

Spatial Targeting of Adaptive Social Protection in South Asia: An Analysis of Climate-Economy-Disease Hotspots and Policy Gaps

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Abstract

Climate elements, economic conditions, and vector-borne diseases are associated with one another. However, existing research has not sufficiently investigated the simultaneous spatiotemporal patterns of these three factors. This study aims to examine these together, focusing on South Asia, which is particularly vulnerable to them. Specifically, it visualizes regions where climate, economic, and disease stresses overlap spatiotemporally as overlapping hotspots, compares these hotspots with existing policy coverage to identify policy gaps, and proposes how Adaptive Social Protection (ASP), as a policy framework that addresses these three stresses, can be implemented. Understanding this is significant for providing evidence to implement equitable and shock-responsive policies in a data-driven manner that would help address sustainable development goals (SDGs). We created an analytical data frame at the administrative area level 1 (ADM1) by including all but one South Asian Association for Regional Cooperation (SAARC) countries from 2012 to 2022 by merging monthly data on temperature, precipitation, nighttime light, and dengue fever from open data sources. Robust stress variables are built, typified, and hotspot analysis is conducted based on the contiguity and spatial correlation of stress variables. Combining classification of regions and hotspot analysis results enabled the identification of areas experiencing sustained high stress levels, which are otherwise difficult to capture within a single sector. Furthermore, these hotspots are compared with existing policy documents at the country-level (ADM0), thereby allowing analysis of policy prioritization. Based on this assessment, policy implications, including the spatial targeting of ASP, are suggested for each country in the SAARC region.

1. Introduction

Climatic elements, such as temperature and precipitation, are important determinants of economic conditions (Bilal & Känzig, 2024; Kotz et al., 2025). The Intergovernmental Panel on Climate Change (IPCC) report says that the variability of climate elements increases exposure to livelihood risks and economic losses (Pörtner et al., 2022), and Linsenmeier (2023) shows that temperature variability is related to the changes in economic activity as proxied by nighttime light intensity. These kinds of climatic impacts on the economy also have an uneven property, which is exemplified by multiple studies. For example, the low-income population suffers from climate shocks when social protection does not work effectively for mitigation (Bangalore et al., 2016), and extreme heat reduces economic growth, particularly in poor tropical regions (Callahan & Mankin, 2022). Bangalore et al. (2017) also show that climate change-driven natural hazards lead to income and consumption losses among poorer populations. In addition, climatic elements are also associated with vector-borne diseases (VBDs). It is said that temperature affects mosquito survival, biting rates, and disease transmission (Mordecai et al., 2019) and that climatic suitability for dengue transmission may expand mainly in tropical regions (Messina et al., 2020). Evidently, in terms of sustainable development goals (SDGs), climate change (SDG13)-related events act as a threat multiplier impacting almost all the SDGs.

On the other hand, disease burdens do not always depend only on climate conditions. Disease burden corresponds to the economic conditions, such as population density, urbanization level, and the capacity to detect disease transmission (Colón-González et al., 2021). Connectivity to urban networks also affects disease spreading (Lee et al., 2021). Romanello et al. (2021) suggest that the vulnerability to VBDs depends on environmental exposure, socioeconomic conditions, and access to healthcare services.

Taken together, based on the literature, there likely exists a triad linkage among climatic elements, economic conditions (or vulnerability), and VBDs. Analyzing these linked components separately may lead to inadequate policy design and loss of resources. For example, if the linkage between climate risks and economic vulnerability is not considered, communities that are vulnerable to VBDs may not be protected sufficiently, and likewise, if we fail to integrate all three stress components (United Nations Development Programme, 2023). Health risks also cannot be captured by assessments focusing only on single hazards (Cissé et al., 2022). To our knowledge, existing studies have not examined these three components simultaneously, and there are few studies that investigate their joint spatiotemporal patterns (Segovia-Dominguez et al., 2022; Lober et al., 2024). This leads us to asking the following questions: 1) where do climatic, economic, and disease stresses overlap in space and time?, 2) whether the existing policy coverage across stress categories aligns adequately with the required stress mitigation needs?, and 3) is it possible to propose a desirable way to implement a policy framework that covers the three compounded stresses, particularly for vulnerable countries in the South Asian Association for Regional Cooperation (SAARC) region?

For the first question, spatiotemporal data analysis would provide an answer by visualizing areas of composite stresses across countries and over the years included in the study. For the second question, the comparison between such data analysis results and policy document analysis would enable the detection of a match or mismatch. In other words, this question focuses on exploring the gap between the current stress situation and the existence of a corresponding policy measure to address those stresses. On the other hand, the third question requires two viewpoints. One is a policy framework called Adaptive Social Protection (ASP). ASP is a framework that connects social protection with climate change adaptation and disaster risk reduction (DRR), which emphasizes support to vulnerable populations (Rana et al., 2022). Compared to traditional social protection programs that do not explicitly state climate concerns, ASP aims to build resilience to climate shocks (Kundo et al., 2023a), and to enhance the capacity of poor and vulnerable households to adapt to climate

shocks (Bowen et al., 2020). ASP or existing social protection programs sharing similar concepts are promoted particularly in countries exposed to climate risks. For example, the Hunger Safety Net Programme in Kenya is a social protection program for drought-prone regions (Maione, 2020). The Benazir Income Support Programme in Pakistan has been used as a platform for shock-responsive social protection (Watson et al., 2017). The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) is a large-scale programme in India that guarantees up to 100 days of wage employment per year to rural households, although its effectiveness may be undermined by administrative rationing and delayed wage payments (Narayanan et al., 2017). These examples represent attempts to connect existing social protection systems to responses to climate shocks. Meanwhile, social protection is not often geographically targeted due to a lack of high-resolution poverty data, which makes it difficult to support the poor and vulnerable areas (Smythe & Blumenstock, 2022). In this context, despite its potential, the spatial targeting of ASP remains insufficient. Thus, proposing how the spatial targeting of ASP can be improved is significant to addressing compounded stresses thereby directly addressing some of the SDGs, such as no poverty (SDG1), zero hunger (SDG2), good health and well-being (SDG3), gender equality (SDG5), and reduced inequalities (SDG10).

As a second viewpoint, more specifically, this research focuses on South Asia as vulnerable countries suitable for examining how ASP should be allocated. The region is highly exposed to climate hazards, such as floods, heatwaves, and tropical cyclones (Lange et al., 2020). Moreover, of the extremely poor and vulnerable people who could be living in the most hazard-prone countries in the following decades, the majority would be from South Asia and sub-Saharan Africa (Chung et al., 2026; Lenhardt et al., 2013). Higher temperatures can also affect dengue transmission and increase epidemic potential in South Asia (Sophia et al., 2025; Damtew et al., 2023; Siraj et al., 2017). Here, the area of interest includes seven out of the eight countries of the SAARC region, comprising Afghanistan (AFG), Bangladesh (BGD), Bhutan (BTN), India (IND), Nepal (NPL), Pakistan (PAK), and Sri Lanka (LKA). We excluded Maldives (MDV) from this study due to non-availability of complete data for the study duration, as explained later in the next section. Given that SAARC is exposed to these compounded risks, spatial targeting of ASP would be necessary for the countries in the SAARC region to reduce such future risks.

