How Jupiter Aligns with the EU Taxonomy

Jupiter's ClimateScore Global provides a complete assessment of physical climate risk for reporting under the EU classification system.

Executive Summary

The European Union Taxonomy Regulation requires companies to begin disclosing their physical and transition climate risk beginning in January 2022. As the world's leading provider of physical climate risk data, Jupiter is well positioned to aid companies with these disclosures.

ClimateScore Global, Jupiter's flagship product, has a scope and granularity that captures the most complete view of climate risk across the globe and across time. This allows business users from multiple industries to project how a portfolio of assets may be affected by climate change: the perils it will be exposed to, the vulnerable segments and locations, and how that risk will change over time and across varying carbon emissions scenarios.

The breadth of data available means that users aren't pigeon-holed into only looking at specific timescales or scenarios; instead, they can select the metrics that are most appropriate for their assets' vulnerabilities and holding periods. In addition, Jupiter can customize metrics to explicitly model the probability of key thresholds being breached, such as the heat thresholds that hinder electrical equipment, or the flood depths where critical infrastructure is damaged.

While regulators may have initially been satisfied with simplistic risk scores, more thorough disclosures of the specific hazard levels that assets are exposed to—and how those hazards might cause loss—are expected to become increasingly required. This document discusses the EU Taxonomy requirements and how Jupiter metrics match up to them. In the cases where the EU requests a metric that Jupiter does not provide, a clear explanation for the gap is given. As will be seen, ClimateScore Global is positioned at the cutting edge of what climate science can offer the business community, not only to support firms' mandatory disclosures, but to help those firms become more resilient to climate change.

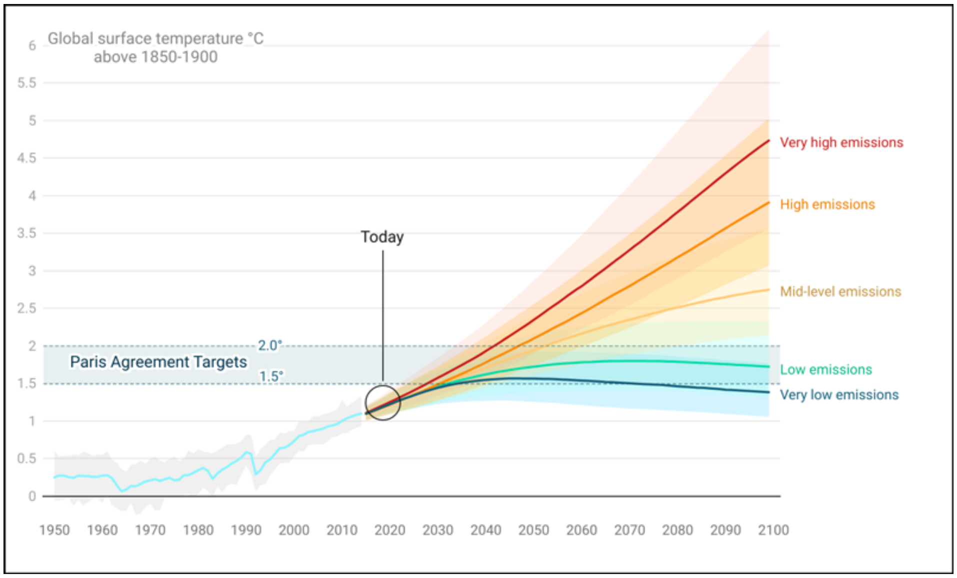
Background

As part of the 2019 [European Green Deal](), a classification system was established to define investments that are environmentally sustainable so that investors can make greener choices and avoid greenwashing. This system is outlined in the European Union Taxonomy Regulation, which requires disclosures by EU companies beginning in January 2022. The EU provided further details in the [EU Taxonomy Climate Delegated Act](), which was adopted on June 4, 2021.

Those documents specify the scenarios, time horizons, and physical hazards that companies should disclose to investors. They also recommend that firms use high-resolution, state-of-the-art climate projections for the task. The remainder of this document describes these requirements in detail and how they are addressed by Jupiter's ClimateScore Global product.

Scenarios

The EU Taxonomy states that: “The climate projections and assessment of impacts are based on best practice and available guidance and take into account the state-of-the-art science for vulnerability and risk analysis and related methodologies in line with the most recent Intergovernmental Panel on Climate Change reports, scientific peer-reviewed publications, and open source or paying models.” A footnote refers to the most commonly used IPCC scenario pathways that can be used for the assessment.



