Sustainable1

Physical Risk Scores and Financial Impact Data

Methodology

Sustainable 1 – March 2024

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Introduction and Context

This document details the datasets, methods and assumptions that underpin the S&P Global Sustainable1 Physical Risk Scores and Financial Impact ("Physical Risk Scores and Financial Impact") data and associated analytics for financial institutions and non-financial corporates.

The release of the Taskforce on Climate Related Financial Disclosures (TCFD) report highlighted the importance of climate change as a driver of material financial risks for companies and investors that should be assessed, disclosed and managed.

The TCFD categorizes the financial risks posed by climate change as Transition Risks (including policy and legal risks, technology risk, market risk and reputational risk) and Physical Risk (both acute and chronic).[1]

Physical risks resulting from climate change can be acute (driven by an event such as a flood or storm) or chronic (arising from longer term shifts in climate patterns) and may have financial implications for organizations such as damage to assets, interruption of operations and disruption to supply chains.

S&P Global Sustainable1 launched a suite of Climate Change Physical Risk Analytics solutions to the market in 2019, offering an asset-based approach to the assessment of physical risk at the company and portfolio level. In 2022, Sustainable1 launched an enhanced physical risk analysis framework, leveraging the expertise and intellectual property of The Climate Service (TCS), which was acquired by S&P Global in January 2022. The 2024 release of the Climate Change Physical Risk Exposure Scores and Financial Impact dataset incorporates a complete update of the asset level database underlying the dataset, and a series of methodology enhancements as described below.

Key features of the 2024 dataset release 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 variable resolution, globally: coastal flood, fluvial flood, extreme heat, extreme cold, tropical cyclone, wildfire, water stress, drought and pluvial flood. The 2024 release incorporates one new hazard (pluvial flood) and modelling enhancements for fluvial flood, wildfire, drought, extreme heat and extreme cold (New in 2024 release).
- Coverage of four climate change scenarios based on the 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.
- Physical risk exposure scores representing point in time exposure to climate hazards, and physical risk financial impact metrics describing the financial consequences arising from changing climate hazard exposure for over 250 unique asset types.
- Built upon a proprietary database of over 3 million asset locations linked to corporate entities and ultimate parent entities—based on S&P Market Intelligence, S&P Commodity Insights, and Sustainable1-assembled datasets—and with flexibility to rapidly analyze client provided asset datasets.
- Physical risk analytics for over 20,000 companies representing over 98% of global market capitalization, ensuring high levels of coverage for equity and fixed income portfolios across all markets.

[1] TCFD. 2017. Recommendations of the Task Force on Climate-related Financial Disclosures. [Online]. Available: https://www.fsb-tcfd.org/wp-content/uploads/2017/06/FINAL-2017-TCFD-Report-11052018.pdf

- Enhanced modelling of companies with low asset counts based on geographic revenue data and country physical risk profiles (New in 2024 release).

Exposure Scores and Financial Impact Metrics

Error! Reference source not found. below describes the interpretation and user applications of physical risk exposure scores and financial impact metrics for financial institutions and non-financial corporate use cases.

Table 1. Exposure Scores and Financial Impact Metrics Explained

	Physical Risk Exposure Scores	Physical Risk Financial Impact
What does this metric represent?	Point in time exposure to climate hazards relative to global conditions, independent of the characteristics of the asset present at a given location	Financial consequences arising from the change in climate hazard exposure vs a baseline, specific to the asset present at a given location
Advantages	• Efficient and high throughput for rapid screening of large asset portfolios. • Offers an expansive view of climate hazards present at a given location, not limited to those hazards that are assumed to be material. • Readily applicable where only limited information (location only) is available on assets to be analyzed.. • Valuable as proxy for risk in a given location (or nearby locations) when asset data is not available.	• Deep dive analysis to quantify the financial impact of changing climate hazard exposure based on the best available data and S&P Global's view on the most material impacts for each asset type. • Granular analysis based on over 250 different asset type profiles and associated financial impact pathways. • Ready integration into downstream financial analysis such as valuation models, credit risk models and the creation of climate risk adjusted financial accounts. • Valuable to inform climate resilience strategies that need to respond to specific risk and mechanisms.

Use Cases	• Risk screening exercises and portfolio analytics to understand:
	    ○ Aggregate physical risk exposure at the asset, company or portfolio level, and in comparison with relevant benchmarks.
	    ○ Which climate hazards represent the greatest exposure.
	    ○ The assets or companies in a portfolio which contribute most to portfolio level exposure.
	• Inform initial TCFD disclosures and risk screening initiatives.
		• Deep dive physical risk analysis focusing on the financial materiality of climate hazard exposures to specific asset types.
		• Inform detailed TCFD disclosures and reporting.
		• Integration of climate physical risk into financial modelling, including the development of adjusted financial accounts, credit risk modelling and equity valuation modelling.
		• Climate resilience strategy.

	Physical Risk Exposure Scores	Physical Risk Financial Impact
	• Focus attention on the most exposed assets, companies or portfolio holdings to direct further investigation to the areas with greatest potential impact.	
What outputs are produced?	Exposure Score: 1-100 score representing the exposure to each hazard relative to global conditions.	Financial Impact: Financial losses (e.g., CapEx, OpEx, and Business Interruption) reflected as a percentage of asset value due to exposure to climate-related physical hazards. MAAL ($US): Modelled Average Annualized Losses in absolute dollar terms. Available for real assets analysis via Climanomics.
Asset classes covered	• Equities • Fixed income • Real assets • Munis, sovereign and other asset classes (planned in Future)	• Equities • Fixed income • Real assets (via Climanomics) • Munis, sovereign and other asset classes (planned in Future)

Indicators and Scenarios

Error! Reference source not found. below presents the climate change physical hazards considered in the Sustainable1 dataset. All hazards are evaluated globally at consistent spatial resolution, with the exception of coastal flood where higher resolution is available for USA.

Table 2. Climate Hazard Coverage

Hazards	Analysis Metric	Indicator Definition	Spatial Resolution	Data Sources
Coastal Flood	Frequency of 100-yr flood	Projected frequency of the historical baseline 100-yr coastal flood depth	30x30m (USA) 90x90m (RoW)	Kopp et al., 2014[2]; Muis et al., 2016[3]
River (Fluvial) Flood	Frequency of 100-yr flood	Projected return period of the historical 100-yr fluvial flood depth within projected flood extents	~1x1 km	Hydro Atlas WRI Aqueduct[9] NEX-GDDP downscaled CMIP6[8]

[2] Kopp, R. E., R. M. Horton, C. M. Little, J. X. Mitrovica, M. Oppenheimer, D. J. Rasmussen, B. H. Strauss, and C. Tebaldi (2014), Probabilistic 21st and 22nd century sea-level projections at a global network of tide-gauge sites, Earth's Future, 2, 383–406, doi:10.1002/2014EF000239.
[3] S. Muis, et al, "A global reanalysis of storm surges and extreme sea levels", Nature Comm., DOI: 10.1038/ncomms11969, 2016.

