



## D.1.2 Climate risk profiles to each Macaronesian island

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## Executive summary

This GENESIS D1.2 report builds climate-risk profiles for the islands of Macaronesia (Canary Islands, Azores, Madeira and Cape Verde). The analysis combines downscaled climate data that accounts for topography (ERA5 with TopoPyScale), curated weather and civil-protection records, machine-learning methods to fill gaps in event histories, and non-stationary extreme-value models. Future yearly levels of extreme events (2025–2100) are estimated with a third-order polynomial and expressed as the probability of alert days.

The main result is a clear rise in heat-alert probabilities by the end of the century. In several islands, heavy-rainfall alerts decline overall but may become shorter and more intense. Wind and coastal risks change depending on exposure and orientation. Seasonal patterns also shift, with more hazards in summer. These trends could increase stress on water resources, ports, coastal areas, and treatment plants.

Even though past alert data are uneven between territories, the profiles give a practical reference for action: improve preparedness for heat and water shortages, review drainage and flood controls where intense rainfall is expected, keep coastal and wind resilience strong in exposed areas, and expand monitoring and impact tracking to improve future evaluations.

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## List of Abbreviations

IPCC

AEMET (Agencia Estatal de Meteorología).

SRPCBA Serviço Regional de Proteção Civil e Bombeiros dos Açores

IPMA

SRPC, IP-RAM Serviço Regional de Proteção Civil, Madeira

INMG Instituto Nacional de Meteorologia e Geofísica

SNPCB Serviço Nacional de Proteção Civil e Bombeiros

Statistical Extreme Value Analysis (EVA)

Generalized Extreme Value (GEV)

Generalized Pareto Distribution (GPD)

Peak-Over-Threshold analysis with GPD (POT/GPD)'

Machine Learning (ML) and AI

# 1-Introduction

## 1.1 Climate Change and Freshwater Resources on Oceanic Islands

Oceanic islands are often described as being on the frontlines of climate change, experiencing a range of intense impacts that threaten their vital resources and infrastructure (1). A key vulnerability is freshwater supply: many small islands rely on limited rainfall and fragile groundwater lenses for their water needs. With few or no large rivers, these islands depend on rain-fed aquifers – thin freshwater lenses that float atop seawater – and intermittent surface catchments. This makes their water resources highly sensitive to drought and over-extraction (2) (3) (4).

Climate change is exacerbating these challenges by raising water demand due to hotter conditions and growing populations. In many small islands, water demand already exceeds sustainable supply. As a result, freshwater systems on small islands are considered among the most threatened globally under climate change. Studies project significant declines in water availability – one analysis estimates an 11–36% reduction in the volume of freshwater lens aquifers on certain low-lying atoll islands under future climate scenarios (5). In Macaronesia (the North Atlantic archipelagos including the Canary Islands, Madeira, Azores, and Cape Verde), regional projections likewise indicate severe impacts: a temperature rise of ~2–3 °C by 2050 could reduce overall water resources by around 30% (6). These trends underscore that island communities in places like Macaronesia are on the front line of emerging water scarcity, as climate change intensifies pressure on their limited freshwater reserves.

## 1.2 Extreme Weather Events: Rising Frequency and Severity

Recent decades have seen a marked increase in the frequency and intensity of extreme weather events around the globe (7). Records are being shattered as heatwaves, heavy precipitation events, and storms grow more severe and frequent. Notably, many of these extremes would be highly unlikely to occur without the influence of long-term climate warming. For example, the modest ~0.25°C rise in global temperature over the last decade has led to record-breaking heat and rainfall extremes that “would be virtually impossible without anthropogenic global warming,” with roughly one in four record-high rainfalls now attributable to climate change (8). These shifts are not simply random variability – human-induced climate trends are “leaking” into the extreme event record. A warmer atmosphere holds more moisture and adds energy to weather systems, fueling heavier downpours and stronger storms, while higher baseline temperatures make heatwaves more intense and long-lasting (7). In short, broad climatic changes are translating into more frequent and more intense extremes, which is a critical concern for climate risk assessments.

### 1.2.1 Key Types of Extreme Climate Events

Different categories of extreme events show clear upward trends in severity or occurrence, as documented by recent studies and assessments:

- **Heatwaves and Extreme Temperatures:** Episodes of extreme heat have become more common and severe on all continents. The IPCC reports with very high confidence that hot extremes (daily high temperatures, heatwaves) have increased in frequency and intensity worldwide since the 1950s. Recent attribution studies reveal that some extraordinary heatwaves – such as the 2020 Siberian heatwave or the 2021 Pacific Northwest heat dome – “simply would not have occurred” without

human-caused climate warming (9). Heatwave duration is also accelerating faster than mean warming, with the longest and most intense heat events rising the fastest (8). These unprecedented hot spells drive cascading impacts (wildfires, health crises, drought), underscoring their growing risk profile.

- **Heavy Rainfall and Flooding:** Warmer air's capacity to hold moisture has led to more intense downpours and flood events. Heavy precipitation extremes have increased across most regions, resulting in higher incidence of flash floods. One analysis found that globally, flood frequency (especially long-duration floods) has risen significantly, with four times more floods in the tropics since the early 2000s compared to previous decades (9). Even in regions where total rainfall is steady or declining, rains are falling in shorter, more intense bursts, overwhelming drainage systems and causing floods. Overall, what used to be "hundred-year" rain events are occurring more often, and extreme flooding has correspondingly become more common (8).
- **Storms:** Large storms can bring heavy rain, sudden flash floods, and landslides on steep slopes, hail, and lightning. On islands, the land drains water quickly and many important buildings are close to the coast, which makes the damage worse. Problems can include blocked drains, muddy water in reservoirs, water-treatment systems being overloaded, landslides blocking main roads, and airports or ports closing because of lightning or poor visibility. These storms can also happen at the same time as coastal flooding or strong winds.
- **Coastal phenomena:** Coastal hazards can cause damage even without a local storm. Long ocean swells from far away can reach the coast during calm weather, leading to rough harbour conditions, waves spilling over seawalls, beach and dune erosion, and flooding of roads near the shore. Wave action can push water higher, causing more overtopping of sea defences. Sudden water level changes can affect semi-enclosed bays or harbours. Key sites at risk include desalination plants, wastewater outlets, ports, ferry terminals, and coastal transport routes.
- **Wind-speed extremes:** Dangerous peak wind gusts are often shaped by the landscape. Strong jets can form in channels between islands, winds can speed up around headlands, and mountain waves or foehn winds can create sudden extreme gusts on sheltered slopes. The trade winds can also bring long periods of strong flow, while rare hurricane or tropical storm systems can produce damaging winds from unusual directions. Low-level jets and storm downbursts can trigger short bursts of very high wind. These events can cause power or communication failures that disrupt pumps and control systems, force shutdowns of cranes, ferries, and airports, and place heavy loads on aqueducts, pipe bridges, and rooftop water tanks.
- **Dust events:** are a separate hazard. They occur when hot, dry air carries sand and dust from the Sahara Desert over the islands. Calima reduces visibility for airports and ports, coats sensitive equipment, and worsens air quality. It can also raise temperatures and lower humidity, increasing water demand for cooling, cleaning, and irrigation. Dust can clog filters, foul water intakes, and strain treatment systems, adding stress to water infrastructure. These events can arrive with calm weather, with alisos, or with strong southerly winds from tropical systems.
- **Wildfires (Compound Extreme Events):** Wildfires themselves are not a direct climate event, but they are driven by extreme heat, drought, and wind conditions that are worsening with climate change. Prolonged high temperatures and dry spells create tinderbox landscapes prone to burning. In recent years there have been unprecedented wildfire seasons all linked to exceptional heat and drought conditions exacerbated by climate trends. Research indicates that climate change has effectively "lengthened" wildfire seasons and doubled or even tripled the area burned in some regions over the past few decades (8). These fires are extreme events in their own right, causing massive

environmental and socioeconomic impacts, and they illustrate how compound extremes (drought + heat + wind) can produce disasters beyond historical experience.

The rise in extreme weather events is evident across multiple hazard types, and scientific observations strongly link this rise to underlying climate shifts (10). This escalation of extremes – from torrential rains and floods to heatwaves, droughts, storms, and wildfire outbreaks – represents a significant challenge for communities. By focusing on the changing behavior of extreme events, it is possible to better understand vulnerabilities and prepare adaptive responses, which is a core goal of the GENESIS project's climate risk assessment efforts.

## 1.3 Warnings and Alerts in Macaronesia: Definitions, Institutional Framework and Operational Use

This section formalizes the concepts of warnings and alerts as they pertain to the Macaronesian archipelagos (Canary Islands, Azores, Madeira and Cape Verde) and delineates the institutional roles of meteorological and civil-protection authorities.

### 1.3.1 Terminological distinctions

For consistency across archipelagos and agencies, the following operational taxonomy is adopted:

- **Warning:** Hazard is imminent or occurring at defined thresholds (e.g., gust, rainfall intensity). Typically uses agency scales (e.g., Yellow/Orange/Red).
- **Civil-protection alert status:** Administrative activation levels that govern inter-agency coordination and public protection measures. These are response postures, distinct from meteorological products, though often escalated by them.

Cross-checking data from both institutions is very important to understand the real impact of an extreme event, since a weather warning may not ultimately result in an extreme event or may not pose a risk to the population, depending on where it happens. Alerts, however, already indicate a higher level of risk for the population and are usually issued when the danger is imminent or already occurring, which means they tend to have a smaller margin of error. On the other hand, weather warnings are usually much more precise geographically, whereas alerts are often declared for an entire island or groups of islands.

### 1.3.2 Institutional landscape

#### Canary Islands (Spain):

- **Meteorological authority:** AEMET (Agencia Estatal de Meteorología). Issues island/zone-specific warnings using a color-coded scale.



- **Civil protection:** Gobierno de Canarias – Dirección General de Emergencias and CECOES 1-1-2. Declare alerts, coordinate Cabildos and municipalities, and disseminate impact-based public guidance (closures, evacuations, operational restrictions).

#### Azores (Portugal):

- **Meteorological authority:** IPMA (Instituto Português do Mar e da Atmosfera). Issues island/zone-specific warnings using a color-coded scale.
- **Civil protection:** SRPCBA (Serviço Regional de Proteção Civil e Bombeiros dos Açores). Activates measures, coordinates municipal services, and issues operational advisories.

#### Madeira (Portugal):

- **Meteorological authority:** IPMA (as above).
- **Civil protection:** SRPC, IP-RAM (Serviço Regional de Proteção Civil, Madeira). Coordinates island-wide alerting, emergency services, and sectoral authorities.

#### Cape Verde

- **Meteorological authority:** INMG (Instituto Nacional de Meteorologia e Geofísica). Issues island/zone-specific warnings.
- **Civil protection:** SNPCB (Serviço Nacional de Proteção Civil e Bombeiros). Leads preparedness/response with island councils and port/airport operators.

## 1.4 The Macaronesian Region: Characteristics, Socio-Economic Importance, and Climate Vulnerabilities

The focus of the GENESIS project is the Macaronesian region, a collection of four North Atlantic archipelagos: the Azores, Madeira, the Canary Islands, and Cape Verde. These islands, though politically part of different nations (Portugal, Spain, and Cape Verde), share a common biogeographic heritage and face similar environmental challenges. Macaronesia is characterized by volcanic islands with varied topography – from high volcanic peaks and lush cloud forests (e.g. Pico Island in the Azores, La Palma in the Canaries) to low-lying desert landscapes (parts of Lanzarote or Sal in Cape Verde). The region hosts a rich biodiversity and a number of endemic species, making it one of Europe’s noteworthy biodiversity hotspots. The climate across Macaronesia ranges from subtropical Mediterranean conditions in Madeira and the Canaries to more humid oceanic climates in parts of the Azores. This diversity of environments underpins agriculture, freshwater availability, and natural habitats across the islands (11).

From a socio-economic perspective, Macaronesian islands have significant importance and unique vulnerabilities. The region’s economy is strongly specialized in the services sector, particularly tourism, which

is a cornerstone of income and employment on many islands. The Canary Islands, for example, receive over 12 million visitors annually, and tourism contributes roughly one-third of the Canarian GDP. Madeira also sees nearly 2 million tourists per year (notably as a cruise and resort destination), and tourism there and in the Canaries drives demand for infrastructure, water, and environmental services. The Azores traditionally had an economy centered more on agriculture (dairy farming, livestock and fisheries), but tourism has grown substantially in the past two decades with the advent of global travel links. In Cape Verde, tourism and fishing are key sectors alongside remittances. This heavy reliance on tourism and services means the islands' economies are highly sensitive to climate impacts: beach erosion, coral reef degradation, water shortages, or storm damage can directly affect the tourism sector and broader livelihoods. Population distribution in Macaronesia also influences vulnerability. The Canaries are the most populous archipelago (over 2 million residents) and, along with Madeira, have very high population densities approaching 300 persons per km<sup>2</sup> on the main islands (12).

Urban and resort development is largely coastal, including major cities like Las Palmas de Gran Canaria and Santa Cruz de Tenerife, as well as critical infrastructure like ports, airports, desalination plants, and power stations situated near sea level. By contrast, the Azores have a smaller population (~250,000 inhabitants) with a density below 60 per km<sup>2</sup> and more dispersed rural communities (12). Cape Verde (~560,000 population) has both densely populated areas (e.g. the capital Praia) and sparsely inhabited islands. Insularity and remoteness define all Macaronesian islands – they are hundreds of kilometers from mainland continents – leading to external dependence for fuels (13). Nevertheless, in the Azorean islands—particularly in São Miguel and Terceira—the integration of high-enthalpy geothermal energy, photovoltaic solar power, and wind energy accounted for approximately 34.6% of total electricity generation in 2024 (14).

This remoteness can amplify the impact of climate hazards: for instance, a severe storm disrupting port operations or supply chains can quickly lead to shortages, and repairing damaged infrastructure may take longer due to logistical challenges. Climate change is already evident in Macaronesia and is projected to intensify a number of hazards. Rising temperatures and shifting rainfall patterns are leading to extended dry seasons and more frequent drought conditions, especially in the drier archipelagos. The Canary Islands and Cape Verde, which are partly arid, have experienced prolonged droughts in recent decades, stressing water supplies and agriculture. In these islands, water availability is naturally scarce and heavily dependent on irregular rain or expensive alternatives like desalination. As one regional assessment notes, Macaronesian islands have “already scarce water availability” which, combined with growing demand from population and tourism, creates deficits and competition among water users (15).

