unicef
for every child

Children’s Climate Risk Report 2026

Technical Documentation

Last updated: 15 June 2026

WASH, Climate and Environment Data Unit

Office of Strategy and Evidence (OSE)

unicef for every child

Contents

Abbreviations and Acronyms

ASI – Agricultural Stress Index

EPP – Emergency Preparedness Plan

ESA – European Space Agency

FAO – Food and Agriculture Organization

HDI – Human Development Index

IIASA – International Institute for Applied Systems Analysis

INFORM – Index for Risk Management

IPCC – Intergovernmental Panel on Climate Change

JRC – Joint Research Centre (European Commission)

MAP – Malaria Atlas Project

NASA – National Aeronautics and Space Administration

ND-GAIN – Notre Dame Global Adaptation Index

OECD – Organisation for Economic Co-operation and Development

P. falciparum – *Plasmodium falciparum* (malaria parasite species)

P. vivax – *Plasmodium vivax* (malaria parasite species)

SCAP – Sustainability and Climate Change Action Plan

SDG – Sustainable Development Goals

SDMX – Statistical Data and Metadata eXchange

SIDS – Small Island Developing States

SPEI – Standardized Precipitation Evapotranspiration Index

SPI – Standardized Precipitation Index

UNDRR – United Nations Office for Disaster Risk Reduction

UNICEF – United Nations Children's Fund

UNSD – United Nations Statistics Division

VHI – Vegetation Health Index

VUB – Vrije Universiteit Brussel

WASH – Water, Sanitation and Hygiene

WHO – World Health Organization

WMO – World Meteorological Organization

Introduction

UNICEF plays a crucial role in protecting and promoting the rights of children worldwide. As children around the world are increasingly exposed to multiple hazards, access to reliable and comprehensive hazard data is essential for effective programming and advocacy. The Children's Climate Risk Report technical documentation provides a detailed look at the methodologies, data sources, and analytical frameworks used to quantify the climate-related threats facing children globally.

UNICEF established the first **Global Child Hazard Database** in 2026 to provide comprehensive, high-resolution, and globally standardized datasets on children's exposure to multiple hazards. The database aims to improve accessibility and provide actionable insights for country and regional offices, host governments, and other key stakeholders, thereby supporting informed decision-making and policy advocacy. The database compiles a wide range of hazard data, primarily focusing on climate and environmental indicators and includes geophysical hazards.

The development of the Global Child Hazard Database is an ongoing process and will be continuously updated as and when new data sets are available.

Data Acquisition and Cataloging

Multiple data sources were considered for each hazard and were carefully evaluated. The final selection was identified based on the following pre-established criteria: All input data must be open, globally available for all countries, quantifiable and comparable but most importantly spatially distributed. The diagram below shows the six criteria used in data selection.

1. Relevance
Directly relate to the impact of climate change and environmental degradation on children's well-being

2. Availability
Global coverage, open-source data with planned regular updates and ease of accessibility

3. Measurability
Quantifiable with reliable data sources spatially distributed both at the national and sub-national levels

4. Comparability
Allow for comparisons across different countries and regions to identify areas of high risk

5. Actionability
Inform policy and programmatic interventions to address child vulnerability and adaptation to climate change

6. Child-Centricity
Identify the disproportionate impact on children including the most vulnerable sub-groups

Proxy indicators were considered where global open data was not available.

Global Child Hazard Database

The functionality of this database is contingent upon precise hazard data processing. This section details the methodologies for data acquisition, standardization, quality control, and integration of diverse hazard datasets. These processes ensure data consistency, accuracy, and interoperability, enabling comprehensive analysis and supporting evidence-based decision-making.

Child population data:

WorldPop's global gridded children population estimate (Under 18) for 2024 at 100m spatial resolution was used for all exposure analysis in Global Child Hazard Database. The constrained population data product was used. Individual country population data is first downloaded and mosaicked into a single, global composite layer for further processing. Worldpop was chosen for its higher resolution, global availability, and accuracy in estimating rural populations (Láng-Ritter et al., 2025).

Limitations:

WorldPop is a modeled product that disaggregates coarser census or projected data onto finer grids using various geospatial covariates; thus, the accuracy of its output is intrinsically linked to the age and reliability of its input data. While some WorldPop datasets are adjusted to align with UN WPP national totals, the underlying spatial distribution might still differ from official national census figures or the detailed demographic structures assumed by the UN's own projections, as WorldPop's modeling cannot fully replicate the granular information gathered through comprehensive national censuses.

Hazard data:

Flood

Floods are the natural hazard with the highest frequency and widest geographic distribution (UNISDR, 2017) and are described in terms of frequency and intensity (water extent and depth). Two types of floods are considered in this analysis.

- Fluvial (riverine)
- Coastal (storm surge / sea level rise)

Relevance: Floods are a critical concern in climate change discussions due to their widespread impact on human and natural systems. The IPCC Sixth Assessment Report (Pörtner et al., 2022) projects that flood risks and societal damages are projected to increase with every increment of global warming (medium confidence). They exacerbate existing vulnerabilities, particularly in communities already facing socioeconomic challenges. Children are especially vulnerable to the impact of floods. Floods can disrupt their access to clean water, sanitation, and healthcare, leading to increased risks of diseases. Additionally, floods can cause significant psychological stress and trauma, affecting children's mental health and development (Pörtner et al., 2022).

Fluvial flood

A fluvial or riverine flood is a rise, usually brief, in the water level of a stream or water body to a peak from which the water level recedes at a slower rate (World Meteorological Organization [WMO], 2012). The primary cause of a fluvial flood is an extended precipitation event that occurs at, or upstream from, the affected area and can also occur when traditional flood-control structures, such as levees and dikes, are overtopped.

Data source: Fluvial flooding has been extensively studied, and multiple global models are freely available at different return periods. JRC's gridded Global Flood Hazard model (Baugh et al., 2024) at 100-year return period and 90m spatial resolution was chosen and water depth above 1cm (defined as data pixel value greater than or equal to in our processing pipeline) has been considered for exposure analysis.

Data processing: Children's exposure to riverine flood hazard was calculated by simple overlay of the flood hazard layer and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicators: Absolute and relative number of children exposed to riverine floods

Data limitations: While major riverine floods have been modelled at higher resolution, data might not cover smaller rivers.

Coastal flood

Coastal flooding is most frequently the result of storm surges and high winds coinciding with high tides (WMO, 2011).

Data source: A few open, global coastal flood models were compared at different return periods. For the Global Child Hazard Database, JRC's gridded Global Coastal Flood Hazard model at 100-year return period and 90m spatial resolution has been chosen (Dottori et al., 2016a). This is a binary layer and all values identified as 1 were considered for exposure analysis.

Data processing: Children's exposure to coastal flood hazard was calculated by simple overlay of the flood hazard layer and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics. Coastal flood does not have any thresholding; it is a binary 0, 1 non-presence or presence of flood used to calculate exposure.

Coverage: Global

Indicators: Absolute and relative number of children exposed to coastal floods

Data limitations: JRC's coastal flood hazard layer does not include intensity (depth) information, which could be crucial to better estimate the exposure to different impacts on children. At the moment there are no freely available global data on pluvial floods.

Drought

A drought is a prolonged dry period in the natural climate cycle that can occur anywhere in the world. It is typically a slow onset phenomenon caused by a lack of rainfall. In this analysis, two common types of drought are considered.

- Meteorological drought
- Agricultural drought

Relevance: Drought has always been a part of the natural variability of Earth's climate. However, climate change is increasingly putting pressure on food production and access, especially in vulnerable regions, and undermining food security and nutrition (United Nations Office for Disaster Risk Reduction [UNDRR], 2020a). The increase in the frequency, intensity and duration of droughts will increase risks to food security (Pörtner et al., 2022). Children are especially impacted by various drought risks. The lack of water can compromise their access to clean drinking water and sanitation, increasing the risk of diseases. Additionally, droughts can lead to food shortages, impacting children's nutrition and overall health. The psychological stress and trauma associated with drought conditions can also affect children's mental health and development (Pörtner et al., 2022).

Agricultural drought

Agricultural drought occurs when there is insufficient soil moisture to meet the needs of a particular crop at a particular time (United Nations Food and Agriculture Organization [FAO], 2020).

Data source: The Agricultural Stress Index (ASI) facilitates the early identification of cropped land with a high likelihood of water stress (drought). The Index is based on the integration of the Vegetation Health Index (VHI) in two dimensions that are critical in the assessment of a drought event in agriculture: temporal and spatial. The first step is a temporal averaging of the VHI, assessing the intensity and duration of dry periods occurring during the crop cycle at the pixel level. The second step determines the spatial extent of drought events by calculating the percentage of pixels in arable areas with a VHI value below 35 percent (this value was identified as a critical threshold in assessing the extent of drought in previous research by Kogan, 1995). Each administrative area is classified according to the percentage of the affected area to facilitate the quick interpretation of results (FAO, 2020). A 100-year return period was generated using the long-term average from 1984- 2023 as a proxy as it depicts the percentage of arable land, within an administrative area, that has been affected by drought conditions over the entire cropping season.

Data processing: Children's exposure to agricultural drought was calculated by simple overlay of the areas where the 100-year ASI return period with over 30% cropland is affected and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicators: Absolute and relative number of children exposed to agricultural droughts

Data limitations: Drought is one of the most complex natural hazards and the impact is felt in places that are in proximity as well as those that rely on the food supply. In other words, drought can occur in one place and the impact can be felt anywhere that depends on the crop production, even in adjacent or far away countries. For lack of a better model, the drought exposure estimates in the database assume only children living in proximity to the location of agricultural drought to be directly affected. It does not consider children living in areas that depend on the affected crop production as their primary food source due to difficulties with modelling such interactions globally.

Meteorological drought

Meteorological drought occurs when dry weather patterns dominate an area. It is defined by the degree of dryness and the duration of the dry period (UNDRR, 2020a).

Data source:

- The Standardized Precipitation Index (SPI) and the Standardized Precipitation and Evapotranspiration Index (SPEI) were derived from TerraClimate (Abatzoglou et al., 2018), available at ~5 km spatial resolution since 1958. SPI measures the deviation of precipitation from the climatological average over a given accumulation period and is widely used to detect and characterize meteorological droughts.
- SPEI adds the effect of evapotranspiration and is better suited to assessing droughts under climate change scenarios where temperature changes are important.