Hazards	Analysis Metric	Indicator Definition	Spatial Resolution	Data Sources
Pluvial (Extreme Rainfall) Flood	Frequency of 100-yr flood	Projected return period of the historical 100-yr pluvial flood depth	~25x25km	NEX-GDDP downscaled CMIP6[8]
Extreme Heat	Projected Tx95p Tx50pAbsChg	Annual percentage of days with maximum temperature warmer than the 95th percentile local baseline daily maximum temperature Absolute change in 50th percentile temperature	~25x25km	NEX-GDDP downscaled CMIP6[8]
Extreme Cold	Projected Tx5p	Annual percentage of days with minimum temperature colder than the 5th percentile local baseline daily minimum temperature	~25x25km	NEX-GDDP downscaled CMIP6[8]
Tropical Cyclone	Frequency of Cat3+ storms	Projected annual frequency of category 3 and higher tropical cyclones	~25x25km	NASHM[4] Hall et al. 2021[5]
Wildfire	Fire Weather Index (FWI)	*Financial Impact*: Annual percentage of days in which the FWI exceeds the historical local 90th percentile. *Exposure Scores*: Annual percentage of days classified as high, very high or extreme wildfire danger	~25x25km	NEX-GDDP downscaled CMIP6[8]
Water Stress	Water Stress Index	Projected future ratio of water withdrawals to total renewable water supply in a given area.	River Basin	WRI Aqueduct[12]
Drought	Standardized Precipitation Evapotranspiration Index (SPEI)	*Financial Impact*: Annual percentage of months in which the SPEI falls below the historical local 10th percentile.	~25x25km	NEX-GDDP downscaled CMIP6[8]

[4] Hall and Jewson, Statistical modeling of North Atlantic tropical cyclone tracks. Tellus, 59A, 485-498 (2007); Hall and Yonekura, North-American tropical cyclone landfall and SST: A statistical model study. J. Climate, 26, 8422-8439 (2013).

[5] Hall, Kossin, Thompson and McMahon, U.S. tropical cyclone activity in the 2030s based on projected changes in tropical sea surface temperature, J. Climate., 34, 1321-1335 (2021).

Hazards	Analysis Metric	Indicator Definition	Spatial Resolution	Data Sources
		Exposure Scores: Annual percentage of months classified as severely dry or extremely dry		

The Sustainable1 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)[6]:

- 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.
- 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 Sustainable1 dataset evaluates climate change physical risks for decadal averages from the 2020s to the 2090s. Financial impact quantification pathways are not currently available for extreme cold but are offered for all other climate hazards. This means that financial impact metrics are not calculated for extreme cold or presented in the Physical Risk Exposure Scores and Financial Impact dataset.

CMIP6 Climate Hazard Modeling

S&P Global Sustainable1 climate change hazard modeling utilizes the CMIP6 climate models, the latest generation of global climate models informing the Intergovernmental Panel of Climate Change (IPCC)[7]. 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[8] downscaled CMIP6 dataset which forms the basis for the Sustainable1 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 nine hazards included in the Sustainable1 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

[6] Ibid.
[7] World Climate Research Programme. 2020. CMIP Phase 6 (CMIP6). [Online]. Available: https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6
[8] 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

and financial impact analysis. A brief description of the methodology utilized to calculate each of the nine 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 heat hazard is quantified based on three metrics: • Tx95p, the percentage of days per year with a maximum temperature that exceeds the 95th percentile of the local historical baseline daily maximum temperature (Exposure Scores and Financial Impact); • Tx90pAbsChng representing the absolute change in 90th percentile maximum temperature vs. a historical baseline (Financial Impact); and • Tx50pAbsChg representing the absolute change in median maximum temperature vs. a historical baseline (Financial Impact).
Extreme Cold	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	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). Basin scale flood frequency projections are overlaid with projected flood extent data sourced from the WRI Aqueduct dataset.[9] 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 SPEI[10] 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. For the financial impact metrics, the hazard variable for a projected decade is the average proportion of months per annum where the SPEI is less than or equal to the historical local 10th percentile. For the exposure scores, the hazard variable is the average proportion of months per annum classified as severely dry

[9] World Resources Institute. 2023. Aqueduct. [Online]. https://www.wri.org/applications/aqueduct/floods/
[10] World Meteorological Organisation. 2012. Standardized Precipitation Index User Guide. [Online]. https://library.wmo.int/idurl/4/39629

Hazard	Methodology Description
	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. For the financial impact metrics, the hazard variable for wildfire is the average proportion of days per decade where the FWI exceeds the historical local 90th percentile. For the exposure scores, 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 derived satellite imagery sourced from the Copernicus Global Land Service dataset.[11] The land cover mask is applied at 3 00x300m 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) 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.

[11] European Commission Joint Research Centre. 2023. Copernicus Global Land Service. [Online]. https://land.copernicus.eu/global/index.html

Hazard	Methodology Description
	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 ground water. 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.[12]

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

Methodology Overview

Analytical Steps

The Sustainable1 Physical Risk Scores and Financial Impact methodology is based on five key analytical steps as shown in Figure 1:

1. Climate Hazard Modelling
2. Physical Risk Exposure Quantification
3. Asset and Company Level Physical Risk Exposure Score Calculation
4. Financial Impact Function Modelling
5. Asset and Company Level Physical Rick Financial Impact Calculation

