TECHNICAL DOCUMENTATION

Physical Risk: Wildfires

Scientific Climate Ratings
An EDHEC Venture

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About Scientific Climate Ratings

Scientific Climate Ratings is a new venture born from EDHEC's Climate Finance applied research ecosystem. It delivers forward-looking ratings that quantify the financial materiality of climate risks for infrastructure companies and investors worldwide. Leveraging high-resolution geospatial data, proprietary climate risk models, and the world's largest financial dataset for infrastructure assets, Scientific Climate Ratings evaluates both transition risks (linked to the shift toward a low-carbon economy) and physical risks (arising from climate hazards such as floods, storms, heatwaves, and wildfires).

The ratings offer a dual perspective:

- Potential Climate Exposure Ratings assess current exposure to future climate risks under a "continuity" scenario, reflecting the most likely pathway based on today's global policies and trends.
- Effective Climate Risk Ratings go further by integrating climate risk data into financial valuation models across multiple scenarios — each weighted by its probability of occurrence — to estimate the financial effects of climate-related risks until 2035 and 2050.

While initially focused on infrastructure, Scientific Climate Ratings will soon extend its methodology to the listed equities segment, applying the same scientific rigor and forward-looking approach to a broader set of financial assets.

Scientific Climate Ratings aims to set a new standard in climate risk management — driving informed and responsible decision-making for a more resilient future.

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This document summarises the development of the physical risk damage model on **Wildfires**, which is part of the ***Potential Climate Exposure Rating (PCER)*** and the ***Effective Climate Risk Rating (ECRR)***. It explains the general approach, provides the data sources used, justifies the methodology, and presents the results. For general information on the Scientific Climate Ratings, please see the respective technical documentations.

All procedures were developed by the *EDHEC Climate Institute*, hereafter referred to as ECI or "we."

1. General Approach

Wildfires, also known as forest fires or bushfires, are uncontrolled and fast-spreading fires that occur in vegetation, such as forests, grasslands, or shrublands. They typically start from a small ignition source, such as lightning, human activity, or volcanic activity, and can quickly grow in size and intensity. Wildfires have a significant impact on drier regions. Economic losses are significant for regions at risk, such as the Mediterranean area, Australia (which faced over USD 110 billion in financial losses in 2019-2020; Haque et al., 2021) and California (which incurred USD 150 billion in damages; Eagleston & Krofcheck, 2022).

Wildfires can spread rapidly under unfavourable conditions, including natural topography, human activities, hot and dry weather, and the presence of abundant fuel. This fuel often includes flammable vegetation, which, especially when combined with strong winds, accelerates the fire's spread. The fire can leap from tree to tree or spread across vast areas, consuming everything in its path. Therefore, wildfires can cause severe damage to ecosystems, destroy homes and infrastructure, and threaten human lives and wildlife. Additionally, they emit smoke and pollutants into the atmosphere, negatively affecting air quality and posing health hazards to nearby communities. We refer to hazard events from wildfires as **burnt events**.

To quantify physical risks stemming from wildfires, our approach follows a stepwise progression from sourcing inputs on assets and hazards to the geospatial transformation. This results in quantified physical metrics, representing the potential damage for each asset. Figure 1 summarises our approach, which we elaborate on in the methodology sections.

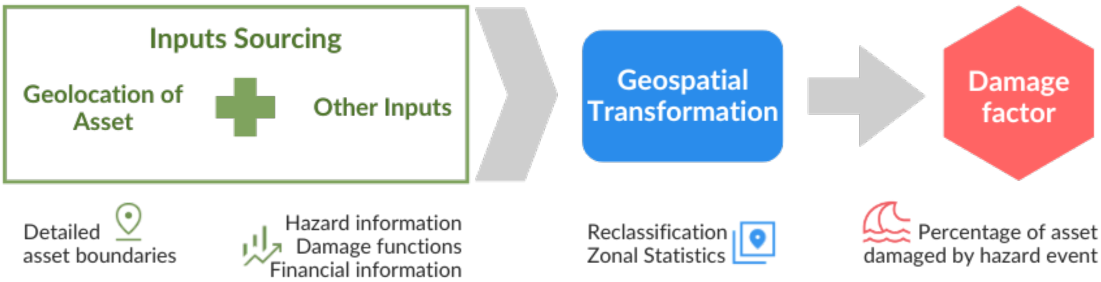


Figure 1: General approach for calculating physical hazard risks

2. Data Sources

To provide quantified wildfire risk metrics for specific physical assets, three key data points are needed:

- We include **financial information** for each identified asset (e.g., total asset value and revenue) as extracted from *infra*Metrics[1] to quantify the financial impact of each physical risk on the asset.
- Global **climate hazard information** (e.g., hazard maps) illustrates which areas would be affected to what extent by a particular hazard and, hence, specifies the proximity to a potential hazard. Table 1 provides details on the considered hazard maps and data sources. We developed this data further to construct a probability map of areas affected by wildfires.
- We also use **detailed asset boundaries** to define each asset's size and geolocation. These boundaries are prepared, checked, and updated regularly.

Combined, these inputs are proxies for an asset's *exposure* (i.e., the presence of assets in settings that could be adversely affected by hazard events) and account for its *vulnerability* (i.e., the propensity of an asset to be adversely affected by a hazard event) to a wildfire event.

3. Methodology

We adopt the framework previously established by Bouwer (2013) and Muis et al. (2015), who consider three main factors when measuring physical risks:

- the changing nature of hazards (due to climate change and natural weather variations),
- assets' vulnerability (the probability that assets will be damaged due to a hazard), and
- their exposure (the placement and characteristics of assets that could be impacted by hazards).

To account for assets' vulnerability and exposure to a given hazard, we utilise damage functions, also known as fragility curves (Prahl et al., 2016). Two types of damage are estimated by damage functions – absolute and relative. The **absolute damage** approach considers the value of assets and outputs the estimated monetary damage of an item or a group of items. The **relative damage** approach quantifies damage as a fraction or percentage of damage against the total damage and, hence, outputs a ratio expressed in percentage instead of a monetary value (Ghimire & Sharma, 2020). Our work focuses on the relative damage approach and its respective damage functions. This allows us to quantify the proportion of damage to each asset first, which can subsequently be transformed into absolute damage.

The following sections explain the steps for calculating physical risks from wildfires, from identifying the location to measuring the damage, and projecting the growth of damages in climate scenarios.

[1] infraMetrics is EIPA's index and data platform, offering asset-level investment metrics for private infrastructure across more than 20 markets by sector, business risk, and corporate structure peer groups. In our models, we update this data on a quarterly basis.

Table 1: *Sources for wildfire hazard maps*

Hazard type	Hazard unit	Maps resolution	Underlying data and models
Wildfire	Burnt date*	Global 500m by 500m	The underlying data consists of NASA's monthly global gridded burnt date from 2001 to 2024. We receive that data per pixel burnt area. NASA derives the information from a combination of surface reflectance imagery and active fire observations. An algorithm employs a burn-sensitive Vegetation Index (VI) to include further information on the vegetation's burn sensitivity. To calculate the VI, NASA combines satellite imagery, specifically bands 5 and 7 of MODIS' shortwave infrared atmospherically corrected surface reflectance (Giglio et al., 2021).
Wildfire	FWI indicator	Global 25km by 25km	The Fire Weather Index (FWI) is a numerical rating of fire intensity, incorporating weather conditions such as temperature, relative humidity, wind speed, and precipitation to assess wildfire risk. The FWI is derived from the NEX-GDDP dataset (Thrasher et al., 2022) that provides daily meteorological variables downscaled from global climate models. To ensure the robust assessment of high-risk fire weather conditions, we consider the most extreme 10 percent of FWI values for each decade (using the 90th percentile). The running periods of ten years allow for a continuous assessment of changes in fire weather conditions while smoothing out short-term variability. We calculate the FWI considering two Representative Concentration Pathways (RCP) scenarios (RCP4.5 and RCP8.5)**.
Wildfire	Tree cover	Global 100m by 100m	The tree cover dataset offers an analysis of forest types to assess vegetation density in a selected area. This data is part of the Copernicus Global Land Service (Buchhorn et al., 2020) that provides annual global land cover maps on 23 classes aligned with the Land Cover Classification System of the Food and Agriculture Organization of the United Nations (Di Gregorio & Jansen, 2000). The data for those maps is derived from PROBA-V satellite observations.