Longer accumulation periods (e.g., 12 months) are associated with persistent droughts and may also reflect agricultural and hydrological drought conditions (Copernicus Global Drought Observation [CGO], n.d.).

Data Processing: Monthly aggregated SPI and SPEI data using a 12-month accumulation period were used for the years 1958–2025. Areas experiencing meteorological drought were identified as those with SPI or SPEI < -1.5, corresponding to high severity events. A dimensionless probability score (ranging from 0 to 1) was calculated to represent drought frequency by dividing the number of months the index fell below the threshold (−1.5) by the total number of months in the study period (804 monthly time steps). The global mean value of this probability score was used to identify areas with a higher risk for drought, 0.09 and 0.06 for SPI and SPEI, respectively. These areas were overlaid with a high-resolution gridded global child population dataset to estimate exposure. Zonal statistics were used to summarize both absolute counts and relative proportions of exposed populations (children and total population, disaggregated by sex) across multiple administrative boundaries.

Coverage: Global

Indicators:

- Absolute and relative number of children exposed to SPI
- Absolute and relative number of children exposed to SPEI

Data Limitations: Return period analysis (e.g., Gumbel fitting for extreme dryness) was not satisfactory due to the sparse frequency of extreme dry events in the observation period. Also, the distribution of SPI and SPEI values across both negative and positive ranges, complicating traditional extreme value fitting.

Tropical Storms

A tropical storm is a type of storm system characterized by a low-pressure center, closed low-level atmospheric circulation, strong winds and a spiral arrangement of thunderstorms that produce heavy rain (WMO, 2023). Tropical storm classification was adopted from WMO's guidance where wind speed greater than 63 km/hr is considered as a named tropical storm (WMO, 2023).

Relevance: Tropical storms can cause significant damage through high winds, heavy rainfall and storm surges, leading to flooding, property destruction and loss of life. Climate change is increasing the intensity of tropical storms. Warmer sea surface temperatures and higher atmospheric moisture levels contribute to more powerful storms with greater precipitation. This intensification is linked to human-induced greenhouse gas emissions, which have led to observable changes in storm patterns and behaviors (Pörtner et al., 2022). Children are particularly vulnerable to the effects of tropical storms. These events can disrupt their access to clean water, food and healthcare, increasing the risk of malnutrition and disease and can lead to psychological trauma.

Data source: The tropical cyclone wind data is derived from UNEP GIRI and indicates the mean value of wind velocity for a return period of 100 years. The map has global coverage and a resolution of 6' (~11.1 kilometers at the equator) (Cardona et al., 2023). The tracks of historical tropical cyclones used in GIRI were obtained from the IBTrACS database and hazard analysis was divided by oceanic basis with different cut off years, based on data availability (Cardona et al., 2023).

Data processing: Children's exposure to tropical storms was calculated by simple overlay of the areas where the wind speed is over 63 km/hr and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicators: Absolute and relative number of children exposed to tropical storms

Data limitations: The accuracy of the probabilistic hazard model depends on the completeness of historical tropical cyclone data, which varies from one ocean to another. Incomplete data can lead to underestimation or overestimation of storm exposure.

Heatwave and Extreme Heat

A heatwave can be defined as a period of time where local excess heat accumulates over a sequence of unusually hot days and nights (WMO, 2009). Heatwaves are complex phenomena and at present, there is no universal consensus on a global metric. The specific criteria for what constitute a heatwave can vary by region, but it generally involves temperatures significantly higher than the average for that area and time of year.

A heatwave is defined as any period of 3 days or more when the maximum temperature each day is in the top 10% of the local 15-day average. The following three dimensions were considered:

- Heatwave frequency (the number of heatwaves per year)
- Heatwave duration (the total number of days an event lasts)
- Heatwave severity (the temperature above the local 15-day average during the heatwave, expressed in degrees Celsius)

Extremely high temperatures (extremely hot days) occur when a day exceeds 35 degrees Celsius.

Relevance:

Temperature is one of the core indicators to describe climate and there is clear evidence that climate change is increasing global temperatures and causing historic heat waves all around the world, with higher frequencies, duration and severity (Pörtner et al., 2022). Children are more vulnerable to the short- and long-term effects, especially from heat stress caused by exposure to heat waves that can negatively affect health and well-being, especially for infants and young children. Children sweat less per kilogram than adults and have a higher metabolism, which means they get hotter quicker. School closures because of heatwaves are becoming increasingly common, leading to a negative impact on children's education.

It is important to note that heatwaves do not lead to negative health consequences in all situations. For instance, with the above definition, heatwave severity increasing in the Nordic countries could lead to ecological impact, which in turn could affect children's ability to have a quality life. It could lead to increased probability of wildfires which could decrease the air quality.

Heat stress represents a significant and growing hazard, particularly for vulnerable populations such as children, due to its direct physiological impact and exacerbation of existing health conditions. While the availability of global data on heat stress exposure is steadily increasing, facilitating broader analysis, a universally accepted global threshold for children's safe exposure levels currently remains undefined, highlighting a critical area for further research and policy development.

Data source:

Temperature input is calculated using daily aggregate temperature data from the ERA5 reanalysis (Muñoz et al., 2019). ERA5, produced by the Copernicus Climate Change Service (C3S) at ECMWF, is the fifth-generation atmospheric reanalysis of the global climate covering the period from January 1940 to present (Hersbach, 2017).

To assess the extremity of climate-related heatwave indicators—including annual frequency, duration, severity and the number of days exceeding 35°C—we estimated multi-year return levels using a non-parametric, empirical approach. For each pixel, annual values were sorted in descending order, and empirical return periods were assigned using Weibull plotting positions, i.e., $T=(n+1)/\text{rank}$, where n is the number of years. Return levels for specific periods (e.g., 10-, 30- , 50-, and 100-year events) were then derived by interpolating the observed annual extremes against their associated empirical return periods. This method avoids distributional assumptions (e.g., Gumbel or GEV) and is particularly suited for short observational records or count-based variables such as event frequency. The approach aligns with recommended practices in climate extremes analysis, especially when parametric assumptions may not be valid or robust (WMO, 2009; Wilks, 2011; Coles, 2001).

For land areas, we used the ERA5-Land dataset, which offers a spatial resolution of approximately 10 km. However, since the ERA5-Land product excludes Small Island Developing States (SIDS) and many island regions due to its land-sea masking, we used the standard ERA5 dataset at a coarser resolution of approximately 24 km for those areas. Data for SIDS was obtained for the same time period as the land areas and processed using the same methodology to ensure consistency across the analysis.

Data processing: Children's exposure to individual dimensions was calculated by simple overlay of the areas where the individual dimension of heatwave is greater than the long-term average and the high-resolution gridded global children's population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all the Member States and territories using zonal statistics.

Coverage: Global

Indicators:

- Absolute and relative number of children exposed to heatwave frequency
- Absolute and relative number of children exposed to heatwave duration
- Absolute and relative number of children exposed to heatwave severity
- Absolute and relative number of children exposed to extreme temperature

Data limitations:

While ERA5-Land offers enhanced resolution (approx. 9 km), it does not cover Small Island Developing States (SIDS) and ERA5's global layer was used at 25km resolution. A significant challenge lies in the lack of a universal definition for "heatwave" or "extreme heat," leading to inconsistencies across different data sources and complicating cross-regional comparisons. The exclusion of humidity metrics can lead to an underestimation of actual physiological heat stress. Observational data sparsity, especially in remote or less developed regions, introduces uncertainties, and current datasets often do not adequately capture the localized amplification of temperatures due to the Urban Heat Island effect. Finally, a critical gap remains in the absence of a globally accepted physiological threshold for children's safe exposure to heat, hindering precise impact assessments for this highly vulnerable demographic.

Sand and Dust Storms

Sand and dust storms (SDS) are caused by intense winds over areas of arid soil that pick up large amounts of ground material into the atmosphere. The most significant dust sources globally are concentrated in arid and semi-arid regions, particularly major deserts such as the Sahara in Africa, the Gobi in Asia and the Arabian in the Middle East. SDS originate from natural sources like deserts, dry lake beds, and, coastal regions with loose sediment. Human activities exacerbate the problem through construction, agriculture, and poor land management practices that strip vegetation and expose soil to wind erosion. Climate change amplifies the occurrence of SDS by altering weather patterns and reducing vegetation cover (United Nations Convention to Combat Desertification [UNCCD], 2021).

Relevance: Over the past few decades, land degradation has contributed significantly to the increased number and size of anthropogenic SDS sources. Current trends in deforestation, agricultural expansion, and more frequent and severe droughts and heatwaves make countries more susceptible to SDS hazards (UNCCD, 2024). Exposure to dust can lead to respiratory problems, allergies, and other health issues. The disruption of daily activities and schooling due to poor air quality can also affect children's education and overall wellbeing.

Data source: UNCCD's SDS susceptibility layer at 1km resolution was used. It employs global datasets of four indicators to estimate the extent of source potential and derive source intensity values: (i) soil texture (proportion of sand, silt and clay), (ii) soil moisture (absolute minimum value), (iii) soil temperature (absolute maximum value), and (iv) land cover (bare land fraction) (UNCCD, 2024).

Data processing: Children's exposure to sand and dust storms was calculated by simple overlay of the areas of SDS susceptibility and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicator: Absolute and relative number of children exposed to sand and dust storms

Data limitations: The SDS susceptibility layer includes areas of original source but not where the wind could transport the particles. This could underestimate overall global exposure. The adopted methods in the SDS base map also have limited precision in identifying lower intensity sources due to the lack of data as well as the high degree of uncertainty associated with soil-related data (UNCCD, 2024).

Fires

Wildfires are uncontrolled burns of vegetation, including forests, shrublands, grasslands, savannas and croplands which can be caused by human activity or natural causes (Kurvits et al., 2022). Fires caused deliberately for land clearance (agriculture and ranching) or accidentally (lightning strikes and human error) are a major factor in land-cover variability and change and hence affect fluxes of energy and water to the atmosphere (WMO, 2025).