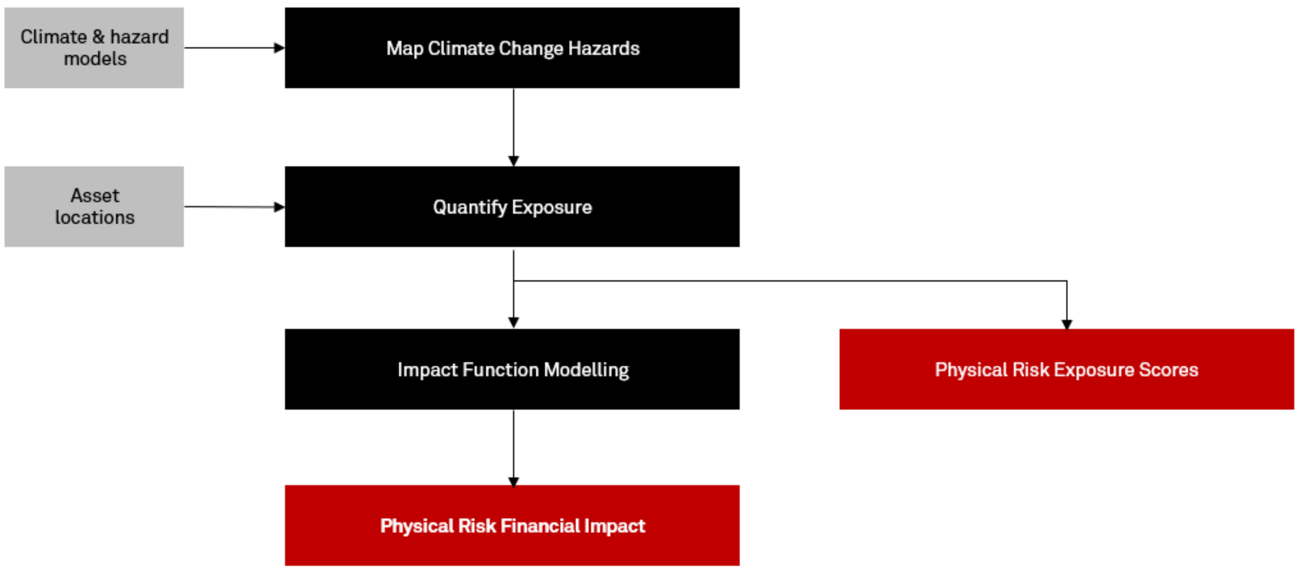

Figure 1: Sustainable1 Physical Risk Analysis Methodology

1. Climate Hazard Mapping

Sustainable1 has assembled models and datasets representing projected absolute exposure to nine discrete climate change hazards globally across four climate change scenarios and nine 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. Physical Risk Exposure Quantification

Exposure to climate change physical hazards is quantified by overlaying asset locations of interest on the climate hazard maps described at step 1. For the purposes of this analysis, 'Assets' represent any structure or real asset owned or leased by a company covered by the Sustainable1 database of over 20,000 companies.

The Sustainable1 Climate Change Physical Risk dataset is generated based on an extensive database of physical asset locations, linked to corporate owners (or lessees), developed and maintained by S&P Global. An equivalent analysis can also be provided on a bespoke basis utilizing asset data provided by clients, such as a real estate, mortgage, infrastructure or project finance portfolio.

Error! Reference source not found. describes the asset level data sources and datapoints utilized in Sustainable1 Physical Risk dataset. This includes a range of established S&P Global datasets focusing in energy, real estate, mining, telecommunications, technology, industrials and manufacturing, supplemented with external datasets including cement and steel production asset databases from the Spatial Finance Initiative (McCarten et al. 2021a[13]; McCarten et al. 2021b[14]), other industrial asset data sourced from Climate Trace,[15] government regulatory datasets (DEFRA, 2022[16]; European Environment Agency 2020[17]; Government of Canada, 2022[18]; and Australian Department for Climate Change, Energy, The Environment and Water 2022[19]) . Each asset is mapped to a unique owner identifier (KeyInstn and CIQ ID) enabling linking to other datasets within the S&P Global Capital IQ database, and to the ultimate parent owner name and identifier, to enable aggregation of physical risk metrics at the owner and parent level. Attribute information for each asset, such as asset type, sector, country, and other details, are also stored to inform the analysis.

[13] McCarten, M., Bayaraa, M., Caldecott, B., Christiaen, C., Foster, P., Hickey, C., Kampmann, D., Layman, C., Rossi, C., Scott, K., Tang, K., Tkachenko, N., and Yoken, D. 2021. Global Database of Cement Production Assets. Spatial Finance Initiative

[14] McCarten, M., Bayaraa, M., Caldecott, B., Christiaen, C., Foster, P., Hickey, C., Kampmann, D., Layman, C., Rossi, C., Scott, K., Tang, K., Tkachenko, N., and Yoken, D., 2021. Global Database of Iron and Steel Production Assets. Spatial Finance Initiative

[15] Climate TRACE -Tracking Real-time Atmospheric Carbon Emissions (2022), Climate TRACE Emissions Inventory, https: //climatetrace.org

[16] UK Department for Environment, Food and Rural Affairs. 2022. UK Pollutant Release and Transfer Register (PRTR) data sets. [Online]. Available: https://prtr.defra.gov.uk/facility-search

[17] European Environment Agency. 2020. European pollutant release and transfer register (E-PRTR). [Online]. Available: https://www.eea.europa.eu/archived/archived-content-water-topic/water-pollution/point-sources/eper

[18] Government of Canada. 2022. National Pollutant Release Inventory. [Online]. Available: https://www.canada.ca/en/services/environment/pollution-waste-management/national-pollutant-release-inventory.html

[19] Australian Department for Climate Change, Energy, The Environment and Water. 2022. National Pollutant Inventory. [Online]. Available: http://www.npi.gov.au/npi-data/latest-data

Table 4. Sustainable1 Physical Risk Analytics: Asset Level Data Coverage and Sources

Sector	Asset Database	Data Source	Asset Count
Urban Environment	Company Headquarters	S&P Global	757,892
	Company Offices	S&P Global	45,626
	Retail Sites	S&P Global	137,243
	Real Estate Investment Trust Properties	S&P Global	87,291
	Bank Branches	S&P Global	478,574
Energy, Industrials and Agriculture	Oil and Gas Production and Industrial	S&P Global	33,462
	Pipelines	S&P Global	634,164
	Gas Storage Facilities	S&P Global	366
	LNG Assets	S&P Global	41
	Automobile Plants	S&P Global	900
	Cement Plants	Spatial Finance Initiative	708
	Iron and Steel Plants	Spatial Finance Initiative	473
	Paper and Pulp Assets	Spatial Finance Initiative	123
	Petrochemical Assets	Spatial Finance Initiative	112
	Beef Cattle Assets	Spatial Finance Initiative	110
	Waste Management Assets	Spatial Finance Initiative	79
	Other Industrial Assets	Climate Trace	3,028
	Regulated Industrial Assets	Government Databases	9,768
Power & Utilities	Power Plants	S&P Global	41,501
	Transmissions Lines	S&P Global	644,588
Metals & Mining	Metals and Mining Assets	S&P Global	6,685
Tech & Telecom	Data Centers	S&P Global	4,272
	Broadcast Stations	S&P Global	2,712
	Cell Towers	S&P Global	181,979
	Other Assets	S&P Global	2,106
Total			3,073,803

Assets are mapped to corporate owners (or lessees) and ultimate parent identifiers in the S&P Capital IQ database using string matching techniques to enable efficient linking to financial and other market datasets in the S&P Global databases. The Sustainable1 asset database will be continually expanded to integrate new asset level datasets sourced within S&P Global and externally.