Climate change exacerbates this by prolonging drought periods and increasing evapotranspiration from soils and forests. Groundwater over-extraction (historically common in e.g. Canary Islands) and reduced recharge under shifting climate can lead to aquifer depletion and saline intrusion. For instance, Tenerife and Gran Canaria have seen declining aquifer levels, and future climate scenarios indicate further reductions in rainfall recharge. All this means water security is a pressing challenge in Macaronesia: without adaptation, deficits will grow, affecting agriculture (such as vineyards, bananas, dairy farms), ecosystems (like laurel forests needing moisture), and basic human needs. In parallel, Macaronesian islands face extreme weather and coastal threats. The North Atlantic can generate powerful winter storms and the occasional tropical cyclone or hurricane remnant that reach the Azores (as seen with Hurricane Lorenzo in 2019). The Canary Islands and Madeira have documented more frequent heavy rainfall events and flash floods in recent decades, likely linked to warming ocean temperatures and changing storm tracks. One dramatic example was the February 2010 storm in Madeira, where the combination of steep slopes and extreme rainfall (with a maximum rainfall of 360.5 mm in 24 hours) triggered flash floods. The intense precipitation mobilized large amounts of solid material transported by streams, resulting in around 50 fatalities and causing extensive damage in the city of Funchal. (16) Climate projections suggest that intense downpours may become more severe but perhaps less frequent – raising the risk of flash flooding when rain does occur on parched ground. Atlantic storm surges and swell events also pose a major risk to coastal settlements. The Macaronesian coasts, especially low-lying towns and beaches, are vulnerable to high-energy wave events that can overtop natural and built defenses. According to a Copernicus-supported analysis, the islands of Macaronesia are becoming increasingly vulnerable to extreme coastal flooding due to powerful Atlantic storms, a trend expected to worsen as

climate change progresses. A stark illustration of this threat occurred in Garachico, Tenerife, where wave overtopping has repeatedly inundated the town. Recognizing this, local authorities (with EU LIFE project support) have implemented innovative coastal defenses and an early warning system, reflecting how urgent the issue of storm surge flooding has become. Other climate-related vulnerabilities include heatwaves (which can threaten public health and endemic species in these normally mild climates), wildfires (periods of drought and heat have already led to devastating forest fires in Gran Canaria, La Palma, and Madeira in recent years), and ecosystem shifts (such as coral bleaching in Cape Verde's seas or the upslope retreat of cloud forests in the Canaries and Azores). Sea-level rise is a slower hazard but one with long-term consequences for Macaronesia. Even a moderate global sea-level rise could lead to permanent inundation of low-lying coastal zones, erosion of the islands' limited beaches (affecting tourism and coastal biodiversity), and increased saltwater intrusion into coastal aquifers (17).

Critical infrastructure like ports will require enhanced protection or redesign as climate conditions change. In summary, the Macaronesian region epitomizes the multi-faceted vulnerability of island systems. The islands' environmental treasures and socio-economic assets are at risk from a cascade of climate impacts: worsening water shortages, extreme storms and floods, coastal erosion, ecosystem degradation, and others. Their insular nature – small size, isolation, concentrated development – means any climate shock can have disproportionate and cascading effects on communities and economies. For instance, a drought not only affects drinking water but also hydroelectric power output and agricultural productivity, potentially necessitating costly measures like importing water or energy. A coastal storm can damage roads and desalination plants, interrupting supply chains and tourism for months. These interconnected risks highlight why a comprehensive understanding of climate threats is needed. Policymakers and local governments in Macaronesia have recognized climate change as a critical issue (e.g., through initiatives like the Macaronesia Climate Change Observatory under the PLANCLIMAC project) and are seeking robust information to guide adaptation. The vulnerabilities identified – especially regarding water and infrastructure – set the stage for developing climate risk profiles for each island, which can inform targeted adaptation and resilience-building strategies.

## 1.5 The Macaronesian Region: Characteristics, Socio-Economic Importance, and Climate Vulnerabilities

Climate risk profiling is an analytical procedure that systematically compiles and organizes evidence of climate-related hazards for a defined territory. In island contexts such as Macaronesia, the approach integrates observational records, historical event inventories, and weather datasets into a coherent picture of how extreme events have occurred in the past and how they may evolve in the future.

The primary goal is to study the historical frequency and intensity of extreme events—such as storms, floods, or heatwaves—and to estimate how the occurrence of these events may increase up to 2100. The emphasis is descriptive and forward-looking: documenting observed extremes and quantifying their potential future changes, rather than prescribing adaptation measures.

Because small islands often concentrate population and critical services in limited coastal or mountainous zones, such profiles help identify how risks differ among islands and how they vary within the same island. The result is a baseline characterization of extreme-event dynamics—comparable across islands and time—that records both historical metrics and future projections.

The profiles remain non-prescriptive by design. They do not recommend strategies, prioritize investments, or define interventions. Instead, they serve as a reference compendium of empirical information (indices, maps, exceedance frequencies, event chronologies, and modeled projections) that can later inform other work packages or external processes focused on planning and decision-making. In this way, climate risk profiling functions as a technical baseline and evidence register, continuously updateable as new data or methodologies become available.

## 1.6 State of the Art in Extreme Event Probability Analysis for Risk Profiling

Analyzing the probabilities of extreme weather events has become a vital component of climate risk profiling. Over the past 15 years, researchers have advanced several methodological approaches to characterize extreme-event likelihoods and produce analytical risk profiles. These approaches blend classical statistical extreme value theory with modern data science techniques, leveraging multi-source datasets and machine learning. Below are outlined the key state-of-the-art methods used to calculate the probability of weather extremes (for hazard analysis, without implying adaptation measures).

### 1.6.1 Statistical Extreme Value Analysis (EVA)

A foundational approach for quantifying extreme-event probabilities is EVA, which models the tails of climate variable distributions. The Generalized Extreme Value (GEV) distribution and the Generalized Pareto Distribution (GPD) are widely used to estimate the frequency and magnitude of rare events (18). The GEV family unifies Gumbel, Fréchet, and Weibull extreme value types, enabling estimation of return levels (e.g. 50-year or 100-year events) beyond the observed range. In practice, analysts often fit a GEV to annual maxima of variables like rainfall or wind, obtaining parameters that describe the tail behavior. This method has a long track record in climate and hydrology studies; for example, “the generalised extreme value (GEV) with the ‘block maxima’ approach” is a model widely used in the literature to assess extreme rainfall probabilities (19). By extrapolating from historical extremes, GEV models provide estimates of rare-event occurrence probabilities (e.g. the intensity associated with a 1% annual chance event). An alternative EVA approach is peak-over-threshold analysis with GPD, which uses all data above a high threshold instead of block maxima. Both the block-maxima/GEV and POT/GPD methods are considered standard tools for extreme weather risk analysis.

### 1.6.2 Non-Stationary Extreme Value Models

A key development in the last decade is incorporating climate change and variability into extreme-event probability models. Traditional EVA assumes stationarity (constant probability distribution over time), but mounting evidence of trend changes in extremes has led to non-stationary extreme value analysis. In these methods, the parameters of distributions like GEV are allowed to vary with time or with covariates (e.g. global temperature or indices). For instance, researchers have fit time-dependent GEV models where the location and/or scale parameter includes a linear or nonlinear trend over years. This captures increasing intensity or frequency of extremes due to climate trends. A recent study demonstrated this by fitting a non-stationary GEV to an ensemble of climate model simulations for heatwaves, finding that making GEV’s location and scale parameters time-varying significantly improved the model. Such approaches can quantify how a rare event’s probability evolves – e.g. showing that an event formerly expected once in 100 years may become far more frequent under warming. This underscores that state-of-the-art risk profiling often accounts for non-stationarity to avoid underestimating future risks. In practice, analysts may either include time as a covariate in GEV models or divide data into periods to detect shifts. Both approaches help identify trends in extreme-event return periods, ensuring that risk profiles remain valid under changing climate conditions (20).

### 1.6.3 Integration of Multi-Source Data and Event Records

Modern risk assessments emphasize assembling comprehensive datasets on past extreme weather events. Multi-source data integration has become common to overcome sparse or incomplete records. By integrating diverse data, analysts capture a more complete history of extremes, which improves the statistical base for probability estimation. For example, global reanalysis products can effectively capture extreme events (21), so they could be used to fill gaps in space and time, ensuring that no major event is missed in the analysis. Historical event chronologies (e.g., dates and impacts of major storms, floods, heatwaves) gleaned from reports and alerts are also used to validate and contextualize the statistical findings. State-of-the-art methodologies often construct unified climate risk databases from these sources. This comprehensive data approach allows correlating hazard occurrences with vulnerabilities, and supports more robust extreme value modeling. Notably, studies have found that blending modelled and observed data can improve the characterization of extreme-event distributions, reducing uncertainty (22).

### 1.6.4 Machine Learning

In parallel with statistical methods, the last 15 years have seen rapid growth in applying machine learning (ML) to extreme weather risk analysis. Machine learning models offer flexible, data-driven ways to estimate the occurrence or magnitude of extreme events, potentially capturing complex nonlinear relationships that traditional models might miss. A notable trend is using ML to augment and support EVA – for example, by reconstructing missing extreme-event data or by identifying patterns that lead to extremes.

Recent work has employed automated machine learning framework (AutoML), which automates the entire ML pipeline, to develop ensemble models, such as bagging, boosting and stacking, capable of predicting extreme event indices from large climate datasets. In particular, the AutoML stacking approaches can evaluate many algorithms (e.g., random forests, gradient boosting, neural networks) and combines the best performers, yielding highly accurate results with minimal human tuning. Research demonstrates that such ensemble AutoML models can outperform single-model methods in hydrometeorological tasks: for instance, an AutoML ensemble was able to reconstruct long-term streamflow series with superior accuracy compared to several traditional ML models. Likewise, classification models (including neural networks and tree-based models) have been used to detect the occurrence of extreme events (e.g. days of unusually high rainfall or temperature) based on atmospheric predictor patterns gaps (23). ML techniques are increasingly used to analyze and even explain extreme events – a recent review highlights that artificial intelligence is being applied to floods, droughts, wildfires, and heatwaves to create more accurate and reliable predictors, despite the challenges of noisy, heterogeneous climate data. These ML approaches contribute to risk profiling by providing alternative estimates of extreme-event likelihood (sometimes as probabilistic forecasts or simulations) and by filling data (24).

### 1.6.5 Time Series Forecast

Using a two columns database with year (1995–2024) and number of extreme-event days, it is possible to fit a ML model with year as the predictor and extreme-day count as the target. The trained model is then evaluated on the historical period and used to generate future predictions for 2025–2100, yielding a forward trajectory of expected extreme-day counts for analytical risk profiling. This setup follows established time-

series forecasting practice in climate applications following a parametric cubic regression on year to project 2025–2100.

In summary, the state-of-the-art methodology for calculating extreme weather event probabilities is multifaceted. It combines *rigorous* statistical extreme value theory (for solid probabilistic foundations) with advanced data integration (to leverage all available observations) and ML techniques (to handle complexity and data gaps). Traditional EVA tools like GEV/GPD remain indispensable for deriving return periods and probabilities, and they are now frequently used in tandem with non-stationary modeling to account for climate change trends (25). Meanwhile, the incorporation of ML signifies a paradigm shift: as one review noted, ML is improving our ability to identify and predict extreme events, provided models are made transparent and reliable. Overall, contemporary extreme-event risk profiling is both data-driven and theory-grounded. It produces probabilistic risk metrics (e.g. frequency of threshold exceedance, return level plots) that help stakeholders understand the hazard without prescribing actions. By not only analyzing historical extremes but also projecting future probabilities, these state-of-the-art approaches ensure that analytical risk profiles remain relevant under evolving climate conditions.

## 2-Materials and Methods

### 2.1 Downscaled reanalysis for hazard indicators

A downscaled atmospheric field was produced within GENESIS Deliverable 1.1. The workflow downscales the ERA5 “hourly data on pressure levels” reanalysis (26) to island scales using the TopoPyScale Python package (27) that performs topography-aware downscaling of gridded climate data. ERA5 provides global, physically consistent fields from 1940 to present (e.g., temperature, wind, humidity on multiple pressure levels). The zone/island-scale hazard indicators (e.g., daily maxima, mean) used in the extreme-value analysis has been computed from the downscaled fields.

### 2.2 Historical records of extreme events

Because official event inventories were not uniformly available across Macaronesia, the data was compiled from island-group-specific sources as follows:

- **Azores (2019–2024):** A CSV file (28) provided by IPMA containing records of meteorological extreme events in the Central Group (Faial, Pico, São Jorge, Terceira, Graciosa) including event date, time, and event type of extreme event - was used as the canonical record for this archipelago subset.
- **Canary Islands (2018–2024).** Two official streams were integrated in a unique CSV file (29):
  - **Civil Protection alerts (Government of the Canary Islands):** Historic declarations (pre-alert, alert, maximum alert, etc.) are available as website notes and PDF bulletins. Dates, phases, affected islands/zones, and phenomena were extracted by digitizing scanned PDFs (using PaddleOCR (30) and Python), followed by manual validation and correction of entries where necessary (31).
  - **SINOBAS (AEMET’s System for the Notification of Singular Atmospheric Observations):** A crowd-sourced, AEMET-moderated database of rare significant weather observations (e.g., severe hail, downbursts, waterspouts). SINOBAS entries include timestamps, geolocation, phenomenon type, and a validation flag. They also include official warnings (32).

Only those records, that were jointly reported by Civil Protection and at least one other source (AEMET or SINOBAS), were retained, in order to minimize the inclusion of alerts or warnings that may have been issued in error.