Relevance: Fires can lead to a significant loss of biodiversity, destruction of property and air pollution in addition to contributing to climate change by releasing large amounts of carbon dioxide and other greenhouse gases into the atmosphere (Pörtner et al., 2022). Climate change is increasing the frequency and intensity of fires. Higher temperatures, prolonged droughts and changes in vegetation patterns create conditions that are more conducive to wildfires, and human activities such as land use changes and deforestation also exacerbate the risk of fires (Pörtner et al., 2022). Children are particularly vulnerable as they are exposed to smoke and air pollutants from fires that can lead to respiratory problems, allergies and other health issues. Fires also impact their overall well-being, education and could cause significant psychological trauma.

Two dimensions are used to better understand fires – frequency and intensity.

Data source: Fire frequency was obtained from NASA's Fire Information for Resource Management System (FIRMS). The average fire frequency from 2001-2023 was used. The Fire and Thermal Anomalies product is available from the Terra (MOD14) and Aqua (MYD14) satellites as well as a combined Terra and Aqua (MCD14). The MODIS Fire and Thermal Anomalies products are derived from the MODIS sensors onboard the Terra (MOD14) and Aqua (MYD14) satellites. A combined product, MCD14, is also available and merges detections from both platforms. The nominal spatial resolution of the MODIS fire detection is 1 km, and the temporal resolution is daily, with up to four observations per day globally (two from each satellite).

Fire radiative power (FRP) is a measure of the energy released by a fire in the form of radiation. It is typically expressed in watts per square meter per steradian per micrometer ($W/m^2/sr/\mu m$). FRP is an important parameter for understanding the intensity and behavior of fires, as well as their impact on the environment. FRP includes fires based on vegetation fires only to capture all climate related events, but it is possible that the data includes human-induced vegetation fires.

Data processing: Children's exposure to fires was calculated by simple overlay of the areas where there is fire frequency above 4.91 $km^{-2}yr^{-1}$ and fire intensity above 37.89 MW and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicator:

- Absolute and relative number of children exposed to fire frequency
- Absolute and relative number of children exposed to fire intensity

Data limitations: Fire frequency and intensity are limited in identifying all areas that have the potential to experience fires. They are adopted as a proxy for the lack of high-resolution global hazard data for Fire Weather Index (FWI) – a combination of which could give a better picture of fire hazard.

Air Pollution

Air pollution refers to the presence of substances in the atmosphere that are harmful to human health and the environment. These substances can include particulate matter, nitrogen dioxide, sulfur dioxide, carbon monoxide and ozone (WHO, 2021).

Relevance: Climate change and air pollution are closely linked. Many activities that produce greenhouse gases also emit air pollutants, which can act as short-lived climate forcers and can warm or cool the Earth's climate over shorter time scales (Pörtner et al., 2022). Air pollution threatens children's health and is the greatest environmental health risk factor (WHO, 2021). Exposure to pollutants can lead to respiratory problems, asthma, and other health issues. Poor air quality can also affect children's development and cognitive function. Air pollution was the second leading risk factor for death among children under five in 2021 (WHO, 2025a).

Particulate Matter 2.5 (PM2.5):

Fine particle air pollution, or PM2.5, refers to airborne particles measuring less than 2.5 micrometers in diameter that could be emitted from vehicles, residential fuel use, coal-burning power plants, agricultural and industrial activities, waste burning, wildfires and many other human and natural sources. Among the key air pollutants that are currently measured, long-term exposure to PM2.5 is the most consistent and accurate predictor of poor health outcomes across populations (Health Effects Institute, 2024).

Data source: Data on estimated global concentrations of PM2.5 from the Atmospheric Composition Analysis Group (ACAG), as estimated using information from satellite-, simulation- and monitor-based sources was used (Shen et al, 2024) to estimate children's exposure to ambient air pollution. Following the established WHO standards for air quality guidance, a threshold of 5 µg/m3 was adopted (WHO, 2021). To account for short term variations, such as the decrease in air pollution during covid-19 pandemic, a ten-year average was used following expert advice.

Data processing: Children's exposure to PM2.5 was calculated by simple overlay of the areas where the observed values of a ten-year average (2012 – 2022) were greater than 5 µg/m3 and the high-resolution gridded global child population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicator: Absolute and relative number of children exposed to air pollution (PM2.5)

Data limitations: On-the-ground air quality monitoring stations are few and far between many regions of the world, particularly in low- and middle-income countries, which could affect the results and hence the exposure analysis. As noted above, there are several other air pollutants that are not included due to a lack of reliably modelled long-term global data at the time of writing. ACAG data is currently available from 68 N to 55 S, and unavailable in higher latitudes, which could be an underrepresentation for some countries.

Vector-Borne Diseases

Vector-borne diseases are human illnesses caused by parasites, viruses and bacteria that are transmitted by vectors.

Relevance: Climate change can alter the distribution and abundance of vectors, leading to changes in the incidence and geographic range of these diseases. Higher temperatures combined with land use and land cover change are making more areas suitable for the transmission of vector-borne diseases (Pörtner et al., 2022). Children are particularly susceptible to severe health problems from vector-borne diseases. For instance, malaria can cause high fever, anemia and neurological complications, which are especially dangerous for young children and can also lead to increased mortality (WHO, 2024). Illnesses can also lead to malnutrition, disrupt education and affect a child's overall well-being.

Note: While there are various vector-borne diseases such as dengue and zika due to a lack of global data availability, only malaria was included in the Global Child Hazard Database.

Malaria

Malaria is a life-threatening disease caused by parasites transmitted to humans through the bites of infected female Anopheles mosquitoes (WHO, 2025b). There are five *Plasmodium* parasite species that cause malaria in humans and two of these species – *P. falciparum* and *P. vivax* – pose the greatest threat. *P. falciparum* is the deadliest malaria parasite and the most prevalent on the African continent. *P. vivax* is the dominant malaria parasite in most countries outside of sub-Saharan Africa (WHO, 2025b).

Data source: Gridded long-term estimates were downloaded from the Malaria Atlas Project (MAP, 2025) and estimated from the global malariometric data (Pfeffer et al., 2018)

- The gridded average number of newly diagnosed *P. falciparum* cases per 1,000 people from 2012-2022 was used as a proxy for the spread of malaria by *P. falciparum*
- The gridded average number of newly diagnosed *P.vivax* cases per 1,000 people from 2012-2022 was used as a proxy for the spread of malaria by *P. vivax*

Data processing: All children living in areas within 5x5 km grids with more than one case are estimated as children exposed to malaria (individually calculated for each species) and overlaid with high-resolution gridded global children's population layer. The results were then summarized to different administrative boundaries as absolute and relative values for all Member States and territories using zonal statistics.

Coverage: Global

Indicator:

- Absolute and relative number of children exposed to malaria (*P. Falciparum*)
- Absolute and relative number of children exposed to malaria (*P.Vivax*)

Data limitations: Due to limitations in data availability, malaria indicators only include estimates based on reported cases and do not include areas that are potentially susceptible to malaria based on climate indicators.

Pixel-Level Multi-Hazard Analysis

This section outlines the process of calculating multi-hazard exposure at the pixel level to assess the compounding exposure of child populations to multiple climate and climate-sensitive hazards. Pixel-level analysis is performed to capture fine-grained variations in climate risks within a country, enabling the identification of hotspots that national averages may overlook. This approach allows for a more precise understanding of climate risks at both local and national levels, with the flexibility to aggregate data to administrative levels 0, 1 or 2 based on the specific use case.

Multi-Hazard Count

Definition and purpose

The multi-hazard count indicator quantifies the number of distinct climate and climate-sensitive hazards that are likely to occur in the same location and overlap with child populations. It is computed at a high spatial resolution (up to 100 meters), allowing for fine-grained analysis of compounding climate risks.

Each hazard is processed with applied thresholds to identify areas where its intensity exceeds a threshold identified in the above section for individual hazards. These binary hazard masks are then stacked to calculate, per pixel, the number of different hazards present. This results in a hazard count map, where pixel values reflect the number of hazards a given location is exposed to which could be a useful measure to better understand the number of hazards children face.

To make the indicator child-focused, this multi-hazard count layer is spatially filtered using high-resolution child population data. The result is a map that highlights only the areas where children are present and exposed to one or more hazards. While the pixel values indicate the number of overlapping hazards, they only appear in locations with non-zero child population.

Child-focused use cases

By filtering the hazard count by child population, the indicator serves as a tool to identify areas where children face compounding climate risks. It enables targeted planning individual sectors and supports more equitable resource allocation.

Aggregation and applications

The pixel-level results can be aggregated to administrative units (e.g., district, province) to calculate:

- Total number of children exposed to one or more hazards
- Number of children exposed to one, two, three, four or more concurrent hazards
- Distribution of hazard count among children within a region

This indicator can support decision-making in disaster risk reduction, climate adaptation, and child-focused program design.

Multi-Hazard Intensity

Definition and purpose

The multi-hazard intensity indicator evaluates not only whether a location is exposed to hazards, but how severe or extreme those hazards are. This high-resolution metric—computed at approximately 10 km spatial resolution—integrates the magnitudes of various climate and climate-sensitive hazards into a composite risk score for each location. Unlike a simple count of hazard types, this indicator distinguishes between areas experiencing frequent but moderate events and those exposed to less frequent but highly destructive climate hazards.

By capturing intensity, this metric offers a more nuanced understanding of risk, enabling local governments, humanitarian actors and climate resilience planners to better prioritize areas that face more severe threats—even if only from one or two hazards.

Data processing

Each hazard layer—such as heatwave frequency, drought severity or flood intensity—is first cleaned and normalized to ensure comparability across different hazard types. This process involves removing non-informative values (e.g., zeros, NaNs), resampling to a consistent 10 km grid using a maximum-value method (to preserve peaks) and applying log transformations followed by z-score scaling to standardize the distributions. Pre-scaled datasets like SPI or soil moisture anomaly are directly included after trimming outliers to improve distribution symmetry.

Once the data layers are harmonized, they are stacked into a multi-dimensional array, where each pixel holds values representing the magnitude of different hazards. Principal Component Analysis (PCA) is then used to reduce this complex dataset to its most informative components—capturing over 90% of total variance with just 6 principal components. These components provide a way to synthesize multiple hazard signals while preserving key differences between regions.