* Here, burnt date refers to the first day in a month a burnt event occurs in a specific area. Accordingly, we know in which month a burnt event happened but cannot draw direct conclusions on the event's duration and severity.

** On demand of the IPCC, the scientific community developed one of the first scenarios – the Representative Concentration Pathways – to explore impacts of (future) greenhouse gas concentrations in the atmosphere on the climate. The RCP4.5 and RCP8.5 represent an intermediate and a worst-case scenario, respectively (Van Vuuren et al., 2011).

3.1. Geospatial Transformation

To derive the expected damage from wildfires, we require several inputs. These inputs undergo a process known as **geospatial transformation**, in which individual data inputs are converted into the necessary format. Consequently, geospatial transformation involves a series of smaller processing steps, from reclassification to zonal statistics, that prepare the inputs unique to each asset.

These are the steps of the geospatial transformation needed to calculate damage from wildfires:

1. First, we extract detailed **geographical boundaries** of each asset and evaluate an asset's exact conditions and environment. This process, known as **geolocation**, involves manually checking that each asset is still operating and retrieving its address. We then proceed to draw the asset boundary and relevant geospatial outlines using a variety of commercial and open-source geographic information system platforms and map sources. Figure 2 shows an example of a geoshape extraction for Wellington International Airport.

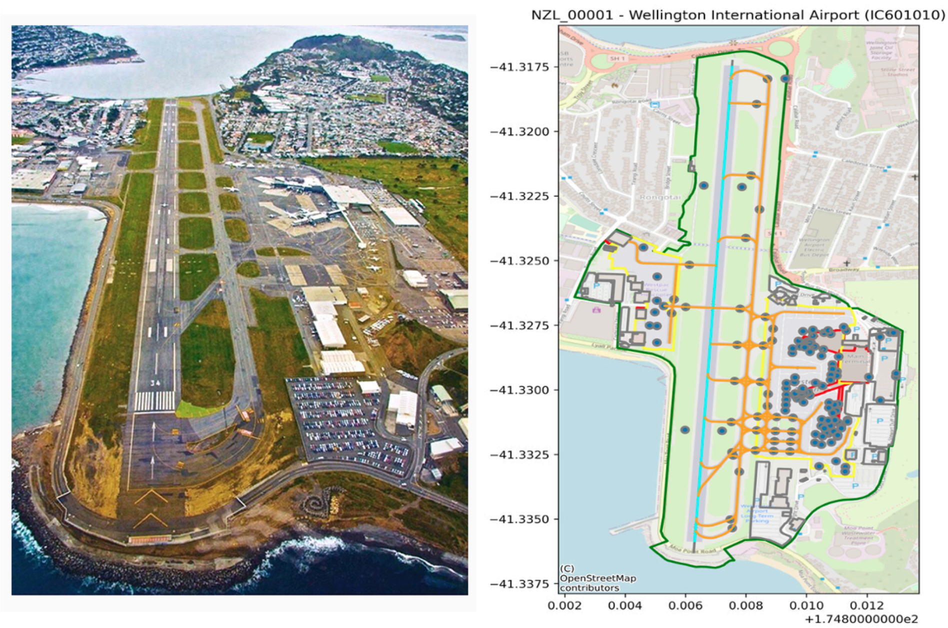


Figure 2: Example of a geoshape extraction for Wellington Airport

2. Second, we extract the days of observed wildfire for each pixel (i.e., a square patch of land at a resolution of 500 by 500 metres) of the **wildfire hazard map**. For each area (i.e., the pixel on the map), the map provides the first day a wildfire was observed for each month (based on an annual count, i.e., 10 for January 10, 365 for December 31)[2]. We convert this information into a **burnt flag**, a binary marker that indicates burnt areas for each year.
   This **reclassification** process transforms the initial hazard map into hazard maps with burnt flags, where pixels with a value of 1 represent an instance of wildfire observation, and pixels with a value of 0 represent no wildfire occurrences in a particular year.