#### 2.2.1 Spatial referencing of events

Event records were mapped to the operational warning zones used by each national service:

- **Azores and Madeira:** district/regions as published by IPMA (33).
- **Canary Islands:** AEMET warning zones were the primary spatial framework (34). Civil Protection alerts were cross-referenced to the same island/zone granularity.

Cape Verde: in the absence of public, standardized warning-zone definitions, hazards events were referenced only at the island level.

It should be noted that historical extreme-event records were only available for the Central Group of the Azores and for the Canary Islands. Due to the lack of institutional datasets for the remaining territories, the occurrence of past extremes were reconstructed using ML methods, ensuring continuity and consistency across the risk profiles.

### 2.2.2 Quality control and harmonization

- **Deduplication and cross-checks:** When AEMET warnings and Civil Protection alerts overlapped in time, dates and areas were cross-checked and removed duplicates.
- **OCR and manual review:** Civil Protection PDFs were parsed via OCR. Low confidence fields (dates, locality names) were manually verified.
- **Standardized schema:** All sources were normalized to a common schema.

## 2.3 Methodological Approach for Climate Risk Profiling in GENESIS

Developing the climate risk profiles for Macaronesian islands in this project required an integrated, innovative methodological approach. The aim was to combine the best available data with advanced analytical techniques to characterize historical and future extreme events, and assess potential impacts on critical water infrastructure. Here is provided an overview of the methods used, which include ML-based estimation of historical extremes, application of Generalized Extreme Value (GEV) distributions for statistical extreme analysis, and non-linear regression for future climate projections. This mix of methods allows us to capture both observed patterns and modeled future scenarios in a robust way.

The first step is to integrate the historical meteorological observations (precipitation, temperature, wind, etc.) from downscaled reanalysis datasets with information on past extreme events – such as dates and area of major storms, floods, or heatwaves gleaned from alerts and warning reports in the Canary Islands and Azores Central Group. By integrating these diverse data sources into a common framework (a Macaronesia climate risk database), it is ensured that the risk profiles are comprehensive and underpin the subsequent analysis, enabling us to correlate climate hazards with specific vulnerabilities of each island’s water systems.

A novel aspect of our methodology is the use of an AutoML to estimate and reconstruct missing data and generate homogeneous time series for extreme event indicators. Employing AutoML, specifically the tool AutoGluon (35), effectively harnesses a “committee” of algorithms (including random forests, gradient boosting machines, neural networks, etc., combined through stacking) to capture complex relationships in the climate data. As said, these models are used to classify and predict occurrences of extreme events (for instance, days of exceptionally high rainfall) based on atmospheric predictor variables like mean daily temperature, shortwave radiation or precipitation. The AutoML stacking-based process automatically tests many model architectures like Gradient Boosting, Random Forest and Neural Networks, and selects the best



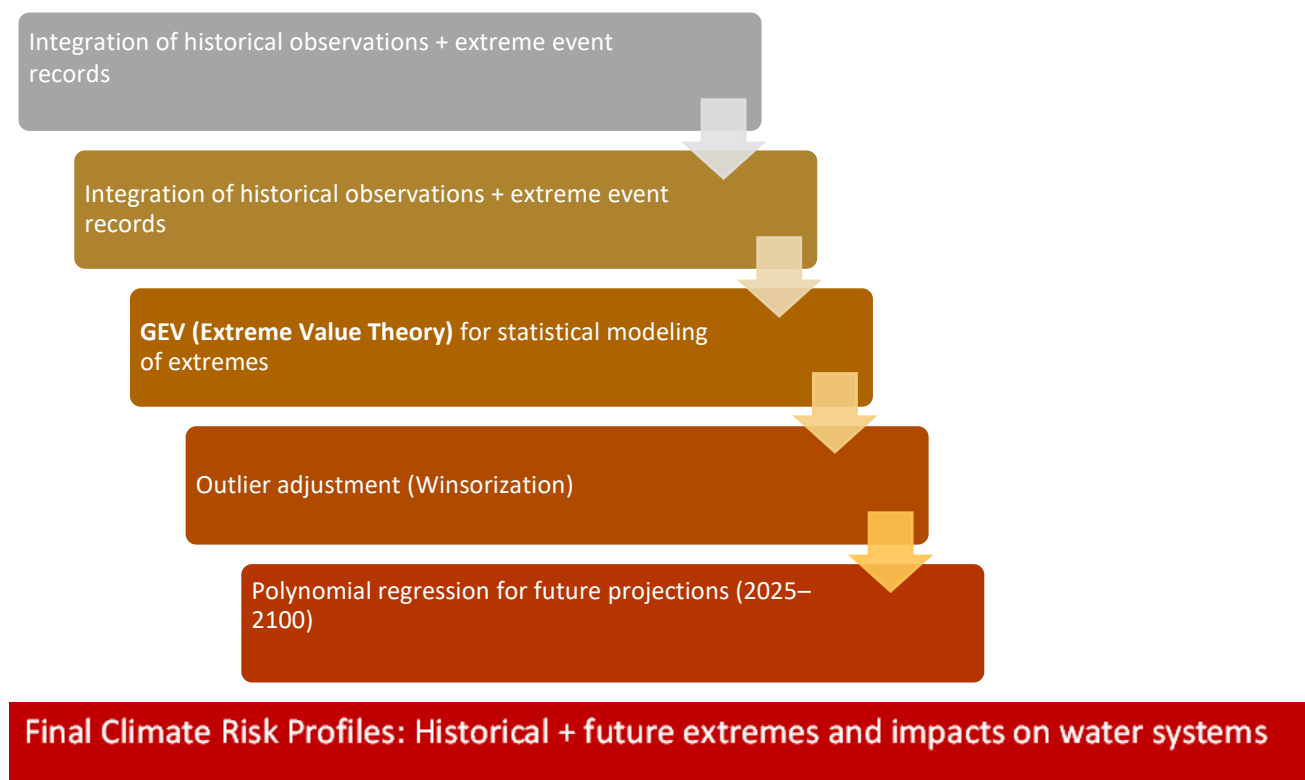
ensemble using the Matthews correlation coefficient (MCC) metric, saving significant development time and likely improving reliability.

In this case a ensemble model —built using AutoGluon’s Tabular Predictor with ‘good\_quality’ preset— was then used to impute missing data models were trained on the historical climate data together with the extreme-event records available for the Canary Islands (2018–2024) and the Azores Central Group (2019–2024). The resulting ensemble of fitted models using the models available in Autogluon ‘good\_quality’ present, was then applied to reconstruct missing information, generating a continuous dataset of extreme events for all Macaronesian archipelagos over the period 1995–2024.

To characterize the behavior of climate extremes statistically, Extreme Value Theory is applied using the GEV distribution with the extRemes package (25). The GEV distribution is a family of probability distributions that is commonly used to model the tails of event data – in other words, it helps estimate the probability of rare events (e.g., return levels for 50-year or 100-year events). It has a long track record in climate and hydrological studies for modeling phenomena like annual maximum rainfall, peak river flows, or extreme wind speeds. In our work, for each island/zone and for each key extreme event, a non-stationary GEV distribution is fitted to the historical extremes. This involves using maximum likelihood estimation to determine the GEV parameters (location, scale, and shape) with the time covariate that best fits the observed extremes. The fitted GEV curves then allow us to estimate the trend of extreme events in the future and a probability of occurrence.

To obtain robust trend estimates of extreme-event frequency, winsorization was applied to years with unusually high or low counts to prevent them from disproportionately influencing the trend. Using Tukey’s method (36), by calculating the first quartile  $Q_1$  (25<sup>th</sup> percentile), third quartile  $Q_3$  (75<sup>th</sup> percentile) of the series and the interquartile range  $IQR = Q_3 - Q_1$ . It is then defined a lower and upper fences as  $Q_1 - 1.5 IQR$  and  $Q_3 + 1.5 IQR$ , respectively, and replaced observations outside these bounds with the corresponding fence. This preserves sample size while limiting the influence of outliers and stabilizing the estimated trend. It is important to note that GEV analysis complements the machine learning approach: while AutoML helps identify and fill in extremes, the GEV provides a theoretically grounded way to extrapolate beyond observed data. Many climate extreme events are indeed well-described by GEV distributions, making this a rigorous tool.

After fitting a non-stationary GEV to the historical extremes, the next step is to compute the the time-varying 1-year return level  $RL_1(t)$  for each year  $t \in [1995, 2024]$ . Then  $RL_1(t)$  is treated as a univariate time series and forecast it with a third-order polynomial regression using Scikit-learn (37): the input is the calendar year and the output is the corresponding  $RL_1$ . Polynomial regression of third degree is particularly effective at capturing non-linear temporal trends, making it a powerful tool to estimate the evolving patterns of climate extremes. The model is trained from 1995–2024 and, once validated, is driven with years 2025–2100 to produce out-of-sample projections of  $RL_1(t)$ . This pipeline leverages the polynomial model’s ability to approximate non-linear structures in time series and provides a coherent, data-driven extension of the GEV-derived baseline into the future. Finally, the projected  $RL_1(t)$  is interpreted as the expected annual count of extreme-event days and calculate a daily probability by dividing those values by the 365 days in one year.



## 2.4 Evaluation of ML Models for Weather Alert Prediction

This section presents a quantitative analysis of different machine learning models (38) used to predict several types of weather alerts: wind, high temperatures, storms, coastal events, low visibility, and heavy rainfall (39).

To assess their performance standard metrics for binary classification are used, with special focus on those that are most useful when the data is unbalanced.

### 2.4.1 Confusion Matrix

The confusion matrix shows the distribution of correct and incorrect predictions. It is used to summarize all prediction outcomes (true/false positives/negatives) and give a full picture of classification performance.:

	Negative Prediction	Positive Prediction
Actual Negative (0)	True Negatives (TN)	False Positives (FP)
Actual Positive (1)	False Negatives (FN)	True Positives (TP)

Table 1 - Confusion matrix explanation

## 2.4.2 Balanced Accuracy

Balanced accuracy is especially useful for unbalanced datasets, since it averages the success rate for each class.

$$\text{Balanced Accuracy} = \frac{1}{2} \left( \frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right)$$

Equation 1 – Balanced Accuracy

It measures the average performance between the positive and negative classes. Its value ranges from 0 (worst) to 1 (perfect).

## 2.4.3 Balanced Error Rate (BER)

It is the complement of balanced accuracy, meaning the average error per class. Low BER values indicate good performance.

$$BER = 1 - \text{Balanced Accuracy}$$

Equation 2 – Balanced Error Rate

## 2.4.4 MCC (Matthews Correlation Coefficient)

The MCC is a robust metric that takes into account all elements of the confusion matrix. It is very informative even when classes are unbalanced. It is also very effective as error metric for the machine learning models predicting extreme events since MCC remains fair and reliable in unbalanced settings, as it reflects the quality of predictions across all four categories of the confusion matrix (TP, TN, FP, FN):

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Equation 3 – Matthews Correlation Coefficient

Its value ranges between:

- +1 → perfect prediction
- 0 → random prediction
- -1 → completely wrong prediction

### 2.4.5 Precision

It measures what proportion of positive predictions are actually positive. High precision means few false positives.

$$Precision = \frac{TP}{TP + FP}$$

Equation 4 - Precision

### 2.4.6 Recall

It indicates what proportion of the actual positives have been correctly identified. High sensitivity means few false negatives.

$$Recall = \frac{TP}{TP + FN}$$

Equation 5 - Recall

### 2.4.7 F1-score

It is the harmonic mean between precision and sensitivity. The F1-score is useful when the goal is to find a balance between precision and recall.

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Equation 6 - F1-score

### 3-Results

#### 3.2 Evaluation of results by type of weather alert

The datasets used in this evaluation were prepared for each prediction zone of extreme events defined by AEMET in the Canary Islands and for the Central Group of the Azores. In total, 14 terrestrial zones and 11 coastal zones were considered, each with daily records spanning approximately 30 years. Historical climate variables were aggregated using daily statistics (maximum, median, mean, and standard deviation) to build a consistent set of predictors. For each type of extreme event (wind, high temperatures, storms, coastal phenomena, low visibility, and rainfall), a binary variable was created: each row represents a single day, with a value of 0 indicating no extreme event and 1 indicating the occurrence of an event.

To ensure robust evaluation, the datasets were split into training and testing subsets. The training data were used to fit the machine learning models, while the testing data—kept independent from training—were used to assess predictive performance. Notice that not all extreme event categories were present in both archipelagos: for example, visibility (dust) events and storms were recorded in the Canary Islands but not in the Azores.

This structured design ensures comparability across zones and event types, while reflecting the real challenges of predicting rare and spatially variable extreme weather events. It is important to note that the numbers reported in the confusion matrices correspond exclusively to the test sets. This choice ensures that the results reflect the true generalization ability of the models on unseen data, rather than their performance on the same data used for training, which could otherwise lead to overly optimistic estimates due to overfitting.

##### 3.2.1 Canary Islands

The predictive models were trained using the downscaled climate data generated for the Canary Islands. As a target variable, the historical extreme-event alerts collected and digitized from the Canary Civil Protection and the Spanish State Meteorological Agency (AEMET) were used. The purpose of this model is to estimate the occurrence of days with official alerts between 1995 and 2024 in the Canary Islands for all considered types of extreme events (high temperature, wind, coastal phenomena, rainfall, visibility/dust, and storms).

