S&P Global Sustainable1 Physical Risk: Municipal Dataset

Methodology

S&P Global Sustainable 1 – March 2024

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Physical Risk: Municipal Climate Hazards and Exposures Introduction and Context

Climate change is generating substantial and rising costs to regional and local economies, subnational governments, and their resident populations. Given that the reporting of climate risk by state and local authorities remains voluntary, there is a clear market imperative to provide information on the materiality of climate exposures for local geographic entities. This is crucial both for subnational authorities that seek to understand and manage their climate risks, and for investors holding municipal instruments.

The S&P Global Sustainable1 (S1) Physical Risk: Municipal Dataset provides information on the climate physical hazard exposure of US county and State issuers and municipal bond instruments. The dataset covers both hazards arising from longer term shifts in climate patterns, namely extreme heat, extreme cold, drought, and water stress, and acute event hazards such as tropical cyclone, wildfire and coastal, fluvial and pluvial flood. The dataset provides insights into the levels, trajectories, and comparative materiality of chronic and acute climate hazards faced by all 3,135 US counties and 50 US states under four climate change scenarios and for all decades from the 2020s-2090s. The dataset enables users to understand the climate hazards projected to present material challenges to each geographic entity in each decade; which counties face compound physical climate challenges, with the potential for impact amplification; and which counties will likely face the greatest risks to property markets, supply chains, tourism and other industries, and fiscal health in both the near- and medium-term.

The S1 Physical Risk: Municipal Dataset forms part of the broader S1 climate change physical risk analytics suite, including solutions for real assets and corporate issuer analytics.

Key features of the new dataset include:

- Robust and science-based climate change physical hazard characterization methodology, leveraging the latest available climate change models (CMIP6) and proprietary methodologies.
- Coverage of nine key climate change physical hazards at consistent resolution, globally: coastal flood, fluvial flood, pluvial flood, extreme heat, extreme cold, tropical cyclone, wildfire, water stress, and drought.
- Coverage of four climate change scenarios based on the Intergovernmental Panel on Climate Change (IPCC) Shared Socioeconomic Pathway (SSP) and Representative Concentration Pathway (RCP) scenarios, and offering annualized decadal averages for all hazards from the 2020s to the 2090s.
- Absolute hazard metrics describing the intensity of each physical hazard on average within the boundaries of each county or state, such as the frequency of extreme heat days or the frequency of a 1-in-100 flood event.
- Physical risk exposure scores representing each locality’s point in time exposure to climate hazards relative to 1) exposures for all scenarios and time periods, globally; and 2) exposures for all US counties for all scenarios during the 2020s-2050s.
- Percent exposures of locality GDP and population for each hazard by scenario and decade; composite percent exposures of locality GDP and population.
- Coverage of all US county and state issuers and associated general obligation municipal bonds tracked in S&P Global databases.

Climate Hazard Metrics, Interpretation and Use Cases

Table 1 below describes the interpretation and use cases of each climate metric.

Table 1 Climate Hazard Metrics and Exposure Scores

Indicator Name	Interpretation	Use Cases
Absolute Hazard	• Absolute exposure to each hazard within the geographic boundaries of each issuer, measured in physical units and weighted by the distribution of GDP generation within the issuer jurisdiction. • Example: Fraction of extreme heat days per annum	• Quantifying exposure to climate physical hazards over time and across scenarios
Exposure Score	• Exposure to each hazard within the geographic boundaries of each issuer relative to global conditions and expressed as a 1 (least exposed) to 100 (most exposed) score. Exposure scores are weighted by the distribution of GDP generation within the issuer jurisdiction. • Example: Exposure score of 100 for extreme heat indicates areas among the most exposed locations to extreme heat globally	• Screening of climate physical hazard exposure to identify the most exposed bonds/issuers in a portfolio • Screening of climate physical hazard exposure within mixed asset class portfolios (e.g. real assets, equities, corporate fixed income) • Targeting of in-depth risk assessment and engagement activities • Regulated and voluntary reporting
US Exposure Score	• Exposure to each hazard within the geographic boundaries of each issuer relative to conditions in the USA and expressed as a 1 (least exposed) to 100 (most exposed) score. Exposure scores are weighted by the distribution of GDP generation within the issuer jurisdiction. • Example: Exposure score of 100 for extreme heat indicates areas among the most exposed locations to extreme heat within the USA	• Screening of climate physical hazard exposure to identify the most exposed bonds/issuers in a US muni bond focused portfolio • Ranking of US muni bond exposure to climate physical hazards • Targeting of in-depth risk assessment and engagement activities • Regulated and voluntary reporting
Composite Exposure Score and Composite US Exposure Score	• Composite exposure scores are calculated as an equally-weighted additive combination of the physical risk score of each hazard for a locality for a given scenario and year, which is then rescaled to	• Screening of climate physical hazard exposure to identify the most exposed bonds/issuers in a US muni bond focused portfolio • Ranking of US muni bond exposure to climate physical hazards