Figure 2 presents coverage of selected S&P Global Dow Jones Indices with asset based and revenue exposure based physical risk scores as of February 2024. As shown, asset level data is available for companies representing almost 100% of index weight in the S&P500, S&P Europe 350, ASX 200 and S&P Global LargeMidCap Index. Coverage of asset level data could increase as additional asset datasets are incorporated.

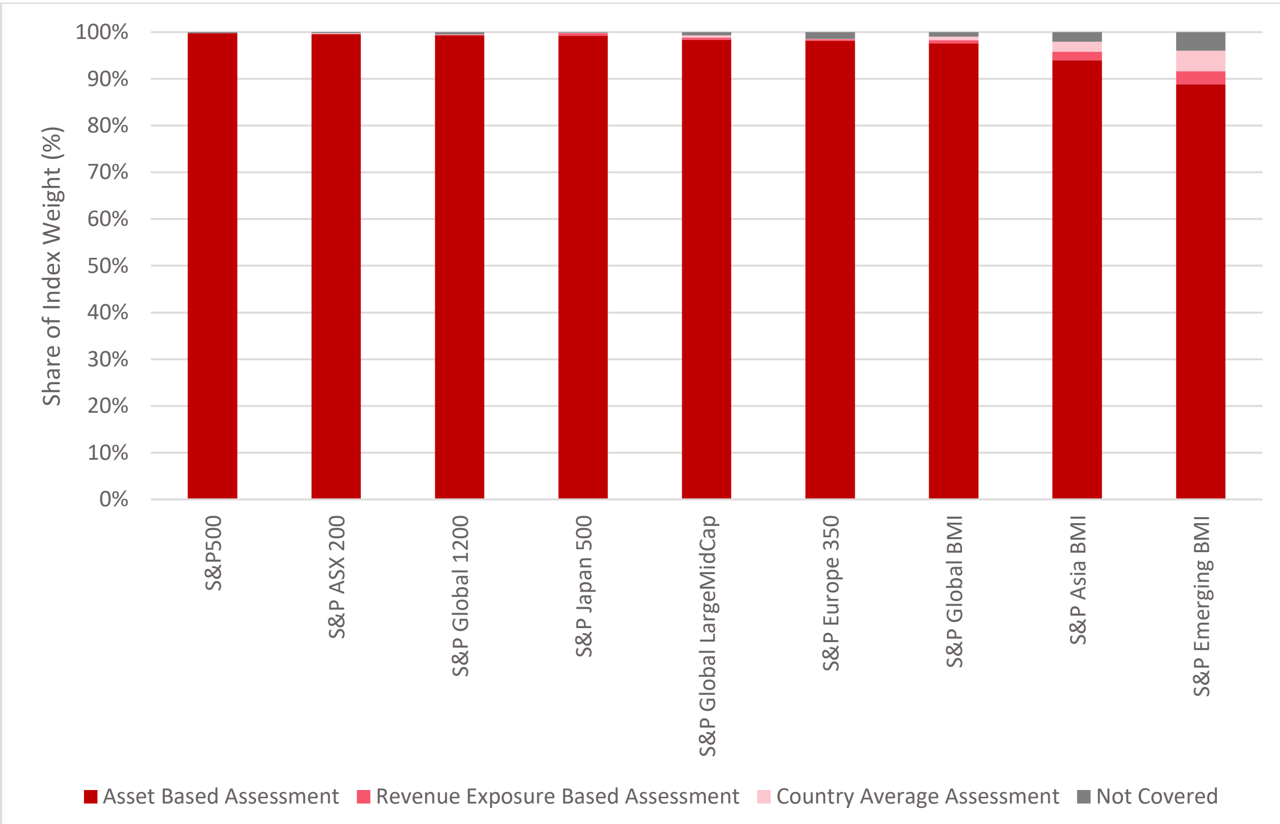

Figure 2: Sustainable1 Physical Risk Analytics: Coverage Summary

3. Asset and Company Level Physical Hazard Exposure Scores

Figure 3 presents an overview of the methodology applied to calculate asset and company level physical risk exposure scores.

The Sustainable1 physical risk exposure score model assigns risk scores from 1 (lowest exposure) to 100 (highest exposure) to each asset in the database based on location within the climate change hazard maps described in Step 1. 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 Equation 1.