##### Wind Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
Actual: No	10802	22
Actual: Yes	35	68

Table 2 - High Wind Alerts evaluation for the Canary Islands

- Balanced Accuracy: 0.7666
- Balanced Error Rate: 0.2334
- MCC: 0.9976

#### Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.86	0.53	0.66

Table 3 – Wind Alerts classification report for the Canary Islands

#### High Temperature Alerts

#### Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10807	21
<b>Actual: Yes</b>	19	80

Table 4 – High Temperature Alerts confusion matrix for the Canary Islands

- Balanced Accuracy: 0.9031
- Balanced Error Rate: 0.0969
- MCC: 0.9983

#### Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.79	0.81	0.80

Table 5 – High Temperature Alerts classification report for the Canary Islands

#### Storm Alerts

#### Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10905	2
<b>Actual: Yes</b>	4	16

Table 6 – Storm Alerts evaluation for the Canary Islands

- Balanced Accuracy: 0.8999
- Balanced Error Rate: 0.1001
- MCC: 0.9998

#### Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.89	0.80	0.84

Table 7 – Storm Alerts classification report for the Canary Islands

#### Coastal Phenomena Alerts

#### Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10843	13
<b>Actual: Yes</b>	24	47

Table 8 – Coastal Phenomena Alerts evaluation for the Canary Islands

- Balanced Accuracy: 0.8304
- Balanced Error Rate: 0.1696
- MCC: 0.9992

#### Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.78	0.66	0.72

Table 9 – Coastal Phenomena Alerts classification report for the Canary Islands

#### Visibility (Dust) Alerts

#### Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10898	4
<b>Actual: Yes</b>	9	16

Table 10 – Visibility (Dust) Alerts evaluation for the Canary Islands

- Balanced Accuracy: 0.8198
- Balanced Error Rate: 0.1802
- MCC: 0.9991

#### Classification Report:

Class	Precision	Recall	F1-score	Support
<b>No</b>	1.00	1.00	1.00	10902

<b>Yes</b>	0.80	0.64	0.71	25
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Table 11 – Visibility (Dust) Alerts classification report for the Canary Islands

## Rainfall Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10869	17
<b>Actual: Yes</b>	8	33

Table 12 – Rainfall Alerts evaluation for the Canary Islands

- Balanced Accuracy: 0.9017
- Balanced Error Rate: 0.0983
- MCC: 0.9989

Classification Report:

Class	Precision	Recall	F1-score	Support
<b>No</b>	1.00	1.00	1.00	10886
<b>Yes</b>	0.66	0.80	0.73	41

Table 13 – Rainfall Alerts classification report for the Canary Islands

## 3.2.2 Azores - Central Group

A second model was developed using the downscaled climate data for the Central Group of islands in the Azores, where alerts provided by IPMA were available. In this case, only those types of events with sufficient historical instances could be modeled reliably, namely rainfall, wind, and coastal phenomena. This model was used to estimate the occurrence of days with official alerts between 1995 and 2024 in the Azores for the available types of extreme events.

## Rainfall Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	205	1
<b>Actual: Yes</b>	0	5

Table 14 – Rainfall Alerts evaluation for Azores – Central Group



- Balanced Accuracy: 0.9976
- Balanced Error Rate: 0.0024
- MCC: 0.9107

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.83	1.00	0.91

Table 15 – Rainfall Alerts classification report for Azores – Central Group

### Wind Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	192	11
<b>Actual: Yes</b>	1	7

Table 16 – Wind Alerts evaluation for Azores – Central Group

Balanced Accuracy: 0.9104

- Balanced Error Rate: 0.0896
- MCC: 0.5612

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	0.99	0.95	0.97
<b>Yes</b>	0.39	0.88	0.54

Table 17– Wind Alerts classification report for Azores – Central Group

### Coastal Phenomena Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	195	10
<b>Actual: Yes</b>	3	3

Table 18 – Coastal Phenomena Alerts evaluation for Azores – Central Group

- Balanced Accuracy: 0.7256
- Balanced Error Rate: 0.2744
- MCC: 0.3119

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	0.98	0.95	0.97
<b>Yes</b>	0.23	0.50	0.32

Table 19 – Coastal Phenomena Alerts classification report for Azores – Central Group

### 3.2.3 Relative approach for territories without data

For territories without historical alert records, a complementary model was constructed by modifying the Canary Islands and Azores Central Group datasets. Specifically, the yearly and monthly mean for each climate variable was calculated and expressed each daily value as a ratio of the value that day against those averages. The rationale is that, although the absolute thresholds triggering an alert differ between regions, extreme event days consistently deviate markedly from average conditions. This relative-anomaly model is therefore used only to provide estimates of extreme event occurrence in regions lacking sufficient historical data. It is important to note that all performance metrics reported here reflect the model's ability to reproduce extreme events in the Canary Islands and Azores Central Group, not in the other territories, since no ground truth alert data exist for them.

#### Wind Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10788	36
<b>Actual: Yes</b>	28	75

Table 20 – Wind Alerts evaluation for the relative approach

- Balanced Accuracy: 0.8624
- Balanced Error Rate: 0.1376
- MCC: 0.6985

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00

<b>Yes</b>	0.68	0.73	0.70
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Table 21 – Wind Alerts classification report for the relative approach

### High Temperature Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10813	15
<b>Actual: Yes</b>	24	75

Table 22 – High Temperature Alerts evaluation for the relative approach

- Balanced Accuracy: 0.8781
- Balanced Error Rate: 0.1219
- MCC: 0.7928

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.83	0.76	0.79

Table 23 – High Temperature Alerts evaluation report for the relative approach

### Storm Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
<b>Actual: No</b>	10903	4
<b>Actual: Yes</b>	2	18

Table 24 – Storm Alerts evaluation for the relative approach

- Balanced Accuracy: 0.9498
- Balanced Error Rate: 0.0502
- MCC: 0.8578

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.82	0.90	0.86

Table 25 – Storm Alerts classification report for Rest of territories

### Coastal Phenomena Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
Actual: No	10847	9
Actual: Yes	24	47

Table 26 – Coastal Phenomena Alerts evaluation for Rest of territories

- Balanced Accuracy: 0.8306
- Balanced Error Rate: 0.1694
- MCC: 0.7439

Classification Report:

Class	Precision	Recall	F1-score
No	1.00	1.00	1.00
Yes	0.84	0.66	0.74

Table 27 – Coastal Phenomena Alerts classification report for Rest of territories

### Visibility (Dust) Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
Actual: No	10892	10
Actual: Yes	8	17

Table 28 – Visibility (Dust) Alerts evaluation for Rest of territories

- Balanced Accuracy: 0.8395
- Balanced Error Rate: 0.1605
- MCC: 0.6535

Classification Report:

Class	Precision	Recall	F1-score
No	1.00	1.00	1.00
Yes	0.63	0.68	0.65

Table 29 – Visibility (Dust) Alerts classification report for Rest of territories

### Rainfall Alerts

Confusion Matrix:

	Prediction: No	Prediction: Yes
Actual: No	10875	11
Actual: Yes	13	28

Table 30 – Rainfall Alerts evaluation for Rest of territories

- Balanced Accuracy: 0.8410
- Balanced Error Rate: 0.1590
- MCC: 0.6991

Classification Report:

Class	Precision	Recall	F1-score
<b>No</b>	1.00	1.00	1.00
<b>Yes</b>	0.72	0.68	0.70

Table 31 – Rainfall Alerts classification report for Rest of territories

## 4. Climate Risk Profiles from Projected Alerts

### 4.1 Canary Islands

The Canary Islands forecasting zones used here follow the regional AEMET (Agencia Estatal de Meteorología) division. These zones are operational areas for issuing warnings and tend to share similar synoptic exposure and local forcing (orography, coastline orientation, and prevailing winds). For the purpose of predicting extreme event probabilities, each AEMET zone can be treated as a coherent unit—consistent with the way warnings are defined and issued.

#### 4.1.1 La Palma Highlands

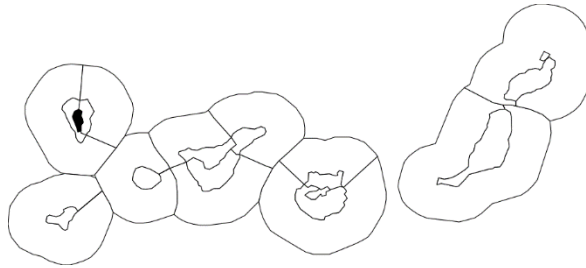


Figure 1 - La Palma Highlands

#### Alert Probability Report

(Region: **La Palma Highlands**; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.4 %	1.6 %	2.5 %	▲ +1.1 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	— 0.0 pp
<b>Precipitation</b>	1.1 %	1.4 %	2.7 %	▲ +1.6 pp
<b>High temperatures</b>	1.9 %	4.9 %	15.9 %	▲ +14.0 pp
<b>Storms</b>	0.3 %	0.5 %	1.4 %	▲ +1.1 pp
<b>Visibility</b>	0.0 %	0.3 %	0.3 %	▲ +0.3 pp

Table 32 – La Palma alerts probability report

#### Seasonality Report

##### Wind:

- Most prone month: February.
- Other relevant months: December, January, November, March.

##### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, January, September.

High temperatures:

- Most prone month: August.
- Other relevant months: July, June.

Storms:

- Most prone month: November.
- Other relevant months: September, March, December, August.

Visibility:

- Most prone month: January.
- Other relevant months: February, September, December.

## Insights

La Palma Highlands show sharp growth in heat extremes, from 1.9 % in 2025 to nearly 16 % in 2100, peaking in August. Wind rises moderately (1.4 % → 2.5 %), focused in winter, while precipitation more than doubles to 2.7 %, centered on November. Storms increase slightly, and visibility becomes marginal but nonzero. Coastal hazards remain absent at this altitude. The zone's risk profile shifts toward intense summer heat as the dominant hazard, while autumn rainfall and storms persist as secondary drivers, underscoring a transition to multi-hazard exposure with heat at the forefront.

### 4.1.2 West of La Palma

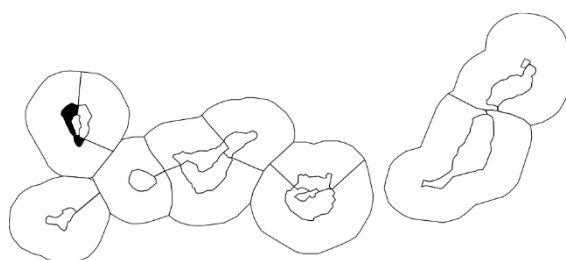


Figure 2 - West of La Palma

## Alert Probability Report

(Region: West of La Palma; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.1 %	0.5 %	0.0 %	▼ 1.1 pp
<b>Precipitation</b>	0.8 %	0.8 %	1.4 %	▲ +0.5 pp
<b>High temperatures</b>	1.6 %	4.1 %	13.7 %	▲ +12.1 pp
<b>Storms</b>	0.3 %	0.5 %	1.1 %	▲ +0.8 pp
<b>Visibility</b>	0.3 %	0.5 %	0.8 %	▲ +0.5 pp

Table 33 – West of La Palma alerts probability report

## Seasonality Report

#### Wind:

- Most prone month: December.
- Other relevant months: February, January, March, November.

#### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, February, January.

#### High temperatures:

- Most prone month: August.
- Other relevant months: July.

#### Storms:

- Most prone month: December.
- Other relevant months: November, September, March, October.

#### Visibility:

- Most prone month: March.
- Other relevant months: February, April, July, October.

#### Insights

The western inland of La Palma shifts toward heat-driven risk. High-temperature alerts rise steeply from 1.6 % in 2025 to 13.7 % in 2100, with summer peaks. Wind decreases to zero by century's end, reducing its role. Precipitation grows slightly to 1.4 %, while storms rise modestly to 1.1 %, both concentrated in autumn–winter. Visibility doubles to 0.8 %, with spring maxima. The long-term profile highlights a transition from wind-dominated winters to extreme summer heat as the principal hazard, with smaller but notable increases in rainfall, storms, and atmospheric dust or haze.

### 4.1.3 East of La Palma

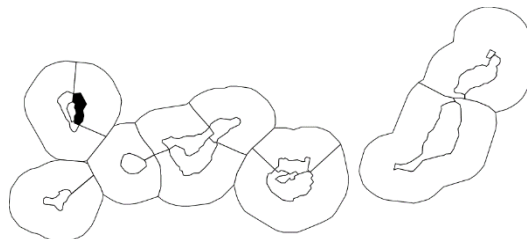


Figure 3 - East of La Palma

#### Alert Probability Report

(Region: East of La Palma; probability = alert days / 365 × 100)



Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.1 %	1.1 %	0.5 %	▼ 0.5 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.5 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	0.3 %	0.5 %	1.1 %	▲ +0.8 pp
<b>Storms</b>	0.3 %	0.5 %	0.8 %	▲ +0.5 pp

Table 34 – East of La Palma alerts probability report

## Seasonality Report

### Wind:

- Most prone month: December.
- Other relevant months: November, February, January, March.

### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, January, February.

### High temperatures:

- Most prone month: July.
- Other relevant months: August.

### Storms:

- Most prone month: November.
- Other relevant months: December, September, March, August.

## Insights

East La Palma shows limited but notable changes. Wind alerts decline slightly, from 1.1 % in 2025 to 0.5 % in 2100, while precipitation disappears after mid-century. High temperatures, though low in absolute terms, rise from 0.3 % to 1.1 %, with peaks in July–August. Storms grow modestly to 0.8 %, concentrated in autumn. Visibility remains absent. Overall, the zone transitions toward a low but mixed hazard profile, with heat and storms gaining relevance as wind and rainfall risks diminish.

### 4.1.4 Coast - West of La Palma

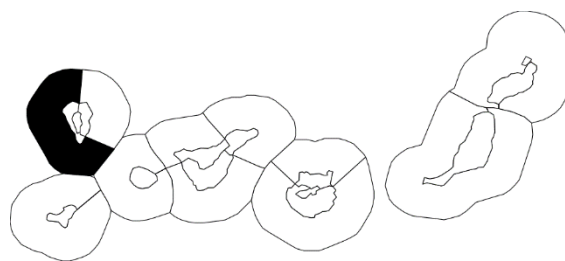


Figure 4 - Coast - West La Palma

## Alert Probability Report

(Region: Coast - West of La Palma; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	1.1 %	0.0 %	0.0 %	▼ 1.1 pp

Table 35 – Coast - West of La Palma alerts probability report

## Seasonality Report

Coastal phenomena:

- Most prone month: January.
- Other relevant months: November, July, December, February.

## Insights

The western coast of La Palma shows a marked reduction in coastal hazards, declining from 1.1 % in 2025 to zero by 2050 and beyond. Present risks concentrate in winter months, especially January and December, with secondary peaks in November and midsummer (July). This decline contrasts with the rising or stable coastal risks projected elsewhere in the archipelago, suggesting localized differences in swell exposure and shoreline orientation that reduce long-term vulnerability.

