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Global Urban Impacts of Future Climate Extremes: Projections of Heatwaves, Droughts, and Floods

Abstract

Cities worldwide face increasing threats from Extreme Climate Change, as hazards such as heatwaves, droughts, and floods pose growing risks to urban populations and infrastructure. However, global regional assessments of exposure to extreme climate hazards under worst-case scenarios remain limited. This study presents a global assessment of regional exposure to heatwaves, droughts, and floods by the end of the century using upper-quartile projections from 20 CMIP6 climate models under the SSP5-8.5 emissions scenario. Changes in these hazards were evaluated individually and in combination across thousands of cities. Results indicate heatwave frequency will increase by over 90% in many tropical and coastal urban areas, and unprecedented temperature extremes up to 12.7 °C above historical values will occur in high-latitude cities. Over 120 cities are projected to exceed critical wet-bulb temperature thresholds for human health. Drought severity is projected to intensify significantly in South America, Africa, and Southeast Asia, becoming up to 3.2 times more severe than historical extremes. Flood risks, measured by river discharge, are projected to increase substantially in South America and Asia, with increases up to 85 times historical levels. Compound hazard analysis further identifies significant overlapping exposure in cities across Africa, Southeast Asia, and South America. These findings highlight substantial regional exposure to extreme climate hazards and emphasise the urgent need for targeted urban adaptation and resilience planning worldwide.

1. Introduction

Climate change is causing significant shifts in global temperatures and weather patterns, which lead to more frequent and intense Extreme Climate Change (ECC) events [1], [2]. These events threaten many aspects of society, from increased heat-related mortality and dehydration to wildfires, crop failures, and ecosystem disruptions [2], [3].

Cities are particularly vulnerable due to their high population density and their position as complex infrastructural nodes, and may face increasing exposure to multiple climate-related challenges, which underscores the need for targeted adaptation. [2], [4], [5], [6], [7]. Although previous studies suggest that the likelihood of future low-probability, high-impact events is low [8], there is substantial uncertainty about cascading Climate Tipping Points (CTPs), even if global warming is limited to 1.5–2 °C, a target that is becoming increasingly difficult to achieve [9]. Furthermore, some evidence indicates that global warming could continue to worsen even with declining greenhouse gas (GHG) emissions, due to factors such as tipping points and carbon cycle feedbacks [10], [11]. This raises the risk of a future climate more extreme than widely anticipated. Therefore, this study addresses these uncertainties by identifying the regional hotspots worldwide that could face multiple and concurrent climate-related challenges by the end of the century due to low-likelihood, high-impact ECC events.

Despite global efforts such as the Paris Agreement, the 1.5 °C threshold has been regularly exceeded since 2023 [6], [12]. Furthermore, business-as-usual scenarios project continued warming that could potentially exceed 2 °C by 2045 [13]. Yet, most research has focused on ensemble-mean climate projections and average outcomes [14]. A systematic analysis of IPCC reports reveals that warming above 3 °C is much less discussed than its estimated likelihood, leaving “bad-to-worst-case” futures critically underexplored [15].

This gap is concerning given that as warming increases, so does the probability of cascading and compound impacts, where multiple ECC events occur together or sequentially, affecting different sectors simultaneously [15] [16]. For example, extreme heatwaves, such as the 2021 Pacific Northwest event, are becoming at least 150 times more likely to occur under ECC [17]. Similarly, droughts are increasing in frequency and severity, with regional hotspots in the Americas, Africa, and Asia [18], [19]. These meteorological droughts can escalate into hydrological and agricultural crises, further increasing societal damages [20]. Flood risks are also rising, not only due to individual drivers but through compound events involving river discharge, surface runoff, storm surge, and sea-level rise [21]. Under a high-emissions scenario, compound flood risks are projected to rise, especially in mid-latitude and coastal regions [22], [23].

Recent research has also explored how the combined effects of multiple hazards can undermine resilience and societal stability. For instance, Steel et al. [24] outline three pathways for societal collapse driven by direct impacts, socio-climate feedbacks, and vulnerability to external shocks. Kemp et al. [15] similarly call for integrated assessments of cascading risks, especially in food, health, conflict, and the economy. Although attention to compound climate risks is growing, many existing studies remain limited in geographic scope, use inconsistent definitions of hazards, or apply different methods, making global comparisons difficult. Previous multi-hazard studies have often focused on local or continental scales, or on selected hazard combinations, rather than globally consistent assessments across multiple hazards [25]. More broadly, multi-hazard risk assessment remains constrained by the continued dominance of single-hazard approaches, differences in hazard characteristics and interrelationships, and the need for harmonised methods, frameworks, and data [26]. Most importantly, there is still no systematic global assessment of city-level exposure to the most severe ECC and their combinations, a gap this study seeks to address by defining the regional boundary conditions cities will face.