The five scenarios in the IPCC’s [sixth report](#).

Jupiter uses scenarios consistent with AR6, the sixth and most recent report from the IPCC. Specifically, AR6 makes use of joint Shared Socioeconomic Pathway (SSP)–Representative Concentration Pathway (RCP) scenarios. SSPs model future population changes, income inequality, climate-induced migration, urbanization, energy policies, and other factors. Integrated Assessment Models (IAMs) translate those systems to projections for future energy use, the associated emissions, and the resulting radiative forcing that defines the RCP. In this way, the Sixth Coupled Model Intercomparison Project (CMIP6) explicitly links socioeconomic conditions with climate conditions for the first time. This more readily allows for linking transition and physical risk scenarios, and it marks a major improvement over CMIP5-era models.

AR6 includes five scenarios, listed from low to high emissions: SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. Jupiter models three of these: SSP1-2.6, SSP2-4.5, and SSP5-8.5. Jupiter does not include SSP1-1.9, which limits warming to 1.5°C, because climate modelers are not optimistic that limiting warming to 1.5°C is feasible. SSP1-2.6 should be used as the low emissions scenario. Jupiter is investigating adding SSP3-7.0 to its suite of scenarios; in the meantime, it recommends using SSP5-8.5 because its warming trajectory does not significantly diverge from SSP3-7.0 until the tail end of the century.

Years

The EU Taxonomy asks that “the climate risk and vulnerability assessment is proportionate to the scale of the activity and its expected lifespan,” including a minimum of 10 to 30 years in the future for “major investments”. Jupiter reported years are fully aligned with these requirements. Metrics are provided for 17 projection periods (every five years from 2020 to 2100), allowing for a range of short-, medium-, and long-term analyses that cover the lifetime of even long-lasting infrastructure projects. In addition, a historical baseline based on the years 1986-2005 is provided to help users understand how much the climate has already changed.

Vulnerability Assessment

The taxonomy lists a broad range of climate hazards and asks firms to take the following steps:

a) *screening of the activity to identify which physical climate risks [listed below] may affect the performance of the economic activity during its expected lifetime;*

b) *where the activity is assessed to be at risk from one or more of the physical climate risks [listed below], a climate risk and vulnerability assessment to assess the materiality of the physical climate risks on the economic activity;*

c) *an assessment of adaptation solutions that can reduce the identified physical climate risk.*

It further asks that the analysis focus on "the most important or significant hazards and is designed to guide the user to consider the most salient physical risks when mapping the sensitivities of a given sector". These hazards, split into four categories with chronic and acute components, are discussed in turn below. Based on client feedback and the requirements from the EU Taxonomy, Jupiter added 29 new metrics in our latest model update in August 2022. Newly added metrics are designated as "2.7 Release".

Identifying Climate Hazards

Overview EU Requirements and Jupiter Data Support

Directly quantified by Jupiter metrics	Risk drivers available	Not available, rationale provided

	Temperature-related	Wind-related	Water-related	Solid-mass related
Chronic	Changing temperature (air)	Changing wind patterns	Changing precipitation patterns and types (rain, hail, snow/ice)	Coastal erosion
	Changing temperature (freshwater)		Precipitation and/or hydrological variability	Soil Degradation
	Changing temperature (marine water)		Ocean acidification	Soil Erosion
	Temperature variability		Saline intrusion	Solifluction
	Heat stress		Sea-level rise	
	Permafrost thawing		Water stress	
Acute	Heat wave	Cyclone, Hurricane, Typhoon	Drought	Avalanche
	Cold wave/frost	Storm (blizzards)	Heavy precipitation (rain, hail, snow/ice)	Landslide
	Wildfire	Storms (dust)	Flood (coastal, fluvial, pluvial)	Subsidence
		Storms (sand)	Flood (groundwater)	
		Tornado	Glacial lake outburst	

Temperature-Related Hazards

In the below table and related tables in other sections, the following color scheme is used:

- Green: Directly quantified by Jupiter metrics
- Yellow: Risk drivers available
- White: Not available; commentary provided on the rationale

	EU Taxonomy Parameter	Jupiter Data Support
Acute	Heat wave	Directly modeled
	Cold wave/frost	Directly modeled
	Wildfire	Directly modeled
Chronic	Changing temperature (air)	Directly modeled
	Changing temperature (freshwater)	Average annual temperature
	Changing temperature (marine water)	Average annual temperature
	Temperature variability	Directly modeled
	Heat stress	Directly modeled
	Permafrost thawing	Average and monthly temperature, heat waves