Against this background, this study aims to spatially analyze stresses from three perspectives – climate, economy, and VBDs – over the study period to identify hotspots in South Asia, assess the existing policy coverage, and propose data-driven ASP allocation. The findings provide evidence for hotspot-based spatial targeting of ASP, helping policymakers prioritize limited resources toward regions facing multiple risks.

The remaining manuscript is structured as follows. Section 2 describes the data used in our analysis next, followed by the methods employed. Section 3 presents the results and a discussion around our findings. Finally, we present conclusion, including limitations and scope for future work.

2. Materials and methods

2.1. Materials

2.1.1. Data

First, the geo-boundary data at the administrative area level 1 (ADM1) for the SAARC region are collected from the geoBoundaries database, an open-source global administrative boundary dataset (Runfola et al., 2020). In parallel, the three categories of indicators are collected: climate (temperature and precipitation), economic activity (nighttime lights), and infectious disease risk (dengue sensitivity). For temperature, monthly temperature data (in °C) from 1958 to 2024 are downloaded from TerraClimate (Abatzoglou et al., 2018). For precipitation, daily precipitation data (in mm) from 1981 to 2025 are downloaded from the Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015). For economy, monthly nighttime light data (in nW/cm²/sr) available from 2012 onward are downloaded from the Visible and Infrared Imaging Suite (VIIRS) Day/Night Band (DNB) composites, provided by the Earth Observation Group at the Payne Institute for Public Policy (Earth Observation Group, n.d.). In general, nighttime light data have been used as a proxy for economic activity in several studies (Gibson and Boe-Gibson, 2021; Chen et al., 2022). For disease, the monthly maps of the Dengue Suitability Index P from 1979 to 2022 are downloaded from the *figshare* dataset (Nakase & Lourenco, 2022). Index P is a proxy measure of the transmission potential of a single mosquito, where higher values of Index P are associated with greater potential for infection spread (Nakase et al., 2023). As an exception, Maldives is excluded from further analysis due to the lack of index P data at this stage. Therefore, the four datasets are downloaded for seven countries in SAARC: Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka. In addition, we have retained the terminologies at the ADM1 level for the SAARC member states included in the study. Primarily, in Afghanistan, Nepal, Pakistan and Sri Lanka it is called a province, in Bangladesh it is a division, in Bhutan it is a district, and in India it is a state.

2.2. Methods

2.2.1. Data preparation and integration

The four datasets are converted into one data frame in a common spatiotemporal unit through the following data harmonization steps. First, daily precipitation is summed to monthly totals for all the datasets to be adjusted to a monthly time scale. Second, zonal means of the monthly datasets are calculated for each ADM1 polygon. Finally, the datasets are merged into one data frame.

All data processing and harmonization are conducted using Python (version 3.12) (Python Software Foundation, 2023), with libraries, such as pandas and geopandas, as well as Google Earth Engine (Gorelick et al., 2017) for processing remote sensing data. As the datasets cover different temporal ranges, the analysis is restricted to the common period for which all indicators are available.

2.2.2. Variable construction

The merged data frame is processed for building variables comparable to each other. In particular, the four indicators undergo a standardization with their directionality aligned, thereby being transformed into “stress” variables. For standardization, robust standardization using median and median absolute deviation (MAD) is employed. While standardization using mean and standard deviation (SD) is sensitive to extreme values, standardization using median and MAD is more robust to outliers (Huber & Ronchetti, 2009). Robust standardization is applied uniformly for obtaining robust z-scores of the four indicators across all countries and periods. The stress variables are then scaled on 0 to 1, ensuring comparability across stresses.

More specifically, the construction for each stress variable is as follows. For temperature, it is treated as a two-sided variable, where extreme high or cold temperature reflects greater stress. The *temperature stress* is computed as the standardized deviation from the seasonal median and mapped to the 0–1 range, and thereby higher values can be interpreted as high heat or cold stress. For precipitation, the *precipitation stress* is measured as a two-sided deviation from the seasonal median, which can reflect both extreme rainfall and drought conditions. The absolute deviation is standardized and rescaled to the 0–1 range, where larger values indicate greater departures from the seasonal median, that is, higher precipitation stress, while values closer to the seasonal median, corresponding to smaller deviations, indicate lower stress. For nighttime light, it is regarded as a one-sided variable, where a lower value reflects a worse condition. The *economy stress* is constructed through an inverted scaling, and thereby darker areas can correspond to higher stress. For index P, it is treated as a one-sided variable, where higher values correspond to greater disease-suitability. The *disease stress* is scaled to the 0–1 range, and thereby higher values can indicate greater disease suitability.

2.2.3. Classification of stresses

Classification of stresses is a supportive analysis for the subsequent hotspot analysis, and these two analyses are conducted in parallel. Namely, hotspot analysis is deepened by investigating the composition of stresses’ discrete categories based on classification for each hotspot derived from continuous stress values. In classification, stresses are categorized into three groups: low (L), medium (M), and high (H) stress, by the 33rd and 66th percentiles. For temperature and precipitation, a composite *climate stress* is defined from temperature stress and precipitation stress using a union rule. For example, if either stress is classified as high, the composite stress is set to high. In this way, climate stress can capture extreme temperature or precipitation at once. For the subsequent hotspot analysis, climate stress is defined as a continuous measure, taking the higher of temperature stress and precipitation stress for each observation.

2.2.4. Hotspot analysis

Spatial concentrations of high stress are detected by the following steps. First, following a standard practice in spatial analysis (Anselin, 2002), neighbors are identified based on Queen contiguity, where polygons sharing either a boundary or a vertex are neighbors. Second, based on this definition of neighbors, local spatial association is computed using local Moran’s I. Local Moran’s I compares each ADM1’s stress value with those of its neighbors and detects statistically significant local clusters (Anselin, 1995). In this study, high-high (HH) clusters are considered as hotspot candidates.

Third, for each ADM1 and each month, *p*-values derived from Moran’s I are adjusted using the Benjamini-Hochberg false discovery rate (FDR) method (Benjamini & Hochberg, 1995) to consider multiple testing. An ADM1-month pair is classified as a hotspot if it meets either of two criteria: whether the HH cluster remains significant after FDR correction, or whether the HH cluster has a *p*-value below 0.10.

Fourth, to reduce sensitivity to fluctuations, the definition of persistence is applied because single-month hotspots can be transient. This idea is consistent with studies showing that climate extremes are defined as sustained patterns lasting consecutive days (Perkins and Alexander, 2013). In particular, economic hotspots must persist for at least three consecutive months to reduce sensitivity to short-term fluctuations, and climate and disease hotspots must persist for at least two months, as these processes can change over shorter time scales.