	a 1-100 range using an exponential scoring curve. • The Composite Exposure Scores for a given locality are generated using all Exposure Scores for each hazard for all scenarios for the 2020s-2090s, and the US Composite Exposure Scores for a given locality are generated using all US Exposure Scores for each hazard for all scenarios for the 2020s-2050s.	• Targeting of in-depth risk assessment and engagement activities • Regulated and voluntary reporting
GDP Exposed	• Proportion of GDP generated within the geographic boundaries of each issuer that is exposed, as defined by pre-determined thresholds, to material changes in each climate physical hazard. • Example: 50% GDP exposed to extreme heat by 2050 indicates that 50% of the GDP generated within an issuer boundary is projected to be exposed to at least three months of extreme heat days by 2050	• Quantification of the significance/ materiality of the exposure of each issuer to each hazard from an economic perspective • Ranking of issuers based on the significance/materiality of the exposure to each hazard from an economic perspective • Targeting of in-depth risk assessment and engagement activities • Regulated and voluntary reporting
Population Exposed	• Proportion of population within the geographic boundaries of each issuer which is exposed, as defined by pre-determined thresholds ,to material changes in each climate physical hazard. • Example: 50% population exposed to extreme heat by 2050 indicates that 50% of the population within an issuer boundary is projected to be exposed to at least three months of extreme heat days by 2050	• Quantification of the significance/ materiality of the exposure of each issuer to each hazard from a social / public welfare perspective • Ranking of issuers based on the significance/materiality of the exposure to each hazard from a social/public welfare perspective • Targeting of in-depth risk assessment and engagement activities • Regulated and voluntary reporting

Use Cases

The S1 Physical Risk: Municipal dataset supports the following client use cases:

Risk Screening and Portfolio Analytics

- Identify localities and issuers which face the most material climate exposures to which climate hazard(s) at any point in time and given scenario.
- Evaluate the climate exposure trajectory for each locality and how it compares to other issuers.
- Identify the issuers and climate hazards which contribute most to portfolio-level exposure.
- Calculate portfolio-level exposure metrics for comparison with relevant benchmarks.

- Identify issuers at high risk to further investigate locality's adaptation and mitigation planning, financial capacity to support, and governance to implement.

Regulated and Voluntary Reporting

- Inform reporting on climate change physical risk exposure and materiality at the portfolio, fund or organizational level.
- Align with the guidelines of the Taskforce on Climate-Related Financial Disclosures, Sustainable Finance Disclosures Regulation, and/or other reporting requirements.

Engagement

- Inform engagement with issuers to better understand mitigation, adaptation, and other management strategies planned to address rising climate physical exposures, and opportunities to strengthen climate resilience.

Indicators and Scenarios

Table 2 below presents the climate change physical hazards considered in the dataset. All hazards are evaluated globally at consistent spatial resolution, with the exception of coastal flood where higher resolution is available.

Table 2 Climate Change Hazard Coverage, Metrics, Resolution and Data Sources

Hazards	Analysis Metric	Indicator Definition	Spatial Resolution	Data Sources
Extreme Heat	Projected Tx95p	Annual percentage of days with maximum temperature warmer than the 95th percentile local baseline daily maximum temperature	~25x25km	NEX-GDDP downscaled CMIP6
Extreme Cold	Projected Tn5p	Annual percentage of days with minimum temperature colder than the 5th percentile local baseline daily minimum temperature	~25x25km	NEX-GDDP downscaled CMIP6
Coastal Flood	Frequency of 100-yr coastal flood	Projected annual frequency of the historical baseline 100-yr coastal flood depth	30x30m (USA) 90x90m (RoW)	GTSR hydrodynamic surge model Kopp et al SLR data; Muis et al 2016 MERIT /US3DEP USGS global coastlines
Fluvial (River) Flood	Frequency of 100-yr fluvial flood	Projected annual frequency of the historical baseline 100-yr flood depth	~1x1km	Hydro Atlas

Hazards	Analysis Metric	Indicator Definition	Spatial Resolution	Data Sources
				NEX-GDDP downscaled CMIP6 WRI Aqueduct
Pluvial (Rainfall) Flood	Frequency of 100-yr rainfall event	Projected frequency of the historical baseline 100-yr daily precipitation rate	~25x25km	NEX-GDDP downscaled CMIP6
Tropical Cyclone	Frequency of Cat3+ storms	Projected annual frequency of category 3 and higher tropical cyclones	~25x25km	NASHM Hall et al 2015
Wildfire	Fire Weather Index (FWI)	Projected annual frequency of days classified as high, very high or extreme wildfire danger based on the FWI. Adjusted for land cover/presence of burnable vegetation	~25x25km	NEX-GDDP downscaled CMIP6 ESA LULC
Water Stress	Water Stress Index	Projected future ratio of water withdrawals to total renewable water supply in a given area	River Basin	WRI Aqueduct
Drought	Standardized Precipitation-Evapotranspiration Index (SPEI)	Projected annual frequency of months classified as severely dry or extremely dry based on the SPEI	~25x25km	NEX-GDDP downscaled CMIP6