Commentary on Supported Hazards

Changing air temperature, **heat stress**, and **temperature variability** are captured by Jupiter using ten metrics:

- Days exceeding 35°C
- Days exceeding 38°C
- Days exceeding historical (1986-2005) 99th percentile temperature
- Annual heating degree days
- Annual cooling degree days
- Days of high wet bulb globe temperature
- Days of dangerous wet bulb globe temperature
- Average monthly temperature (2.7 release)
- Average annual temperature (2.7 release)
- Maximum annual temperature (2.7 release)

While there are infinite metrics that can be derived from climate models, Jupiter chose these metrics for their utility in directly mapping to the financial consequences of climate risk for firms. The "days exceeding…" metrics help users understand how often extreme temperatures are to be expected and whether air conditioning will become a mandatory feature of a home or business. In addition, the annual heating and cooling degree days more directly map to the costs of heating and cooling a home or business.

Risk to human health is captured via Jupiter's wet bulb globe temperature metrics. These metrics consider the combined effects of temperature and humidity, and they quantify the frequency with which humans are exposed to high and dangerous levels of heat stress.

Chronic temperature hazards are measured in average and maximum annual temperatures as well as average temperature for each month of the year. These metrics empower customers to capture temperature variability over annual or monthly timeframes and respond directly to the EU Taxonomy's reporting requirements.

Heat waves are explicitly measured in both absolute and relative terms:

- Count of three-day periods with high temp above 35°C and low temp above 24°C
- Count of three-day periods with high temp above historical 95th percentile

The first metric is useful for absolute levels of continuous heat exposure. It is well suited to industrial use cases, where high overnight lows reduces the ability of machinery to cool down at night. The second metric defines heat waves by comparing them to historical temperatures. It is better suited to changing design standards by region, and it can also be used to understand acclimatization of the local population to high heat.

Cold waves and frost are captured from four metrics:

- Days with low temp below 0°C (frost days)
- Days with low temp below -10°C
- Count of three-day periods with average temp below -5°C
- Count of three-day periods with low temp below historical 10th percentile

Just as with heat metrics, these were chosen to map to critical thresholds that can cause loss, including breached design thresholds, survivable ranges for agricultural pests, and mortality risk.

Wildfire risk is captured using the annual number of wildfires within the local 1 sq km grid. This is designed to map to direct damage and economic consequences from wildfires.

State of the Science for Hazards Not Directly Modeled

Changing temperature (freshwater). Risk drivers such as average annual temperature provide indicators of freshwater temperature change. Climate projections of the additional factors in freshwater temperature change require explicitly modeling the links between parameters from climate models and models that simulate hydrology and lake hydrodynamics and thermal regimes. These links remain elusive for stakeholders and the water scientific community, though recent seasonal climate forecasts produce probabilistic predictions of meteorological variables (Mercado-Bettin, et al. 2021). That work provides a potential resource to predict the influence of seasonal climate anomalies on water balance in catchments, lakes, and reservoirs in future research.

Changing temperature (marine). Jupiter metrics currently cover the land surface, though it is reasonable to assume that the air over oceans will warm as the air over lands do, even if not at the same rate. Some GCMs provide sea-surface temperature output. But because of the range of time and space scales involved and the necessary computational resources required, accurately and robustly modeling planet-scale ocean temperature with useful granularity has eluded scientists. Because the ocean covers 71% of Earth's surface, scientists need a record of sea temperature to understand how the ocean and the atmosphere exchange thermal energy. Climate models project significant changes in the ocean state over the coming century. Under the high emissions scenario (RCP8.5), the impacts by 2090 are substantially larger and more widespread than for the low emissions scenario (RCP2.6) throughout the surface and deep ocean (Bindoff, et al. 2019). In Jupiter models, sea-surface temperatures are a critical input to future tropical cyclone intensities.

Permafrost thawing. Risk drivers such as average annual and monthly temperatures provide indicators of permafrost thawing, though should be used with caution. Because of the simplified treatment of a complex process, GCMs today do not skillfully reproduce the historical permafrost thawing. Projections are thus subject to substantial uncertainty and may not be useful in a risk analysis. Recent work (Yokohata et al. 2020) has made improvements to one model. No resulting data has been shared, and risk analysis based on a single model not yet widely subject to peer review is poor practice. Other work predicts a near total loss of the periglacial environment by 2100 (Aalto et al. 2017), though also states that their "response to contemporary climate change is unclear." Acute hazards such as rockslides resulting from permafrost thawing in steep terrain have been observed locally, but are not predictable.