In this study, a hotspot is defined as an ADM1 region that forms a statistically significant HH cluster of stress values relative to its neighboring regions and satisfies the persistence criteria described above. Accordingly, the hotspot analysis identifies relatively high and spatially persistent stresses rather than temporary or localized shocks. As a result, acute events like short-term disasters do not always appear as hotspots in our study if their impacts are limited to specific areas or not sustained over time.

2.2.5. Qualitative policy coverage assessment

The identified hotspot patterns are compared with accessible policy documents at the ADM0 level. We assess policy documents published between 2007 and 2026, limited to English-language documents. Policy documents are reviewed to identify themes, with ChatGPT (a large language model) (OpenAI, 2025) used to support text summarization and preliminary review where necessary. The authors also manually review the policy documents to corroborate the findings generated by ChatGPT. We find a strong convergence between the results obtained through the ChatGPT-assisted review and the authors’ independent assessments.

Given that the hotspot analysis identifies the areas where high stress persists over time relative to surrounding areas and that such areas require long-term support, in the policy coverage assessment, policy documents are reviewed to assess whether or not the areas with chronic stress are prioritized within the existing policy focus with relevant policy implementation or spending. Specifically, hotspot analysis results are compared with disaster risk management (DRM), social protection, and vector control strategies, and where possible, with budget allocations or climate mitigation and adaptation planning. These comparisons identify spatial matches or mismatches between observed hotspot patterns and existing policy frameworks.

3. Results and discussion

3.1. Data preparation and integration

The merged data frame covers the common period from April 2012 to December 2022 (129 months) and 121 ADM1 regions: 34 in Afghanistan, 8 in Bangladesh, 20 in Bhutan, 36 in India, 7 in Nepal, 7 in Pakistan, and 9 in Sri Lanka. Table 1 shows summary statistics for the four indicators.

Table 1 Summary statistics of the four indicators				
The number of observations (n), missing values, minimum, maximum, mean, and standard deviation (SD) for precipitation, temperature, nighttime light, and index P.				
Indicators	min	max	mean	SD
Precipitation (mm)	0.00	1,352.8	99.9	142.4
Temperature (°C)	-19.4	37.9	17.8	10.5
Nighttime light (nW/cm ² /sr)	-0.19	44.6	0.95	3.19
Index P	0.00	3.84	0.34	0.71

There are 15,609 observations for each indicator, and no missing values are found. For precipitation, it shows a large SD reflecting a difference across regions and months. For temperature, it varies from – 19.4 to 37.9 with mean = 17.8, which means a more stable distribution than the other indicators. For nighttime light, its distribution is skewed with mean = 0.95 and maximum = 44.6, reflecting that most observations are low while a few observations are high. Likewise, index P is skewed (mean = 0.34, SD = 0.71), meaning that most values are low while some are high.

3.2. Variable construction

Processing the merged data frame resulted in obtaining stress variables. Figure 1 shows the distribution of stress variables.

The distribution of stress values normalized to the range 0–1 for temperature, precipitation, economy, and disease.

Temperature stress is mostly near zero, while a small number of observations (5.91%) are between 0.2 and 1.0. Precipitation stress also has values near zero, but compared with temperature, more observations (99.84%) are concentrated near zero. In contrast, economy-related stress is mostly between 0.7 and 1.0, while a small number of observations (6.36%) are between 0.0 and 0.4. Disease stress is mostly around 0.4–0.5 with a few extreme values (20.81%). Evidently, the stresses differ in their distributions. Using these stress variables

allows the hotspot analysis to capture stress from multiple perspectives by detecting areas where different types of stress are concentrated.

3.3. Classification of stresses

Stresses are categorized into three groups, namely climate (C), economy (E), and disease (D), each of which is further categorized into three levels (H: high, M: medium, L: low). Figure 2 shows the 27 type frequencies aggregated across all periods and regions.

The frequency of the combinations of climate (C), economy (E), and disease (D) levels (H: high, M: medium, L: low).

The top three combinations (C = H, E = M, D = M; C = H, E = H, D = M; C = H, E = L, D = M) account for 34.49% of total observations. That is, climate stress is high while economy and disease stress are moderate to high. In contrast, the types where all three stresses are high (C = H, E = H, D = H) or low (C = L, E = L, D = L) do not occur frequently (3.47%, 0.51%, respectively). This distribution indicates that high climate stress is widely spread in South Asia, whereas economy and disease stress are not always high simultaneously. Considering this pattern, social protection systems should incorporate climate risks as a baseline condition rather than responding only after economic or health crises emerge, with the ideal scenario being integrating all of them (Nenning et al., 2023; Tenzing, 2020; Ulrichs et al., 2019).

3.4. Hotspot analysis

The hotspot for each stress (climate, economy, and disease) was detected and the map overlaying these three hotspot maps was visualized using Python libraries, including geopandas and matplotlib. Figure 3 shows the spatial distribution of hotspot overlap from 2012 to 2022.

The spatial distribution of hotspots overlaps across countries from 2012 to 2022.

Brighter colors indicate areas where climate, economic, and disease hotspots overlap within the same region. For example, if a region meets the criteria for hotspots for climate stress and disease stress but not for economy stress, the number of overlaps is 2, and the color in the figure becomes light green.

In this study, all stress variables are treated with equal importance, and the overlap measure reflects only the number of co-occurring stresses rather than their relative severity or specific combinations. Therefore, areas with the same number of overlaps may differ in their underlying stress composition (e.g., climate–disease versus climate–economy). Such differences are examined through the type composition analysis in Fig. 4.

While Fig. 3 identifies the spatial location and extent of hotspot overlaps, Fig. 4 shows the composition of stress types within spatially contiguous hotspot clusters for each year. Each stacked bar represents one hotspot cluster, and the number of clusters varies by year depending on the spatial distribution and connectivity of overlapping hotspots across the study region. For each cluster, the bars display the shares of climate, economy, and disease stress classified as low, medium, or high. The figure illustrates how the mix of stress types within hotspot clusters varies across regions and changes over time.

For each year, the figure shows the composition of climate, economy, and disease levels (H, M, L) in major high-stress regions.

To facilitate interpretation at the country level and to better understand vulnerability across the SAARC nations, the following subsections describe hotspot patterns by country, highlighting the specific ADM1 regions where hotspots persist over time. Hereafter, areas with an overlap of two or three hotspots are defined as “overlapping hotspots”, while those with zero overlaps (i.e., areas that are not hotspots for any of the stresses) are defined as “cold spots”.

3.4.1. Afghanistan

In Afghanistan, overlapping hotspots are concentrated in the western to southern parts of the country. Southern Helmand province is an overlapping hotspot from 2012 to 2013, 2015–2017, and 2019–2022, showing the persistent concentration over the study period. Southern Kandahar province is an overlapping hotspot in 2012, 2016–2017, and 2019–2021, while western Farah province in 2012, 2015–2017, and 2019–2021. Southern Zabul province is identified as a hotspot in 2012–2013, 2015, 2017 and 2019–2022, and Southwestern Nimruz province in 2012, 2016–2017, and 2019–2020. Overlapping hotspots repeatedly appear in western and southern Afghanistan. The type composition bars (Fig. 4) show that clusters around Helmand are characterized by medium to high levels of stresses across the climate, economy, and disease domains. This suggests the need for integrated responses in western and southern Afghanistan, where multi-stress hotspots persist over time.