Due to the slow pace at which cities and infrastructure evolve, decisions made today regarding urban expansion, infrastructure design, and management will directly influence conditions decades from now. Therefore, identifying vulnerable cities is essential for strategic decisions that ensure sustainable and resilient urban development in the long term. This study aims to address this important gap and supports decision-making by providing a comprehensive global-scale assessment of cities exposed to the most extreme regional climate impacts by the end of the century. It considers extreme temperatures, droughts, and floods from ECC scenarios, both individually and in combination, under worst-case conditions. Previously, a systematic global analysis at the city scale, covering each hazard individually and in combination, has not been undertaken. This study categorises global cities based on their potential exposure, identifying those likely to face the highest combined exposure to climate-related hazards and determining which hazards or hazard combinations dominate each region. The analysis uses projections from the SSP5-8.5 scenario, the most extreme pathway, which predicts continued heavy reliance on fossil fuels and rapid economic development [27]. While SSP5-8.5 is often regarded as a low-likelihood high-emissions pathway in recent literature, it remains valuable for examining high-end climate risks and for stress-testing the long-term exposure of cities and infrastructure to severe future conditions [27], [28]. This is further supported by recent evidence suggesting that warming thresholds associated with high climate risk may be reached sooner than previously expected [29], [30]. Accordingly, this study applies SSP5-8.5 as a high-end scenario to identify upper-bound regional exposure to extreme climate hazards by the end of the century, rather than as a projection of the most likely future pathway.

Although the coarse resolution of Global Climate Models limits the simulation of urban microclimates [31], these models remain the primary mechanism for defining the regional climatic boundary conditions that govern future exposure. Particularly, coarse-resolution climate models do not fully resolve urban heat island effects, urban land-surface characteristics, or fine-scale thermal contrasts within cities [32], [33]. Recent multi-scale urban modelling studies further highlight the value of higher-resolution urban-scale representation for capturing microscale processes that coarse-resolution models cannot resolve [34]. Therefore, the projections presented here should be interpreted as regional climatic conditions within which urban heat risks may develop, rather than as precise estimates of local urban temperatures. Given the long operational lifespan of urban infrastructure, adaptation strategies must be grounded in these high-end regional projections today, rather than deferring critical planning until high-resolution global urban modelling becomes operationally feasible. The following sections outline the data and methods and discuss the key findings with additional details on methodology and results available in the Supplementary Materials.

2. Data and Methods

This study presents a global-scale assessment of regional exposure to three major hazards: heatwaves, droughts, and floods for urban locations using the SSP5-8.5 scenario [2], [35]. These are hydroclimatic hazards, a distinct subcategory of natural hazards characterised by their combined atmospheric and hydrological drivers and potentially severe societal impacts [36]. While the coarse resolution of Global Climate Models (GCMs) limits the representation of urban microclimates, this approach integrates upper-percentile projections to quantify the broad regional boundary conditions that will govern future urban risk. This approach is therefore intended to capture broad-scale climatic forcing relevant to urban areas, rather than fine-scale local thermal variability. The approach integrates hazard-specific indices, spatial and statistical analysis to quantify future risks in a consistent manner. Two time periods are analysed: a recent baseline from 2015 to 2030, which reflects current climate conditions and aligns with CMIP6 simulations beginning in 2015, and an end-of-century period from 2080 to 2100 that is widely used to assess long-term changes under strong warming trends [37]. Although the 15-year baseline is shorter than the standard 30-year climatology and may therefore be more sensitive to decadal variability, it allows for a direct comparison between the immediate near-future and long-term extremes within the same model runs, serving as a consistent stress-test for high-end scenarios. The analysis is based on climate outputs from 20 CMIP6 General Circulation Models (GCMs) [38], daily river discharge data from the Global Runoff Data Centre [39], and city data from Natural Earth [40]. The full data processing workflow and extended methodological details are provided in the Supplementary Materials. Figure 1 provides a schematic overview of the methodology used in this study.

2.1. Climate Model Ensemble and Upper-Percentile Approach

Daily and monthly climate variables, including near-surface air temperature, maximum and minimum temperature, wet-bulb temperature, and precipitation, were collected from 20 CMIP6 models run under the SSP5-8.5 scenario. To specifically characterise high-end climate risks which are critical for defining safety margins in long-term infrastructure planning, a 75th percentile threshold was applied across the model ensemble for each variable, rather than the multi-model mean. To develop this high-end (upper-bound) climate scenario, a two-step procedure was applied to the multi-model ensemble. First, through model-level temporal averaging, daily climate variables were averaged over a 21-year future period (2080–2100) at each spatial grid cell, resulting in a smoothed annual cycle of 365 daily average values. Second, through multi-model percentile computation, the 75th percentile was calculated across the 20 GCM-specific average daily values for each grid cell and each day of the year. The same two-step process was applied separately to the historical period of 2015–2030 to provide a consistent baseline for comparison.