Wind-Related Hazards

	EU Taxonomy Parameter	Jupiter Data Support
Acute	Cyclone, Hurricane, Typhoon	Directly modeled
	Storm (blizzards)	Directly modeled
	Storms (dust)	Extreme winds, drought
	Storms (sand)	Extreme winds
	Tornado	Severe storms
Chronic	Changing wind patterns	Directly modeled

Commentary on Supported Hazards

Extreme wind speed events as well as changing wind patterns are captured from eight metrics:

- Wind speed at the 10-, 20-, 50-, 100-, 200-, and 500-year return period
- Average annual wind speed
- Maximum annual wind speed

The extreme return periods for acute wind speed events are designed to capture events that could cause damage to an asset. These wind speeds may result from **tropical cyclones / hurricanes / typhoons** (which are modeled separately and layered on top of climate model output), European windstorms, **blizzards**, and other factors.

Jupiter's standalone modeling of tropical cyclones has enabled it to take advantage of the recent advances in determining the scientific consensus in this space (Knutson et al. 2020). The current release incorporates expected changes in the intensity of the wind and rain in tropical cyclones globally. A forthcoming release will incorporate expected changes in the frequency of tropical cyclones and expected changes in their tracks.

Changing wind patterns are directly captured by two new metrics, average and maximum annual wind speeds. Max annual wind speed—the fastest the winds are expected to blow in a given year—captures the strength of the particularly windy conditions from severe convective storms that strike a location at least annually. They do not explicitly capture wind speeds due to events that strike less frequently than annually, like tropical cyclones; however, such extreme events are still captured in the return period wind speeds. Annual average wind speeds can be used to understand the characteristic winds of a region.

State of the Science for Hazards Not Directly Modeled

Storms (dust, sand). Risk drivers such as extreme winds and drought provide indicators of changing dust storm probabilities. Sand and dust storm (SDS) events require local soil composition and moisture information that can be used to model how particles loft into the atmosphere. Existing implementations of dust emission schemes in climate models are not currently skillful on a continental to global scale (Evan et al. 2014). Validation of SDS events at scale is a major limitation because remotely sensed data is required for a global perspective, but the detection techniques are still relatively simplistic (threshold based). As this area of research improves, a validation dataset could emerge which would allow us to move forward with this work.

Tornado. Risk drivers such as days with severe storms provide indicators for changing tornado occurrence, though should be used with caution. The confidence in projected changes to tornado frequency is low due to relatively short data records of a few decades. Lack of observing capabilities mean data are unreliable before the modern radar era that began in the 1970s (Elsner et al. 2015, Tippett 2014). Also, the spatial resolution of most global climate models is not adequate to explicitly simulate tornadoes. Therefore, proxies to tornado occurrence, which include large-scale environments favorable for development of severe convective storms, are used to define future changes in tornado characteristics. Most proxy-based studies suggest an increase in frequency of severe convective storm environments, especially during the early portion of the typical tornado season (Diffenbaugh et al. 2013, Seeley and Romps, 2015). These remain low-confidence results because of the high uncertainty in both the climate-change signals in convective storm environments, and the specific relationships between severe convective storms and tornado frequencies. Tornadoes are not currently predictable in weather forecasts, indicating the challenge of linking even skillful large-scale predictions with the tornado hazard.

Water-Related Hazards

	EU Taxonomy Parameter	Jupiter Data Support
Acute	Drought	Directly modeled
	Heavy precipitation (rain, hail, snow/ice)	Directly modeled
	Flood (coastal, fluvial, pluvial)	Directly modeled
	Flood (groundwater)	Tidal flooding
	Glacial lake outburst	Lacking data and science to support global analysis
Chronic	Changing precipitation patterns and types (rain, hail, snow/ice)	Directly modeled
	Precipitation and/or hydrological variability	Directly modeled
	Ocean acidification	Lacking data and science to support global analysis
	Saline intrusion	Lacking data and science to support global analysis
	Sea-level rise	Directly modeled
	Water stress	Directly modeled

Commentary on Supported Hazards

Drought and water stress are measured with four metrics:

- Local and total water stress
- Months per year with the 3-month and 6-month rolling average of the Standardized Precipitation Evapotranspiration Index at critical levels
- Annual precipitation
- Monthly precipitation

Chronic precipitation and/or hydrological variability are a key input into Jupiter's **drought** metrics, which the EU Taxonomy classifies here as an acute hazard. They are also a critical input into Jupiter's local and total **water stress** metrics, which consider both water supply and water demand in the local watershed and local+upstream watersheds, respectively.