The dataset focuses on four future climate change scenarios based on IPCC Representative Concentration Pathways and Shared Socioeconomic Pathways and informed by the TCFD technical guidelines (FSB, 2017)[1]:

- High Climate Change Scenario (SSP5-8.5): Low mitigation scenario in which total greenhouse gas emissions triple by 2075 and global average temperatures rise by 3.3-5.7 °C by 2100.
- Medium-High Climate Change Scenario (SSP3-7.0): Limited mitigation scenario in which total greenhouse gas emissions double by 2100 and global average temperatures rise by 2.8-4.6 °C by 2100.
- Medium Climate Change Scenario (SSP2-4.5): Strong mitigation scenario in which total greenhouse gas emissions stabilize at current levels until 2050 and then decline to 2100. This scenario is expected to result in global average temperatures rising by 2.1-3.5 °C by 2100.

[1]Financial Stability Board, 2017. *Recommendations of the Task Force on Climate-Related Financial Disclosures.*

- Low Climate Change Scenario (SSP1-2.6): Aggressive mitigation scenario in which total greenhouse gas emission reduce to net zero by 2050, resulting in global average temperatures rising by 1.3-2.4 °C by 2100, consistent with the goals of the Paris Agreement.

The dataset evaluates climate change physical risks for decadal averages from the 2020s to the 2090s.

CMIP6 Climate Hazard Modeling and Enhancements

S1 climate change hazard modeling utilizes the CMIP6 climate models, the latest generation of global climate models informing the IPCC[2]. Temperature and precipitation data from 35 CMIP6 models were recently downscaled from the varying native spatial resolution of the models to a uniform 0.25° latitude-longitude grid, comprising the NEX-GDDP[3] downscaled CMIP6 dataset which forms the basis for the S1 hazard model. The NEX-GDDP dataset was processed for a historical baseline plus four scenarios, SSP126, SSP245, SSP370, and SSP585; however, not all of the 35 underlying CMIP6 models were available for all scenarios. The data format, spatial maps at time slices, were first reprocessed to generate daily time series to year 2100 at each grid cell. Model-mean time series were then generated for the daily precipitation and temperature minimum and maximum, data which constitute the primary drivers for five of the eight hazards included in the S1 model.

Driven by the downscaled CMIP6 data and other sources, the hazard models summarized below have been used to "preprocess" all hazard variables at the global scale. That is, hazard variable values are generated and archived in decadal-mean values (historical baseline and the 2020s through 2090s) on global grids for four climate scenarios. This preprocessed data is then accessed for subsequent scoring and financial impact analysis. A brief description of the methodology utilized to calculate each of the eight hazards is provided in Error! Reference source not found.Error! Reference source not found..

Table 3 Climate Change Hazard Modelling

Hazard	Methodology Description
Extreme Heat Extreme Cold	The measure of extreme heat is Tx95p, the percentage of days per year with a maximum temperature that exceeds the 95th percentile of the local historical baseline daily maximum temperature. The measure of extreme cold is Tn5p, the percentage of days per year with a minimum temperature below the 5th percentile of the local historical baseline daily minimum temperature. These hazard variables are derived directly from each downscaled CMIP6 model, then averaged across models and years in a projected decade.
Fluvial Flood	Basin Scale Frequency Projections: The 10-yr and 100-yr return-period (RP) river discharges are related statistically to seven variables ("covariates") based on a published analysis of historical data over the USA. Four covariates are topographic in nature and three are climatological (5-day precipitation maxima and numbers of consecutive dry days and frosts days). For future decades, the climate covariates are derived from the downscaled CMIP6 dataset. The projected 10-yr and 100-yr discharges are interpolated to obtain the projected frequency (reciprocal of RP) corresponding to the baseline 100-yr discharge. The grid for the analysis is comprised of the geometric intersection of the downscaled CMIP6 0.25° grid and the topographic-data grid of irregular drainage-basin polygons (HydroAtlas level 12).

[2] World Climate Research Programme. 2020. CMIP Phase 6 (CMIP6). [Online]. Available: https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6

[3] NASA Center for Climate Simulation. 2022. NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). [Online]. Available: https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp

Hazard	Methodology Description
	Flood Extent Overlay: Basin scale flood frequency projections are overlaid with projected flood extent data sourced from the WRI Aqueduct dataset[4]. Flood extent data (100-year return period) at 0.0083° (~1x1km) resolution is used as a 'mask' to identify areas exposed to flood within each basin under two scenarios (RCP 4.5 and RCP 8.5) and three decades (2030, 2050, 2080). Flood extent data for RCP 4.5 was used to represent SSP1-2.6, RCP8.5 was used to represent SSP3-7.0 and missing time period projections were mapped to the nearest available decade in the absence of better available data. WRI Aqueduct projections for five GCMs (MIROC-ESM-CHEM, IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M, NorESM1-M) were used to create an ensemble flood extent 'mask', identifying pixels as floodable where at least three of the five available GCMs projected flood within that pixel.
Drought	The drought hazard is derived from the Standardized Precipitation and Evapotranspiration Index (SPEI), as computed by SPEIbase from the Spanish National Research Council (CSIC) which provides SPEI10 based on observational and reanalysis data. SPEI utilizes daily solar radiation and daily surface wind as an input, in addition to temperature and precipitation from the downscaled CMIP6 models. The hazard variable in a projected year is the average proportion of months per annum classified as severely dry or extremely dry based on SPEI. The spatial resolution for drought is 0.25° (~25x25km) globally.
Wildfire	The wildfire hazard is defined based on the Fire Weather Index (FWI) of the Canadian Forest Fire Danger Rating System and assesses if meteorological conditions are favorable for wildfire development. The FWI is computed based on downscaled CMIP6 temperature, precipitation, relative humidity, and surface wind speed projections. The hazard variable is the average proportion of days per annum that are classified as high, very high or extreme wildfire danger based on the FWI. The spatial resolution for wildfire is 0.25° (~25x15km) globally. Modelled wildfire conditions are overlaid with a land cover mask to differentiate pixels containing burnable vegetation and thus susceptible to wildfire, from pixels that do not contain burnable vegetation such as urban areas. The land cover mask is derived satellite imagery sourced from the Copernicus Global Land Service[5] dataset. The land cover mask is applied at 300x300m resolution and sets the wildfire hazard to zero in locations where less than 20% of the wildfire hazard pixel and its surrounding is covered with burnable vegetation.
Tropical Cyclone	The Tropical Cyclone (TC) hazard is calculated via a statistical-stochastic model that simulates the lifecycle of TCs, trained on historical TC track data in each of the world's TC-sustaining ocean basins. Included in the training are statistical relationships between TC variability and sea-surface temperature (SST). For future decades, SST data directly from 10 CMIP6 models are used to drive new TC simulations in future climate states. The TC metric derived from the simulations is annual rate of category 3 and higher TCs in 0.25° grid cells globally. Due to rapidly increasing uncertainty, TCs projections are only made through the 2040s. Subsequent decades are held at the 2040s value.
Coastal Flood	Historical storm-tide (surge plus tide) levels at 9 return periods from the GTSR global hydrodynamic system are combined with sea-level rise (SLR) projections (Kopp et al.,

[4] World Resources Institute. 2022. Aqueduct. [Online]. Available: https://www.wri.org/aqueduct

Hazard	Methodology Description
	2019[5]) to model flood levels in coastal regions. A flood-water path-finding algorithm is applied to determine the interior points that are subject to flooding in response to different coastal water levels. The algorithm makes use of topographic elevation data at 30-meter resolution over the US and 90-meter resolution elsewhere, and this defines the resolution of the coastal flood analysis. From the resulting flood depths at different return periods, we compute the projected frequency of the historical baseline 100-yr flood depth as the primary hazard variable. Note that components of the Kopp SLR data use CMIP5 inputs, not CMIP6. To include certain CMIP6 scenarios, we have applied an interpolation procedure to the CMIP5-based SLR.
Pluvial Flood	Pluvial flood hazard associated with extreme rainfall events is modelled using daily precipitation data from an ensemble of NEX-GDDP-downscaled CMIP6 models (25-km resolution worldwide). A statistical model of Generalized Extreme Value analysis is used to determine the intensity of extreme rare events. The model uses a simplifying assumption that topography and natural or artificial drainage capacity is constant in time thus avoiding the requirement for high-resolution topographic or drainage data. This generation of Pluvial hazard modelling is limited to projections of annual frequency of the historical baseline 100-year precipitation rate which relates to the pluvial hazard metric of annual frequency of 100-year flood depth.
Water Stress	The Water Stress Index is the ratio of total water withdrawals within an area to the available water resources in surface and groundwater. The analysis covers water consumptive and non-consumptive withdrawals for domestic, industrial, irrigation and livestock use. Water availability considers the impact of upstream consumptive water users and dams. Higher values indicate more competition among users for available water resources. Water stress index data is sourced from the World Resources Institute and classified into ten categories from lowest to highest water stress.[6]

[5] Kopp, R. E., E. A. Gilmore, C. M. Little, J. Lorenzo Trueba, V. C. Ramenzoni, and W. V. Sweet (2019). Usable Science for Managing the Risks of Sea-Level Rise. Earth's Future 7, 1235–1269.