From the PCA results, a weighted combination of principal component loadings—informed by each component's explained variance—is used to derive a final composite hazard intensity score for each land pixel. This produces a raw indicator of multi-hazard intensity, which is then normalized to a 0–10 scale using min-max scaling. The final result is a single raster layer where each valid land pixel carries a score representing the cumulative severity of climate risks in that location.

The purpose of PCA was twofold:

Dimension reduction – to minimize multicollinearity among highly correlated hazard variables and simplify the structure without losing most of the information.

Deriving data-driven weights – the loadings from the principal components provide a statistically consistent way to reflect the relative importance of each hazard indicator when constructing the overall hazard index.

Child population exposure estimate

The thresholds are applied to categorize child populations based on different levels of high intensity multi-hazard exposure at various percentile thresholds. A percentile is a statistical measure indicating the relative position of a data point within a dataset, representing the percentage of values that fall below a specific score. It divides data into 100 equal units; for example, the 90th percentile means a score is higher than 90% of all other scores.

Child-focused application

To center the metric on children, the composite intensity surface is overlaid with high-resolution child population data. This overlay allows for the estimation of the number of children exposed to varying levels of climate hazard severity—from average exposure to the top 1% of most at-risk zones. This approach highlights not only where the most intense risks occur but also who is affected—making it a powerful tool for guiding investments in individual sectors. It also allows for threshold-based analysis, helping governments and agencies understand the scale of exposure at critical risk levels (e.g., above the 90th percentile).

Sensitivity and limitations

The method allows for robust sensitivity testing, including the effect of resampling strategies, the number of PCA components used and alternative normalization approaches. However, it also carries assumptions—such as the linearity of PCA and the weighting of components—which must be carefully validated in different contexts.

Despite these limitations, the multi-hazard intensity metric offers a scalable, data-driven approach to understanding where high-severity climate risks intersect with children population—a critical step toward effective and equitable climate resilience planning.

Child Vulnerability

Children face unique vulnerabilities that make them particularly susceptible to climate and climate-sensitive hazards. Given their unique metabolism, physiology and developmental needs, children are more vulnerable to extreme events and societal changes than adults. Additionally, children are less able to protect themselves from harm and are more dependent on adults for their safety and care. Addressing these vulnerabilities is crucial for creating resilient and supportive environments that promote children's growth and development.

All the indicators chosen for child vulnerability are directly obtained from the UNICEF data warehouse.

Health

Three sub-components are considered under health: child health, maternal health and access to electricity.

Child health

Immunization is one of the most cost-effective public health interventions. The first dose of the diphtheria-tetanus-pertussis-containing vaccine (DTP1) serves as a proxy for access to immunization services, while coverage of the third dose (DTP3) is often used as an indicator of how effectively countries are delivering routine immunization services to children (a good proxy for child health). Access to life-saving vaccines to combat diseases varies across regions and countries (source).

Indicators:

- Percentage of surviving infants who received DTP1
- Percentage of surviving infants who received DTP3

Coverage: Data is available for 195 countries and territories.

Source: WHO/UNICEF estimates of national immunization coverage (WUENIC)

Data Limitations: WUENIC is informed by reported administrative data and household surveys, both of which can have limitations including incomplete reporting, misclassification or bias. When data gaps, inconsistencies without explanation or unreliable data exist, WUENIC uses various statistical methods such as interpolation or extrapolation, which may not accurately reflect the reality on the ground. The most recent year's estimates are informed by less data as surveys for the youngest cohorts are not available.

Maternal health

Despite recent progress, millions of births still occur without any assistance from a skilled attendant each year. The attendance of deliveries by skilled health personnel is a good proxy for maternal health in a country.

Indicator: Skilled birth attendant - percentage of deliveries attended by skilled health personnel

Coverage: Data is available for 192 countries and territories.

Source: Joint UNICEF-WHO Database on Skilled Birth Attendance 2024.

Data Limitations: This indicator measures the extent to which the health system can support mothers during childbirth; however, it alone does not show whether delivery care is available or accessible when needed or the quality of delivery care being provided. Another limitation is related to the standardization of the qualifications of skilled health personnel across countries and regions, as different countries use different job titles for healthcare workers. In some areas, duties are shifted from trained professionals to less experienced staff, which can affect the accuracy of the data collected.

Health system performance

Electrification is a proxy of health system performance, which strongly correlates to a variety of other covariates. Access to basic utilities like electricity can enhance the quality of healthcare facilities and services, impacting outcomes like antenatal care coverage (at least four visits) (ANC4) and skilled attendance at births.

Indicator: Percentage of population with access to electricity

Coverage: Data is available for 212 countries and territories.

Source: World Bank

Data Limitations: The indicator only measures whether people have access to electricity, which is usually defined as the ability to connect to the official grid provided by the industry. It does not consider quality (voltage fluctuations), reliability (blackouts) or duration (number of hours per day electricity is available). Further, it does not measure whether people can afford to use electricity once they have access. In many countries, people use off-grid sources (solar panels, private small-scale grids) or informal connections, which might not be officially registered, leading to underreporting the data.

Nutrition

Two indicators are considered: stunting and child food poverty

Stunting

Stunting is the result of chronic or recurrent undernutrition in-utero and early childhood. Children suffering from stunting may never reach their full possible height nor their full cognitive potential. Stunted children not only earn less as adults because of less schooling and learning difficulties but are also more likely to be at risk of overweight and obesity (Source).

Indicator: Prevalence of stunting (height for age less than -2 standard deviations from the median of the World Health Organization (WHO) Child Growth Standards) among children under 5 years of age

Coverage: Data is available for 163 countries and territories.

Source: UNICEF/WHO/World Bank Joint Child Malnutrition Estimates Expanded Database: Stunting (Survey Estimates) 2023.

Data Limitations: Survey estimates have uncertainty due to both sampling error and non-sampling error (e.g., measurement technical error, recording error, etc.). The JME modelled estimates for stunting account for estimates of sampling error around survey estimates. While non-sampling errors cannot be accounted for or reviewed in full, when available, a data quality review of weight, height and age data from household surveys supports the compilation of a time series that is comparable across countries over time.

Child food poverty

Child food poverty is a distinct metric that refers to a child's inability to access and consume a nutritious and diverse diet in early childhood. It is measured using UNICEF and WHO dietary diversity scores. Children are defined as living in severe child food poverty if they consume foods from two or fewer out of eight food groups (Source).

Indicator: Percentage of children 6–23 months of age consuming foods and beverages from zero, one or two out of eight defined food groups during the previous day (severe child food poverty)

Coverage: Data is available for 108 countries and territories.

Source: UNICEF Global Database on Infant and Young Child Feeding. Child food poverty, December 2023.

Data Limitations: As household surveys are the primary source of data on child food poverty, the estimates come with levels of uncertainty due to both sampling and non-sampling error (e.g. misclassification of food items in food groups, recording error etc.).

WASH

Securing access to safe drinking water, sanitation and hygiene reduces illness and death, especially among children, and is critical for their survival and growth. Three indicators are considered under WASH.

Water

At least basic drinking water refers to water from an improved source, provided collection time is not more than 30 minutes for a round trip, including queuing (source), where the improved sources must be accessible on premises, available when needed and free from contamination.

Indicator: Proportion of population using improved drinking water sources no more than 30 minutes roundtrip

Coverage: Data is available for 207 countries and territories

Source: WHO/UNICEF Joint Monitoring Programme – WASH in households 2023 update.

Sanitation

At least basic sanitation refers to the use of improved facilities that are not shared with other households (source) and have a 'safely managed' service. Excreta must either be safely disposed of in situ or removed and treated offsite.

Indicator: Proportion of population using improved sanitation facilities not shared with other households

Coverage: Data is available for 206 countries and territories.

Source: WHO/UNICEF Joint Monitoring Programme – WASH in households 2023 update.

Hygiene

Basic hygiene refers to availability of a handwashing facility with soap and water at home (source).

Indicator: Proportion of population with a handwashing facility with soap and water available at home

Coverage: Data is available for 84 countries and territories.

Source: WHO/UNICEF Joint Monitoring Programme – WASH in households 2023 update.

Data Limitations for WASH: JMP produces internationally comparable estimates based on national data sources. Estimates are modelled using all available data points and at-least basic WASH is preferred over safely managed WASH (SDG indicators) due to data availability.

Education

The education and training that children receive in secondary school equips them with skills that are necessary to fully participate in society. Though the duration in each country varies, secondary education typically covers ages 12 to 17 and is divided into two levels: lower secondary education (spanning three to four years) and upper secondary education (spanning two to three years). Although notable progress has been made in the past few decades, challenges remain in reducing regional disparities and inequalities among secondary school students from different socioeconomic backgrounds. (source).

Three indicators are considered under education: Lower secondary out of school rate, lower secondary completion rate, and learning poverty.

Lower secondary out of school

Indicator: Percentage of children out of school in lower secondary education

Coverage: Data is available for 115 countries and territories.

Source: UNICEF global databases, 2024, based on DHS, MICS and other national surveys.

Data Limitations: The main limitation lies in the data sources. Administrative records are not well-suited to capture out-of-school populations, as they only include children who are registered within the education system. The recommended approach is to estimate out-of-school rates using household survey data. However, such surveys are not always conducted regularly or widely—particularly in countries or regions with high rates of children not attending school.

Lower secondary completion rate

Percentage of cohort of children or young people three to five years older than the intended age for the last grade of lower secondary education who have completed that level of education.

Indicator: Completion rate for adolescents of lower secondary school age

Coverage: Data is available for 112 countries and territories.

Source: UNICEF global databases, 2024, based on DHS, MICS and other national surveys.

Data Limitations: A key limitation of this indicator is that it measures school completion three to five years after the expected age of graduation. As a result, it can only be calculated when at least three years have passed since a child was expected to complete a given level of education.

Learning poverty

The learning poverty indicator was launched by the World Bank and the UNESCO Institute for Statistics in 2019 to help better understand the global learning crisis. High rates of learning poverty are an early signal that education systems are failing to ensure children develop critical foundational skills (source).

Indicator: Share of children at the end-of-primary age below minimum reading proficiency adjusted by out-of-school children (%)

Coverage: Data is available for 122 countries and territories.

Source: UNICEF global databases, 2024, based on DHS, MICS and other national surveys.