This approach deliberately isolates the upper tail of model projections, capturing a "bad-to-worst-case" trajectory that accounts for higher climate sensitivity. By establishing this high-end baseline before calculating hazard-specific extremes, the methodology effectively constructs a compound extreme scenario. Given the 20-model ensemble used in this study, higher percentiles such as the 90th or 95th percentile would be determined by only a very small number of models. The 75th percentile was therefore selected to represent a high-end scenario while retaining input from a broader share of the ensemble. This choice provides an upper-bound estimate without over-reliance on a small number of model outcomes. This ensures that the assessment reflects the maximum plausible regional boundary conditions for urban exposure, addressing the "low-likelihood, high-impact" risks that standard ensemble-mean approaches often obscure. Full details of model selection and data pre-processing are described in the Supplementary Materials.

2.2. Heatwaves and Heat Stress

Heatwaves were identified as periods of at least three consecutive days where both daily maximum and minimum temperatures exceeded the 95th percentile for each grid cell (location), based on the baseline period. This method follows previous work [35] and ensures robust detection of significant extremes. To map these indices globally, the analysis utilised longitude, latitude, and day-of-year metadata, standardising longitude values from a 0–360° range to a -180° to 180° format where necessary to ensure geographic consistency. To accurately capture heatwave frequency in different climatic zones, the analysis was restricted to the warm-season months relevant to each hemisphere, rather than analysing the full calendar year globally. The dataset was segmented as follows: for the Northern Hemisphere (latitudes above 23.5°N), analysis was limited to the warm-season months of May through September; for the Southern Hemisphere (latitudes below -23.5°S), analysis focused on the warm-season period from November through March; and for Tropical and Monsoon Zones (between 23.5°N and 23.5°S), data was analysed year-round due to the consistent warm temperatures and lack of a distinct cool season.

The same thresholds were applied to the future period to identify projected changes. Applying these event-specific thresholds (95th percentile) within the high-end climate trajectory (75th percentile ensemble) serves to isolate the most severe tail-risks projected for the region. Two main heatwave indicators were calculated:

1) Percentage of Change in Heatwave Days (HW Days): This metric represents the increase in the percentage of days classified as heatwave days in the future period (2080–2100) compared to the historical baseline (2015–2030).
2) Change in Maximum Heatwave Temperature (HWTmax): The highest daily maximum temperature recorded during any heatwave event was extracted for both the historical and future periods. The difference between these peak values was calculated for each location.

In addition, wet-bulb temperature (WBT) was calculated to indicate heat stress, using the approach developed by Buzan et al. [41] and Davies-Jones [42]. This physically consistent method derives WBT from near-surface air temperature, relative humidity, and surface pressure from the GCMs. Further technical details are provided in the Supplementary Materials.

2.3. Drought Assessment

Drought risk was assessed using the 12-month Drought Severity Index (DSI-12) [43] [44], which measures deviations in monthly precipitation relative to a baseline. The analysis utilised daily precipitation datasets for the historical and future periods, which included precipitation rates (kg m^{-2} s^{-1}), geographic coordinates, and temporal metadata. Prior to calculation, precipitation rates were converted to mm/day, and longitude values were standardised to a -180° to 180° range to ensure consistent geographic representation.

To characterise long-term drought trends, daily values were aggregated into monthly precipitation totals for each grid cell. Monthly precipitation anomalies were then calculated and subsequently summed over a 12-month rolling window to capture the persistence of accumulated precipitation deficits. The DSI-12 was derived by expressing these 12-month cumulative anomalies as a percentage of the mean annual rainfall calculated independently for each period, normalising historical anomalies against the historical mean and future anomalies against the future mean. In this index, negative values indicate precipitation deficits relative to the trend of that specific period.

Changes in drought characteristics were evaluated using two key indicators derived from the maximum DSI-12 values identified in both the historical and future datasets. First, the probability of exceedance was calculated as the proportion of future months where the DSI-12 surpassed the historical maximum DSI-12. Second, a change factor was computed as the ratio of the future maximum DSI-12 to the historical maximum DSI-12, quantifying how the intensity of the most extreme droughts is projected to change. These results were compiled for all locations to map shifts in drought frequency and severity.

2.4. Flooding Assessment

In order to quantify the impact of flooding on a global scale, a flood frequency analysis was conducted, where regression relations were established between flood characteristics and climatic variables. This method ensures that a consistent approach was applied across all examined locations. To simplify the process, the analysis is carried out continent by continent. Flood hazard analysis was conducted based on daily discharge records from the GRDC [39]. In this analysis, GRDC daily discharge records considering 1920-2024 timeframe, 9 years of continuous data and less than 5% missing daily discharge record were initially chosen for each continent. For each river location, the 10-year return level of annual maximum daily discharge (Q10) was estimated using the Generalized Extreme Value (GEV) distribution, which is a standard approach for hydrological extremes [35]. A GEV distribution was applied to each gauge to calculate the 10-year return levels of annual maximum daily discharge (Q10) for the basins. This distribution was chosen because it is well-suited for modelling the maximum values in a dataset, which is crucial for evaluating extreme discharge events. By fitting the GEV to the annual discharge data, the Q10 values and their 95% confidence intervals were estimated, providing a statistical foundation for analysing and managing extreme flooding in the basins.