### 4.1.5 Coast - East of La Palma

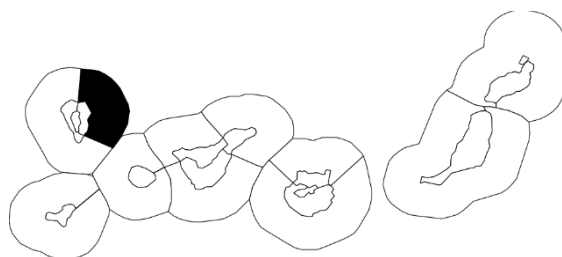


Figure 5 - Coast - East of La Palma

## Alert Probability Report

(Region: Coast - East of La Palma; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	1.4 %	0.5 %	0.0 %	▼ 1.4 pp

Table 36 – Coast - East of La Palma alerts probability report

#### Seasonality Report

Coastal phenomena:

- Most prone month: January.
- Other relevant months: July, November, December, February.

#### Insights

The eastern coast of La Palma is projected to see coastal hazards disappear, declining from 1.4 % in 2025 to zero by 2100. Currently, risks peak in January, with additional exposure in July and late autumn–winter months. This downward trend contrasts with the growing coastal risks in some other islands, suggesting a localized reduction in swell influence along this shore. Despite the decline, periodic winter and summer events highlight the need for continued monitoring of vulnerable coastal settlements.

#### 4.1.6 El Hierro

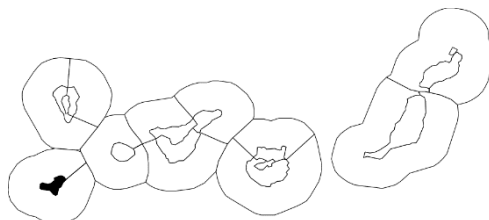


Figure 6 – El Hierro

#### Alert Probability Report

(Region: El Hierro; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.9 %	2.5 %	4.7 %	▲ +2.7 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.0 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	2.2 %	5.2 %	16.2 %	▲ +14.0 pp
<b>Storms</b>	0.3 %	0.5 %	1.4 %	▲ +1.1 pp
<b>Visibility</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp

## Seasonality Report

### Wind:

- Most prone month: March.
- Other relevant months: December, February, January, November.

### Precipitation:

- Most prone month: November.
- Other relevant months: December, October, February.

### High temperatures:

- Most prone month: July.
- Other relevant months: August, June.

### Storms:

- Most prone month: December.
- Other relevant months: September, March, November, August.

### Visibility:

- Most prone month: October.
- Other relevant months: February, April, July, August.

## Insights

El Hierro's inland zone is projected to undergo a sharp rise in heat alerts, from 2.2 % in 2025 to 16.2 % in 2100, with maxima in July–August. Wind also grows steadily (1.9 % → 4.7 %), peaking in late winter and spring. Storms increase slightly to 1.4 %, while precipitation alerts disappear after 2025. Visibility grows modestly but remains minor. Overall, the island's hazard profile shifts strongly toward heat as the main driver, with wind as a secondary contributor, replacing rainfall as a key climatic risk.

### 4.1.7 Coast - El Hierro

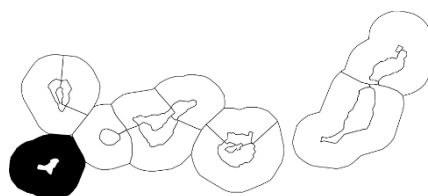


Figure 7 - Coast - El Hierro

## Alert Probability Report

(Region: Coast - El Hierro; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	1.6 %	0.5 %	0.0 %	▼ 1.6 pp

Table 38 – Coast - El Hierro alerts probability report

#### Seasonality Report

Coastal phenomena:

- Most prone month: July.
- Other relevant months: January, November, May, March.

#### Insights

El Hierro's coast shows a projected decline in maritime hazards, with coastal phenomena dropping from 1.6 % in 2025 to none by 2100. Current risks peak in July, reflecting summer swell exposure, with secondary maxima in winter months like January and November. The long-term downward trend contrasts with other Canary coasts where risks persist or rise, highlighting localized reductions in wave-driven exposure for this island's shoreline.

### 4.1.8 Coast - Metropolitan area of Tenerife

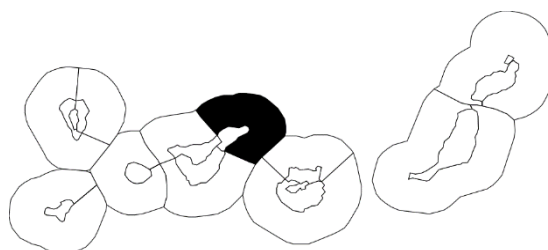


Figure 8 - Coast - East of La Palma

#### Alert Probability Report

(Region: Coast - Metropolitan area of Tenerife; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	0.3 %	0.3 %	0.8 %	▲ +0.5 pp

Table 39 – Coast - Metropolitan area of Tenerife alerts probability report

#### Seasonality Report

Coastal phenomena:

- Most prone month: November.

- Other relevant months: January, December, March, February.

## Insights

The metropolitan coast of Tenerife experiences a modest rise in coastal phenomena, from 0.3 % in 2025 to 0.8 % by 2100. Seasonality peaks in late autumn and winter, with November, January, and December as the most active months. Summer remains practically hazard-free. Although the absolute increase is small, the dense population and infrastructure along this shoreline make even slight growth in coastal hazards significant for local risk management and urban resilience planning.

### 4.1.9 Coast - East, south and west of Tenerife

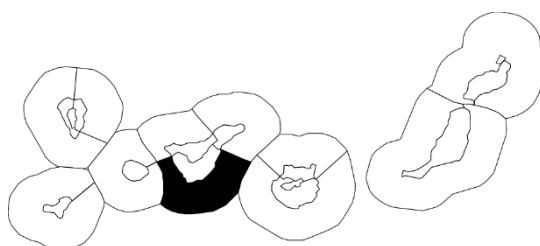


Figure 9 - Coast - East, south and west of Tenerife

## Alert Probability Report

(Region: Coast - East, south and west of Tenerife; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	1.9 %	1.9 %	2.2 %	▲ +0.3 pp

Table 40 – Coast - East, south and west of Tenerife alerts probability report

## Seasonality Report

Coastal phenomena:

- Most prone month: May.
- Other relevant months: July, April, August, March.

## Insights

This coastal sector of Tenerife shows only a slight increase in hazards, with coastal phenomena rising from 1.9 % in 2025 to 2.2 % in 2100. Seasonality peaks in late spring and summer, especially May and July, reflecting exposure to prevailing swell and trade-wind waves. Autumn and winter remain comparatively less affected. While the trend is moderate, the persistence of coastal risk underscores the need for continued monitoring of shorelines exposed to ocean-facing orientations.

4.1.10 Coast - North of Tenerife

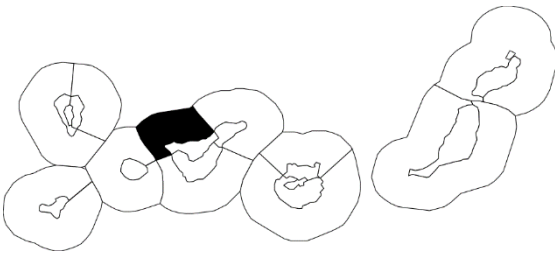


Figure 10 - Coast - North of Tenerife

Alert Probability Report

(Region: Coast - North of Tenerife; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Coastal phenomena	0.8 %	0.0 %	0.0 %	▼ 0.8 pp

Table 41 – Coast - North of Tenerife alerts probability report

Seasonality Report

Coastal phenomena:

- Most prone month: January.
- Other relevant months: December, February, November, March.

Insights

The northern coast of Tenerife shows a projected decline in coastal phenomena, falling from 0.8 % in 2025 to zero by 2050 and beyond. Hazards today cluster in winter months, particularly January and December, with secondary events in February and November. Summer is largely unaffected. This contrasts with other Canary coasts where maritime hazards are stable or rising, highlighting a localized reduction in wave-driven risk for this sector.

4.1.11 East, south and west of Tenerife

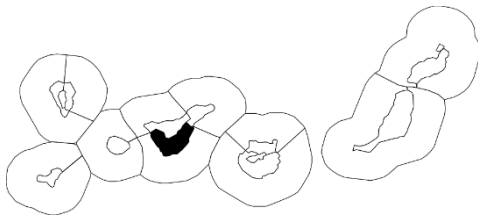


Figure 11 - East, south and west of Tenerife

Alert Probability Report

(Region: East, south and west of Tenerife; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.9 %	3.3 %	8.2 %	▲ +6.3 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	1.1 %	1.6 %	3.6 %	▲ +2.5 pp
<b>High temperatures</b>	2.7 %	6.8 %	23.3 %	▲ +20.5 pp
<b>Storms</b>	0.3 %	0.5 %	0.8 %	▲ +0.5 pp

Table 42 – East, south and west of Tenerife alerts probability report

### Seasonality Report

#### Wind:

- Most prone month: March.
- Other relevant months: February, December, January, July.

#### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, February, January.

#### High temperatures:

- Most prone month: July.
- Other relevant months: August, June, October, May.

#### Storms:

- Most prone month: December.
- Other relevant months: November, September, March, August.

### Insights

This inland region of Tenerife undergoes a dramatic rise in heat hazards, with high-temperature alerts surging from 2.7 % in 2025 to 23.3 % in 2100, concentrated in July–August. Wind also strengthens (1.9 % → 8.2 %), with winter–spring peaks, while precipitation more than triples to 3.6 %, centered in late autumn. Storms increase slightly, while visibility remains absent. By century’s end, this area’s risk profile is dominated by extreme summer heat, complemented by growing wind and rainfall variability, marking it as one of the most climate-sensitive zones in the archipelago.

#### 4.1.12 Metropolitan area of Tenerife



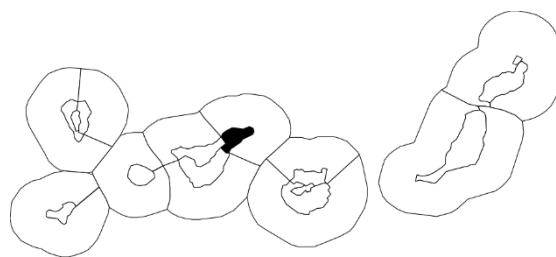


Figure 12 - Metropolitan area of Tenerife

## Alert Probability Report

(Region: Metropolitan area of Tenerife; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.4 %	1.9 %	3.8 %	▲ +2.5 pp
<b>Precipitation</b>	0.5 %	0.3 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	1.9 %	4.4 %	13.7 %	▲ +11.8 pp
<b>Storms</b>	0.3 %	0.3 %	0.8 %	▲ +0.5 pp
<b>Visibility</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp

Table 43 – Metropolitan area of Tenerife alerts probability report

## Seasonality Report

### Wind:

- Most prone month: February.
- Other relevant months: March, January, December, April.

### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, September, January.

### High temperatures:

- Most prone month: July.
- Other relevant months: August, June.

### Storms:

- Most prone month: November.
- Other relevant months: March, September, August, October.

### Visibility:

- Most prone month: July.
- Other relevant months: August, February, April, September.

Insights

The metropolitan zone of Tenerife shows strong growth in summer heat, with high-temperature alerts climbing from 1.9 % in 2025 to 13.7 % in 2100. Wind nearly triples (1.4 % → 3.8 %), peaking in winter–spring, while visibility increases slightly. Precipitation declines from 0.5 % to zero, reducing rainfall-driven alerts, and storms remain marginal, only reaching 0.8 %. Overall, the region evolves into a risk profile dominated by extreme summer heat and secondary wind impacts, a concerning trend given its high population density and urban exposure.

4.1.13 North of Tenerife

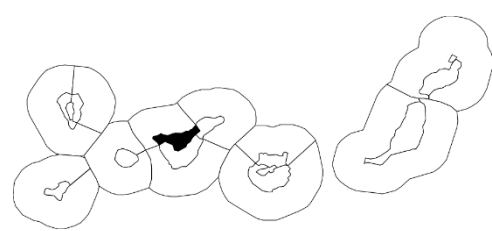


Figure 13 - North of Tenerife

Alert Probability Report

(Region: North of Tenerife; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Wind	0.8 %	0.0 %	0.0 %	▼ 0.8 pp
Precipitation	0.8 %	1.4 %	3.6 %	▲ +2.7 pp
High temperatures	0.8 %	1.4 %	3.6 %	▲ +2.7 pp
Storms	0.3 %	0.3 %	0.3 %	— 0.0 pp
Visibility	0.3 %	0.3 %	0.8 %	▲ +0.5 pp

Table 44 – North of Tenerife alerts probability report

Seasonality Report

Wind:

- Most prone month: December.
- Other relevant months: November, January, February, March.

Precipitation:

- Most prone month: November.
- Other relevant months: October, December, January, September.

High temperatures:

- Most prone month: July.
- Other relevant months: August, June.

Storms:

- Most prone month: November.
- Other relevant months: December, September, March, August.

Visibility:

- Most prone month: July.
- Other relevant months: August, February, November, October.

Insights

North Tenerife presents a mixed evolution. Wind alerts vanish after 2025, while precipitation and heat both rise from 0.8 % to 3.6 % by 2100, peaking in autumn and summer respectively. Visibility also grows modestly, reaching 0.8 %, with summer maxima. Storm activity remains stable at very low levels. The hazard balance thus shifts toward rainfall variability and extreme summer heat, with a reduction in wind relevance. This evolving profile indicates a transition from winter wind exposure to greater heat and precipitation-driven risks by century's end.

#### 4.1.14 Gran Canaria Highlands

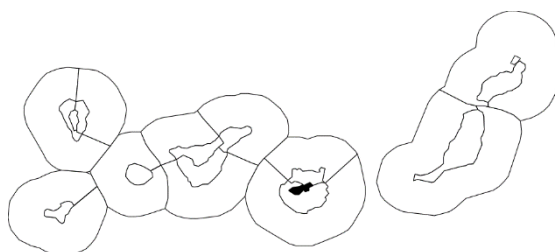


Figure 14 - Gran Canaria Highlands

#### Alert Probability Report

(Region: Gran Canaria Highlands; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.5 %	0.0 %	0.0 %	▼ 0.5 pp
<b>Precipitation</b>	0.5 %	0.5 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	2.5 %	6.3 %	20.5 %	▲ +18.1 pp
<b>Storms</b>	0.3 %	0.5 %	1.1 %	▲ +0.8 pp
<b>Visibility</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp

Table 45 – Gran Canaria Highlands alerts probability report

#### Seasonality Report

#### Wind:

- Most prone month: February.
- Other relevant months: January, March, December, November.

#### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, September.

#### High temperatures:

- Most prone month: August.
- Other relevant months: July, June.

#### Storms:

- Most prone month: September.
- Other relevant months: November, March.

#### Visibility:

- Most prone month: December.
- Other relevant months: September, January, August, October.

#### Insights

Gran Canaria Highlands face a dramatic rise in heat alerts, jumping from 2.5 % in 2025 to over 20 % in 2100, concentrated in July–August. Storms also intensify modestly, from 0.3 % to 1.1 %, with autumn peaks. Wind and precipitation decline to near zero, suggesting reduced relevance of these hazards. Visibility grows slightly but remains marginal. The long-term outlook points to heat becoming the dominant driver of climate risk in the highlands, reshaping the seasonal hazard profile from winter storms and rainfall toward extreme summer heat events by the end of the century.

#### 4.1.15 North of Gran Canaria

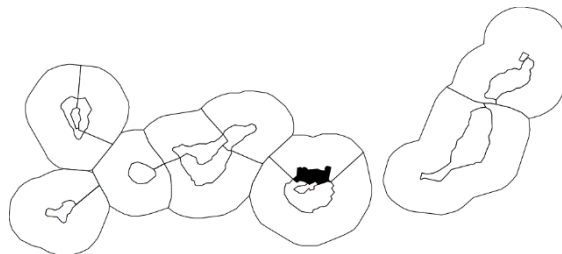


Figure 15 - North of Gran Canaria

#### Alert Probability Report

(Region: North of Gran Canaria; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.8 %	2.2 %	▲ +1.9 pp
<b>Precipitation</b>	0.5 %	0.5 %	0.5 %	— 0.0 pp
<b>High temperatures</b>	1.4 %	3.0 %	9.3 %	▲ +7.9 pp
<b>Storms</b>	0.3 %	0.5 %	1.4 %	▲ +1.1 pp
<b>Visibility</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp

Table 46 – North of Gran Canaria alerts probability report

## Seasonality Report

### Wind:

- Most prone month: January.
- Other relevant months: March, November, December, February.

### Precipitation:

- Most prone month: November.
- Other relevant months: October, December.

### High temperatures:

- Most prone month: July.
- Other relevant months: August, June.

### Storms:

- Most prone month: November.
- Other relevant months: September, March, August, October.

### Visibility:

- Most prone month: August.
- Other relevant months: July, February, November, October.

## Insights

North Gran Canaria shows strong warming trends, with high-temperature alerts rising from 1.4 % in 2025 to over 9 % by 2100, centered in July–August. Wind grows moderately (0.3 % → 2.2 %), with winter peaks, while storms increase slightly, reaching 1.4 % by century's end, concentrated in autumn. Precipitation remains stable at 0.5 %, and visibility edges up to 0.5 %, mainly in summer. The hazard profile transitions toward summer heat dominance, supported by modest increases in wind and storm activity, while rainfall contributes little change.

4.1.16 East, south and west of Gran Canaria

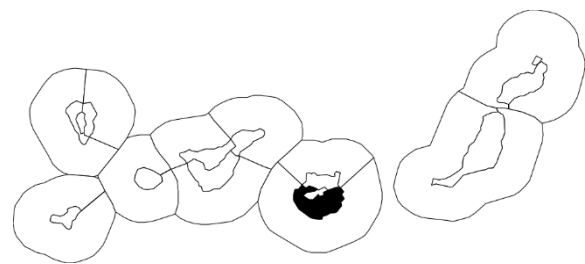


Figure 16 - East, south and west of Gran Canaria

Alert Probability Report

(Region: East, south and west of Gran Canaria; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Wind	2.2 %	4.7 %	14.2 %	▲ +12.1 pp
Visibility	0.0 %	0.0 %	0.0 %	NA
Precipitation	0.5 %	0.5 %	0.3 %	▼ 0.3 pp
High temperatures	3.0 %	6.8 %	21.4 %	▲ +18.4 pp
Storms	0.3 %	0.5 %	1.1 %	▲ +0.8 pp

Table 47 – East, south and west of Gran Canaria alerts probability report

Seasonality Report

Wind:

- Most prone month: March.
- Other relevant months: February, July, January, December.

Precipitation:

- Most prone month: November.
- Other relevant months: October, December.

High temperatures:

- Most prone month: July.
- Other relevant months: August, June, October.

Storms:

- Most prone month: November.
- Other relevant months: September, March, December, August.

Insights

The terrestrial south, east, and west of Gran Canaria face a marked shift toward heat and wind dominance. High-temperature alerts rise dramatically from 3.0 % in 2025 to over 21 % by 2100, peaking in July–August. Wind also intensifies sharply (2.2 % → 14.2 %), with winter–spring maxima. Storms increase modestly, while precipitation declines slightly to 0.3 %, and visibility remains absent. By century’s end, this zone transforms into a high-risk environment where extreme summer heat and strong winds drive the hazard profile, eclipsing rainfall and storm relevance.

### 4.1.17 Coast - North of Gran Canaria

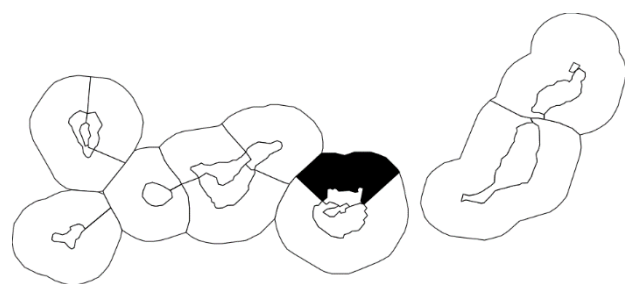


Figure 17 - Coast - North of Gran Canaria

#### Alert Probability Report

(Region: Coast - North of Gran Canaria; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Coastal phenomena	0.5 %	0.0 %	0.0 %	▼ 0.5 pp

Table 48 – Coast - North of Gran Canaria alerts probability report

#### Seasonality Report

Coastal phenomena:

- Most prone month: January.
- Other relevant months: December, November, April, February.

#### Insights

The northern coast of Gran Canaria shows a decline in coastal phenomena, dropping from 0.5 % in 2025 to near zero by 2100. Risk is concentrated in winter months, especially January and December, with minor events in November and April. Summer remains largely free of hazards. This suggests a diminishing relevance of coastal alerts for this shoreline, contrasting with other Canary coasts where maritime risk is projected to intensify.

### 4.1.18 Coast - East, south and west of Gran Canaria

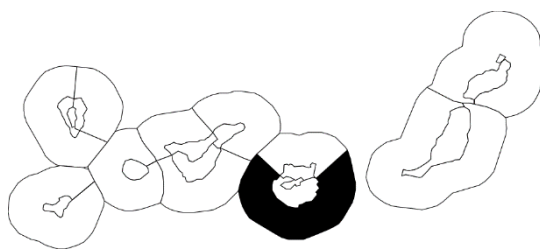


Figure 18 - Coast - East, south and west of Gran Canaria

## Alert Probability Report

(Region: Coast - East, south and west of Gran Canaria; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	1.9 %	2.2 %	3.3 %	▲ +1.4 pp

Table 49 – Coast - East, south and west of Gran Canaria alerts probability report

## Seasonality Report

Coastal phenomena:

- Most prone month: July.
- Other relevant months: May, April, January, August.

## Insights

This coastal arc shows a steady rise in maritime hazards, with coastal phenomena climbing from 1.9 % in 2025 to 3.3 % by 2100. Seasonality is strongest in summer, with July leading, and secondary peaks in May and April. Winter also registers occasional events, while autumn remains less exposed. The pattern highlights growing exposure of the southern and western shorelines to wave-driven risks, aligning with their open-ocean orientation.

### 4.1.19 Fuerteventura

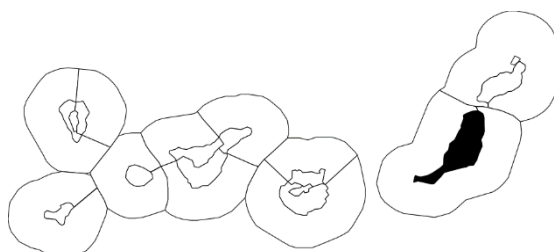


Figure 19 - Fuerteventura

## Alert Probability Report

(Region: Fuerteventura; probability = alert days / 365 × 100)



Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.5 %	1.6 %	4.9 %	▲ +4.4 pp
<b>Precipitation</b>	0.5 %	1.4 %	4.7 %	▲ +4.1 pp
<b>High temperatures</b>	2.5 %	6.0 %	19.5 %	▲ +17.0 pp
<b>Storms</b>	0.3 %	0.3 %	0.8 %	▲ +0.5 pp
<b>Visibility</b>	0.3 %	0.0 %	0.0 %	▼ 0.3 pp

Table 50 – Fuerteventura alerts probability report

## Seasonality Report

### Wind:

- Most prone month: February.
- Other relevant months: March, January, December, April.

### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, September, April.

### High temperatures:

- Most prone month: July.
- Other relevant months: August, June, October.

### Storms:

- Most prone month: September.
- Other relevant months: March, November, August, December.

### Visibility:

- Most prone month: February.
- Other relevant months: August, April, March, May.

## Insights

Fuerteventura faces rapid intensification of climate hazards. High-temperature alerts surge from 2.5 % in 2025 to nearly 20 % in 2100, with July–August peaks. Wind also grows (0.5 % → 4.9 %), concentrated in winter and spring, while precipitation rises from 0.5 % to 4.7 %, centered in late autumn. Storms remain modest, increasing only slightly, while visibility alerts disappear after 2025. By century's end, Fuerteventura's hazard profile is dominated by summer heat, with secondary risks from wind and rainfall, signaling a transition to a hotter, more variable environment.

4.1.20 Coast – Fuerteventura

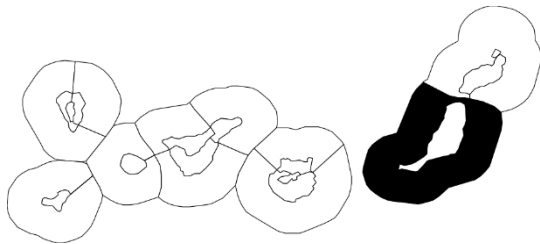


Figure 20 - Coast – Fuerteventura

Alert Probability Report

(Region: Coast - Fuerteventura; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Coastal phenomena	0.8 %	0.0 %	0.0 %	▼ 0.8 pp

Table 51 – Coast - Fuerteventura alerts probability report

Seasonality Report

Coastal phenomena:

- Most prone month: November.
- Other relevant months: December, January, February, March.

Insights

The Fuerteventura coast shows a decline in coastal hazards, dropping from 0.8 % in 2025 to near zero by 2100. Current seasonality is concentrated in winter, especially November through March, when Atlantic swell is most active. Summer remains largely hazard-free. Unlike other Canary coasts where maritime risk grows, this shoreline appears to lose relevance in future projections, suggesting possible shifts in storm-track exposure or local wave regimes.

4.1.21 Lanzarote

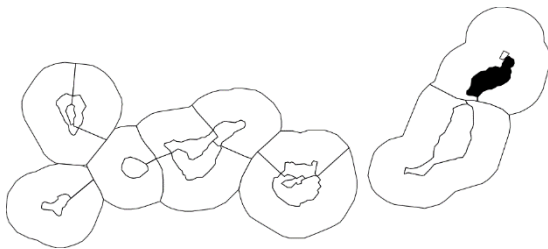


Figure 21 - Lanzarote

Alert Probability Report

(Region: Lanzarote; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.8 %	1.9 %	6.8 %	▲ +6.0 pp
<b>Precipitation</b>	0.5 %	1.9 %	6.8 %	▲ +6.3 pp
<b>High temperatures</b>	1.4 %	3.3 %	10.7 %	▲ +9.3 pp
<b>Storms</b>	0.3 %	0.3 %	0.8 %	▲ +0.5 pp
<b>Visibility</b>	0.3 %	0.3 %	0.3 %	— 0.0 pp

Table 52 – Lanzarote alerts probability report

## Seasonality Report

### Wind:

- Most prone month: February.
- Other relevant months: January, March, December, July.

### Precipitation:

- Most prone month: November.
- Other relevant months: October, December, September.

### High temperatures:

- Most prone month: July.
- Other relevant months: August, June, October, April.

### Storms:

- Most prone month: March.
- Other relevant months: September, August, December.

### Visibility:

- Most prone month: October.
- Other relevant months: August, May, September, March.

## Insights

Lanzarote is projected to face significant increases across most hazards. High temperatures rise steeply from 1.4 % in 2025 to 10.7 % in 2100, centered on July–August. Wind and precipitation also surge (both 0.8–0.5 % → 6.8 %), with wind peaking in winter–spring and rainfall in late autumn. Storms remain marginal, growing slightly to 0.8 %, while visibility stays stable at low levels. The island’s future risk profile is dominated by heat, wind, and precipitation, pointing to stronger seasonal extremes and a more volatile climate regime.

4.1.22 Coast – Lanzarote

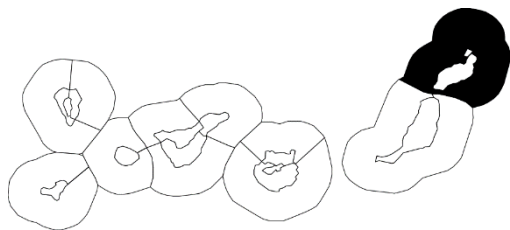


Figure 22 - Coast - Lanzarote

Alert Probability Report

(Region: Coast - Lanzarote; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Coastal phenomena	1.1 %	0.8 %	0.0 %	▼ 1.1 pp

Table 53 – Coast - Lanzarote alerts probability report

Seasonality Report

Coastal phenomena:

- Most prone month: January.
- Other relevant months: February, March, April, May.