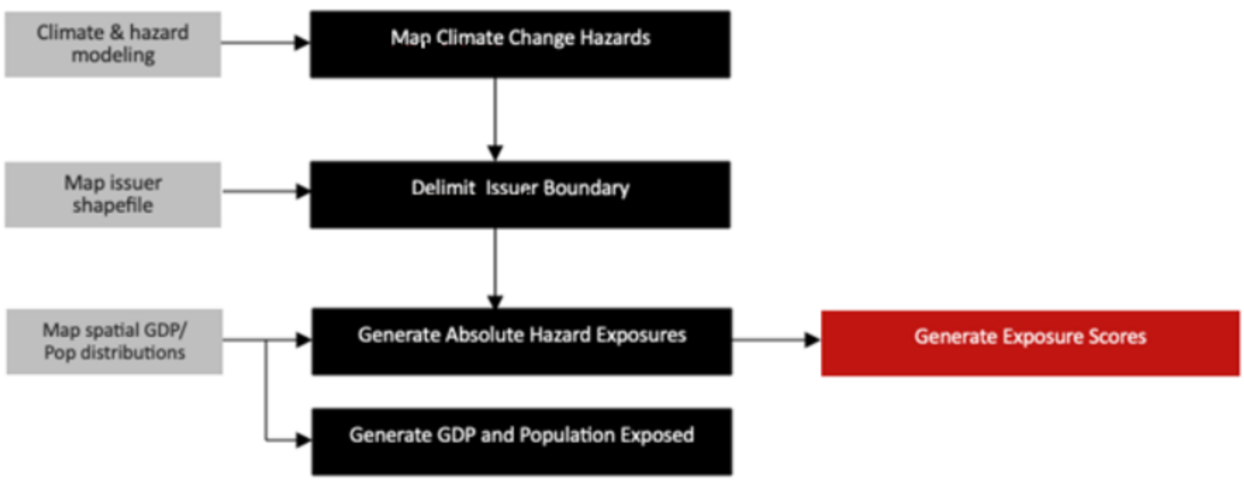
[6] World Resources Institute. 2022. Aqueduct. [Online]. Available: https://www.wri.org/aqueduct

Methodology Overview

The S1 Physical Risk: Municipal Dataset Absolute Hazards and Exposure Scores methodology is based on four steps as shown in Error! Reference source not found.:

1. Climate Hazard Modelling
2. Shapefile Mapping
3. GDP and Population Mapping
4. Exposure Metric Calculation

Figure 1: S1 Physical Risk: Municipal Methodology



1. Climate Hazard Mapping

S1 has assembled models and datasets representing projected absolute exposure to nine discrete climate change hazards globally across four climate change scenarios and eight time periods (See: Indicators and Scenarios section), to produce global climate change physical hazard maps. Each indicator, scenario and time period is represented as a geospatial dataset with hazard values assigned to location at a resolution deemed suitable to each hazard. This enables the modelling of exposure to each climate hazard at a given time period and the change in hazard exposure over time and relative to a historical baseline.

2. Boundary Mapping

Geographic boundaries for all US counties and states were mapped based on the Database of Global Administrative Areas (GADM), licensed from Rastera LLC[7]. This dataset provides geographic boundary data for all administrative divisions globally.

[7] https://gadm.org

3. GDP and Population Mapping

Data on the spatial distribution of GDP and population globally was derived from the following sources:

- *GDP*: Kummu et al. 2018[8] provides data on GDP PPP generation at 0.0083° (~1x1 km) resolution globally for the year 2015.
- *Population:* The SEDAC Gridded Population of the World (GPW) v4[9] dataset provides data on population spatial distribution globally at a resolution of 0.0083° (~1x1 km) for the year 2010.

Spatial distribution of GDP and population were overlaid with climate hazard data for use as a weight in the calculation of muni/state averages, and in the calculation of GDP and population exposed metrics.

4. Exposure Metric Calculation

The S1 Physical Risk: Municipal dataset incorporates four key metrics which are calculated as follows:

Weighted Average Absolute Hazard Metrics

For each hazard, scenario and time period combination, hazard data is overlaid with spatial GDP data and the GADM administrative boundary dataset. For each administrative unit (county or state), the hazard and GDP pixels are multiplied together, summed and then divided by the total sum of GDP pixels within the administrative boundary, to calculate a weighted average hazard metric. This approach overweights the hazard within GDP-generating areas of the county or state, and underweights non-economically productive areas. Adjustments are made to account for GDP or hazard pixels that span the boundary of a county or state. See Appendix for further detail.

Weighted Average Exposure Scores

The S1 Physical Risk Exposure Score model assigns risk scores from 1 (lowest exposure) to 100 (highest exposure) to each hazard pixel, and the pixel level scores can be aggregated to county or state level exposure scores as GDP-weighted averages for each scenario and time period (as described for the weighted average absolute hazard metrics above). The exposure score is intended to represent the relative level of exposure to each hazard at each location relative to global conditions across all scenarios and time periods. A score of 100 indicates an asset location at the highest level of exposure to a given hazard globally (above a threshold defined by S&P Global for each hazard), and a score of 1 indicates the lowest level of exposure (below a threshold defined by S&P Global for each hazard). Physical risk metric values are normalized to scores based on the formula described in Figure 2.