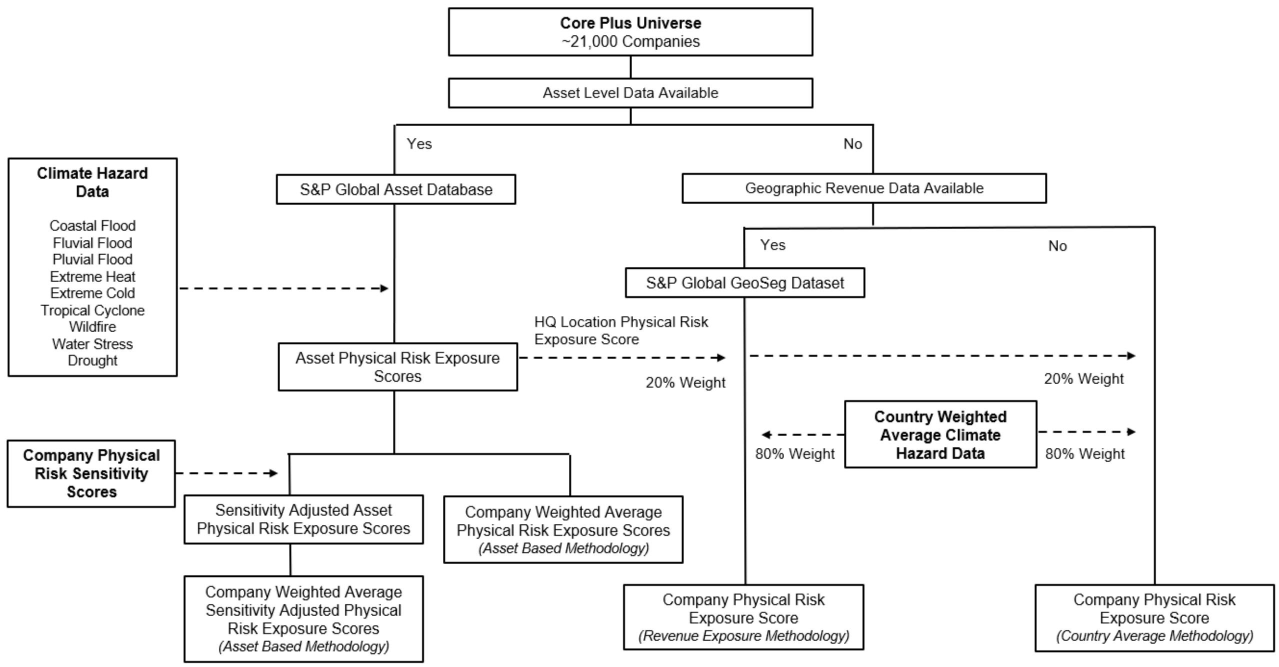

Figure 3: Company and Asset Level Physical Risk Score Calculation Overview

Equation 1: Climate Change Physical Risk Score Normalization

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

Where:

$S_{a,h,s,y}$	is the physical risk exposure score for asset (a) for hazard (h) under scenario (s) and time-period (y)
$R_{a,h,s,y}$	is the absolute exposure metric value for asset (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)

Asset level physical risk exposure scores are aggregated to company level scores as a weighted average of all assets mapped to the company of interest, based on assumed asset values for each asset type. Assumed asset values were derived from a literature review and are intended to be indicative of the relative value of each asset type (see examples in Table 5). Further details on the sources and methods used to calculate the assumed asset value are available in the Impact Function Whitepapers for each asset type, which can be provided on request. Companies evaluated using asset level data are assessed using the 'Asset Level Data' analysis methodology.

Table 5. Example Assumed Asset Values per Asset Type

Asset Type	Assumed Asset Value ($US Million)
Light Manufacturing - Owner/Occupier (Urban)	150
Cement Manufacturing - Owner/Occupier (Urban)	150
Power Generation (General) - Owner/Operator	1,200
Natural Gas-Fired Power Plant - Owner/Operator	640
Data Center - Owner/Occupier	300
Hotel - Owner/Occupier (Urban)	75
Office - Owner/Occupier	25

For some companies in the Sustainable1 CorePlus universe, insufficient asset level data is available to calculate physical risk exposure scores. In these instances, a two-tier methodology is applied as described below in descending order or preference:

- *Revenue Exposure Based Methodology*: Where both the location of the company headquarters and a geographic revenue exposure breakdown is available, physical risk exposure scores are estimated based on a combination of physical risk exposure score at the company headquarters location (20% weight), and a revenue weighted average of the country average physical risk exposure scores in those countries where the company generates revenues (80% weight). Country physical risk profiles are calculated as a GDP weighted average within the country boundaries, drawing on the climate hazard data described at step 1, and downscaled spatial GDP data sourced from Kummu et al. (2018).[20]

- *Country Average Methodology*: Where only the headquarters location for a company is known, physical risk exposure scores are estimated based on the exposure scores for the headquarters location (20% weight) and the country average physical risk exposure scores for the country in which the company is headquartered. Country physical risk profiles are calculated as a GDP weighted average within the country boundaries, drawing on the climate hazard data described at step 1, and downscaled spatial GDP data sourced from Kummu et al. (2018).

A data field is included in the dataset designating the analysis methodology used to calculate the physical risk metrics i.e. Asset Level Data, Revenue Exposure and Country Average.

Equation 2: Revenue Exposure Based Physical Risk Exposure Score Estimation

$$S_{h,s,y} = S_{hq,h,s,y} \times 20\% + (80\% \times \Sigma^{n}_{c=1} Rev_c \times S_{c,h,s,y})$$

Where:

$S_{h,s,y}$	is the physical risk exposure score for a company for hazard (h) under in scenario (s) and time period (y)
$S_{hq,h,s,y}$	is the physical risk exposure score for the company headquarters (hq) for hazard (h) under scenario (s) and time period (y)
Rev_c	is the company revenue share (%) generated in each country (c)
$S_{c,h,s,y}$	is the country GDP weighted average physical risk exposure score for hazard (h) under scenario (s) and time period (y)

Composite Exposure Score Calculation

The composite score is intended to provide a combined measure of company exposure to all nine climate change physical hazards. Two forms of the composite score are presented in the Sustainable1 Climate Change Physical Risk analysis:

Composite Physical Risk Score: An equal weighted additive combination of the company physical risk score on each hazard for a given scenario and year, and then rescaled to a 1-100 range using a logarithmic scoring curve. The scoring curve is designed to ensure that assets or companies 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 the exposure of an asset or company to climate change physical risk in cases such as this. The Composite Physical Risk Score is calculated as described in Equation 4.

[20] Kummu, M., Taka, M., Guillaume, J.H.A. 2018. Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. Scientific Data volume 5, Article number: 180004 (2018).

Equation 3: Composite Physical Risk Score Calculation

$$C_{x,s,y} = -100 \times 0.49^{\wedge(SUM_{x,s,y} \times 0.01)} + 100$$

Where:

$C_{x,s,y}$ is the composite exposure score for company (x) in scenario (s) and time period (y)

$SUM_{x,s,y}$ is the sum of hazard physical risk exposure scores for company (x) in scenario (s) and time period (y)

Sensitivity Adjusted Composite Physical Risk Exposure Score: The Sensitivity Adjusted Physical Risk Exposure Score is intended to account for both exposure to climate hazards, and the expected sensitivity of companies and assets to each hazard. The sensitivity adjustment is applied based on a set of sensitivity scores calculated as follows at the company level (and applied to all assets mapped to each company):