Insights

Lanzarote’s coast shows a projected decline in maritime hazards, with coastal phenomena falling from 1.1 % in 2025 to zero by 2100. Presently, risk is concentrated in winter and spring, particularly January through May, when North Atlantic swells dominate. Summer remains largely unaffected. This contrasts with other Canary coasts where ocean-driven risks are projected to intensify, suggesting localized differences in exposure and future wave climate.

4.1.23 La Gomera

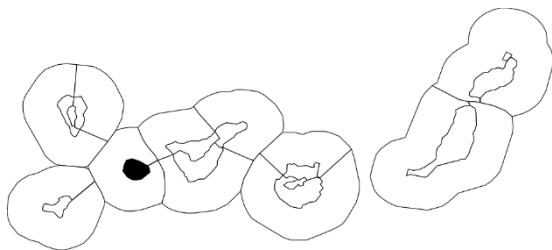


Figure 23 - La Gomera

Alert Probability Report

(Region: La Gomera; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.9 %	2.2 %	3.6 %	▲ +1.6 pp
<b>Precipitation</b>	0.5 %	0.0 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	2.5 %	5.5 %	17.3 %	▲ +14.8 pp
<b>Storms</b>	0.3 %	0.8 %	1.4 %	▲ +1.1 pp
<b>Visibility</b>	0.3 %	0.3 %	0.3 %	— 0.0 pp

Table 54 – La Gomera alerts probability report

## Seasonality Report

### Wind:

- Most prone month: March.
- Other relevant months: February, December, January, November.

### Precipitation:

- Most prone month: November.
- Other relevant months: December, October, January, September.

### High temperatures:

- Most prone month: July.
- Other relevant months: August, June, October.

### Storms:

- Most prone month: December.
- Other relevant months: September, November, March, August.

### Visibility:

- Most prone month: February.
- Other relevant months: April, March, May, November.

## Insights

La Gomera's inland zone is projected to experience sharp growth in summer heat, with alerts increasing from 2.5 % in 2025 to 17.3 % by 2100, peaking in July–August. Wind also rises modestly (1.9 % → 3.6 %), with maxima in late winter and spring. Storms grow slightly to 1.4 %, centered in December. Precipitation alerts disappear after 2025, and visibility remains stable at low levels. Overall, the island shifts toward a heat-dominated hazard profile, with wind and occasional storms as secondary risks.

### 4.1.24 Coast - La Gomera

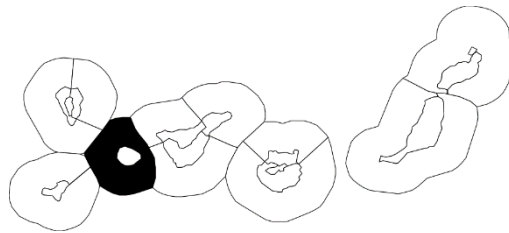


Figure 24 - Coast – La Gomera

#### Alert Probability Report

(Region: Coast - La Gomera; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Coastal phenomena</b>	1.6 %	0.3 %	0.0 %	▼ 1.6 pp

Table 55 – Coast - La Gomera alerts probability report

#### Seasonality Report

Coastal phenomena:

- Most prone month: July.
- Other relevant months: January, December, March, November.

#### Insights

La Gomera’s coast shows a clear decline in coastal hazards, with alerts dropping from 1.6 % in 2025 to none by 2100. Current risk is seasonal, peaking in July and secondarily in winter months such as January and December. This reduction contrasts with many other Canary coasts where maritime hazards remain stable or grow. The trend suggests a localized decrease in wave-driven risk, although the island’s steep and exposed shores may still warrant careful monitoring for episodic events.

## 4.2 Azores

The Azores archipelago, as defined by the Portuguese Institute for Sea and Atmosphere (IPMA), is organized into three island groups: the Eastern Group (São Miguel and Santa Maria), the Central Group (Terceira, Graciosa, São Jorge, Pico and Faial), and the Western Group (Flores and Corvo). This division is not only geographical but also meteorological, since islands within the same group share relatively similar climatic regimes, oceanic exposure, and synoptic-scale weather patterns.

For the purpose of predicting extreme event probabilities, each island group can be treated as a coherent unit, consistent with the classification applied by IPMA.

For the Azores, historical alert data were obtained for wind, coastal phenomena, precipitation, and high temperatures. For the other alerts, the model trained with relative values from the Canary Islands was used.

## 4.2.1 Central Group

### Alert Probability Report

(Region: Azores – Central Group; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	6 %	8.5 %	17.0 %	▲ +11 pp
<b>Coastal phenomena</b>	2.2 %	2.7 %	5.8 %	▲ +3.6 pp
<b>Precipitation</b>	5.2 %	3.8 %	0 %	▼ –5.2 pp
<b>High temperatures</b>	0 %	0 %	0 %	NA
<b>Storms</b>	0 %	0 %	0 %	NA
<b>Visibility</b>	0 %	0 %	0 %	NA

Table 56 – Central Group alerts probability report

### Seasonality Report

#### Wind alerts (VI):

- Most prone month: December.
- Other relevant months: March, January, February, November.

#### Coastal phenomena:

- Most prone month: December.
- Other relevant months: March, January, February, November.

#### Heavy Precipitation:

- Most prone month: December.
- Secondary peaks: October, January, March, November.

### Insights

The Central Group shows a pronounced shift in hazard probabilities. Wind alerts rise from 6 % in 2025 to 17 % in 2100, becoming the dominant risk with a clear winter maximum. Coastal phenomena increase more moderately but peak in the same months, reinforcing their seasonal overlap. In contrast, heavy precipitation declines steadily and vanishes by century's end, removing what is now a recurrent winter hazard. High temperatures, storms, and visibility alerts remain negligible. Overall, the region evolves toward a risk regime where wind and coastal hazards intensify while precipitation alerts disappear, reshaping the seasonal distribution of extremes.

## 4.2.2 Western Group

### Alert Probability Report

(Region: Açores - Western Group; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.8 %	0.5 %	0.0 %	▼ 0.8 pp
<b>Coastal phenomena</b>	0.3 %	0.5 %	1.1 %	▲ +0.8 pp
<b>Precipitation</b>	0.3 %	0.5 %	1.1 %	▲ +0.8 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.0 %	0.0 %	0.0 %	NA
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 57 – Western Group alerts probability report

### Seasonality Report

#### Wind:

- Most prone month: March.
- Other relevant months: February, December, January, April.

#### Precipitation:

- Most prone month: October.
- Other relevant months: December, January.

#### Coastal phenomena:

- Most prone month: January.

### Insights

In the Western Group, overall alert probabilities remain very low. Wind decreases from 0.8 % in 2025 to zero by 2100, while coastal and precipitation alerts show a slow but steady rise, both reaching about 1.1 % by century's end. Seasonality reveals wind as a late-winter hazard with a March maximum, whereas precipitation peaks in October. Coastal phenomena, storms, visibility, and high temperatures remain negligible throughout, with no meaningful seasonal signal. The long-term narrative is therefore one of declining wind influence and a modest emergence of precipitation and coastal hazards, leaving the group with a persistently low hazard profile

## 4.2.3 Eastern Group

### Alert Probability Report



(Region: Açores Eastern Group; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.1 %	0.8 %	0.8 %	▼ 0.3 pp
<b>Coastal phenomena</b>	0.5 %	0.8 %	1.6 %	▲ +1.1 pp
<b>Precipitation</b>	0.5 %	0.8 %	1.6 %	▲ +1.1 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.0 %	0.0 %	0.0 %	NA
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 58 – Eastern Group alerts probability report

## Seasonality Report

### Wind:

- Most prone month: March.
- Other relevant months: February, January, December, April.

### Precipitation:

- Most prone month: October.
- Other relevant months: December, January.

### Coastal phenomena:

- Most prone month: January.

## Insights

In the Eastern Group, wind alerts remain minor and slightly decline from 1.1 % to 0.8 % by 2100, with activity concentrated in late winter and early spring. In contrast, both precipitation and coastal hazards show steady increases, rising from 0.5 % to 1.6 %, with October and December as the key precipitation months. Despite these upward trends, absolute levels stay modest. Other hazards—heat, storms, and visibility—remain negligible across the period. Overall, the Eastern Group transitions toward a modest rise in precipitation and coastal risks, while wind retains a limited but persistent seasonal peak in the early part of the year.

## 4.3 Madeira

The Azores archipelago, as defined by IPMA, divides the island of Madeira as three significant zones (South Coast, North Coast and Mountain Region) and leaves Porto Santo as a unique zone. This division is not only geographical but also meteorological, since islands within the same group share relatively similar climatic regimes, oceanic exposure, and synoptic-scale weather patterns.

### 4.3.1 Madeira Island – South Coast

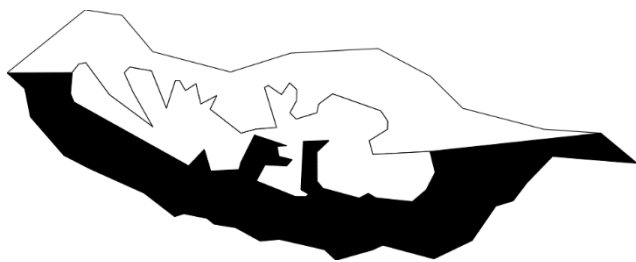


Figure 25: Madeira Island – South Coast

#### Alert Probability Report

(Region: Madeira - South Coast; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
Wind	1.9 %	1.6 %	1.4 %	▼ –0.5 pp
Precipitation	0.3 %	0.3 %	0.3 %	— OPP
Coastal phenomena	0 %	0 %	0 %	NA
High temperatures	0 %	0 %	0 %	NA
Storms	0 %	0 %	0 %	NA
Visibility	0 %	0 %	0 %	NA

Table 59 – Madeira Island – South Coast alerts probability report

#### Seasonality Report

Wind:

- Most prone month: April.
- Other relevant months: December, March, February, January.

Precipitation:

- Most prone month: October.
- Other relevant months: November, December.

#### Insights

On the South Coast of Madeira, wind is the only notable hazard, affecting about 7 days per year and showing a slight decline toward 2100. Seasonality highlights peaks in spring and early winter, with minimal summer activity. Precipitation remains low and stable at 0.3 %, with October and November as the main months. All

other hazards, including heat, storms, coastal, and visibility alerts, remain absent. The long-term pattern is therefore one of persistently low hazard activity, dominated by modest wind episodes that gradually lessen in frequency as the century progresses.

#### 4.3.2 Madeira Island – North Coast

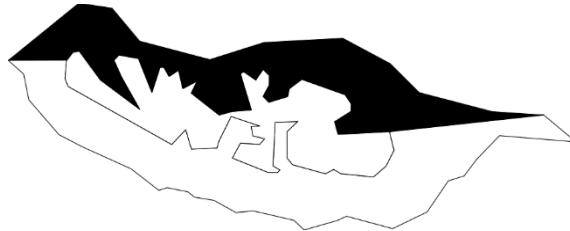


Figure 26: Madeira Island – North Coast

##### Alert Probability Report

(Region: Madeira Island – North Coast; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	1.4 %	1.4 %	1.6 %	▲ +0.2 pp
<b>Visibility</b>	0 %	0.3 %	0.3 %	▲ +0.3 pp
<b>Precipitation</b>	0.3 %	0.3 %	0 %	▼ –0.3 pp
<b>Coastal phenomena</b>	0 %	0 %	0 %	NA
<b>High temperatures</b>	0 %	0 %	0 %	NA
<b>Storms</b>	0 %	0 %	0 %	NA

Table 60 – Madeira Island – North Coast alerts probability report

##### Seasonality Report

###### Wind:

- Most prone month: December.
- Other relevant months: February, March, January, April.

###### Visibility:

- Most prone month: April.
- Other relevant months: February, May, November.

###### Precipitation:

- Most prone month: October.
- Other relevant months: November, December.

## Insights

The North Coast exhibits a modest increase in wind, rising slightly to 1.6 % by 2100, with winter months—especially December—most affected. Visibility emerges at very low levels from mid-century onward, while extreme precipitation declines and disappears after 2050 despite present autumn peaks. Storms and other hazards remain negligible. The result is a subdued hazard profile with two signals: persistent but minor winter wind activity and the appearance of marginal visibility episodes. Compared to the South Coast, precipitation becomes less relevant here, while wind and visibility sustain a weak but distinct seasonal presence.

### 4.3.3 Madeira – Mountain Region

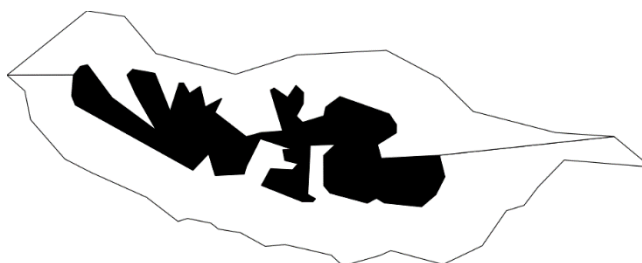


Figure 27: Madeira – Mountain Region

## Alert Probability Report

(Region: Madeira – Mountain Region; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>High temperatures</b>	2.2 %	5.5 %	18.4 %	▲ +16.2 pp
<b>Wind</b>	1.6 %	1.4 %	0 %	▼ –1.6 pp
<b>Storms</b>	6.6 %	0.5 %	0 %	▼ –6.6 pp
<b>Precipitation</b>	0 %	0 %	0 %	NA
<b>Coastal phenomena</b>	0 %	0 %	0 %	NA
<b>Visibility</b>	0 %	0 %	0 %	NA

Table 61 – Madeira – Mountain Region alerts probability report

## Seasonality Report

Wind:

- Most prone month: December.
- Other relevant months: March, January, February, April. Marked minimums: October, June, July, August, September.

Storms:

- Most prone month: December.
- Other relevant months: November, March, October, April.

High temperatures:

- Most prone month: July.
- Other relevant months: August, June.