These steps were done in Python. Then, the monthly climate data for current/historical period was used for the basin average annual and monthly values of the input parameters. Key inputs included precipitation, as well as maximum, mean, and minimum near-surface air temperature (tasmax, tas, and tasmin). A basic indicator of snowpack was also included, defined as the quantity of average monthly precipitation occurring when the minimum monthly temperature is below zero for each climate grid cell. Additionally, Potential Evapotranspiration (PET) was calculated for each basin using the Thornthwaite equation, which considers latitude and the mean monthly temperature of the basin. Although the Thornthwaite method is widely used because of its low data requirements, its accuracy may vary across climates relative to reference evapotranspiration methods and can be improved through correction or calibration [45], [46]. To simplify the process, due to the equation's low sensitivity to minor latitude variations, the latitude of the gauge station was used instead of the basin's centroid latitude. Snowpack and PET values were calculated using the monthly precipitation and temperature data and latitudes of the GRDC stations.

The monthly climate data, precipitation, and temperature data (pr, tas, tasmax and tasmin), along with snowpack, basin area and PET are the variables that were considered in conducting a regression analysis to predict the future values of Q10 in 2080-2100 period.

In the flooding assessment, multiple regression models including Random Forest, Gradient Boosting, and XGBoost regressors were evaluated and tuned to identify the optimal model for each continent. These ensemble learning methods are widely applied in hydrological studies due to their ability to capture complex, non-linear relationships between predictors and flood magnitude [47], [48], [49], [50], [51], [52], [53].

Models for each continent were trained using log-transformed Q10 values (annual maximum daily discharge) as the target variable, alongside a range of climate and geographic predictors. Interaction terms were also engineered from predictor variables, reflecting relevant physical relationships in flood dynamics.

Model performance was assessed based on Root Mean Square Error (RMSE), R^2 score, and Adjusted R^2 score, aiming to balance predictive accuracy and generalisation. Cross-validation further ensured robust evaluation. (See Table S2 in Supplementary Materials for performance metrics). The best-performing regression model per continent was then applied to estimate future Q10 values for river basins larger than 500 km^2. Finally, a Change Factor (CF) was computed at each location by dividing future Q10 by historical Q10, quantifying the relative projected changes in flood magnitude.

Although the resulting R^2 values are moderate for some continents, these models represent the best possible performance after extensive testing of different methods, predictor combinations, and interaction terms. The limitations in model performance mainly reflect the complexity and heterogeneity of flood processes at the global scale, as well as data availability. Accordingly, the projected Q10 ratios should mainly be interpreted as indicators of relative spatial change and broad regional pattern, rather than as precise local estimates of future discharge magnitude. These projections reflect regional changes in river flood hazard, while local catchment and urban characteristics may further influence impacts at the city scale [54]. Nevertheless, the chosen models capture the major spatial and relative trends in flood risk needed for global-scale assessment and adaptation planning.

2.5. City Exposure Analysis

Urban exposure to each hazard was evaluated by matching climate and hazard data to cities from the Natural Earth dataset with reported populations over 1,000. To represent the regional climatic conditions surrounding each city, hazard values were extracted for each city using a 50-kilometre buffer. This buffer-based extraction is intended to represent the regional hazard conditions surrounding each city rather than to downscale climate projections to the urban scale. It does not capture fine-scale local variability, and the resulting city-level values should therefore be interpreted as regional exposure conditions. This step was done within a Geographic Information System (GIS) environment [55]. Cities that lacked data coverage within the buffer were excluded from the analysis for that specific hazard. To assess the sensitivity of this assumption for smaller urban areas, the city-level analysis was repeated after excluding cities with populations below 50,000, for which a 50-kilometre buffer is more likely to include substantial non-urban terrain.

2.6. Köppen-Geiger climate classes and city population size

Hazard indicators were further analysed by the projected Köppen-Geiger climate class and city size groups, based on the future Köppen-Geiger map by Beck et al. [56]. To ensure robust statistical comparisons, data distributions were first assessed using the Shapiro-Wilk test [57] for normality and Levene's test [58] for homogeneity of variances.