Figure 2 Climate Change Physical Risk Score Normalization for (global) Exposure Scores

[8] Kummu, M., Taka, M. & Guillaume, J. Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. *Sci Data* **5**, 180004 (2018). https://doi.org/10.1038/sdata.2018.4

[9] Gridded Population of the World, Version 4 (GPWv4): National Identifier Grid. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://dx.doi.org/10.7927/H41V5BX1.

$$S_{a,h,s,y} = (100 - 1) * \frac{(R_{a,h,s,y} - R_{min,h}}{(R_{max,h} - R_{min,h})} + 1$$

Where

$S_{a,h,s,y}$	is the physical risk exposure score for locality (a) for hazard (h) under scenario (s) and time period (y)
$R_{a,h,s,y}$	is the absolute exposure metric value for locality (a) for hazard (h) under scenario (s) and time period (y)
$R_{min,h}$	is the lower threshold absolute risk metric value globally across all scenarios and time periods for hazard (h)
$R_{max,h}$	is the upper threshold absolute risk metric value globally across all scenarios and time periods for hazard (h)

For US Exposure Scores, the R_{max} and R_{min} reflect US maxima and minima (without thresholds) for the US for each hazard across all scenarios for the 2020s to 2050s, as described in Figure 3.

Figure 3 Climate Change Physical Risk Score Normalization for US Exposure Scores

$$S_{a,h,s,y} = (100 - 1) * \frac{(R_{a,h,s,y} - R_{min,h})}{(R_{max,h} - R_{min,h})} + 1$$

Where

$S_{a,h,s,y}$	is the physical risk exposure score for locality (a) for hazard (h) under scenario (s) and time period (y)
$R_{a,h,s,y}$	is the absolute exposure metric value for locality (a) for hazard (h) under scenario (s) and time period (y)
$R_{min,h}$	is the minimum absolute risk metric value for the US across all scenarios for the 2020s-2050s for hazard (h)
$R_{max,h}$	is the maximum absolute risk metric value for the US across all scenarios for the 2020s-2050s for hazard (h)

The composite score is intended to provide a combined measure of county exposure to nine climate change physical hazards. The composite exposure score is calculated as an equally-weighted additive combination of the county physical risk score on each hazard for a given scenario and year, which is then rescaled to a 1-100 range using an exponential scoring curve. The scoring curve is designed to ensure that counties with high exposure to one hazard, but low exposure to all others, will be assigned a moderate to high composite physical risk exposure score. Alternative approaches, such as a simple average of hazard exposure scores within a given scenario and time period, risk understating county exposure to climate change.

The Composite Physical Exposure Score is calculated as described in Figure Error! Reference source not found..

Figure 4 Composite Physical Risk Score Calculation

$$C_{x,s,y} = -99 * 0.49 \wedge (SUM_{x,s,y} * 0.009) + 100$$

Where

$C_{x,s,y}$	is the composite score for composite score for issuer x in scenario s and time period y
$SUM_{x,s,y}$	is the sum of hazard physical risk exposure scores for issuer x in scenario s and time period y

US Exposure Scores

The US Exposure Scores are calculated using the same approach as the Exposure Scores described above, except that the scoring range is set against the hazard exposure range for US counties and states only, as opposed to all locations globally, for the 2020s, 2030s, 2040s and 2050s decades. The US Exposure Scores help to simplify the comparison of exposure levels among US states and counties since the full range of exposure scores is contained within the boundaries of the USA, in contrast with the Exposure Scores where the most and least exposed locations may be outside of the USA. The analysis time horizon is also limited to the 2020s-2050s as this is more representative of the duration of bonds issued by municipal bond issuers.

GDP Exposed and Population Exposed Metrics

The GDP and population exposed metrics quantify the proportion of GDP or population located within pixels in which the hazard is greater than or equal to the materiality thresholds detailed in Error! Not a valid bookmark self-reference.4.

Table 4 Climate hazard materiality thresholds for computing percent GDP and population exposed

Climate Hazard	Hazard Materiality Threshold	Rationale
Extreme Heat	0.246	Equivalent to three months of extreme heat days
Extreme Cold	0.1	Equivalent to 36 days of extreme cold
Drought	0.246	Equivalent to three months of high drought likelihood days
Wildfire	0.246	Equivalent to three months of high wildfire likelihood days
Fluvial Flood	0.01	A 1% annual probability of the one-in-100-year flood depth, in flood-exposed areas
Coastal Flood	0.01	A 1% annual probability of the one-in-100-year flood depth, in flood-exposed areas
Pluvial Flood	0.02	A 2% annual probability of the one-in-100-year flood depth
Tropical Cyclone	0	All exposure to category 3+ tropical cyclones is considered material
Water Stress	0.4	High water stress as defined by the WRI Aqueduct dataset

The sum of GDP or population located in pixels exceeding the thresholds above within each county or state boundary is divided by the total GDP or population within the county or state boundary to calculate the percentage of GDP or population exposed (respectively) to each hazard under each scenario and time period. See Appendix for further detail.

The composite GDP and population exposed metrics are calculated as the sum of the GDP or population exposed to all nine hazards under a given scenario and time period. The composite GDP and population exposed metrics are capped at 100%.