3.4.2. Bangladesh

In Bangladesh, there are few overlapping hotspots in the country. The southern coastal Barisal division is an overlapping hotspot in 2014 and 2018, but most of the other parts are not. Dhaka is a cold spot in 2012, 2014–2017, 2019–2020, and 2022, and western Rajshahi in 2012 and 2015–2022. Overall, the results indicate that hotspots do not persist over time. The type composition bars show that climate (H), economy (H), and disease (H) make up a large share in Barisal in 2014 and 2018. This pattern may reflect the influence of climatic factors such as precipitation variability and flood risk in coastal areas, as well as Barisal's proximity to the Bay of Bengal, which may increase exposure to climate-related stresses. This suggests the need for targeted interventions in coastal regions facing episodic multi-stress conditions. Bangladesh could also adapt from the successful measures taken by the Odisha state government in India, which has led to significant reduction in negative impacts among vulnerable coastal communities who were exposed to climate-driven super cyclones.

3.4.3. Bhutan

In Bhutan, overlapping hotspots tend to concentrate over the years from the southern to the eastern parts of the country. The southern Sarpang district is identified as an overlapping hotspot in 2012–2013, 2017–2020, and 2022. In the south-central Zhemgang district, an overlapping hotspot appears in 2013–2014, 2017–2020, and 2022. The east Trashigang district is an overlapping hotspot in 2012–2014, 2017–2020, and 2022, and the southeastern Samdrup Jongkhar district is an overlapping hotspot in 2013, 2017–2018, and 2021. In addition, the southeastern Pemagatshel district is identified in 2012–2015, 2017–2018, 2020, and 2022. Overall, overlapping hotspots are observed over time from the southern to eastern districts of Bhutan, while the northern to western districts tend to be cold spots. Looking at the type composition, it is notable that all stresses are often medium to high, but the total share of D = M and D = H tends to be relatively higher. This suggests the importance of addressing disease-related risks in persistent hotspot regions.

3.4.4. India

In India, overlapping hotspots are detected across multiple regions at different times. In the northeastern region, overlapping hotspots are identified in Nagaland in 2012–2014, 2017–2018, and 2021–2022, in Arunachal Pradesh in 2012–2014 and 2017–2018, and 2021–2022, in Assam in 2013, 2017, and 2020–2022, Manipur in 2012–2013, 2016–2017, and 2021–2022, and in Mizoram in 2013, 2017, and 2021–2022. In the eastern regions, Odisha is an overlapping hotspot in 2013 and 2020. West Bengal is also identified in 2015 and 2020–2021. In the inland east, Bihar and eastern Jharkhand are detected in 2020–2021. In the western to central regions, Madhya Pradesh appears in 2014–2016 and 2018, while Chhattisgarh is identified in 2013–2016 and 2018. In addition, west-central Maharashtra appears in 2013–2016 and 2018–2019. In the northern and northwestern regions, Rajasthan is identified in 2012, 2014, 2016–2018, and 2021. Jammu and Kashmir appears in 2012–2018 and 2020, while Ladakh is detected in 2013–2014 and 2018. Himachal Pradesh is also identified in 2012, 2014, 2017–2018, and 2021. Uttarakhand appears in 2014, 2016, 2018, and 2021, and northern Uttar Pradesh is identified in 2018 and 2020–2021. In the southern regions, Tamil Nadu and Andhra Pradesh are overlapping hotspots in 2014–2019. Telangana appeared in 2014–2016 and 2018–2019. Kerala was identified in 2015 and 2018–2019, and Karnataka in 2013–2016 and 2018–2019.

According to the type composition bars, disease stress is mostly medium. Economic and climate stresses are mostly medium to high, and the share of C = H is often higher than that of E = H. As such, in India, climate stress would play a more dominant role than disease or economic stress. This highlights the need for flexible, region-specific responses to climate-related multi-stress conditions.

3.4.5. Nepal

In Nepal, overlapping hotspots tend to concentrate in the eastern part of the country. Koshi Province (Province 1) is identified in 2015, 2018–2019, and 2021–2022, with neighboring Bagmati Province, also identified in 2021–2022. In contrast, other provinces, including Madhesh Province (Province 2), Gandaki Province, Lumbini Province (Province 5), Karnali Province, and Sudurpashchim Province, are often cold spots. Regarding the type composition bars, all stresses are mostly medium to high, and the share of C = H is relatively higher, which suggests that climate stress would play a larger role than economic or disease stress in Nepal. This suggests the need to address climate-related risks in eastern hotspot regions such as Koshi and Bagmati.

3.4.6. Pakistan

In Pakistan, overlapping hotspots are observed over long periods, mainly in the southern part. Southwestern Balochistan province shows persistent hotspots from 2012 to 2015 and again from 2017 to 2022, with strong hotspots in 2013–2014 and 2017–2018. Southern Sindh province shows a similar pattern. There are overlapping hotspots from 2013 to 2015 and from 2017 to 2022, as well as strong hotspots in 2014, 2017, and 2022. In the northern Gilgit-Baltistan region, overlapping hotspots are observed in 2015–2016 and 2018. In the northeastern Azad Kashmir region, hotspots appear in 2012 and 2017–2018. In contrast, the central Punjab province and the northwestern Khyber Pakhtunkhwa are often cold spots. Overall, overlapping hotspots persist in the southern and southwestern regions and appear only in specific years in the northern mountain areas. With regard to the type composition bars, Balochistan and Sindh are medium or high across the three stresses. Gilgit-Baltistan and Azad Kashmir are mostly medium or high in climate and economy, while disease is mainly low. This may seem counterintuitive, but in high-altitude, mountainous regions such as Gilgit-Baltistan and Azad Kashmir, factors including

elevation, low population density, low availability of standing water for vector breeding, and cooler temperatures at higher elevations may limit the transmission of vector-borne diseases. This suggests the need for integrated approaches in southern Pakistan and targeted climate-economic strategies in northern mountainous regions.

3.4.7. Sri Lanka

In Sri Lanka, overlapping hotspots concentrate in the northern to western parts. The Northern province experienced an overlapping hotspot from 2014 to 2016 and from 2018 to 2020, and the Western province from 2013–2016, 2018, and 2020. Overlapping hotspots are also observed in other parts, but the occurrence period is relatively limited. Overlapping hotspots are in the Central province in 2014–2015 and 2017, in the Eastern province in 2014–2015, and in the northern central province in 2018. Looking at the type composition bars, the Northern province is mostly high across climate, disease, and economy. In contrast, in the Western province, economic stress is mostly low, while disease stress is low to medium, and climate stress is medium to high. This highlights the need for region-specific responses, including integrated interventions in the Northern province and climate-focused strategies in the Western province.

In the next section, we present the findings based on the qualitative analysis of accessible policy documents at the country-level (ADM0) that help us determine if existing policy measures adequately addresses the levels of stress. The gaps, if any, will help in policy prioritization with an aim to help mitigate the stresses in future, which will potentially have a positive impact on addressing several SDGs.