Sea-level rise is measured using the annual tidal inundation depth metric. A direct measure of sea-level rise is not useful to understand the risk that sea-level rise poses. A handful of millimeters of sea-level rise may be irrelevant in many areas of the world, and yet catastrophic in others—and those areas could be just down the coast from each other. It is more important to understand how sea-level rise results in “sunny day” or tidal flooding, and how sea-level rise increases storm surge risk, which is a nonlinear response. For that reason, Jupiter provides the annual tidal inundation depth, which is the depth of the water over land at the highest high tide over the course of a year. Sea-level rise is also incorporated into coastal flooding metrics at more extreme return periods; these events are associated with storm surge.

Chronic and acute precipitation as well as hail are measured with four metrics:

- Maximum daily precipitation at the 10-, 20-, 50-, 100-, 200-, and 500-year return periods
- Annual precipitation
- Monthly precipitation
- Number of days per year where large hail (>2 in /5 cm in diameter) is possible

Heavy precipitation is modeled as the maximum 24-hour total water equivalent precipitation at the 10-, 20-, 50-, 100-, 200-, and 500-year return period. For, say, the 100-year return period, this metric can be thought of as the rainiest day in 100 years. “Total water equivalent precipitation” means that frozen precipitation (snow, sleet, etc.) is converted to liquid water.

Changing precipitation patterns are directly captured by two new metrics, annual and monthly precipitation, both measuring the accumulated precipitation amount in millimeters of total water equivalent precipitation. These new chronic precipitation metrics can be used alongside ClimateScore Global’s existing drought metrics to isolate the expected changing precipitation patterns over time. Users are particularly encouraged to examine the monthly precipitation metrics in parallel with their assessment of the existing drought metrics, since it is a common effect of climate change that wet seasons are getting shorter but more intense (more rainfall), while dry seasons are lengthening.

Hail is a complicated, localized peril that is difficult to simulate even for modern numerical weather forecasting systems, and Jupiter has developed own alternations of known hail data models to make them more globally applicable, by estimating how likely the local atmospheric conditions will support large (>5cm) hail development.

Jupiter’s **flood depth** metrics, which are also available at the 10-, 20-, 50-, 100-, 200-, and 500-year return periods, consider the effects of both **fluvial** and **coastal** flooding. Coastal flood includes the combined effects of sea-level rise and storm surge from tropical cyclones and other surge-producing storms. **Pluvial** flood risk is expected to be incorporated into the flood model in early 2023.

State of the Science for Hazards Not Directly Modeled

Flood (groundwater). Risk drivers such as tidal flooding provide indicators for acute flooding from rising groundwater, because coastal groundwater levels are controlled by sea level in many places near the coast. Local detailed analysis that considers subsurface geology and subsurface freshwater is needed to reduce uncertainty. See also the discussion about saline intrusion below.

Glacial lake outburst. The data and science behind glacial lake outbursts are insufficiently mature to provide useful future climate-change information. A global perspective on some of the factors, such as the size of glacial lakes, that could increase risks from glacial lake outbursts has only recently become available (Shugar et al. 2020). That work shows that the number and size of glacial lakes has risen substantially since the 1990s. Assessment of the remaining critical factors influencing this risk requires knowledge of local and regional geology that controls whether the natural barriers supporting glacial lakes will fail, and research to date focuses on individual regions.

Ocean acidification. The data and science behind ocean acidification are insufficiently mature to provide useful future climate-change information. Ocean acidification and climate change are different problems, but share the same root cause: emission of large amounts of carbon dioxide as a byproduct of human activities. Roughly one-third of the carbon dioxide pumped into the atmosphere by human activities is absorbed by the ocean. Prediction of this acidification is difficult (Field et al. 2011). Not only are the chemical interactions complex and often poorly known, the current state of the ocean temperature predictions have too much uncertainty to be effective.