5. Linking to Muni Bond CUSIP Identifiers

Muni bond CUSIPs were retrieved via R search in S&P Capital IQ on county name and potential variants, complemented by manual review of missing entries. Bond name was further filtered for General Obligation/GO/G.O. to isolate general obligation instruments.

Assumptions and Limitations

Key limitations of S1's Physical Risk: Municipal Dataset analytics include:

- Modelling Uncertainty: The climate models underpinning the physical risk analysis are complex and subject to uncertainty. S1 assumes physical risk assessment based on averages of the output of all available CMIP6 GCMs is broadly representative of the future paths of hazard values. Future analysis could consider the range of GCM hazard values and other approaches for uncertainty assessment.
- Focus on Productive Areas: Regional hazard metrics are calculated using component cell (1km x 1km) GDP to weight cell hazard inputs for computing representative regional averages. Future iterations may consider using cell population for weighting hazard inputs, as an alternate approach for gauging socioeconomic exposure.
- Materiality: S1 currently defines hazard metrics using climate extremes and recognizes hazard thresholds of major magnitude in the measurement of GDP and population exposed, to ensure the capture of significant climate trend developments beyond natural variability. Differences in the vulnerability of specific locales could mean significant impacts exist at hazard levels far below the extremes and thresholds defined.
- Threshold Materiality: Expert judgment is the basis for the hazard thresholds used to calculate percent GDP and population exposed (Table 4), which were chosen to reflect a significant level of hazard beyond year-to-year variation. Our review of external sources did not identify any literature that would define the basis for the US thresholds.
- Spatial Resolution: S1 has sought to integrate climate modelling at sufficient spatial resolution to enable a robust estimation of the physical risk exposure, however this analysis could be enhanced in the future.
- Hazard Correlation: All hazards are modeled independently, and correlation or vulnerability associated with the co-occurrence of multiple hazards is not currently specifically modelled. For example, the tropical cyclone hazard metric encompasses the frequency of associated wind risks while coastal flooding hazard metric independently includes storm surge flooding, likely capturing flooding associated with tropical cyclone.

  Further analysis could consider compound or concurrent hazard extremes, as data becomes available.
- Data Timelines: The datasets used to represent the distribution of population and GDP are historical and infrequently updated due to their reliance on country census collections. The datasets chosen currently are the definitive sources, and any future updates (or new datasets made available that supersede these in data quality) will be incorporated into the modeling in a timely fashion. In addition, population and GDP distributions are held constant in the future scenario projections. The distribution of population and the production of GDP is expected to change with time as economies and communities develop, and these changes will not be reflected in the metrics presented in this dataset.

Dependencies

While the S1 Physical Risk: Municipal Dataset is a standalone product, known dependencies are:

- S1's corporate physical risk dataset will use US state- or county-level hazard exposures as a proxy where asset geolocation is not specified, yet information exists to specify state or county. Such hazard metrics will be used in calculations of financial impact to an asset based on specific impact functions.

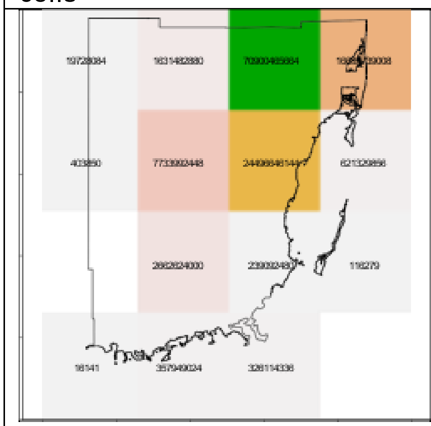
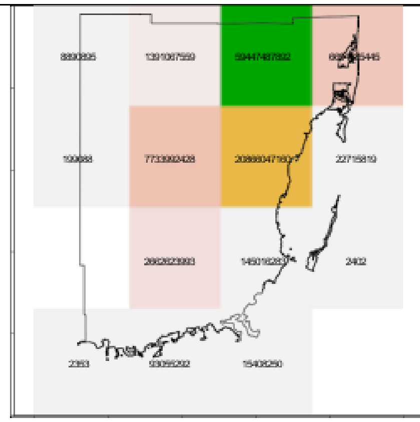
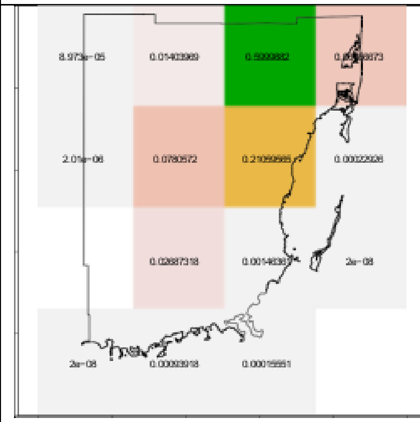
- S&P Global Ratings Public Finance will use US state- and county-level hazard exposures in due diligence engagement with municipal issuers, in evaluating the materiality of climate physical risk exposure for government issuers in the credit ratings process, and providing commentary on issuer-relevant climate physical risks.