3.5. Qualitative policy coverage assessment

The following is a country-level (ADM0) policy coverage assessment, which examines matches and mismatches by comparing hotspot analysis results with information in policy documents. Here, “match” and “mismatch” refer to the presence of policies targeting hotspots and to a discrepancy between hotspots and existing policies, respectively. To improve transparency and reproducibility, the policy documents reviewed in the qualitative assessment are listed in Supplementary Material.

3.5.1. Afghanistan

A range of climate risk management and adaptation measures have been implemented at the national level. On the fiscal side, the Fiscal Strategy Paper 2021 by the Ministry of Finance regards social protection as a sector supporting vulnerable groups. While the public expenditure is classified at the sector level, the document does not indicate whether social protection spending is geographically targeted toward specific areas (Ministry of Finance, Afghanistan, 2021).

On the health side, the World Health Organization (WHO) has published situation reports on surveillance (World Health Organization, 2025). These reports monitor the reported cases, including dengue fever cases, indicating that they rely on a case-based approach. According to the United Nations Office for Disaster Risk Reduction (UNDRR), DRM policy has been adopted by the Afghanistan Disaster Risk Reduction National Strategy (United Nations Office for Disaster Risk Reduction, 2021). This policy reflects limited institutional capacity for transforming national strategies into place-specific action.

When compared with overlapping hotspots mainly in the western to southern parts of Afghanistan, we believe there would be mismatches between current policy approaches and spatial targeting. Although sectoral frameworks are in place, they are sector-based, event-based, or case-based. In this context, the hotspot analysis provides a complementary perspective for informing where ASP could be targeted at the subnational level.

3.5.2. Bangladesh

The National Plan for Disaster Management notes that Bangladesh is exposed to water-related hazards. The plan reports that recent disasters have caused economic losses of about 0.8–1.1 percent of GDP and identifies low-lying coastal areas as especially high-risk regions (Ministry of Disaster Management and Relief, 2020). For DRM, national policies are set at the country level, and long-term planning documents recognize spatial differences in risk by identifying multiple hotspot regions, including coastal areas. However, they do not explicitly prioritize specific regions, such as coastal Barisal (Government of Bangladesh, 2018). For social protection, Bangladesh has an established framework, the National Social Security Strategy (NSSS), while programs by different ministries are still fragmented (Government of the People's Republic of Bangladesh, 2022). Geographic targeting and the prioritization of chronically vulnerable areas are also not clearly stated. For dengue control, it relies on surveillance and post-outbreak actions. As a result, the current situation is insufficient to decrease future dengue risk (Hossain et al., 2023). Taken together, while the targeting approach for social protection is unclear and vector control is primarily retroactive, the DRM policies recognize overlapping hotspots, including the southern coastal areas, such as Barisal. Thus, hotspots and policies “partially match”. This cannot be considered a complete match, as it is not explicitly stated that policies are being implemented in a way that prioritizes regions like Barisal.

3.5.3. Bhutan

According to a review of the social protection system by the Government of Bhutan and the United Nations Children's Fund (UNICEF), social protection is defined as a national responsibility under Article 9 of the Constitution, and the 13th Five-Year Plan sets a goal to build a social protection system by 2029. However, current programs are fragmented across several institutions, and data systems are not well integrated (United Nations Children's Fund & Office of Cabinet Affairs & Strategic Coordination, 2025).

Dengue control is implemented under the Aedes Vector Surveillance and Control Guideline, which is based on the idea that dengue outbreaks are seasonal and sets actions for different transmission periods (Ministry of Health, 2020). However, the guideline does not address areas where dengue risk continues or explain how dengue control should be linked with long-term social protection. DRM policies also include hazard and vulnerability assessments and district-level planning, focusing on emergency response and recovery, but they do not explicitly prioritize specific regions, such as the southern or eastern areas (Ministry of Works and Human Settlement, 2021). Comparing these policies with the overlapping hotspots in the south and east for multiple years indicates that there would exist mismatches between short-term, event-based policies and areas facing long-term vulnerability. From the perspective of ASP, this suggests a need for long-term, place-based support in hotspot areas that link health risks, disaster risk, and social protection.

3.5.4. India

Between 2012 and 2022, India experienced climate shocks, such as heatwaves, heavy rainfall, floods, and cyclones. These events did not happen in a particular location, and they hit multiple states in different years, which means that the risk pattern is transitive (India Meteorological Department, 2022). To address such situations, India has several national-level climate policies. For example, the National Action Plan on Climate Change (NAPCC) sets mitigation goals and gives a framework for sector plans (Government of India, 2008). Thereafter, the mitigation targets were updated in the Nationally Determined Contribution (NDC), which put an emphasis on low-carbon growth (Government of India, 2022).

At the subnational level, states have different priorities. Odisha's State Action Plan on Climate Change (SAPCC) (2018–2023) focuses on coastal risks and adaptive planning across sectors (Government of Odisha, 2018). The Rajasthan Action Plan on Climate Change (RAPCC) focuses on dry conditions relative to chronic water stress, drought, and heat (Government of Rajasthan, 2012). Assam's SAPCC emphasizes flood risk across the sector (Government of Assam, 2015). This demonstrates the existence of subnational-level plans, though implementation differs by capacity and finance. This finding is corroborated by Chaudhry et al. (2025) who studied the status of State Action Plan on Climate Change and Human Health (SAPCCHH) across four Indian states and concluded that inadequate funding and poor planning has limited the capacities of several existing plans to obtain their desired levels of outcome. This reiterates the importance of integrating climate-related mitigation plans with hotspot-based findings for obtaining efficient and desirable outcomes.

For dengue risk, India has clinical guidelines and prevention measures, but these are often season-based ones (Government of India, 2023). For social protection, the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) supports resilience, but the link to climate risk remains uneven across locations (Steinbach, 2020). For DRR, India improves the national framework with the National Disaster Management Plan (NDMP), with an emphasis on prevention and preparation (Government of India, 2016).

Compared with hotspot results, one match is that several hotspot states, such as coastal Odisha, dry Rajasthan, and flood-prone Assam, often overlap with areas that receive policy attention. However, a mismatch is that hotspots shift throughout regions and years, while many tools are still separated by sector and not well linked to a long-term and multi-risk spatial targeting. Thus, one policy implication is to design ASP that connects hotspot-based early warning and state-specific risk, so that policy can be adjusted over time to obtain outcomes that demonstrate overall societal development.

3.5.5. Nepal

Recent climate shocks have caused significant damage to human life leading to a long-term policy problem (Prakriti Resources Centre, 2025). A large proportion of Nepal's population faces a situation where their income fluctuates severely based on variations in monsoon rainfall in rural areas (Shidiq et al., 2016). To respond to such a situation, Nepal has gradually developed a climate change adaptation policy. In the early stage, the Local Adaptation Plan of Action (LAPA) was introduced to link national climate goals with action at the local level (Government of Nepal, 2011). Later, the National Adaptation Plan (NAP) showed a long-term view up to 2050, and the policy focus changed from mainly project-based and short-term responses to more planned and systematic adaptation (Government of Nepal, 2021).