Data Limitations: While this indicator combines two critical aspects of education—school access and learning outcomes—it is significantly limited by the availability and coverage of data on learning outcomes. In many cases, these data are either outdated, infrequent or not representative, which restricts the robustness of the measure.

Child Protection

Two indicators are considered under protection: child labour and child marriage

Child labour

Children around the world are routinely engaged in paid and unpaid forms of work that are not harmful to them. However, they are classified as child labourers when they are either too young to work or are involved in hazardous activities that may compromise their physical, mental, social or educational development. A child is considered to be involved in child labour under the following conditions: (a) children 5–11 years old who, during the reference week, did at least one hour of economic activity and/or more than 21 hours of unpaid household services, (b) children 12–14 years old who, during the reference week, did at least 14 hours of economic activity and/or more than 21 hours of unpaid household services, (c) children 15–17 years old who, during the reference week, did at least 43 hours of economic activity.

Indicator: Percentage of children 5–17 years old involved in child labour (economic activity and household chores)

Coverage: Data is available for 85 countries and territories.

Source: UNICEF global databases, 2024, based on DHS, MICS and other national surveys.

Data Limitations: While the concept of child labour includes working in activities that are hazardous in nature, to ensure comparability of estimates over time and to minimize data quality issues, work beyond age-specific hourly thresholds is used as a proxy for hazardous work. Further methodological work is needed to validate questions specifically aimed at identifying children in hazardous working conditions. Similarly, the worst forms of child labour are not currently captured in regular household surveys given difficulties in accurately and reliably measuring them. In addition, the production of goods for one's own use, including activities such as fetching water and collecting firewood, have been classified as unpaid household services (i.e., household chores). (UNICEF, 2020).

Child Marriage

Marriage before the age of 18 is a fundamental violation of human rights. Many factors interact to placing a child at risk of marriage, including poverty, the perception that marriage will provide protection, family honor, social norms, customary or religious laws that condone the practice, an inadequate legislative framework and the state of a country's civil registration system. While the practice is more common among girls than boys, it is a violation of rights regardless of sex (source).

Indicator: Percentage of women (aged 20-24 years) married or in union before age 18.

Coverage: Data is available for 131 countries and territories.

Source: UNICEF global databases, 2024, based on DHS, MICS and other national surveys.

Data Limitations: The measure of child marriage is retrospective in nature by design, capturing the age at first marriage among a population that has completed the risk period (i.e., adult women). Thus, there is an inherent time lag between the moment at which child marriages occur and when they show up in the data. Prevalence estimates reflect child marriages that occurred at least two years and as many as six or more years prior to the reported year. While it is also possible to measure the current marital status of girls under age 18, such measures would provide an underestimation of the level of child marriage, as girls who are not currently married may still do so before they turn 18 (UNICEF, 2020).

Poverty

Two indicators are considered under poverty: multi-dimensional poverty and under five covered by social protection

Multi-dimensional poverty

Child poverty measures the means (or the lack thereof) to realize child rights that crucially and directly rely on continuously/periodically using material elements such as goods and services. These rights include clothing, education, health, housing, information, nutrition, play, sanitation and water. The lack of these basic needs often results in deficits that cannot easily be overcome later in life. Even when not clearly deprived, having fewer opportunities than their peers can limit future opportunities (source).

Indicator: Percentage of children suffering at least one deprivation. Homogeneous severe standards

Coverage: Data is available for 72 countries and territories.

Source: UNICEF global databases

Data Limitations: To ensure international comparability and to be able to aggregate across countries, the indicators and thresholds used to establish severe deprivation do not necessarily coincide with more nuanced measures at the national level.

Under fifteen covered by social protection

Social protection is a set of measures that allow all members of society to access essential care and provide them with income security. Child-sensitive social protection systems – programs such as cash transfers, health insurance and education subsidies – can help make sure that no child is left behind because of poverty. But globally, few children benefit. For almost three out of every four children, social protection programs remain out of reach (source).

Indicator: Percentage of children under fifteen covered by social protection

Coverage: Data is available for 182 countries and territories.

Source: UNSD SDG Database

Data Limitations: This indicator only includes cash transfers, not all elements of social protection.

Child Survival

Under five mortality

The under five mortality rate refers to the probability a newborn would die before reaching five years of age, expressed per 1,000 live births (source).

Indicator: Mortality rate under five per 1000 live births

Coverage: Data is available for 199 countries and territories.

Source: UN Inter-agency Group for Child Mortality Estimation

Data Limitations: Under five mortality data, while crucial, often faces limitations such as varying reporting standards and data collection methodologies across different countries. Additionally, the data may not always capture the specific causes of death or adequately reflect localized disparities within countries.

Children's Climate Risk Framework

The analysis in this report builds on the 2021 Children's Climate Risk Index (CCRI), but rather than aggregating multiple indicators into a single unified risk score it adopts a differentiated approach to combining information on hazard exposure and vulnerability for different contexts and purposes. The framework contextualized risk as a function of hazard exposure and vulnerability.

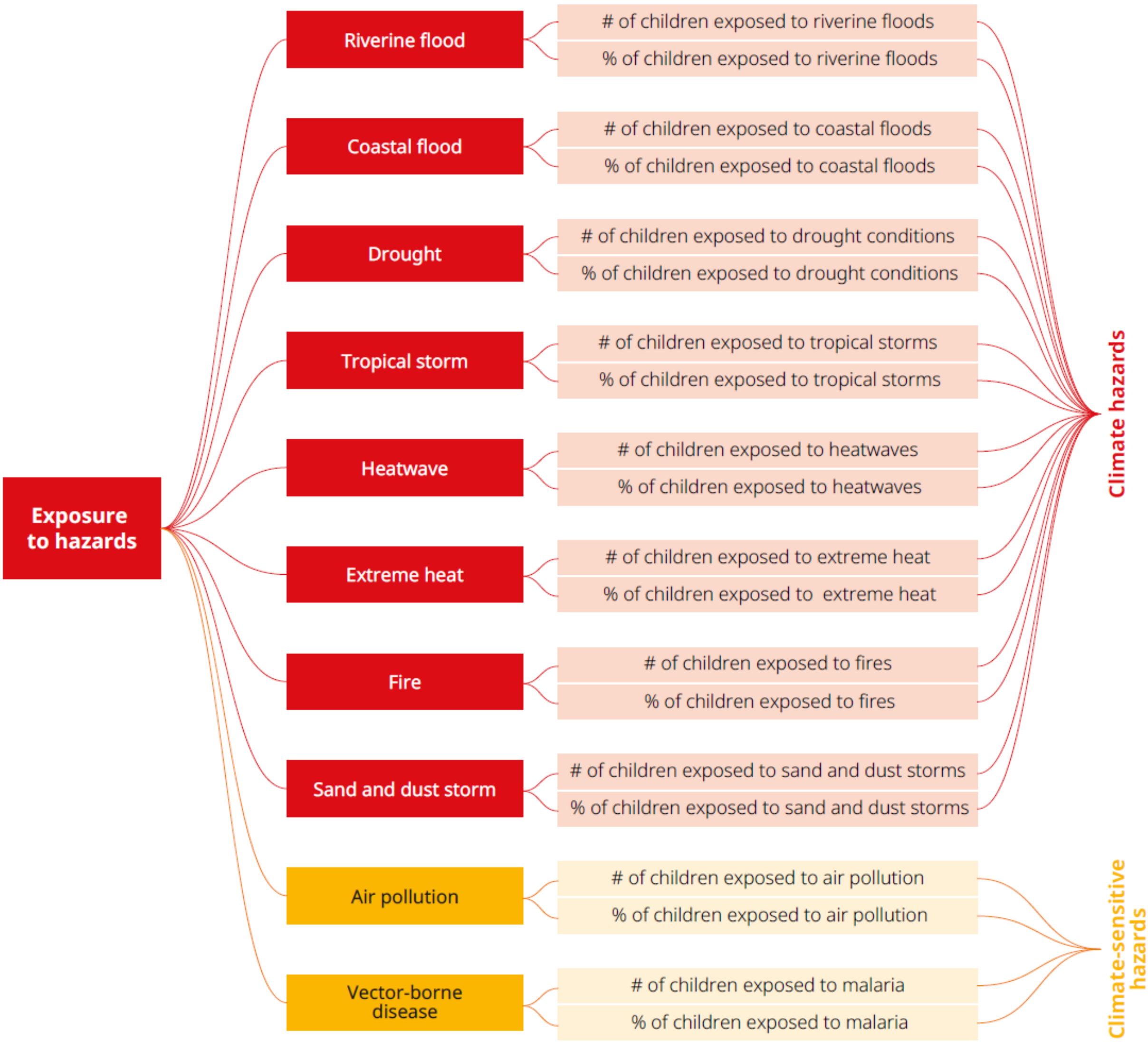
- **Risk** refers to the potential of adverse consequences, resulting from dynamic interactions between climate-related hazards with the exposure and vulnerability of children or associated assets and systems to the hazards
- **Hazards** refer to the potential occurrence of climate-related events
- **Exposure** refers to presence of children, child-critical infrastructure or related assets that could be affected by a climate-related event
- **Vulnerability** is defined as the propensity or predisposition of children to be adversely affected by climate-related hazards

Hazards, exposure and vulnerability may each be subject to uncertainty in terms of magnitude and likelihood of occurrence, and each may change over time and space due to socio-economic changes and human decision-making.