- Water Stress and Drought Sensitivity Score: Water intensity is assumed to be an indicator of sensitivity to water stress since companies with high water demands are more likely to be impacted by constrained water supply or increased water costs. Water intensity (direct and purchased water consumption (m3) / revenue ($US Million) is calculated for all companies in the Sustainable1 Core Plus universe of 20,000+ companies, trimmed to cap outliers beyond the 1st and 99th percentile, and then normalized to a 1-100 score using the normalization formula shown below and included in the methodology report at Equation 1. This score reflects the relative water intensity of each company compared to all other companies in the Sustainable1 Core Plus universe.
- Extreme Heat and Extreme Cold Sensitivity Score: Labour intensity is assumed to be an indicator of sensitivity to extreme heat and cold since temperature extremes can impact on labour force productivity, and therefore labour intensive companies may be more severely affected. Labour intensity (total employees (count) / revenue ($US Million)) is calculated for all companies in the Sustainable1 Core Plus universe, trimmed to cap outliers beyond the 1st and 99th percentile, and then normalized to a 1-100 score using the normalization formula shown at Equation 1. This score reflects the relative labour intensity of each company compared to all other companies in the Sustainable1 Core Plus universe.
- Wildfire, Fluvial Flood, Pluvial Flood, Tropical Cyclone and Coastal Flood Sensitivity Score: Tangible asset intensity is assumed to be an indicator of sensitivity to physically destructive hazards since companies with large investments in fixed assets and inventories which can be damaged, are more likely to be severely impacted. Tangible asset intensity ((Plant and Equipment ($US Million) + Inventories ($US Million)) / Total Assets ($US Million)) is calculated for all companies in the Sustainable1 Core Plus universe, trimmed to cap outliers beyond the 1st and 99th percentile, and then normalized to a 1-100 score using the normalization formula shown at Equation 1. This score reflects the relative tangible asset intensity of each company compared to all other companies in the Sustainable1 Core Plus universe.

Using the sensitivity scores above, the sensitivity adjusted hazard and composite scores are calculated as follows:

- Sensitivity adjusted hazard scores (e.g., for wildfire) are calculated by multiplying the physical risk exposure score for a given hazard/scenario/year with the corresponding sensitivity score and then dividing by 100.
- Sensitivity adjusted composite scores are calculated by multiplying each hazard physical risk exposure score with the corresponding sensitivity score, summing the results for a given scenario

and year, and rescaling to 1-100 based on a logarithmic scoring curve. The Sensitivity Adjusted Composite Physical Risk Exposure Score is calculated as described in Equation 5.

Equation 4: Sensitivity Adjusted Composite Physical Risk Score Calculation

$$C_{x,s,y} = -99 \times 0.25^{\,(SUMP_{x,s,y} \times 0.00005)} + 100$$

Where:

$C_{x,s,y}$	is the sensitivity adjusted composite exposure score for company (x) in scenario (s) and time period (y)
$SUMP_{x,s,y}$	is the sum product of hazard physical risk exposure scores and hazard sensitivity scores for company (x) in scenario (s) and time period (y)

4. Financial Impact Function Modelling

The Sustainable1 physical risk model quantifies the expected financial consequences of changes in physical risk exposure at both the asset and company level. This model is based on a library of 'Impact Functions' developed by S&P Global which describe the relationship between the degree of change in climate hazard exposure and the financial impact on a given asset type across time and climate change scenarios. Impact functions have been developed for over 250 unique asset types, each focusing on a set of pathways by which climate change hazards may impact on the value, revenues, operations or other value drivers for that asset type. The impact function database has been developed over several years through extensive literature research and analytical development.

At the asset level, Financial Impact is quantified as the projected financial costs associated with changing climate hazard exposure, expressed as a percentage of the asset value. The Financial Impact metric is calculated at the asset level for each hazard and can be summed to produce a composite Financial Impact metric, and aggregated to the company level as a weighted average based on assumed asset value weights (see Table 5). Financial Impact is expressed as a relative metric because accurate data or estimates of the actual value of each asset is currently not available.

For some companies in the Sustainable1 CorePlus universe, insufficient asset level data is available to calculate physical risk financial impact metrics. In these instances, a two-tier methodology is applied as described below in descending order or preference:

Revenue Exposure Based Methodology: Physical risk financial impact metrics are estimated based on the financial impact metrics for the company headquarters location and country / GICS Industry financial impact profiles based on a representative asset type for each GICS Industry and GDP weighted average hazard profiles for each country in which the company generates revenue. The company level financial impact metrics are calculated as a weighted average of the headquarters financial impact metrics (20% weight) and a geographic revenue weighted average of the country / GICS Industry financial impact profiles described above (80% weight). Country physical risk profiles are calculated as a GDP weighted average within the country boundaries, drawing on the climate hazard data described at step 1, and downscaled spatial GDP data sourced from Kummu et al. (2018).[21]

[21] Kummu, M., Taka, M., Guillaume, J.H.A. 2018. Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. Scientific Data volume 5, Article number: 180004 (2018).

- *Country Average Methodology*: Where only the headquarters location for a company is known, physical risk financial impact metrics are estimated based on the financial impact metrics for the company headquarters (20% weight) and the country / GICS Industry financial impact profile for the company GICS Industry and headquarters country (80% weight). Country physical risk profiles are calculated as a GDP weighted average within the country boundaries, drawing on the climate hazard data described at step 1, and downscaled spatial GDP data sourced from Kummu et al. (2018).

A data field is included in the dataset designating the analysis methodology used to calculate the physical risk metrics i.e. Asset Level Data, Revenue Exposure and Country Average.

Equation 5 Revenue Exposure Based Physical Risk Financial Impact Estimation

$$FI_{h,s,y} = FI_{hq,h,s,y} \times 20\% + (80\% \times \Sigma^{n}_{c=1} Rev_c \times FI_{c,h,s,y})$$

Where:

$FI_{h,s,y}$	is the financial impact metric for a company for hazard (h) under scenario (s) and time period (y)
$FI_{hq,h,s,y}$	is the financial impact metric for the company headquarters for hazard (h) under scenario (s) and time period (y)
Rev_c	is the company revenue share (%) generated in each country (c)
$FI_{c,h,s,y}$	is the country GDP weighted average financial impact metric for the relevant GICS Industry under hazard (h) under scenario (s) and time period (y)

The following example describes the process applied to developing impact functions for a single hazard and asset type combination.

Step 1. Identify Material Impacts

S&P Global has developed over 1,200 impact functions linked to over 250 asset types for application in the physical risk dataset and related tools (e.g., the Climanomics platform). The following example shows the extreme heat impact function for the office building asset type from the owner/occupier perspective. The temperature hazard metric used in this impact function is projected Tx50pAbsChg, measuring the absolute change in the annual 50th-percentile local daily maximum temperature (degree Celsius), relative to the historical value (1950-1999). To analyze the impact of increasing maximum temperature on owned/occupied office properties, a review of available research literature was conducted to identify a range of impact pathways, or avenues by which the operations and value of an office building may be impacted by increasing temperature. The following impact pathways were identified as material to the office building asset type:

- Cooling Costs: Excess operating expenses associated with increased use of cooling equipment/systems to maintain optimal temperatures for employees and plant/equipment in the context of rising temperatures.
- HVAC Degradation: Annualized costs of reduced operating life and early replacement of HVAC systems due to increased operation in response to rising temperatures.
- Employee Productivity: Costs associated with reduced employee productivity and associated expenses caused by increasing ambient temperatures (including employees working indoors).