All three hazard indicators failed to meet the assumptions of normality and homogeneity (all $p < 0.05$; see Table S3 in Supplementary Materials), which are required for parametric ANOVA. Consequently, the non-parametric Kruskal-Wallis test [59] was selected to evaluate differences in hazard indicator values across climate classes and city size groups. For post-hoc analysis, Dunn's test with Holm correction [60] was used to identify significant pairwise group differences, and Cliff's delta was calculated to quantify the strength of these differences. This approach ensured that the analysis was robust to the underlying data distributions and provided reliable group comparisons for all hazard indicators.

2.7. Comprehensive Hazard Index

Finally, a composite hazard index was constructed by standardising (z-score) and summing the three hazard indicators: heatwave days, drought severity, and log-transformed Q10 ratio. Each indicator was then given equal weight, enabling consistent comparison across hazards with different units. This standardisation and equal-weighted summation approach is widely used in composite hazard and risk indices. Equal weighting was retained here as a transparent aggregation strategy, particularly in the absence of robust and replicable quantitative evidence to justify differential weighting across hazards. [61], [62], [63]. Cities without available flood data were excluded from the compound analysis to maintain comparability. Wet-bulb temperature was not included in the compound index, as it measures human physiological heat stress rather than the physical frequency or intensity of climate events. All data processing and analysis were performed in Python, using open-source libraries such as xarray, pandas, and numpy.

3. Results & discussion

The results are presented in four parts, reflecting the main climate hazards analysed in this study (heatwaves, droughts, and floods) and their compound impacts. For each hazard, changes in both intensity (such as temperature peaks, drought severity) and frequency or probability are examined. These analyses directly address the study's aim to identify urban areas globally at highest risk under extreme climate conditions by the end of the century. In addition to these absolute and relative changes, spatial patterns of these changes are analysed, identifying where the most severe impacts are projected and how these overlap with cities on a global scale. The heatwave assessment includes both dry-bulb temperature indicators and WBT, allowing for the identification of areas facing increasing risks of heat-stress on humans under future conditions.

Statistical analyses are also conducted to evaluate how hazard indicator values differ across city size categories and future projected Köppen-Geiger climate classes [56].

3.1. Global Patterns of Urban Heatwave and Heat Stress Risk

The findings reveal that cities worldwide are projected to experience significant increases in both heatwave frequency (HW Days) and intensity (HWTmax) by the end of the century. Frequency increases are especially evident in tropical and coastal cities, with many projected to see increases above 90%. Specifically, 76.2% of cities in South America, 29.7% of cities in Asia and nearly 50% of cities in Australia are projected to experience major increases in heatwave frequency. Changes in HWTmax show strong regional variability. High-latitude urban areas, particularly Alaska and central Canada, show unexpectedly large temperature spikes (up to 12.7 °C), while historically warmer regions, such as Southeast Asia, the Mediterranean and Central Europe (e.g., Germany, Poland), experience moderate but significant increases (5–9 °C) [64], [65]. Smaller yet notable intensity changes (1–5 °C) are projected for coastal cities in South and Southeast Asia, where frequency increases are most dominant. Figure 2 illustrates the global distribution of projected heatwave intensification across continents and climate classifications, showing the variability in both temperature peaks and event duration.

Urban implications are especially severe for smaller cities, identified as outliers with notable HWTmax increases (see Figure S2 in Supplementary Materials), which suggests critical vulnerabilities that necessitate targeted adaptation. Increases in HW Days are broadly consistent across city size categories (Kruskal-Wallis, $p < 0.01$), though large metropolitan areas (500k–1M population) show slightly lower increases.

Furthermore, WBT, combining dry-bulb temperature and humidity, is projected to exceed the 31°C critical threshold in over 120 cities globally by 2100, mainly in tropical and subtropical climates. Subtropical cities in West and Central Africa, northern India, and parts of Latin America, such as urban regions in India (29 cities), Brazil (21 cities), Mexico, Vietnam, and Nigeria are likely to experience frequent dangerous conditions. Among these, 50 cities, concentrated in South Asia, West Africa, and Latin America, are projected to surpass the even higher threshold of 32 °C, with maximums reaching up to 34.6 °C. Moreover, significant differences are seen across Köppen climate classifications (Kruskal-Wallis, $H = 4213.4$, $p < 0.001$). Dunn's post-hoc tests revealed notable contrasts, including Aw vs. Dfc ($p < 0.001$, Cliff's $\delta = 0.47$; moderate effect) and BWh vs. Cfb ($p < 0.001$, Cliff's $\delta = 0.52$; large effect). This result highlights increased exposure in historically moderate subtropical zones (Cfa, Cwa), which emphasises urgent adaptation efforts. The shift in maximum wet-bulb temperatures across continents and climate classifications is shown in Figure 3.