Children's exposure to multiple hazards

With 10 components and 30 indicators, multi hazard exposure aggregates the absolute and relative exposure to individual hazards at a country level. The 10 hazards include:

1. Riverine flood
2. Coastal flood
3. Drought (agricultural, meteorological)
4. Tropical storm
5. Heatwave (frequency, intensity, duration)
6. Extreme Heat
7. Sand and Dust Storm
8. Fire (frequency, intensity)
9. Air Pollution
10. Vector Borne Diseases (malaria)



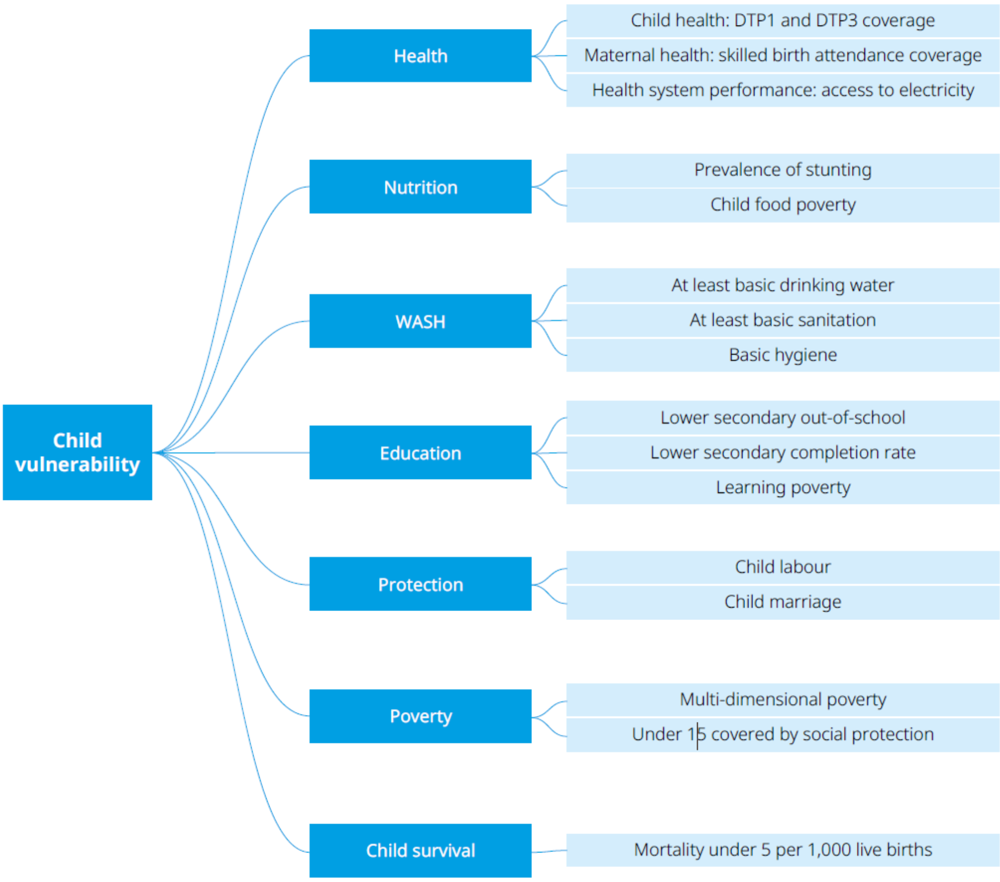
Individual dimensions are aggregated separately.

Considerations for hazard indicators:

- Probabilistic models were given higher priority to define hazards that could potentially happen at any given point and any given time.
- A 100-year return period is considered the default, which signifies an event that is probable, impactful and likely to happen within a child's lifetime.
- Where there is a lack of probabilistic models, long-term observation data has been chosen as a proxy to estimate both absolute and relative exposure.
- The number of years considered varies from hazard to hazard, depending on the data availability and to compensate for the influence of climate change.
- The estimates include all children who could potentially be exposed to a particular hazard and does not account for exposure in any specific year.

Components of Child Vulnerability

Child vulnerability includes seven child-specific vulnerability components with 17 indicators across health, nutrition, WASH, education, protection, poverty and child survival.



Considerations for vulnerability indicators:

- Child vulnerability indicators were chosen after extensive internal consultations with sector-specific and data experts; while the indicators are not comprehensive, they give the best proxy representation for each individual sector.
- All vulnerability indicators are at the country level, and the last available data has been assumed to be current.
- All definitions and data on child vulnerability are obtained from data.unicef.org.
- Each added indicator increases complexity and reduces coverage. Efforts have been made to conduct an extensive sensitivity analysis to best combine individual indicators and components.
- When a particular indicator is not available for a country, it is not considered on the average where the weights of individual indicators are not evenly applied. Since the indicators are highly correlated, our sensitivity analysis has limited to no impact on the final score.

unicef for every child

Methodology

Data Preparation

For hazard data, raw raster data collected from various established data sources was processed using Google Earth Engine. Raster data was first uploaded as an Image Collection asset representing each hazard. Image Collections were processed into a single layer by spatially assembling them into a continuous image using mosaicking. All raster tiles were merged and clipped to represent global land boundaries using a coastline layer and, as discussed earlier, a 100-year return period was used for probabilistic models and the most recent ten- year average of long-term observations.

For vulnerability, all indicators were obtained from UNICEF's Data Warehouse through the existing SDMX API.

Thresholding

For hazard data, thresholds were chosen based on consultations with external experts and meticulous review of the existing literature. It is important to note that by choosing global thresholds, it is possible to over- or under-estimate the exposure of children to individual hazards. The following table highlights the thresholds used for individual hazards.

Hazard	Threshold
Riverine Flood	>1 cm depth
Coastal Flood	All
Tropical Storm	>17.5 m/s (63km/hr)
Agricultural Drought	>30% cropland affected
Meteorological Drought	> Global mean probability of SPI values and SPEI values <-1.5
Fire	>Global mean (frequency, intensity)
Heatwave	>Global mean (frequency, duration, severity)
Extreme Heat	>35 C
Sand and dust storm	All
Air pollution	>5 µg/m3 annual
Malaria	>1 case per 1000 people

Overlay and Summarizing

For overall hazard data, using Worldpop's gridded child population layer, both the absolute (total number of children) and relative (percentage of children) exposure of children were calculated for every hazard using a simple overlay technique. Zonal statistics were used to summarize the total number and percentage of children exposed by country and territory.

Imputation of Missing Values

Imputation is a statistical technique used to estimate and fill in missing values within a dataset.

All indicators used in CCRR 2026 are chosen on the basis of the six established criteria, but most indicators still lack global coverage and are not regularly updated. This results in a significant number of missing values. For an overall vulnerability score, if the data for the most recent year was not available, the most recent data from the past ten years were considered. The next approach was a complete case analysis, or case deletion. This means that if a particular record (e.g., for a specific country or sub-national unit) has at least 60% of its data points missing for the vulnerability variables being analyzed, that entire record was excluded from the analysis. This approach is aligned with international best practices and guidance from both the OECD Handbook on Constructing Composite Indicators (OECD, 2008) and the INFORM Risk Index Methodology (European Commission, 2023).

It is crucial to acknowledge the inherent limitation of this method: this approach risks ignoring potential systematic differences between the complete and incomplete samples, which could lead to results that do not fully represent the entire population or all geographic areas.

Normalization

Normalization is a statistical technique to adjust data from different sources to a common scale without distorting differences in the ranges of values. Common methods include min-max normalization, where data is scaled on a range of 0 to 1 and z-score normalization, which adjusts data based on the mean and standard deviation.

Min-max normalizes indicators to an identical range by subtracting the minimum value and dividing it by the range of the indicator values, noting that extreme values or outliers can distort the transformed indicator. One notable advantage of this technique is that it can widen the range of indicators within a small interval, increasing the effect on the composite indicator.

The min and max values are considered where skewness is lower than 2 and kurtosis is lower than 3.5. Skewness and kurtosis are calculated iteratively for the whole dataset without the obvious outliers, until pre-set conditions are met. The minimum and maximum data points of the remaining dataset are taken as the min and max.

Normalized indicator score (0-10): 10- (baseline maximum – raw data value) / (baseline maximum – baseline minimum) x 10

To ensure a similar trend in normalization for all indicators, where higher values show worse conditions, 10 of the vulnerability indicators have been reversed as highlighted in the table below.

Aggregation

Aggregation involves combining multiple indicators or data points into a single score. This step typically uses weighted averages or other statistical methods to summarize the data. Aggregation helps in simplifying complex data sets into a more understandable and actionable format.

The **arithmetic mean** is the sum of a set of values divided by the number of values. It is the most common measure of central tendency and is easy to calculate and understand. However, it can be heavily influenced by outliers, which can skew the mean and give a misleading representation of the data set. It is best used when the data is symmetrically distributed without extreme values and where there is compensability between the indicators.

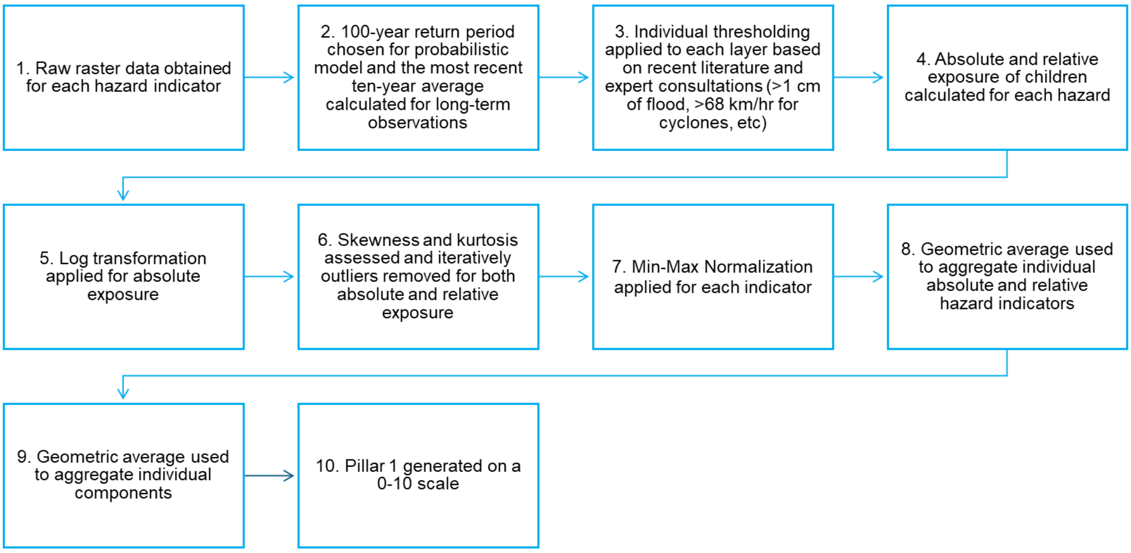
The **geometric mean** is the nth root of the product of n values. It is particularly useful for data sets with values that are multiplicative or which vary exponentially, such as growth rates. The geometric mean is less affected by extreme values compared to the arithmetic mean, providing a more accurate measure for skewed distributions. However, it is more complex to calculate and interpret, and it cannot be used with data sets containing zero or negative values.