Step 2. Model Impact Pathway

For each impact pathway a series of relevant research studies and data sources are assembled to quantify the impact of a unit change in hazard on relevant financial performance metrics, as described below:

- Cooling Costs: Excess energy consumption associated with higher temperatures were estimated based on trends identified in a series of papers focusing on changes in energy demand and power generation[22], and estimated economic damages arising from climate change in the USA.[23] Based on this data, cooling energy demand is projected to increase by 5% per one-degree Celsius increase in average maximum temperature.
- HVAC Degradation: Excess costs associated with reduced operating lifespan for HVAC systems per unit change in temperature were estimated from a series of studies including Fenaughty and Parker (2018).[24] Based on this data, HVAC lifespan is projected to decrease by 6.76% per one-degree Celsius increase in average maximum temperature.
- Employee Productivity: Reductions in employee productivity were estimated based on a global study of the effects of heat on working populations.[25] Based on this data, workforce productivity is projected to decrease by 1.14% per one-degree Celsius increase in average maximum temperature.

Step 3. Quantify Financial Impact

To quantify the total financial impact on asset value, the impact pathways described in the prior section are weighted based on a set of financial ratios reflecting the proportion of the total value of a given asset type that is represented by the value driver impacted by temperature change for each pathway. The asset value metric for the owned/occupied office building asset type is the replacement value, and the financial ratios applied to each impact function described below (These assumptions are based on literature review and analysis by S&P Global):

- Cooling Costs: 1.19% of asset value
- HVAC Degradation: 13.29% of asset value
- Employee Productivity: 7.84% of asset value

The financial impact (%) for each impact pathway is multiplied by the corresponding financial ratio and summed to quantify the aggregated financial impact (%) on the asset value of an owner-occupied office building per one-degree Celsius increase in average maximum temperature, and extrapolated across the range of projected future temperature increases. Figure 4 presents the impact function curve for the owner-occupied office building asset type, showing the residual asset value remaining as the change in average maximum temperature increases.

[22] Larsen, Kate et al., 2017: Assessing the Effect of Rising Temperatures: The Cost of Climate Change to the U.S. Power Sector. Rhodium Group, LLC, https://rhg.com/wp-content/uploads/2017/01/RHG_PowerSectorImpactsOfClimateChange_Jan2017-1.pdf
[23] Hsiang, Solomon et al., 2017: Estimating economic damage from climate change in the United States. Science 356, 1362–1369, https://www.science.org/doi/10.1126/science.aal4369.
[24] Fenaughty, Karen and Parker, Danny, 2018: Evaluation of Air Conditioning Performance Degradation: Opportunities from Diagnostic Methods. University of Central Florida, Florida Solar Energy Center, accessed April 2020, http://publications.energyresearch.ucf.edu/wp-content/uploads/2018/09/FSEC-PF-474-18.pdf.
[25] Kjellstrom, Tord et al., 2009: The Direct Impact of Climate Change on Regional Labor Productivity. Archives of Environmental & Occupational Health, 64, 4, pp. 217–227, https://doi.org/10.1080/19338240903352776.

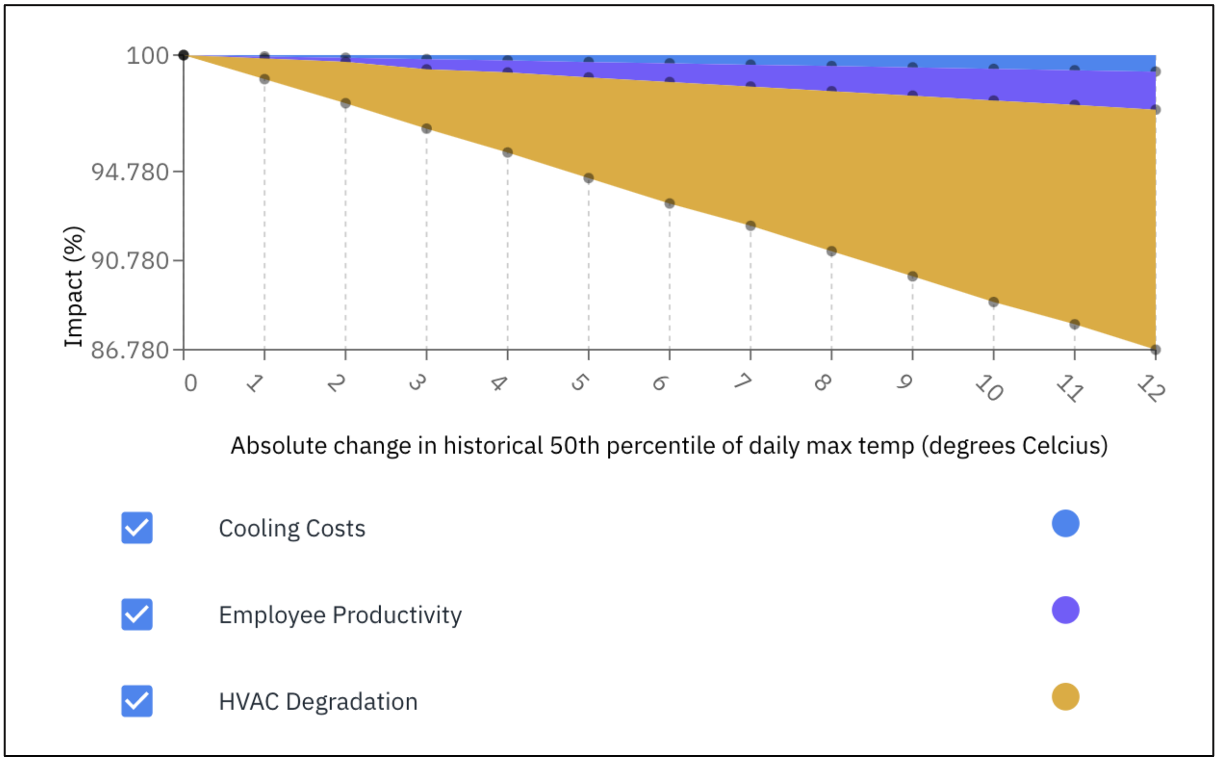

Figure 4: Impact Function Curve for the Effect of Temperature Change on Asset Value for Owner Occupied Office Buildings

In Figure 4, the x-axis represents the extreme heat hazard metric (tx50pAbsChg) and the y-axis represents the change in asset value, represented as a multiplier. For example, for a 2-degree Celsius absolute temperature change relative to the historical 50th percentile of daily maximum temperature, the aggregated impact on an owned-occupied office building would be 2.16% of asset value.