The heatwave assessment shows highest average increases in heatwave days in South America (91.0%), Africa (88.0%), and South Asia (85.3%), closely aligning with studies projecting rising heat extremes in Southeast and South Asia [66], [67], [68], [69], North and Southwestern Africa [70], [71], [72]. Projections of a 5°C temperature increase in Senegal by 2100 and permanent spring heatwaves in the Sahel by the 2070s [73] align with our findings of a 60–90% increase in heatwave days across West Africa. Similarly, our results for South America are consistent with recent studies highlighting the vulnerability of the Amazon Basin and adjacent regions to heat [74], [75], [76], [77].

3.2. Regional Variability and Urban Exposure to Future Drought Severity

Many cities will face significant increases in drought frequency and severity, with greatest intensification in regions already vulnerable to drought. Specifically, cities in South America, sub-Saharan Africa, and Asia are projected to experience drought conditions up to three times more severe than historical extremes.

Figure 4 quantifies projected drought intensification, highlighting the high probability of future events exceeding historical maximum severity levels.

In South America, drought severity could reach up to 3.2 times historical conditions, particularly in Brazil, Argentina, and the Andes region, where 54 of 506 analysed cities (approximately 11%) show probabilities exceeding 70% of exceeding the historical maximum, potentially leading to critical impacts on ecosystems, such as the Amazon basin. African cities also face substantial risks, with drought severity projected to exceed historical maximum by up to 2.55 times, mainly in southeastern regions, (62 of 708 analysed cities, ~9%), highlighting existing water security issues and potential impacts on social and economic vulnerabilities. Similarly, Asian cities, notably in India, China, and the Middle East, face severity increases of up to 2.17 times.

Cities in regions historically less exposed to severe drought, such as parts of Europe (18 locations, primarily southern and eastern Europe, including Spain, Italy, and Greece), also show notable increases (up to 1.43 times), indicating a shift toward more frequent drought in previously lower-risk cities. Similarly, western North America, despite experiencing moderate drought severity increases (up to 1.54 times) compared to southern hemisphere cities, exhibits the highest number of cities projected to exceed historical drought extremes (77 of 529 analysed cities, ~15%, primarily in the western United States and Mexico), therefore pointing to widespread regional vulnerability. Additionally, 5 locations in Australia are highly vulnerable. In contrast, polar and high-latitude regions (Antarctica, northern Canada) show no increase (0% probability) in exceeding historical drought severity.

Statistical analysis across Köppen climate classes reveals significant variations in drought severity projections (Kruskal-Wallis $H = 75.94$, $p < 0.001$), but these differences are small in magnitude. While median increases were broadly similar across most climate zones, classes Dfa, Dfb, and Dwa exhibited slightly higher central tendencies. Dunn's post-hoc pairwise tests identified small to moderate significant contrasts, including Dfa vs. Cfb ($p < 0.01$, Cliff's $\delta = 0.24$) and Dwa vs. Csa ($p < 0.01$, Cliff's $\delta = 0.21$). Despite these differences, interquartile ranges showed substantial overlap, indicating generally consistent intensification trends across urban climates.

Findings also closely align with recent research on global drought risk, which identifies Africa, South America, South Asia, and Australia as the regions most vulnerable to increasing drought hazard under high-emission scenarios [78], [79], [80]. These studies similarly highlight that future risks will be greatest in areas already affected by frequent drought, which emphasises the need for targeted adaptation in the Southern Hemisphere and other emerging vulnerable hotspots.

3.3. Projected Urban Flood Hazard Magnitude and Spatial Distribution

Future flood risk projections indicate significant increases in urban flood severity globally. High flood risk in regions like Asia and South America aligns with current expectations, but the magnitude of projected increases is profound. Figure 5 illustrates the global intensification of 10-year flood magnitudes, showing substantial increases across all continents and major climate classifications. In Asia, where 89% of vulnerable cities are near populated areas, maximum discharge ratios reach 67.2 times historical levels, with an average increase of 6.1 times. Recent work in the Asian Monsoon Region has shown that extreme precipitation can be strongly shaped by interacting meteorological drivers, offering a possible explanatory context for the pronounced flood hazard increases projected for parts of Asia in this study [81]. Similarly, South America faces the highest extremes, with maximum ratios up to 84.7 times (average 6.4-fold increase), representing increasing threats for urban infrastructure and severe disruption. Africa and Oceania also exhibit critical vulnerabilities, with maximum discharge increases of 51.8 and 70.3 times respectively, particularly in central coastal Africa and coastal Australia.

Another finding is the increased vulnerability of cities in North America and Europe, where nearly half (48.5% and 48.7% respectively) of at-risk cities are in densely populated areas (notably in the western United States and southern/eastern Europe). While flooding severity in these regions is moderate compared to others (up to 48.9 times historical discharge in North America and 14.7 in Europe), the average increases of 4.95 and 1.75 times still pose considerable risk to these developed urban centres.