At the subnational level, there are regional differences in policy. In Koshi Province, there is a health emergency response plan that includes disease control, such as dengue, and addresses floods and landslides as major risk factors, while climate change is mainly treated as a background driver of health risk rather than a central policy focus (Government of Koshi province, 2025). When compared with the hotspot

analysis, Koshi Province is detected as an overlapping hotspot in several years, and in this sense, there is a match because subnational planning frameworks exist in this area. However, the main driver of the hotspots is climate stress rather than economic or disease stress, and many policies are still sector-based and reactive, so a mismatch with spatial risk remains. From this point, Nepal should strengthen ASP by using hotspot-based spatial targeting with a long-term view.

3.5.6. Pakistan

At the national level, the national climate change policy in 2012 presented an adaptation strategy framework for Pakistan, focusing on water resources, agriculture, DRR, and health (Government of Pakistan, 2012). Moreover, this policy has been updated by absorbing new insights and concepts towards a comprehensive response to climate change mitigation and adaptation (Government of Pakistan, 2021).

At the subnational level, the southern Sindh province set the state climate change strategy in which it prioritizes the response to floods or coastal risks (Government of Sindh, 2022). Likewise, the south-western Balochistan province has a state policy report that focuses on composite vulnerability, including droughts or health risks (Government of Balochistan, 2024). On the other hand, responses to dengue fever or disasters have been enhanced, driven by the occurrence of large-scale disasters or an increase in patients in most cases (World Health Organization, 2022).

Thus, compared with the overlapping hotspots in the south and south-western parts, hotspots and DRM policies match. Meanwhile, the policy is not always based on long-term spatial targeting. From the ASP perspective, the policy implication for Pakistan would be to design policies considering chronic hotspots.

3.5.7. Sri Lanka

At the national level, as adaptation and mitigation strategies against climate change, Sri Lanka submitted its NDC in 2016 and updated it in 2021. But the framework for prioritizing high-stress regions has not been well organized (World Bank Group & Asian Development Bank, 2021).

For vector control, Sri Lanka has a national plan for dengue management, in which surveillance and environmental management are implemented, while this plan does not sufficiently focus on the preparedness for chronic high-risk regions (National Dengue Control Unit, Ministry of Health, 2019). For DRM, Sri Lanka has a National Disaster Management Plan (NDMP) that assumes roles of subnational governments, but the direct relationship with persistent hotspots is not always obvious (The Disaster Management Centre, 2022). For social protection, expenditures on social assistance account for about 0.63 percent of GDP, and social insurance for about 1.97 percent (Bird et al., 2022). One of the institutions is exemplified by Samurdhi, a national social assistance programme that provides support to low-income households through cash transfers, microfinance, and livelihood development. However, it is designed based on households, and the link to regional vulnerability is not always explicit (United Nations Children's Fund, 2021).

At the subnational level, for instance, the Western province implements an enhanced dengue control program, showing that some provinces take actions specific to the province. Hotspot analysis results show that persistent hotspots are mainly in the Northern and Western provinces, and therefore, hotspots are consistent with such regions taking specific actions. Our analysis therefore drives home the argument of integrating hotspot-based findings with existing climate, disease, and poverty alleviation-related programmes to obtain better outcomes.

3.5.8. Overall assessment

In this section, we present a summary of the policy coverage assessments examined by country. Table 2 organizes the matches and mismatches assessment. Each of the seven studied countries are assessed based on the triad indicators, leading to 21 possibilities.

Table 2
Matches and mismatches assessment table The table shows the matches and mismatches for disaster risk management, social protection, and vector control by country. (✗: mismatch, ✓: match)

Afghanistan	Disaster risk management	Social protection	Vector control
	✗	✗	✗
Bangladesh	✓ (partially)	✗	✗
Bhutan	✗	✗	✗
India	✓	✗	✗
Nepal	✗	✗	✓
Pakistan	✓	✗	✗
Sri Lanka	✗	✗	✓

Out of 21 possibilities, there are four matches and one partial match. However, even in matches, the policy applications do not cover all detected overlapping hotspots. Therefore, it remains necessary to improve the scope of policy application based on hotspot analysis. Furthermore, no country matches in the social protection category. In other words, none of the countries has adopted the perspective of targeting social protection toward regions that are chronic hotspots. Indeed, there are differences in institutional stages of social protection among SAARC countries. For example, while social protection systems exist in Afghanistan and Bhutan, shock-responsive social protection systems are limited. In contrast, Pakistan and India have social protection systems linked to responses to climate and economic shocks, such as the Benazir Income Support Programme and MGNREGS. However, these tend to expand after large-scale disasters or economic shocks, meaning they are often retroactive.

Given this situation, this study proposes a data-driven spatial targeting of ASP for chronic hotspots and proactive policy implementation alongside existing social protection schemes across SAARC countries. Specifically, by linking hotspot analysis and policy document comparison with early warning systems, chronically high-stress areas can be identified annually or even monthly. This enables the development of a proactive framework for deploying social assistance before events occur, rather than post-event. Expanding existing systems in response to disasters is important, but it is also considered that establishing a system for anticipatory resource allocation to chronic risk areas will lead to the advancement of ASP, as proactive policy measures are infinitely more effective compared to retroactive ones. Apart from integrating existing social protection schemes, we must also include other contextual factors such as wars, conflicts and the politics within SAARC nations to make social protection truly rewarding to its societies.

Wars, internal conflicts and climate-related shocks are likely to pose a challenge in effectively implementing adaptive social protection schemes (Birch et al., 2023) that would address the triad stresses included in this study. For example, war in Afghanistan has limited the capacity on several fronts to implement ASP (Babajanian et al., 2014), including financing challenges (Swithern et al., 2025). In addition, there is a greater need to generate updated empirical evidence on the existence and impact of social protection schemes in Afghanistan as the existing ones are likely dated (Arnall et al., 2010). Newer evidence will aid in designing and implementing effective and efficient social protection programmes. Afghanistan and any other SAARC nations impacted by war crimes and internal conflicts may use existing evidence from other parts of the world, such as the African continent to find ways of effective implementation of social protection programmes (Azoukalne & Zaki, 2025).

Alongside contextual factors of climate change and conflicts that are evident across few SAARC nations, we must continue to identify newer dimensions of vulnerabilities (Nagano & Sekiyama, 2023). Failing to do so could undermine the efforts towards ASP schemes. In addition, we must also address the politics of linking social protection with climate adaptation and disaster risks (Kundo et al., 2023b).

4. Concluding remarks

This study contributed to the spatiotemporal visualization of the overlap of stress variables, including climate, economy, and disease, at the ADM1 level in South Asia. Combining robust variable construction and hotspot analysis enabled persistent high-stress regions that are difficult to capture within a single sector. Furthermore, comparing these hotspots with existing policy frameworks for DRM, social protection, and vector control provided policy implications for the spatial targeting of ASP.

