised facility may already have substantial resilience measures in place, while a lower-priority facility may still contain important vulnerabilities not represented in the current framework.

From a public-policy perspective, the geographic concentration of robust hotspots identifies areas where infrastructure-level adaptation may provide benefits across multiple production locations. Transport corridors,

drainage systems, bridges, urban flood-management measures, and industrial heat-adaptation programmes often extend beyond the responsibility of individual factories.

5.7 Limitations

Several limitations define the interpretation and application of the framework.

First, the final score represents a relative climate-priority index rather than a probability model. It does not estimate expected economic losses, probability of factory failure, or likelihood of production interruption.

Second, the analysis relies on coordinate-group representation. Some coordinates represent multiple factories or industrial areas, and the framework does not assume building-level precision for every individual facility.

Third, the river-flood component is based on modelled inundation exposure from GloFAS and should not be interpreted as building-specific flood depth. It does not represent urban pluvial flooding, local drainage performance, or observed historical damage.

Fourth, the spatial resolution of CHIRPS and ERA5-Land is coarser than the scale of individual factory locations. Thus, rainfall and heat values are not exact facility measurements, but rather values at the climate-cell level. Moreover, the rainfall-intensification comparison uses the five-year recent period (2021–2025) against the 1991–2020 baseline. Because the recent period is relatively short, the estimated changes may also reflect interannual variability and should not be considered evidence of a long-term rainfall trend.

Fifth, ambient heat should not be interpreted as occupational heat stress. The framework does not include indoor temperature, humidity, workload, ventilation, clothing, building characteristics, or cooling conditions.

Sixth, the climate-logistics component is an exposure proxy derived from OpenStreetMap road geometry and flood-depth sampling. It does not directly measure observed traffic disruption, road passability, travel-time changes, traffic capacity, destination-specific routing, or post-event recovery.

Seventh, the framework does not include a comprehensive adaptive-capacity dimension. Information regarding production value, buyer dependence, inventory strategies, financial resilience, structural protection, backup power, insurance coverage, and emergency planning is not available consistently across the represented factory population.

Finally, the weighting-robust hotspot set demonstrates stability only across the six tested weighting specifications. It should not be interpreted as universal stability across all possible hazard models, normalisation procedures, weighting choices, or future climate scenarios.

6 Conclusion

This study developed a transparent and spatially explicit framework to identify climate-priority locations within the represented RMG production network in Bangladesh. The framework linked 4,784 factory records not marked as closed, represented by 2,579 coordinate groups, with four climate-relevant dimensions: direct river-flood exposure, ambient heat burden, positive extreme-rainfall intensification, and climate-logistics vulnerability.

A total of 2,576 coordinate groups were suitable for complete four-component assessment. Under the equal-weight primary specification, 2,299 factories were classified within High or Very High priority groups. The resulting national rankings remained highly consistent across alternative weighting scenarios, although upper-tail membership showed greater sensitivity, particularly when increasing the weight assigned to rainfall.

Using a conservative intersection approach, 128 coordinate groups representing 179 factories remained within the top decile across all six weighting scenarios. These weighting-robust hotspots were predominantly multidimensional, with 117 groups representing 166 factories concentrated within Dhaka, Gazipur, and Narayanganj.

The main contribution of this study is not a prediction that these locations will experience the greatest future losses. Instead, the framework identifies a relatively small set of production locations where multiple climate-relevant factors combine to maintain high prioritisation under reasonable changes in component importance. These locations provide defensible candidates for further facility-level assessment, including occupational-heat, flood, infrastructure, and logistics-resilience evaluations.

Data Availability

Datasets used in this study were sourced from openly available or research-accessible sources, including Open Supply Hub, JRC/Copernicus Emergency Management Service, CHIRPS, ERA5-Land, geoBoundaries, and OpenStreetMap/Geofabrik data. Derived analytical outputs supporting the findings reported in this study are available from the corresponding author upon reasonable request, subject to the terms and restrictions associated with the underlying source datasets.

Code Availability

Analysis code used to generate the results presented in this study is available from the corresponding author upon reasonable request.

Funding

This research received no specific funding from any public, commercial, or not-for-profit funding agency.

Competing interests

The authors declare no competing interests.

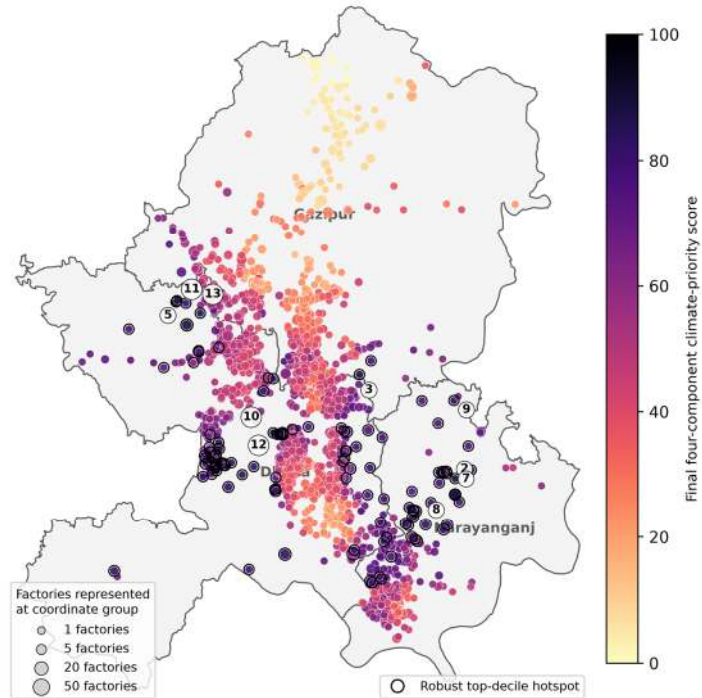
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A. Industrial-belt detail

Climate-Priority Hotspots in Bangladesh's Principal RMG Industrial Belt Dhaka, Gazipur, and Narayanganj



Black rings indicate locations remaining in the national top decile under all weighting scenarios. Numbers identify national final-priority ranks for the ten highest-scoring locations within the three-district belt.

Figure A1: Final climate priority in the Dhaka–Gazipur–Narayanganj industrial belt.

Note. Colour denotes the final climate-priority score. Black rings identify coordinate groups in the 128-group weighting-robust national top-decile intersection. Labels show the existing national final-priority ranks for the highest-scoring industrial-belt locations; no scores or rankings were recalculated for this figure.