Financial impact may be negative in instances where exposure to a hazard is projected to decrease compared to the baseline under a given scenario and time period. This implies that the cost associated with exposure to that hazard is projected to decrease relative to the baseline. Negative financial impact is capped at -5% in recognition of the uncertainty regarding the ability of an asset owner or company to realize the financial benefits of reduced hazard exposure.

5. Asset and Company Level Physical Rick Financial Impact Calculation

Figure 5 presents an overview of the methodology applied to calculate asset and company level physical risk financial impact metrics.

The Sustainable1 physical risk model quantifies financial impact for each asset based on:

A. The change in climate change physical hazard under a given scenario and time period relative to a historical baseline.

B. The asset type classification, and associated impact functions, for the asset located at a given location.

Asset level Financial Impact is aggregated to company level as a weighted average of all assets mapped to the company of interest, based on assumed asset values for each asset type. Assumed asset values were derived from a literature review and are intended to be indicative of the relative value of each asset type (see examples in Error! Reference source not found.). Where insufficient asset level data is available for a given company, financial impact metrics are estimated based on the 'Revenue Exposure' and 'Country Average' methodology as described in Section 3.

Asset and company level Financial Impact is calculated for each climate hazard under each scenario and time period and are summed to a combined Financial Impact metric covering all hazards.

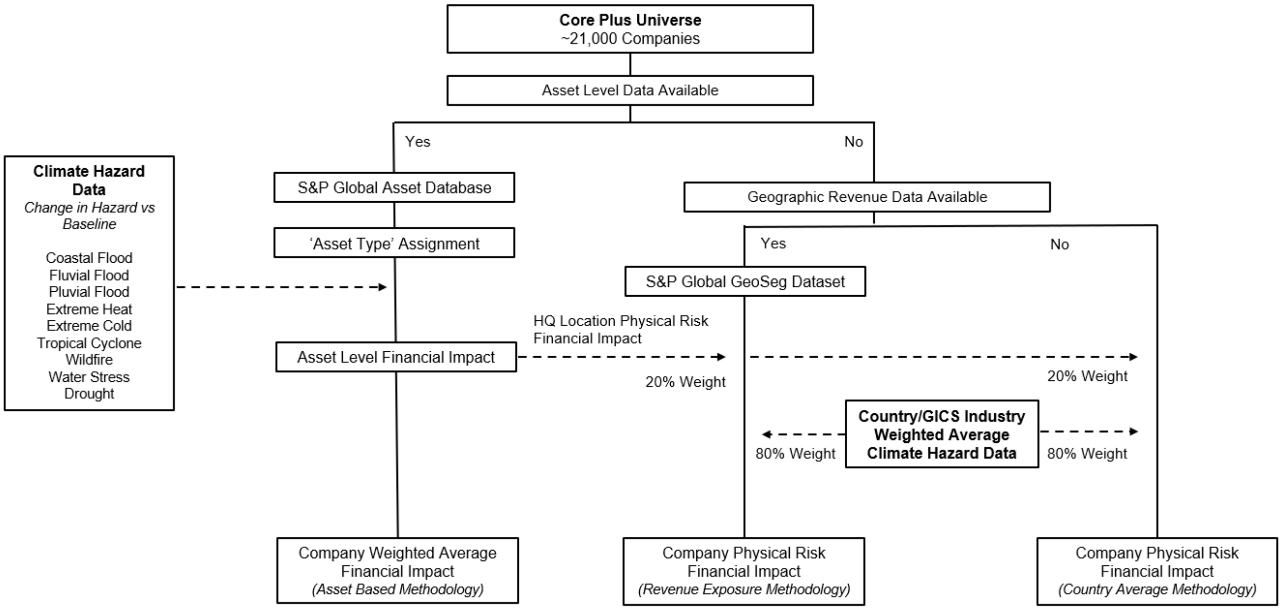

Figure 5: Company Level Physical Risk Financial Impact Calculation Overview

Limitations

Key limitations of Sustainable1's physical risk analytics include:

- Modelling Uncertainty: The climate models underpinning the physical risk analysis are complex and subject to uncertainty. Sustainable1 has sought to mitigate this uncertainty by basing the physical risk assessment on averages of the output of all available CMIP6 GCMs.
- Asset Location Uncertainty: The Sustainable1 physical risk assessment incorporates a range of asset location datasets, some of which are actively managed and updated regularly, whereas others are updated less frequently. Consequently, it is possible that the database does not reflect changes in asset ownership and activity that have occurred in the recent past. The latest update of the asset level database was conducted in October and November 2023. Sustainable1 has sought to mitigate this uncertainty by limiting data sourced from historical datasets to the past three years.
- Company Asset Coverage: It is not currently possible to determine what proportion of a company's material asset locations that are covered in the Sustainable1 asset database for most sectors. Sustainable1 is exploring opportunities to calculate or estimate an asset level coverage confidence measure for future releases.
- Spatial Resolution: Sustainable1 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 wind risks associated with the event, while the coastal flooding hazard metric includes storm surge flooding, so the flooding associated with the tropical cyclone would be captured in that metric. Finally, the precipitation models and topographic variables in each basin included in the fluvial flooding hazard metric would integrate any fluvial flooding associated with a tropical cyclone event.
- Sensitivity Framework: The sensitivity weighting framework is designed to weight the nine physical risk indicators based on the expected sensitivity of individual companies to each indicator. The framework will be enhanced in the future to better reflect the financial materiality of different forms of physical risk to companies across sectors and regions.

Data Timeliness: 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.

Related Documentation

There are several supporting documents specific to Physical Risk Scores and Financial Impact Data on the Support Center website:

- Physical Risk User Guide – This user guide provides an overview of Physical Risk Scores and Financial Impact Data, including package description, database schema, and specific details about working with the data.
- Physical Risk Scores and Financial Impact 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 Scores and Financial Impact Data Item List: This spreadsheet provides details on the data items, including *dataItemId*, *dataItemName*, and *dataItemDefinition*.
- Physical Risk Scores and Financial Impact Release Notes: The Release Notes describe the Physical Risk Scores and Financial Impact data, by providing an overview of the dataset, data coverage, history, the new packages, and the new tables by package.
- Physical Risk Scores and Financial Impact 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.

Significant Updates

The changes made to this document include the following:

Version	Date	Changes
2.0	31/01/2024	Updated version for 2024 release
1.0	09/01/2022	Initial version

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