On the other hand, this study has several limitations. First, the policy coverage analysis does not fully capture fine-grained regional issues because it depends mainly on the country-level policy documents. Second, economic activity and disease risk are measured using proxy

indicators that may not correspond to actual income or disease incidence data. Third, this study addressed four elements, including temperature, precipitation, nighttime light, and dengue sensitivity, but there remains room to consider the existence of other factors.

Therefore, future work will require the use of ADM1-level policy documents to examine the policy match or mismatch more precisely. Additionally, it is crucial to analyze hotspots with more varied datasets, including other factors. Furthermore, there is a necessity to explore ASP design considering measurement of social welfare, early warning systems, and institutional constraints specific to each country. In particular, future work will examine how different definitions of social welfare, such as poverty reduction, vulnerability reduction, or resilience improvement, can be incorporated into spatial targeting. If limitations are surmounted through these attempts, better data-driven spatial targeting of ASP would be realized for protecting the vulnerable population in the SAARC region.

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Funding statement

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Ethics statement

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Clinical trial number

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Consent to participate declaration

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Author contributions statement

M.O. conceived the study, developed the methodology, curated the data, performed the formal analysis, prepared the figures, and wrote the original draft. P.G. supervised the study, validated the results, and reviewed and edited the manuscript. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare no competing interests.

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The corresponding author has read the journal policies and submit this manuscript in accordance with those policies.

Permission to use third-party material

All of the material is owned by the authors and no permissions are required.

Data availability

The processed dataset generated during this study is available in the *figshare* repository at <https://figshare.com/s/d42c5c44011c539de999>.

The original datasets are publicly available from TerraClimate, CHIRPS, VIIRS Day/Night Band composites, and the dengue suitability dataset cited in the manuscript.

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Figures

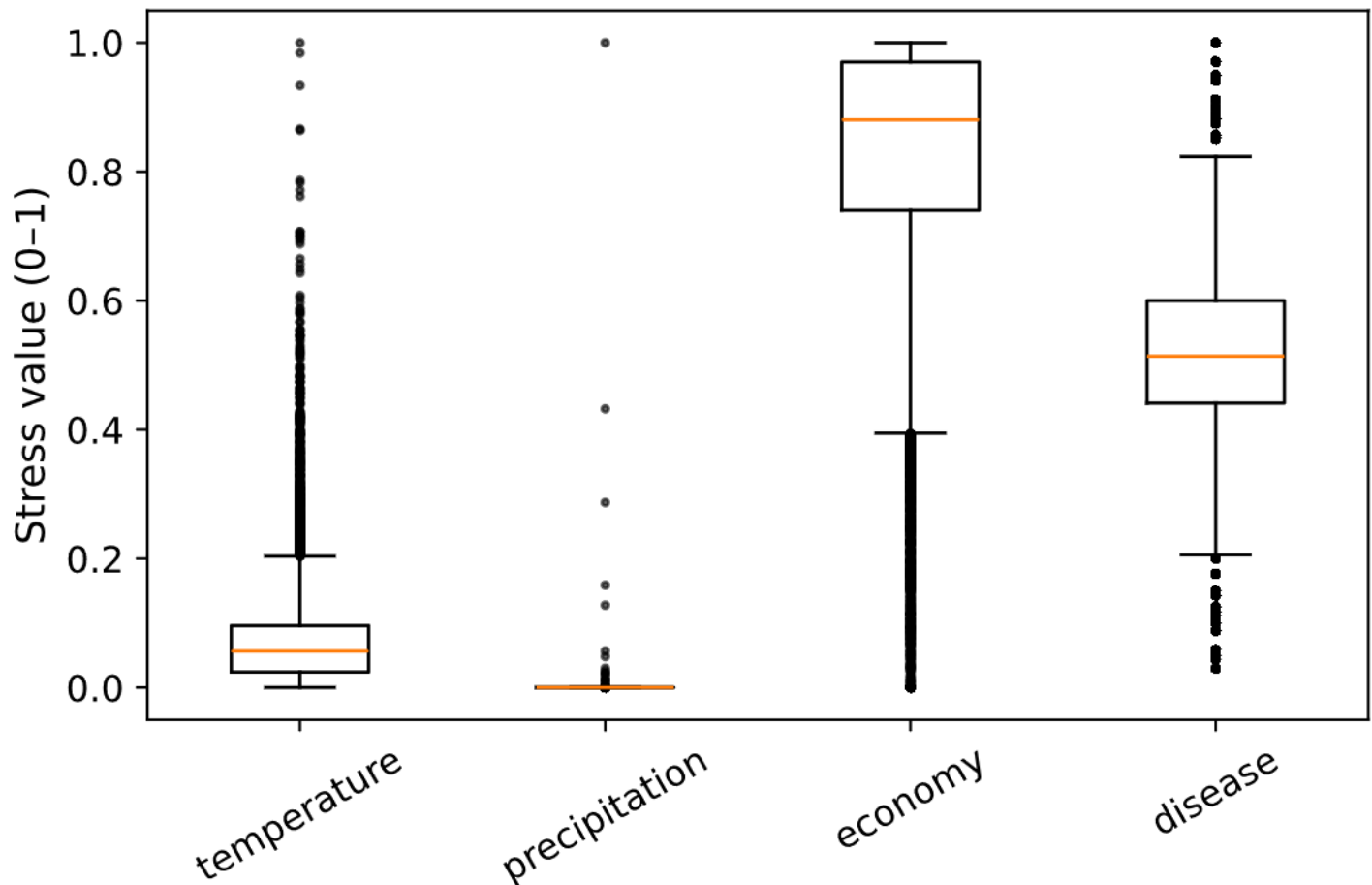


Figure 1

Distribution of stress values across variables

The distribution of stress values normalized to the range 0–1 for temperature, precipitation, economy, and disease