Saline intrusion. The data and science behind saline intrusion are insufficiently mature to provide useful future climate-change information. Science today cannot explain the various factors controlling seawater intrusion and the mitigation strategies. Saline intrusion requires knowledge of local geology and sub-surface hydrodynamics, both of which vary dramatically across a region. The regions are continually changing and may never be in a steady state. Coastal aquifers are highly sensitive to both regional and global phenomena that include sea-level rise, storm surges, change in climatic condition, shoreline erosion, and coastal flooding. Human activities are enhancing the salinization process in coastal regions. Apart from the coastal aquifers, surface water sources also are affected due to their interaction with the seawater. The rivers and estuaries allow the natural inflow of seawater due to the backwater from the sea, and make the surface water saline. A synoptic view of the factors affecting the hydrodynamic equilibrium between the freshwater and seawater with the causes of seawater intrusion in coastal aquifers has remained a challenge. A significantly large number of studies have been conducted in coastal areas across the globe to understand the problem of seawater intrusion. Attempts to connect these individual studies for a broader understanding of the seawater intrusion process and its remedial measures have not been satisfying (Barlow and Reichard, 2010).

Solid Mass-Related Hazards

	EU Taxonomy Parameter	Jupiter Data Support
Acute	Avalanche	Lacking data and science to support global analysis
	Landslide	Extreme precipitation
	Subsidence	Drought, chronic precipitation
Chronic	Coastal erosion	Lacking data and science to support global analysis
	Soil Degradation	Anthropogenic factors dominate
	Soil Erosion	Extreme rainfall, drought, chronic precipitation, extreme winds
	Solifluction	Lacking data and science to support global analysis

State of the Science for Hazards Not Directly Modeled

Avalanche. The data and science behind avalanches are insufficiently mature to provide useful future climate-change information. While we may hypothesize that avalanche frequency and characteristics may change with climate change, knowledge about if and how avalanches may change is lacking. Any analysis would be mostly speculation at this point (c.f. Strappazon et al. 2021). Slope angles and whether or not the local climate includes snowfall are first-order indicators for where avalanches can and cannot occur.

Landslide. Risk drivers such as extreme rainfall provide indicators for changing landslide potential, though should be used with caution. Most landslides are created by rainfall. Climate change can increase landslide potential in some regions where increased rainfall intensity is expected, and decrease it in other regions that are drying. They are often part of a cascade of events, such as a wildfire followed by heavy rains. As such, prediction is difficult to impossible at this time. The current state of the science most applicable to climate change is focused on studies limited to regional analyses, and data paucity currently prevents global efforts beyond emerging situational awareness tools (Stanley et al. 2021). Improved satellite-borne sensing capability and machine learning methods are showing promise (Stanley et al. 2020), though skillful extension beyond regional studies is not yet possible.

Subsidence. Risk drivers such as drought and chronic precipitation provide indicators for subsidence, particularly where active groundwater extraction is known to occur, though should be used with caution. Subsidence time scales range from seasons to centuries. Long-term, slow subsidence is well measured in many key locations via Global Navigation Satellite Systems and other methods, and can be extrapolated in some cases when it results primarily from isostatic rebound. Short timescale subsidence can be driven primarily through human activity, which may be intertwined with a climate hazard such as drought. An example is accelerated aquifer depletion during a drought. Recently, satellite radar measurements have been used successfully to measure subsidence in key areas, over periods of a few years (e.g. Wu et al. 2022). That work shows that a number of coastal cities are sinking faster than absolute sea level is rising. Those measurements by themselves do not result in the capability that would be needed to assess future climate risk. Additional factors such as groundwater, oil, and gas extraction would need to be explicitly linked to the measured subsidence to be able to perform predictive analytics or scenario analysis.

Coastal erosion. The data and science behind coastal erosion are insufficiently mature to provide useful future climate-change information. Coastal erosion mainly occurs when wind, waves, and longshore currents move sediment from shore and deposit it somewhere else. It is caused by a complex process that depends on beach sediment properties (sands, clays), beach slope, vegetation, and wave parameters (height, period, direction, and storm duration), surge and timing of tidal and littoral currents, and deflation. The determination of coastal erosion is very complex and highly variable from location to location. It involves integrating a multi probability density function of wave, sediment, and current parameters. The details of these parameters are poorly understood and lead to inaccurate estimates, even locally.

Soil degradation. While climate can directly affect soil function through altered temperature and moisture regimes and increase erosion via increased frequency of extreme precipitation events (Lal et al 2011), soil degradation is largely anthropogenic. Agricultural management decisions, urbanization, and ecosystem disruption/destruction are all major factors. There is a growing body of literature concerning “climate smart” agriculture management practices, but these studies are often regional and have not been scaled to understand global impacts on soil function (Kaye and Quemada 2017).