Log transformation

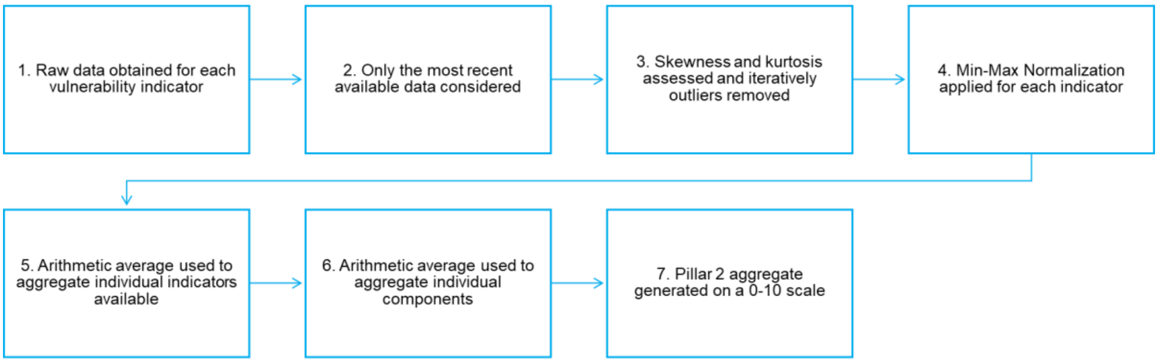
Log transformation is used to convert data to a logarithmic scale. This transformation helps in stabilizing variance, making the data more normally distributed and reducing the impact of outliers. It is particularly useful for data sets with a wide range of values or exponential growth patterns.

The geometric mean is used to aggregate the data multi hazard exposure score, as well as to aggregate relative and absolute exposure to individual hazard components. The arithmetic mean is used where we have two indicators that show compensability and to aggregate the indicators and components in an overall vulnerability score.

If there are no values for a specific indicator, it is not counted towards the aggregation. For multi-hazard exposure layers, all pixels with no values are assumed to be no hazard and multi-hazard score is calculated only when all hazards are available



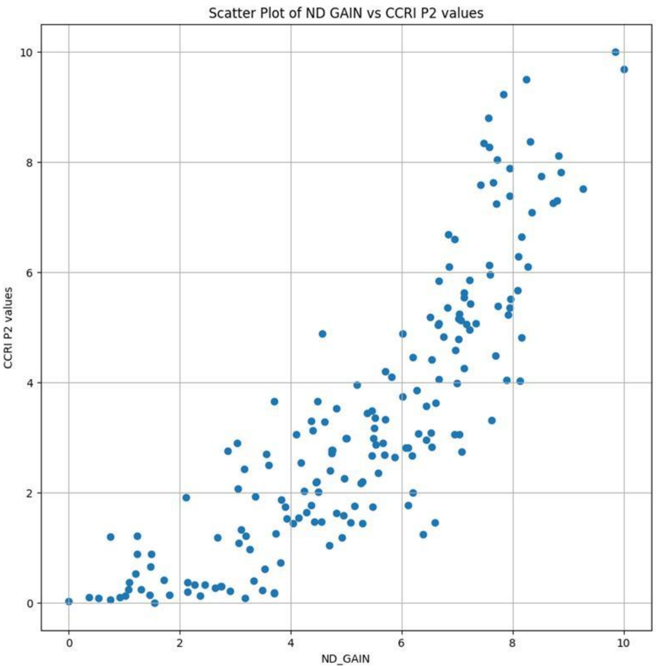
Multi-hazard exposure workflow



Overall vulnerability workflow

Comparison of overall vulnerability score with global development indices

In the first part of the analysis, we compared overall vulnerability score values—which reflect children's vulnerability as a function of the services and systems they depend upon—with two well-known global indices: the ND-GAIN Country Index and the Human Development Index (HDI). The comparison shows a very strong positive correlation (P = 0.86), indicating that countries scoring low on child-specific resilience factors tend to also perform poorly in broader climate adaptation and human development metrics.



Countries with low child vulnerability also show low climate adaptation (ND-GAIN) and human development (HDI) capacity. P = 0.86

Children's climate risk analysis

Using the normalized indicators, the framework proposed multiple ways to conduct risk analysis.

1. **Hazard specific risk analysis**: In many contexts, a single high-intensity hazard can have lasting impacts on vulnerable communities. Hazard-specific risk analysis evaluates the distinct threats posed by individual climate shocks and stresses, by combining the severity of a single physical hazard with the underlying vulnerabilities of the affected population. Single-hazard exposure scores could be combined with multi-vulnerability scores or sector-specific scores.

2. **Sector specific risk analysis**: Climate-related hazards do not impact all areas of a society equally, and broad, generalized or multi-factor risk assessments can often mask deep, localized vulnerabilities. By disaggregating risk into distinct sector vulnerabilities, such as WASH, nutrition, education, health, child protection and social protection, governments can better understand the ways in which different climate hazards are clustering and cascading in various policy sectors.

3. **Multi-dimensional risk analysis**: Rather than addressing specific hazards or sectors in isolation, this holistic approach combines multi-hazard exposure score with overall child vulnerability scores.

Key Considerations and Limitations

It is important to understand the following considerations and limitations when interpreting the data presented in this database:

- **Children's Climate Risk Framework scope:** The framework conceptualizes risk as hazard x exposure x vulnerability. There are inherent limitations in the definitions of the individual components. A single composite index is insufficient to accurately represent the complex climate reality of the world and the different country specific deprivations. The framework with the associated national-level estimates is provided to be used as a starting point to better understand diverse risk profiles.
- **Population data:** The population estimates, including all 2025 figures derived from WorldPop data, are subject to the inherent limitations of that dataset. These limitations specifically apply to estimates of the number of children and often do not account for dynamic population movements, such as internal migration or displacement. The estimates may also not fully match national data.
- **Hazard data characteristics:** It is also useful to note the distinction between hazard data types; some hazards are represented by probabilistic models (e.g., likelihood), while others are based on historical observations (e.g., past events). This distinction influences their interpretation. The hazard data presented comprises global estimates derived from a range of publicly available datasets. These estimates do not necessarily represent or align with official datasets collected by national governments. While measures were taken to ensure the thresholds could be applied globally, it is important to note that the impact could vary widely depending on the local context. In the context of small countries, for some hazards the resolution might not be sufficient to understand and estimate the exposure of children.
- **Data gaps in hazard coverage:** While striving for comprehensive coverage, certain critical hazards, despite their relevance, currently lack globally available, open-source data that meets the necessary standards for inclusion in this database. These are noted where applicable. Particularly for coastal flood, considering the feedback from UNICEF country offices, mainly from SIDS we have marked countries as insufficient data where JRC flood hazard models showed zero exposure but higher resolution flood models showed exposure. Further validation will be carried out in the future to update the coastal flood datasets.
- **Vulnerability:** The database and tools have adapted the vulnerability dimensions recognized by the IPCC. They do not include data on biological sensitivity or additional country specific structural constraints such as macroeconomic diversification and structure, governance quality, cultural capital and ecosystem conditions.

- **Vulnerability measurement challenges**: While critical for a holistic understanding of risk, some dimensions of vulnerability are inherently difficult to measure consistently across diverse countries. This presents a challenge for their inclusion in a standardized global measure, leading to a focus on indicators with greater cross-country comparability.
- **Vulnerability data handling and limitations:** Information on the number of countries with available survey data for specific vulnerability dimensions, along with detailed explanations of how missing data are managed (e.g., complete case analysis, where records with at least 75% missing data are omitted, with acknowledgement of potential biases), is provided in relevant sections. All vulnerability data are valid as of date and most recent estimates might be available at national level that are not considered in this analysis.

CCRR Data Dashboard:

Please access the full data dashboard using this link: https://geosight.unicef.org/en-us/login/?next=/en-us/project/ccrr2026

CCRR Data Excel:

Data can also be downloaded as an excel using this link: https://data.unicef.org/wp-content/uploads/2026/06/ccrr_2026.xlsx

Annex

Data licensing and copyrights

All data used in CCRR 2026 is open source.

Acknowledgement

Data processing and analysis: Rui Huang, Dohyung Kim, Rohini Sampoornam Swaminathan, Tom Slaymaker, Angelly de Jesus Pugliese Villoria from UNICEF Headquarters Climate and Environment Data Unit, Data & Analysis Section

Data input: Tashrik Ahmed, Garen Avanesian, Jorge Bica, Savvy Brar, Claudia Cappa, Alessandro Catalini, Joel Conkle, Yadigar Coskun, Enrique Delamónica, Ayca Donmez, Graeme Wilson Fell, Lauren Francis, Attila Hancioglu, Karoline Hassfurter, Chika Hayashi, Lucia Hug, Yves Jaques, Benjamin Johnson, Robert Johnston, Munkhbadar Jugder, Chibwe Lwamba, Tatjana Karaulac, Yoshito Kawakatsu, Julia Krasevec, Yang Liu, Sakshi Mishra, Vrinda Mehra, Taleen Vartan Nakashian, Colleen Murray Gastón, Maria Muniz, George Mwinnyaa, Daniele Olivotti, Sebastián Palmas, Lauren Pandolfelli, Nicole Petrowski, Eva Quintana, Anshana Ranck, David Sharrow, Alberto Pedro Sibileau, Khaing Soe, Turgay Ünalan, Sameen Wajid, Dee Wang, Danzhen You, Sahar Zandinia, UNICEF Headquartres Data & Analysis Section, Office of Strategy and Evidence.

Technical input: Swathi Manchikanti, Tamara Plush, Joan Yolande Pegram, Nicholas Rees, Abheet Solomon, Sean Storr, Amy Wickham and Nadia Zaidi, UNICEF Climate Resilience Practice; Chloe Angood, UNICEF Child Nutrition and Development Practice; Jorge Alvarez-Sala and Fiona Ward, UNICEF WASH Practice; UNICEF Education Practice; Laura Linda Healy, UNICEF Child Protection and Migration Practice; Marcia Brophy, Zeinab Hijazi, and Malvikha Manoj, UNICEF Health Practice; and Nupur Kukrety, UNICEF Economic and Social Policy Practice.