Appendix

Details the calculation of GDP-weighted absolute hazard metric, and GDP/population exposed metric.

The GDP-weighted average absolute hazard is intended to give more weight to hazard cells within a county that provide a higher share of GDP, to reflect the risk to economic activity. The GDP values for each hazard cell are adjusted to account for area contribution of the cell to the county by multiplying cell GDP by cell area weight. This adjusted GDP is used as a weight to calculate the GDP-weighted average hazard values.

If Figure 1a is the aggregated GDP (USD) contribution of each 25-km hazard cell in Miami-Dade, with hazard levels indicated by color; Figure 1b is the GDP value adjusted to reflect the area of each cell with respect to county boundaries; and Figure 1c is the contribution of each component cell to overall GDP:

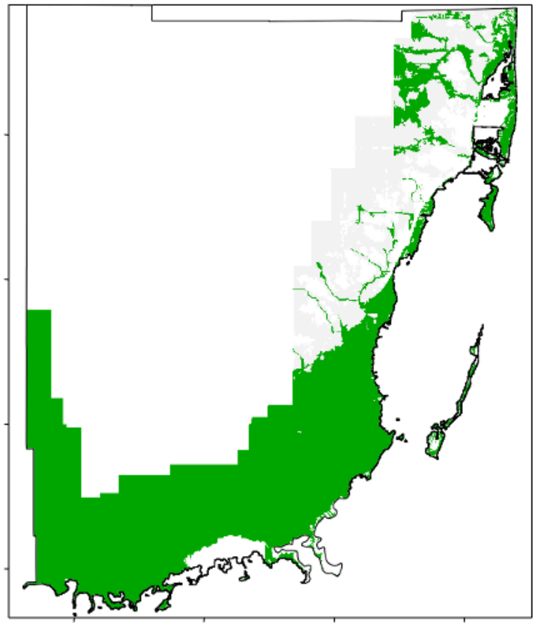
Figure 1a. Aggregate GDP associated with 25-km hazard cells	Figure 1b. GDP associated with cells with respect to county boundaries	Figure 1c. Contribution of component cells to overall GDP
		

Then the respective GDP contributions from 1c are used to weight each cell's hazard level to generate the final regional hazard level.

For GDP and population exposed, the metric represents GDP or population within a county which have material exposure to a hazard, for a given scenario and decade. "Material" is defined using thresholds derived by expert judgment. The metric, a percentage, is derived by summing the GDP (or population) of hazard cells that are above the threshold, and dividing by the total GDP (or population) of the county.

For example, in Figure 2 Coastal flood cells above threshold, the GDP of cells which are above the defined threshold - in green – would be summed and then divided by overall GDP, to generate the % GDP exposed to coastal flooding.

Figure 2 Coastal flood cells above threshold (Miami-Dade county)



Significant Updates

S&P Global Sustainable1 applies a rigorous quality assurance process to the development and ongoing maintenance and enhancement of the S1 Physical Risk: Municipal Dataset based on input data validation, model unit testing, output data validation and benchmarking against current solutions (Physical Risk Exposure Scores and Financial Impact Dataset), and delivery channel validation.

The changes made to this document include the following:

Version	Date	Changes
1.0	11/10/2023	Initial version
1.1	12/07/2023	Revised to add QA
1.2	01/15/2023	Revised to enhance discussion of assumptions, add Sec 7 Dependencies
1.3	01/17/2023	Revised to reflect discussion of assumptions and dependencies, add Appendix.

Related Documentation

There are several supporting documents specific to the Physical Risk: Municipal Dataset on the Support Center website (https://www.marketplace.spglobal.com/en/datasets/physical-risk-municipal-(1707421548)):

- Physical Risk User Guide – This user guide provides an overview of Physical Risk: Municipal Dataset, including package description, database schema, and specific details about working with the data.
- Physical Risk: Municipal Dataset Data Guide: This spreadsheet provides information on all the columns and data Item IDs in every single table by package, along with their corresponding definitions.
- Physical Risk: Municipal Dataset Data Dictionary: This spreadsheet provides details on the data items, including *dataItemId*, *dataItemName*, and *dataItemDefinition*.
- Physical Risk: Municipal Dataset FAQ Document: This FAQ Document provides quick orientation to the data set, including assumptions, usage, and limitations.
- Physical Risk: Municipal Dataset Release Note: The Release Note describe the Physical Risk Scores data, by providing an overview of the dataset, data coverage, history, the new packages, and the new tables by package.
- Physical Risk: Municipal Dataset Xpressfeed File Format: This spreadsheet contains the Xpressfeed package description, zip file prefixes, text file names, and database column details, such as column name, data type, filed size, primary keys, and encoding format.

If you are linking to other S&P Global Market Intelligence data sets, supporting documents are available on the Support Center website.

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