Soil erosion. Risk drivers such as extreme and chronic precipitation, drought, and extreme winds provide indicators for changing future changes in soil erosion, though should be used with caution. Soil erosion is complex and mostly under human control, particularly with good practices with agriculture. Increased drought frequency or extreme rainfall may be indicators that local land management practices should evolve, but simple and local mitigation strategies are likely to be effective at controlling erosion as long as they are in practice. The Taxonomy documentation points to planting unproductive fields, improving drainage, and similar approaches to mitigating soil erosion.

Solifluction. Outside of a recognition that we can expect solifluction to increase, spatial and temporal coverage of solifluction studies are insufficient to provide additional details. Local controls exert a strong influence on solifluction rates, limiting opportunities for generalizing results. Examples of local and regional approaches are Ridefelt et al. (2010) and Kellerer-Pirklbauer (2018), which present analysis restricted to regions within single nations.

Risk Identification and Materiality Assessment

The EU Taxonomy requires companies to not only report on exposure to a set of climate hazards (as shown above), but also to identify economic activities who are therefore at risk of such climate hazards. In order to help customers quantify and understand risk to economic activities within the climate hazard landscape, we suggest a two-step approach:

Step One - Use ClimateScore Global Hazard Scores to identify risk

The EU Taxonomy states:

> *… where the activity is assessed to be at risk from one or more of the physical climate risks [listed below], a climate risk and vulnerability assessment to assess the materiality of the physical climate risks on the economic activity*

	Heat 2020 – 2050 Chan..	Wind 2020 – 2050 Change	Fire 2020 – 2050 Chan..	Flood 2020 – 2050 Change	Hail 2020 – 2050 Chan..	Precipitation 2020 – 205..	Cold 2020 – 2050 Chan..
Asset 1	87.0	15.0	6.0	0.0	-18.0	28.0	0.0
Asset 2	82.0	3.0	10.0	49.0	4.0	30.0	0.0
Asset 3	81.0	5.0	4.0	0.0	4.0	43.0	0.0
Asset 4	79.0	-3.0	60.0	1.0	20.0	1.0	-36.0
Asset 5	77.0	-1.0	59.0	0.0	21.0	41.0	-50.0
Asset 6	76.0	14.0	5.0	14.0	-41.0	26.0	0.0
Asset 7	71.0	5.0	43.0	0.0	-34.0	29.0	-1.0
Asset 8	69.0	5.0	-2.0	1.0	-24.0	54.0	-60.0
Asset 9	68.0	4.0	2.0	0.0	-27.0	5.0	0.0
Asset 10	65.0	5.0	1.0	24.0	-55.0	45.0	-2.0
Asset 11	64.0	0.0	9.0	0.0	12.0	32.0	-38.0
Asset 12	62.0	11.0	-4.0	0.0	-39.0	35.0	-52.0
Asset 13	61.0	3.0	13.0	-1.0	-27.0	48.0	-44.0
Asset 14	58.0	5.0	7.0	59.0	27.0	29.0	-2.0
Asset 15	58.0	8.0	23.0	0.0	-35.0	27.0	-2.0
Asset 16	58.0	-2.0	11.0	0.0	-6.0	30.0	-31.0
Asset 17	52.0	2.0	5.0	0.0	-36.0	19.0	-45.0
Asset 18	40.0	0.0	16.0	0.0	0.0	11.0	-48.0
Asset 19	57.0	0.0	-3.0	0.0	-15.0	25.0	-49.0
Asset 20	51.0	8.0	39.0	0.0	24.0	5.0	-51.0
Asset 21	42.0	7.0	35.0	10.0	0.0	8.0	-50.0
Asset 22	55.0	22.0	7.0	64.0	57.0	57.0	-1.0
Asset 23	54.0	0.0	-4.0	0.0	47.0	4.0	-12.0
Asset 24	41.0	2.0	55.0	7.0	0.0	8.0	-47.0
Asset 25	40.0	-4.0	7.0	-8.0	0.0	15.0	-34.0
Asset 26	53.0	-2.0	19.0	0.0	-11.0	16.0	-61.0
Asset 27	57.0	6.0	-2.0	0.0	8.0	30.0	-49.0
Asset 28	40.0	1.0	22.0	-38.0	0.0	13.0	-59.0
Asset 29	55.0	-1.0	25.0	0.0	36.0	10.0	-41.0
Asset 30	54.0	10.0	6.0	8.0	-50.0	19.0	-49.0
Asset 31	52.0	0.0	40.0	0.0	-24.0	-2.0	-60.0
Asset 32	54.0	1.0	-19.0	1.0	-58.0	27.0	-58.0
Asset 33	26.0	-3.0	21.0	44.0	-43.0	8.0	-49.0

To identify the economic assets at risk, a risk threshold needs to be applied to triage the data. Jupiter recommends using ClimateScore Global's specifically developed Hazard Scores to be able to easily identify sites "at risk". An approach derived from best practices of some of our biggest customers is to set a risk level, e.g. "above 60", and then test each economic activity for each Hazard Score (Present) against the threshold. As you can see in the image on the left, this way, a selection of "at risk" sites can be conducted easily.