UNICEF climate and environment external data advisory group:

Prof. Wenjia Cai, Department of Earth System Science, Tsinghua University; Pierre Chrzanowski and Mattia Amadio, World Bank; Kristina Dahl, Vice President for Science, Climate Central; Dr. Delphine Deryng, Partnership & User Engagement specialist, European Centre for Medium-Range Weather Forecasts; Levke Caesar, Potsdam Institute for Climate Impact Research; Arlene Fiore, Peter H. Stone & Paola Malanotte Stone Professor, Massachusetts Institute of Technology; Andrew Kruczkiewicz, Senior Researcher, National Center for Disaster Preparedness, Columbia University; Rachel Lowe, Barcelona Supercomputing Center; Robert Emberson, NASA Disasters; Fraser Macdonald, Massimo Bollasina and Gary Wamough, Data for Children Collaborative; Karmen Poljansek and Sepher Marzi, EU Joint Research Center; Rochelle Schneider, European Space Agency; Lisa Thalheimer, Climate Scientist, International Institute for Applied Systems Analysis and Visiting Scientist, Harvard T.H. Chan School of Public Health; Prof. Dr. Wim Thiery, Full Professor, Vrije Universiteit Brussel, Department of Water and Climate; Chi Zhang, Professor, School of Management, Assistant Dean, School of Global Governance, Beijing Institute of Technology;

Rosa Pietroiusti, Vrije Universiteit Brussel for contribution on extreme heat attribution analysis.

unicef for every child

References

- Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data*, *5*, Article 170191. https://doi.org/10.1038/sdata.2017.191

- Baugh, C., Colonese, J., D'Angelo, C., Dottori, F., Neal, J., Prudhomme, C., & Salamon, P. (2024). *Global river flood hazard maps* [Dataset]. European Commission, Joint Research Centre (JRC). http://data.europa.eu/89h/jrc-floods-floodmapgl_rp50y-tif

- Bondarenko, M., Priyatikanto, R., Tejedor-Garavito, N., Zhang, W., McKeen, T., Cunningham, A., Woods, T., Hilton, J., Cihan, D., Nosatiuk, B., Brinkhoff, T., Tatem, A., & Sorichetta, A. (2025). *Estimates of total number of people under the age of 18 years old and broken down by male and female for each year 2015–2030 at a resolution of 3 arc (approximately 100m at the equator), R2025A* (Version v1) [Dataset]. WorldPop, University of Southampton. https://doi.org/10.5258/SOTON/WP00847
- Bondarenko, M., Priyatikanto, R., Zhang, W., McKeen, T., Cunningham, A., Tejedor-Garavito, N., Woods, T., Hilton, J., Cihan, D., Nosatiuk, B., Brinkhoff, T., Tatem, A., & Sorichetta, A. (2024). *Unconstrained and constrained estimates of 2024 total number of people under the age of 18 per grid square at a resolution of 3 arc (approximately 100m at the equator), R2024A* (Version v1.0) [Dataset]. WorldPop, University of Southampton. https://doi.org/10.5258/SOTON/WP00799
- Cardona, O. D., Bernal, G. A., Villegas, C. P., Molina, J. F., Herrera, S. A., Marulanda, M. C., Rincón, D. F., Grajales, S., Marulanda, P. M., Gonzalez, D., & Maskrey, A. (2023). *Multi-hazard disaster risk model of infrastructure and buildings at the global level*. GIRI. https://giri.unepgrid.ch/sites/default/files/2023-11/2.4-INGENIAR-CDRI-Background-Report-Risk-model.pdf
- CDRI. (2023). *Global infrastructure resilience: Capturing the resilience dividend — A biennial report from the Coalition for Disaster Resilient Infrastructure*. Coalition for Disaster Resilient Infrastructure.
- Coles, S. (2001). *An introduction to statistical modeling of extreme values*. Springer.
- Copernicus Global Drought Observation. (n.d.). *Standard precipitation index* [Factsheet]. https://drought.emergency.copernicus.eu/data/factsheets/factsheet_spi.pdf
- Dottori, F., Salamon, P., Alfieri, L., Bianchi, A., Feyen, L., Hirpa, F., & Lorini, V. (2016a). *Flood hazard maps at European and global scale* (JRC103765). European Commission, Joint Research Centre. https://publications.jrc.ec.europa.eu/repository/handle/JRC103765
- Dottori, F., Salamon, P., Bianchi, A., Alfieri, L., Hirpa, F. A., & Feyen, L. (2016b). Development and evaluation of a framework for global flood hazard mapping. *Advances in Water Resources*, *94*, 87–102. https://doi.org/10.1016/j.advwatres.2016.05.002.
- Health Effects Institute. (2024). *State of global air 2024* [Special report]. https://www.stateofglobalair.org/resources/report/state-global-air-report-2024.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F.,

Villaume, S., Thépaut, J-N. (2017): Complete ERA5 from 1940: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service (C3S) Data Store (CDS). DOI: 10.24381/cds.143582cf

- International Federation of Red Cross and Red Crescent Societies, United Nations Office for the Coordination of Humanitarian Affairs, & Red Cross Red Crescent Climate Centre. (2022). *Extreme heat: Preparing for the heatwaves of the future*. https://www.unocha.org/publications/report/world/extreme-heat-preparing-heatwaves-future-october-2022
- Intergovernmental Panel on Climate Change. (2021). *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/
- Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., & Rama, B. (Eds.). (2022). *Climate change 2022: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://doi.org/10.1017/9781009325844
- Láng-Ritter, J., Keskinen, M., & Tenkanen, H. (2025). Global gridded population datasets systematically underrepresent rural population. *Nature Communications*, *16*, Article 2170. https://doi.org/10.1038/s41467-025-56906-7
- Malaria Atlas Project. (2025). *Malaria Atlas Project*. https://malariaatlas.org/
- OECD. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD Publishing. https://doi.org/10.1787/9789264043466-en
- Pfeffer, D. A., Lucas, T. C., May, D., Harris, J., Rozier, J., Twohig, K. A., Dalrymple, U., Guerra, C. A., Moyes, C. L., Thorn, M., & Nguyen, M. (2018). malariaAtlas: An R interface to global malariometric data hosted by the Malaria Atlas Project. *Malaria Journal*, *17*, Article 352. https://doi.org/10.1186/s12936-018-2500-5
- Reisinger, A., Howden, M., Vera, C., et al. (2020). *The concept of risk in the IPCC Sixth Assessment Report: A summary of cross-working group discussions*. Intergovernmental Panel on Climate Change. https://www.ipcc.ch/site/assets/uploads/2021/02/Risk-guidance-FINAL_15Feb2021.pdf
- Shen, S., Li, C., van Donkelaar, A., Jacobs, N., Wang, C., & Martin, R. V. (2024). Enhancing global estimation of fine particulate matter concentrations by including geophysical a priori information in deep learning. *ACS ES&T Air*. https://doi.org/10.1021/acsestair.3c00054.
- United Nations. (2023). *International Day of Combating Sand and Dust Storms*. https://www.un.org/en/observances/day-of-combating-sand-and-dust-storms
- United Nations Children Emergency Fund (UNICEF). (2020). *A generation to protect: Monitoring violence, exploitation and abuse of children within the SDG framework*. https://www.unicef.org
- United Nations Convention to Combat Desertification (UNCCD). (2024). *Global sand and dust storm base map* [Technical brief]. https://www.unccd.int/sites/default/files/2024-10/UNCCD-WMO%20Technical%20Brief_SDS%20Source%20Base%20Map_Nov%202024.pdf
- United Nations Food and Agriculture Organization. (2020). *Drought and agriculture*. https://www.fao.org/land-water/water/drought/droughtandag/en/

- United Nations Office for Disaster Risk Reduction. (2017). *Flood hazard and risk assessment* (Words into Action Guidelines: National Disaster Risk Assessment, Module 4). UNISDR. https://www.unisdr.org/files/52828_04floodhazardandriskassessment.pdf
- United Nations Office for Disaster Risk Reduction. (2020a). *Drought*. https://www.undrr.org/understanding-disaster-risk/terminology/hips/mh0035
- United Nations Office for Disaster Risk Reduction. (2020b). *Flood*. https://www.undrr.org/hips-cluster/flood
- United Nations Office for Disaster Risk Reduction. (2020d). *Fluvial (riverine) flood*. https://www.undrr.org/understanding-disaster-risk/terminology/hips/mh0007
- Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Bianchi, A., Dottori, F., & Feyen, L. (2018). Climatic and socioeconomic controls of future coastal flood risk in Europe. *Nature Climate Change*, *8*(8), 776–780. https://doi.org/10.1038/s41558-018-0260-4
- Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Verlaan, M., Jevrejeva, S., Jackson, L. P., & Feyen, L. (2018). Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard. *Nature Communications*, *9*, Article 2360. https://doi.org/10.1038/s41467-018-04692-w
- Wilks, D. S. (2011). *Statistical methods in the atmospheric sciences* (3rd ed.). Academic Press.
- World Health Organization. (2021). *WHO global air quality guidelines: Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. https://www.who.int/publications/i/item/9789240034228
- World Health Organization. (2024a). *Vector-borne diseases* [Fact sheet]. https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases
- World Health Organization. (2024b). *World malaria report 2024: Addressing inequity in the global malaria response*. https://www.who.int/publications/i/item/9789240104440
- World Health Organization. (2025a). *Air pollution* [Fact sheet]. https://www.who.int/news-room/fact-sheets/detail/air-pollution
- World Health Organization. (2025b). *Malaria* [Fact sheet]. https://www.who.int/en/news-room/fact-sheets/detail/malaria
- World Meteorological Organization. (2009). *Guidelines on analysis of extremes in a changing climate in support of adaptation decision-making* (WMO-TD No. 1500). https://www.wmo.int
- World Meteorological Organization. (2011). *Manual on flood forecasting and warning* (WMO-No. 1072). https://www.wmo.int
- World Meteorological Organization. (2012). *International glossary of hydrology* (WMO-No. 385). https://www.wmo.int
- World Meteorological Organization. (2025). *Fires*. Global Climate Observing System. https://gcos.wmo.int/site/global-climate-observing-system-gcos/essential-climate-variables/fire
- World Meteorological Organization. (2023). *Classification of tropical cyclones*. https://wmo.int/content/classification-of-tropical-cyclones