[2] For example, if a wildfire occurred from January 10 to 15, the pixel would indicate this with a 10; if a wildfire lasted from January 29 to February 2, the pixel would indicate this with a 29 for January and 32 for February.

3. Next, we combine the burnt flags from all years and transform them into **wildfire maps with an annual probability**. Based on the assumption that wildfires can happen randomly across a larger area than the dataset's 500-metre resolution, we also include the surrounding areas of 2.5 and 25 kilometres into the calculation of wildfire probabilities of a given pixel. Furthermore, we assume that burnt events follow a binomial distribution. In order to improve the probabilistic understanding of wildfire risk, we compare the actual number of burnt event occurrences with the theoretical probabilities. Confidence intervals can then provide information on the probability range of an event happening.

4. Lastly, we apply **zonal statistics** to the asset's boundaries and the annual probability maps to derive asset-specific damage from wildfires. This approach overlays a given asset boundary on the corresponding wildfire probabilities map and calculates the average of all wildfire probabilities per pixel that fall within that boundary. This value represents an asset's average wildfire probability.
   In this step, we apply a **damage function** for wildfires that specifies the damage in percent and monetary value. Damage functions are mathematical models that convert the severity of a physical hazard into the damage sustained by specific assets, considering the assets' exposure and vulnerability (Prahl et al., 2016). The output of these relative damage functions is the **damage factor**, typically defined as the ratio of repair costs to replacement costs (ibid.). The calculated damage factors range from 0 to 1, where 0 indicates no damage, and 1 signifies complete damage. In the latter case, the cost of repair is equivalent to the cost of replacement. Consequently, damage factors are interpreted interchangeably as the percentage of the asset value that requires repair or replacement.

3.2. Expected Damage from Wildfires

We developed our physical risk model for wildfires (as of April 2025) around one unique damage function, based on the work by Lüthi and colleagues (2021). In the case of wildfires, we assume that the damage factor is equivalent to 1 for all instances of burnt events. This approach aligns with the conservative perspective of Lüthi et al. (2021), who found that assets are entirely destroyed when a fire of a specific intensity is detected in a pixel of a 1-by-1 kilometre hazard map. The damage function approach considers that the average annual damage from wildfires equals the average probability of wildfire for a given year and asset, multiplied by the damage factor.

Additionally, we consider the presence of vegetation when calculating the expected damage from wildfires. Assuming a higher risk for assets surrounded by more vegetation, we adjust the probability for wildfire occurrence if the tree cover map indicates a significant presence of vegetation within a 2-kilometre radius around an asset (Buchhorn et al., 2020). The adjusted probability directly translates into a minimum 2 percent annual damage from wildfire when the tree cover is more than 50 percent and a minimum of 1 percent damage per year when the tree cover is between 20 and 50 percent.[3] Additionally, if the presence of dense vegetation within the same radius is less than 20 percent, we reduce the probability of wildfire occurrence based on the tree cover value.

3.3. Growth of Wildfire Damages in Climate Scenarios

In order to calculate wildfire damages for climate scenarios and make future predictions, we need to estimate the hazard intensity in future climate scenarios and adapt the expected damage accordingly. This is possible using the FWI (Thrasher, 2022) as an indicator to estimate the increase in wildfire intensity. Based on the initially calculated annual growth rate of the most extreme FWI values (90th percentile), we can combine present wildfire probabilities with average annual intensity increases to derive future wildfire risk for the RCP4.5 and RCP8.5 scenarios.

4. Results

Our findings are precise and widely applicable, spanning across various sectors and countries.