Large and very large cities generally face higher increases in flood risk compared to smaller cities, particularly in Oceania and South America (see Figure S6 in Supplementary Materials). Although overall statistical differences between city size categories were marginally significant (Kruskal-Wallis, $H = 6.29$, $p < 0.1$), this urban scale dependency points to critical considerations for urban planning in large metropolitan areas, in which the future flooding severity may be underestimated.

Log-transformed Q10 ratios were analysed to reduce skewness and stabilise variance. Köppen climate classification analysis showed statistically significant flood risk variations across different climate classes (Kruskal-Wallis $H = 61.2$, $p < 0.001$), especially between tropical rainforest (Af) versus hot desert (BWh) ($p = 0.002$, Cliff's $\delta = 0.35$, moderate effect size) and humid subtropical (Cfa) versus subarctic (Dfc) climates ($p = 0.011$, Cliff's $\delta = 0.29$). These findings indicate the need for climate-specific urban adaptation strategies.

The results of the flooding assessment in this study are consistent with several key regional studies. For example, Di Sante et al. [82] and Lane et al. [83] both report increased flooding in Western Europe and Great Britain, which they attribute to more frequent high-magnitude rainfall. Our results match these findings. For South America, our study identifies increased flood risk, similar to other research that shows shorter return periods for extreme floods in Brazil and the Amazon basin [84], [85]. Tabari et al. [86] also project the greatest increases in flood risk in the Southern Hemisphere, especially in eastern and southern Africa. Our results show similarly large increases for these regions by the end of the century. There are, however, some discrepancies. While localised increases are identified here, broader regional declines in flood risk, such as those projected for northeastern Europe and Scandinavia due to reduced snow accumulation [82], are not as prominent in our results. In China, prior studies project substantial increases in flood hazard and urban flood risk, including at least a twofold increase in some cases [84], [87], whereas China does not emerge as a high-risk region in this assessment. . These differences likely reflect methodological differences across studies. Di Sante et al. use a higher-resolution European modelling framework and interpret declines in northeastern Europe and Scandinavia in relation to reduced snowmelt-driven flooding, while He et al. [79] assess basin-scale Q100 return periods and population exposure across six countries, and Jiang et al. [82] examine inundated urban land in major Chinese urban agglomerations under climate change and urban expansion. In addition, recent work suggests that local processes such as ground subsidence can amplify flood inundation, meaning that discharge-based projections may underestimate effective impacts in some urban areas [88].

3.4. Spatial Overlap and Distribution of Comprehensive Climate Hazards

A comprehensive hazard index, combining standardised indicators of heatwaves, drought, and floods, revealed statistically significant differences across both Köppen climate classes (Kruskal-Wallis $H = 1070.67$, $p < 0.001$) and city size groups ($H = 61.76$, $p < 0.001$). Figure 6 summarises the comprehensive hazard index, showing the distribution of combined climatic risks by continent and climate classification.

Climate class analyses indicated higher median compound hazard values for tropical rainforest (Af), monsoon-influenced humid subtropical (Cwa), tropical savanna (Aw), and hot desert (BWh) climates. Interquartile ranges revealed broad distributions in classes such as BWh and Af, which confirmed substantial multi-hazard exposure and the presence of outliers in these climates. On the other hand, temperate oceanic (Cfb), hot-summer Mediterranean (Csa), and subarctic (Dfc) climates showed lower hazard exposure. Statistically significant differences between classes (e.g., Af vs. Dfc, large effect; BWh vs. Cfb, moderate effect) highlight variations in multi-hazard vulnerability.

While median comprehensive hazard values were similar across city-size categories, small cities (<50k) exhibited the highest extremes, indicating severe compound risks in specific smaller urban areas. Dunn’s post-hoc tests confirmed significant differences, particularly between small and very large cities ($p < 0.001$). (See Figure S7 in Supplementary Materials). Because a uniform 50-kilometre buffer may capture proportionally more non-urban terrain for smaller urban areas, the city-level analysis was repeated after excluding cities with populations below 50,000 in order to test the sensitivity of this assumption, The resulting plots show that the main continental patterns remained broadly unchanged for the heatwave, drought, and comprehensive hazard indicators. For flooding, the broad continental pattern was also retained, although greater variation was observed across Köppen-Geiger climate classes after excluding smaller cities. These sensitivity results suggest that the main multi-hazard spatial patterns identified in this study are not primarily driven by the inclusion of small cities. The corresponding figures are provided in the Supplementary Materials.