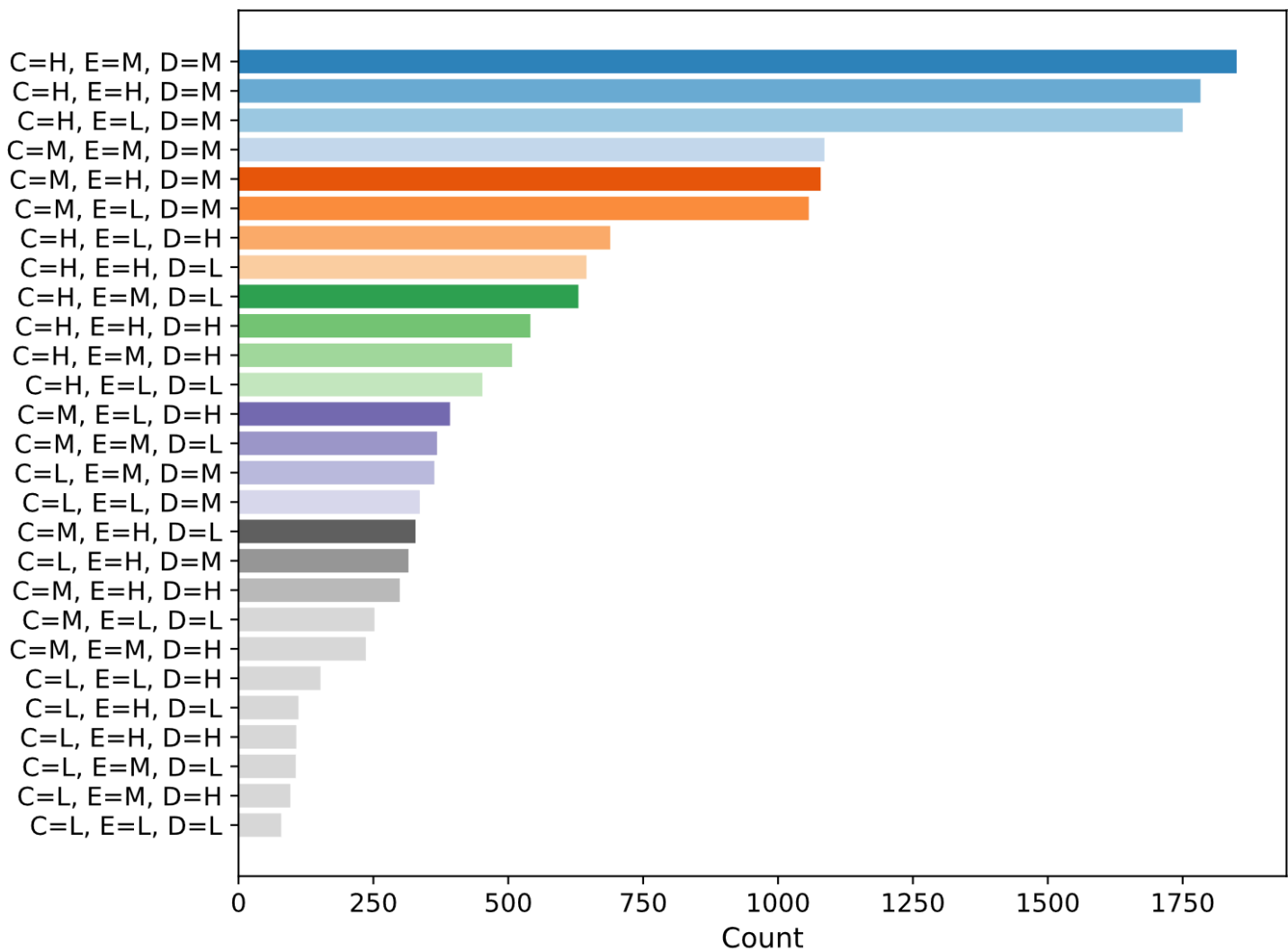


Figure 2

Frequency of stress type combinations across all periods and regions

The frequency of the combinations of climate (C), economy (E), and disease (D) levels (H: high, M: medium, L: low).

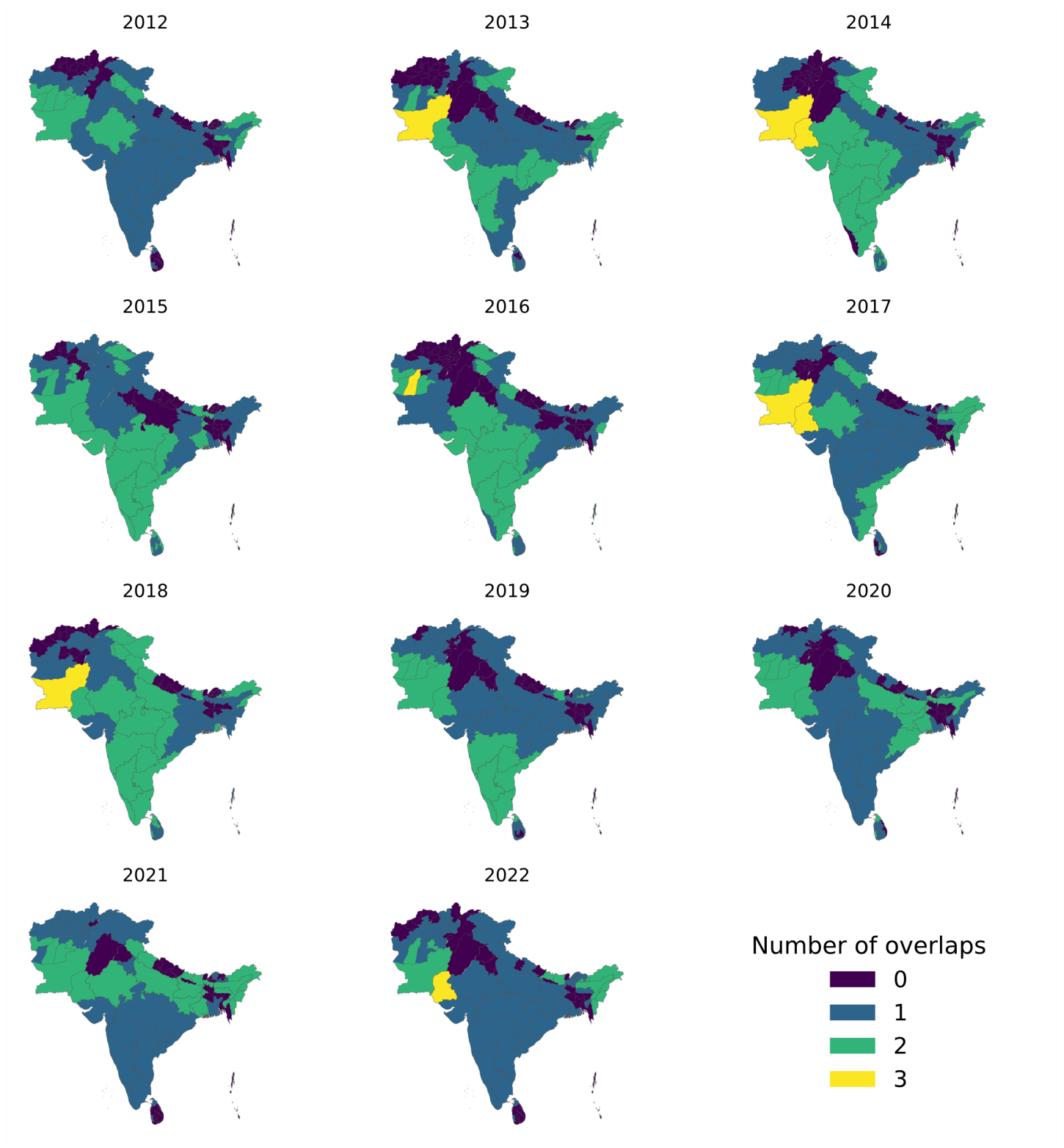


Figure 3

Spatial distribution of hotspot overlaps across years (2012–2022)

The spatial distribution of hotspots overlaps across countries from 2012 to 2022.



Figure 4

Composition of stress types within contiguous hotspot clusters

For each year, the figure shows the composition of climate, economy, and disease levels (H, M, L) in major high-stress regions.

Supplementary Files

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