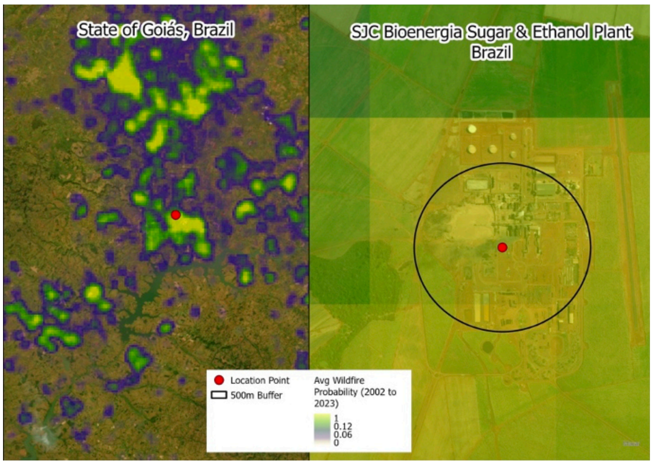
4.1. Generic Radius vs Detailed Asset Boundaries

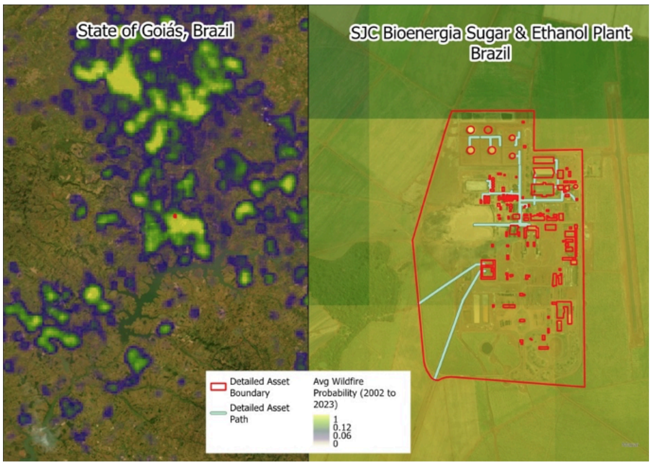
Typical market solutions assess physical risks using an approximate buffer and a single coordinate representing the asset's location (a point provided by the user). This simplified data results in risk estimations that are less accurate than those derived from detailed asset boundaries. We illustrate the benefits of our method with detailed asset boundaries in our example of the *SJC Bioenergia Sugar & Ethanol* plant in Brazil and average wildfire probability calculations. As shown in Figure 3, the generic radius approach has produced an underestimation of wildfire damage and value-at-risk by at least USD 8 million compared to the damage estimations of the detailed asset boundary approach.

As infrastructure assets can span over large, irregular areas (like airports or utilities) or stretch across hundreds of kilometres (such as roads and wind farms), physical risk metrics based on single-point or vector geolocation are unlikely to represent an asset's physical risk exposures correctly. A more accurate assessment requires knowing the precise spatial footprint of assets and the varying levels of physical risk that could materialise across its entire length or area.

[3] We only adjusted cases where the initial probability (i.e., annual damage from wildfire) is below the margins of 2 and 1 percent, respectively.

Figure 3: *Example of wildfire damage to the the SJC Bioenergia Sugar & Ethanol Plant in Brazil*





Typical solution: Generic buffer of 500 metres and resulting wildfire risk estimation.

Average wildfire probability:	16.7 %
Physical Damage at Risk:	20.0%
Physical Value at Risk:	USD 121 million

Our solution: Detailed asset boundary and resulting wildfire risk estimation, which is more accurate.

Average wildfire probability:	17.2 %
Physical Damage at Risk:	21.4%
Physical Value at Risk:	USD 129 million

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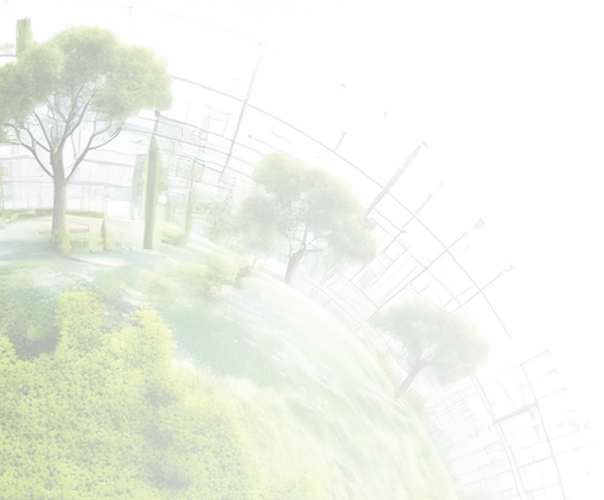

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