Figure 7 identifies urban hotspots in the top quartile of projected risk, mapping the spatial overlap of heatwaves, droughts, and floods to highlight cities facing multiple concurrent hazards. Among cities assessed for simultaneous exposure to upper-quartile heatwave, drought, and flood hazards, only four (St. George, Tucumán, Porto União, and Pukekohe) were found at high risk from all three. Dual-hazard assessments indicated higher occurrences, with 347 cities (6.1%) exposed to heatwave and drought, 48 cities (6.5%) to heatwave and flood, and 40 cities (5.3%) to drought and flood. Countries frequently represented in dual-hazard groups included Brazil, the United States, Australia, Thailand, Mexico, Canada, Russia, Afghanistan, and Argentina. These findings demonstrate that while triple-hazard exposure is rare, dual hazard exposure poses significant risks to many cities worldwide. Other studies on compound drought and heatwave events identify North America, Australia, and South America as especially vulnerable to increases in the frequency and severity of these events [66], [89], [90], [91]. This matches the trends found in our study.

However, discrepancies exist. Other regions, such as the Russian Arctic, the Caribbean, and parts of the Middle East, are flagged by some studies as hotspots for compound hazards [66], [89]. Our analysis does not find these areas to be as prominent. Possible reasons include differences in spatial resolution, the climate data used, or in the way hazard thresholds are defined.

The comprehensive hazard index here assumes equal weighting and does not account for hazard interactions, but it provides a simplified and spatially consistent approach to identifying multi-hazard vulnerability. Limitations, particularly data availability, spatial resolution, and absence of infrastructure or adaptive capacity analysis and the use of a temperature-based

PET formulation in the flood modelling workflow may influence projected vulnerabilities. For example, India was excluded from the flooding assessment due to lack of river discharge data. As a result, the flood and compound hazard results do not provide full geographical coverage of Asia and should not be interpreted as a complete continent-wide assessment. There are also uncertainties associated with the use of climate model ensembles and scenario selection. Furthermore, while future Köppen-Geiger climate classes were used to group cities for comparison, there is considerable climate variability within the same Köppen class in some regions, such as Southeast Asia and tropical Africa. In addition, the number of cities differed across climate classes, so the statistical comparisons should be interpreted with caution, as some groups were more strongly represented than others. Future research should explore finer spatial scales, consider critical infrastructure exposure, and investigate weighted approaches to better capture hazard interdependencies and support local adaptation planning.

4. Conclusion

In this study, a global-scale regional assessment of a worst-case climate change scenario was conducted. Cities worldwide were analysed based on their potential vulnerabilities and exposure to extreme climate threats, using different hazard-specific methods to derive risk metrics from extreme temperature and precipitation projections. The aim was to identify urban areas most at risk from individual and combined climate hazards under extreme conditions projected by the end of the century. The worst-case scenario outlined in this study is based on end-of-century projections from the upper quartile of the CMIP6 model ensemble under the SSP5-8.5 emissions pathway. This scenario choice and percentile selection are used to evaluate high-end risk trajectories and low-likelihood, high-impact outcomes.

Overall, this study provides a spatially consistent and hazard-specific global assessment of regional exposure to the most severe climate extremes. The identification of cities vulnerable to single and concurrent ECC events supports informed policy decisions and prioritisation of adaptation investments. These results can also support first-stage screening of cities and regions where more detailed local assessment and adaptation planning may be required [92], [93]. For flood-prone urban areas, such follow-up work may draw on recent local-scale studies evaluating infrastructure and planning interventions to improve urban flood resilience, such as Di et al [94]. Adaptation strategies should prioritise targeted investments in heat-resilient urban design, water-security planning, and flood-resilient infrastructure, with particular emphasis on fast-growing urban areas that currently lack sufficient adaptive capacity. The findings highlight significant worsening heatwave conditions by the end of the century, with peak temperatures rising to 12.7 °C, particularly in Eastern Europe, northeastern North America, and South and Southeast Asia. Heatwave occurrences could increase by over 90% in coastal regions of South America, southern North America, Africa, Asia, and Australia. Drought severity is projected to increase considerably, up to 3.2 times, particularly across South America, Africa, and Asia, while many regions in North America, Europe, and Asia may experience exceedance of historical drought extremes, with probabilities reaching 100%. Flood risks, indicated by 10-year river flow return value ratio (projected increases of up to 85 times), highlight regional vulnerabilities, particularly in parts of the Americas, Asia, and Australia.

This study also identifies comprehensive climate impacts affecting multiple global regions. Cities in tropical savanna (Aw), monsoon (Am), and humid subtropical (Cfa/Cwa) climates, particularly in Africa, Southeast Asia, and parts of South America, are exposed to concurrent increases in heatwave frequency, drought severity, and flood magnitude. While concurrent exposure to all three hazards is rare, dual hazard overlaps are more common, particularly across South America, Southeast Asia, and parts of the U.S. and Australia. Finally, although the coarse resolution of climate models means that localised urban processes remain a source of uncertainty, the identification of high comprehensive hazard scores across diverse regions highlights critical vulnerabilities that necessitate urgent, targeted adaptation efforts.

Data availability

Data supporting this study are documented in the Supplementary Materials. The source code for the analysis presented in this study is publicly accessible via Zenodo at doi: 10.5281/zenodo.16842901

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