Step Two - Use ClimateScore Global Peril Metrics to assess materiality risk

Now that you successfully identified the "at risk" sites, a deep dive into these sites is needed in order to assess the materiality of the risk. This can be done by using the breadth of Jupiter's peril metrics to assess risk levels from different perils. The table below shows an exemplary approach to dive into the risks associated with an "at risk" site:

Climate Peril	Peril Metrics (Selection)	SSP1-2.6 (1.8°C)		SSP2-4.5 (2.7°C)		SSP5-8.5 (4.4°C)	
		2020	2070	2020	2070	2020	2070
Heat	Days per year with temperature >35°C	31.67	40.23	31.62	46.89	32.61	66.20
Cold	Annual number of days below 0°C	26.58	21.26	24.90	15.95	26.14	11.63
Fire	Number of wildfires expected in a 1 sq km grid cell per 1000 years	10.20	13.34	10.70	14.99	11.95	20.30
Coastal Flood	Annual depth of the water (in meters) in coastal areas due to high tides	0.00	0.00	0.00	0.00	0.00	0.00
Fluvial Flood	Depth of the water (in meters) at the 100-year return period	0.00	0.00	0.00	0.00	0.00	0.00
Precipitation	Maximum daily total water equivalent precipitation (in mm) experienced at the 100-year return period	59.35	62.38	60.93	63.07	60.12	64.91
Hail	Number of days per year where large hail (>2 in / 5 cm in diameter) is possible	0.00	0.00	0.00	0.00	0.00	0.00
Drought	Total water stress: human water demand / water supply for the local and upstream watersheds	0.20	0.25	0.20	0.26	0.21	0.34
Wind	Maximum 1-minute sustained wind speed (in km/hr) experienced at the 100-year return period	86.19	86.33	85.84	86.30	86.49	85.76

Adaptation Assessments

Part (c) of the climate analysis requires "an assessment of adaptation solutions that can reduce the identified physical climate risk". Jupiter does not provide adaptation recommendations or quantify their potential to reduce risk. Instead, it can make recommendations to various engineering and consulting firms with this expertise.

Scale and model quality

The EU Taxonomy guidance requests that climate risk assessments be performed "using the highest available resolution, state-of-the-art climate projections".

Highest available resolution. Jupiter's ClimateScore Global ultimately provides metrics at a 90-meter resolution. The data is originally derived from global climate models (GCMs), which most commonly have approximately 100-kilometer resolution. It is empirically downscaled in two steps. First, during the bias correction step, it is downscaled to match the 30-kilometer resolution of a state-of-the-art historical reanalysis dataset (the European Centre for Medium Range Weather Forecasts Re-Analysis version 5, or ERA5). Second, it is further downscaled to 90 meters using a combination of bilinear interpolation and machine learning based on observations, elevation, and other land-cover characteristics. (The flood inundation models natively run at the 90-meter resolution of the digital elevation model or DEM.)

There are other regional climate models (RCMs) and regional DEMs that may provide higher-resolution data. Because of the inconsistent implementation and output from RCMs, including at times conflicting trends, Jupiter prefers using the globally consistent GCMs for the core analysis. RCMs are used primarily for comparison with the empirically downscaled data during the verification and validation process. Regional DEMs are patched in over the global 90-meter DEM where they prove to be of high quality, and they are also used for uncertainty metrics.

State-of-the-art climate projections. Jupiter primarily uses GCMs from the CMIP6 suite of model comparison simulations. These represent the latest advances in climate modeling, incorporating new knowledge and understanding since previous CMIP projects (such as CMIP3 and CMIP5), and they represent the state-of-the-science at this time. CMIP6 models also underpin the latest AR6 report from the Intergovernmental Panel on Climate Change.

Jupiter considers a number of factors when deciding which GCMs to include in the projections for each peril and metric. This includes data availability for the required output variables and scenarios, and whether there are issues or concerns with the quality of a particular GCM that could make it inappropriate for the analysis. The latter is analyzed according to published literature in the climate modeling community.

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