Insights

The Mountain Region of Madeira undergoes a marked shift. High-temperature alerts escalate dramatically, from 2.2 % in 2025 to 18.4 % by 2100, with a strong seasonal maximum in July. At the same time, wind declines steadily to zero, and storms—once frequent at 6.6 %—vanish completely after mid-century. Other hazards remain absent. The seasonal profile confirms the transition: extreme heat dominates summer, while storm peaks that once defined late autumn and winter fade away. This creates a striking reconfiguration of the hazard regime, where intense and prolonged heat events replace the historical prominence of wind and storms.

#### 4.3.4 Porto Santo

Alert Probability Report

(Region: Porto Santo; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.0 %	0.0 %	▼ 0.3 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.5 %	1.9 %	▲ +1.6 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 62 – Porto Santo alerts probability report

Seasonality Report

Wind:

- Most prone month: February.

- Other relevant months: December, January, April, November.

#### Storms:

- Most prone month: March.
- Other relevant months: November, December.

#### Precipitation:

- Most prone month: November.
- Other relevant months: December.

#### Insights

Porto Santo shows a mixed but low-intensity hazard profile. Wind, initially present at 0.3 % in 2025, disappears entirely after mid-century. Precipitation remains minor but grows slightly to 0.5 % by 2100, concentrated in November–December. Storms, however, rise gradually to 1.9 %, with a spring maximum in March and secondary peaks in late autumn. All other hazards remain absent. The resulting profile highlights the island’s overall low exposure, with only storms showing a modest upward trajectory toward the end of the century.

## 4.4 Cape Verde

Since no institutional zoning was available, each island was treated as an independent zone.

### 4.4.1 Santiago

#### Alert Probability Report

(Region: Santiago, Cape Verde; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Storms</b>	7.7 %	9.6 %	17.0 %	▲ +9.3 pp
<b>Wind</b>	0.8 %	1.1 %	2.5 %	▲ +1.7 pp
<b>High temperatures</b>	0.3 %	0.5 %	0.8 %	▲ +0.5 pp
<b>Precipitation</b>	0.5 %	0.3 %	0 %	▼ –0.5 pp
<b>Coastal phenomena</b>	0 %	0 %	0 %	NA
<b>Visibility</b>	0 %	0 %	0 %	NA

Table 63 – Santiago alerts probability report

#### Seasonality Report

#### Storms:

- Most prone month: February.
- Other relevant months: November, January, March.

#### Strong Wind:

- Most prone month: November.
- Other relevant months: February, January, March.

#### High temperatures:

- Most prone month: September.
- Other relevant months: August.

#### Extreme Precipitation:

- Most prone month: September.
- Other relevant months: October and November.

#### Insights

In Santiago, storms are the defining hazard, rising from 7.7 % in 2025 to 17 % in 2100, with a clear concentration in the boreal winter months, especially February. Wind shows a modest increase, remaining secondary but aligned with the same seasonal window. High-temperature alerts, though still limited, emerge distinctly in late summer, peaking in September, contrasting sharply with the absence of heat risk in the first half of the year. Precipitation alerts decline to zero, reinforcing the seasonal dryness. Overall, Santiago evolves toward a regime dominated by winter storms and summer heat, with other hazards negligible or absent.

### 4.4.2 Boa Vista

#### Alert Probability Report

(Region: Boa Vista; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.3 %	0.0 %	▼ 0.3 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.3 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.0 %	0.0 %	0.0 %	NA
<b>Visibility</b>	0.0 %	0.0 %	0.3 %	▲ +0.3 pp

Table 64 – Boa Vista alerts probability report

## Seasonality Report

### Wind:

- Most prone month: November.
- Other relevant months: February.

### Visibility:

- Most prone month: January.
- Other relevant months: May.

### Precipitation:

- Most prone month: August.
- Other relevant months: December, February, September, January.

## Insights

Boa Vista displays a very low hazard profile, with most alert types either absent or negligible. Wind declines from 0.3 % to zero by 2100, showing only a small seasonal signal in November. Precipitation also fades, dropping from 0.5 % to none by century's end, despite an isolated August peak in the present record. Visibility appears slightly at the end of the century but remains marginal. Storms, heat, and coastal phenomena are effectively absent throughout. Overall, Boa Vista maintains one of the lowest projected alert probabilities in Cape Verde, with no dominant or persistent hazard across the century.

### 4.4.3 Brava

#### Alert Probability Report

(Region: Brava; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.5 %	1.1 %	4.1 %	▲ +3.6 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.5 %	0.8 %	▲ +0.3 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.3 %	0.3 %	NA
<b>Visibility</b>	0.0 %	0.0 %	0.3 %	▲ +0.3 pp

Table 65 – Brava alerts probability report

## Seasonality Report

### Wind:



- Most prone month: February.
- Other relevant months: November.

Visibility:

- Most prone month: May.
- Other relevant months: January and December.

Precipitation:

- Most prone month: September.
- Other relevant months: October, December, February, January.

Insights

Brava shows a clear upward trajectory in wind risk, increasing from 0.5 % in 2025 to 4.1 % by 2100, with peaks in February and November. Precipitation remains low but steady, with a September maximum, while storms persist at marginal levels without growth, centered mainly in December. Visibility emerges slightly by late century, though still minimal. High temperatures and coastal hazards remain absent. Overall, Brava's profile evolves toward a wind-dominated regime with a consistent but modest contribution from rainfall, while other hazards remain secondary or negligible throughout the century.

#### 4.4.4 Fogo

Alert Probability Report

(Region: Fogo; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.8 %	3.0 %	▲ +2.7 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.8 %	1.9 %	▲ +1.4 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 66 – Fogo alerts probability report

Seasonality Report

Wind:

- Most prone month: November.
- Other relevant months: February, January, December.

#### Storms:

- Most prone month: January.
- Other relevant months: March, December, April, August.

#### Precipitation:

- Most prone month: January.
- Other relevant months: September, December, February, November.

#### Insights

Fogo shows a clear strengthening of wind and precipitation risks. Wind rises from 0.3 % in 2025 to 3 % by 2100, with activity centered on November to February. Precipitation also grows steadily, from 0.5 % to nearly 2 %, with seasonal peaks in January, September, and December. Storms remain marginal but show a slight increase, while visibility, heat, and coastal alerts stay negligible throughout. The island's risk profile thus evolves from low to moderately active, with wind and precipitation emerging as the defining hazards toward the end of the century, concentrated mainly in the cool and transitional months.

### 4.4.5 Maio

#### Alert Probability Report

(Region: Maio; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.3 %	0.5 %	▲ +0.3 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.5 %	0.3 %	▼ 0.3 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.0 %	0.0 %	0.0 %	NA
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 67 – Maio alerts probability report

#### Seasonality Report

#### Wind:

- Most prone month: November.
- Other relevant months: February.

#### Precipitation:

- Most prone month: December.

- Other relevant months: September, November, October, August.

## Insights

Maio maintains very low alert probabilities throughout the century. Wind remains nearly constant at 0.3–0.5 %, with November as its main seasonal peak. Precipitation stays modest and slightly decreases by 2100, with December and September as key months. Storms appear marginally in September but do not grow, while coastal, heat, and visibility alerts remain absent. Overall, Maio presents a stable and subdued hazard profile, with limited seasonal variability and no significant long-term shifts beyond a slight reinforcement of late-year rainfall and minimal wind activity concentrated in early winter.

## 4.4.6 Sal

### Alert Probability Report

(Region: Sal; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.3 %	0.3 %	— 0.0 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.5 %	0.5 %	— 0.0 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.3 %	0.0 %	▼ 0.3 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 68 – Sal alerts probability report

### Seasonality Report

#### Wind:

- Most prone month: November.
- Other relevant months: February and December.

#### Storms:

- Most prone month: February.
- Other relevant months: July, September, October, January.

#### Precipitation:

- Most prone month: August.
- Other relevant months: September, December, January, February.

## Insights

Sal's hazard profile is equally limited. Wind remains static at 0.3 %, peaking weakly in November. Precipitation stays steady at 0.5 %, though seasonality shows a distinct August maximum. Storms, starting at 0.3 %, decline to zero by 2100, with no persistent pattern. Visibility, heat, and coastal phenomena remain negligible. The overall trajectory is one of continuity: risks neither intensify nor diversify, leaving Sal with a low and seasonally constrained hazard regime dominated by occasional late-summer precipitation episodes, while other alert types remain essentially absent across the projection horizon.

#### 4.4.7 Santo Antão

##### Alert Probability Report

(Region: Santo Antão; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.5 %	1.6 %	▲ +1.4 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.3 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.3 %	0.3 %	— 0.0 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 69 – Santo Antão alerts probability report

##### Seasonality Report

###### Wind:

- Most prone month: February.
- Other relevant months: November, January, December.

###### Storms:

- Most prone month: January.
- Other relevant months: December, August, October.

###### Precipitation:

- Most prone month: August.
- Other relevant months: September, December, February, January.

##### Insights

Santo Antão shows modest change, with wind increasing slightly from 0.3 % to 1.6 % by 2100, peaking in February and November. Precipitation declines steadily to zero, despite seasonal peaks in August and early

winter in the present climate. Storms persist at a low, unchanging level, while other hazards remain absent. The long-term pattern is thus defined by the replacement of rainfall risk with a minor but growing wind signal, leaving Santo Antão with a relatively subdued overall hazard profile, modest winter wind activity, and diminishing rainfall extremes as the century progresses.

#### 4.4.8 São Nicolau

##### Alert Probability Report

(Region: São Nicolau; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.5 %	0.5 %	0.8 %	▲ +0.3 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.3 %	0.0 %	▼ 0.5 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.3 %	0.3 %	— 0.0 pp
<b>Visibility</b>	0.0 %	0.0 %	0.0 %	NA

Table 70 – São Nicolau alerts probability report

##### Seasonality Report

###### Wind:

- Most prone month: November.
- Other relevant months: February, January.

###### Storms:

- Most prone month: April.
- Other relevant months: January, February, September, October.

###### Precipitation:

- Most prone month: August.
- Other relevant months: September, February, October, January.

##### Insights

São Nicolau maintains a very low hazard profile, with little change through the century. Wind rises only slightly from 0.5 % to 0.8 %, showing a November maximum. Precipitation, initially at 0.5 %, disappears entirely by 2100, despite present peaks in August and September. Storms remain static and marginal, while visibility, coastal, and heat alerts stay absent. Overall, the island evolves toward a near-neutral hazard

regime: wind provides a minimal but consistent winter signal, while rainfall hazards fade entirely, resulting in one of the least active profiles in the archipelago.

#### 4.4.9 São Vicente

##### Alert Probability Report

(Region: São Vicente; probability = alert days / 365 × 100)

Alert type	2025	2050	2100	Trend 2025 → 2100
<b>Wind</b>	0.3 %	0.5 %	1.6 %	▲ +1.4 pp
<b>Coastal phenomena</b>	0.0 %	0.0 %	0.0 %	NA
<b>Precipitation</b>	0.5 %	0.5 %	0.5 %	— 0.0 pp
<b>High temperatures</b>	0.0 %	0.0 %	0.0 %	NA
<b>Storms</b>	0.3 %	0.3 %	0.3 %	NA
<b>Visibility</b>	0.0 %	0.0 %	0.3 %	▲ +0.3 pp

Table 71 – São Vicente alerts probability report

##### Seasonality Report

###### Wind:

- Most prone month: November.
- Other relevant months: February, January.

###### Visibility:

- Most prone month: January.
- Other relevant months: September.

###### Precipitation:

- Most prone month: August.
- Other relevant months: February, September, January, December.

##### Insights

São Vicente sees a slight increase in wind, from 0.3 % to 1.6 % by 2100, with a November peak. Precipitation remains stable at 0.5 %, with August as its main seasonal maximum. Visibility emerges weakly at 0.3 % late in the century, while storms persist at low but steady levels, with a September concentration. Coastal and heat risks remain absent. The overall narrative is of a modest reinforcement of wind, consistent summer precipitation peaks, and minor visibility signals, while other hazards remain negligible, keeping the island's overall risk profile limited but slightly

## 5. Conclusions

The projections presented here suggest that the hazard landscape of Macaronesia could undergo substantial reorganization during the 21st century. The most consistent signal across multiple regions is the potential rise of high-temperature alerts. In mountain and inland zones of Madeira, the Canary Islands, and Santiago (Cape Verde), extreme heat that is currently a rare occurrence might become far more frequent by late century, in some cases representing weeks of alerts each year. While these values come from probabilistic modelling with limited historical baselines, the trend points to a possible shift in which prolonged summer heat could emerge as the dominant stressor for communities, with implications for health services, water demand, and energy systems.

Precipitation and storm hazards show more divergent futures. In the Azores Central Group and parts of Cape Verde, the probabilities indicate a steady decline of heavy rainfall alerts, potentially vanishing by 2100. If this signal holds, it would mark a loss of a long-standing winter hazard. Conversely, in the eastern Canary Islands, precipitation alerts appear to increase, which might reflect a tendency toward fewer but more concentrated rainfall extremes. These contrasting tendencies highlight that not all islands follow the same trajectory, and localized responses would be required if such patterns materialize.

Wind and coastal phenomena present mixed signals. In Madeira and the western Azores, alerts might decline, while in some Canary sectors wind is projected to rise significantly, sometimes in the same seasons when coastal hazards are more likely. This seasonal overlap could mean that compound events—strong winds combined with coastal swell—become more relevant, though this remains uncertain given the limitations of the input datasets.

The temporal narrative is nevertheless clear in direction: by mid-century, heat alerts could already double relative to today in many zones, while by late century certain hazards might fade (precipitation in the Azores, storms in Madeira's mountains) and others dominate (heat and wind in parts of the Canaries). What this implies operationally is that the calendar of risk may shift—from winter-centred emergencies toward summer-centred challenges. This could affect how early warning systems, health preparedness, and infrastructure planning are designed.

Importantly, these findings must be read with caution. The analysis is based on probabilistic projections, trained in part on limited or uneven historical alert data, and not all types of events were available for all territories. For instance, some alerts such as dust, storms, or visibility were incompletely recorded. The absence of systematic follow-up data also means it is difficult to know whether an alert translated into real impacts on population or infrastructure. And it also makes the methodology to have slightly different results if executed multiple times.

Even with these uncertainties, the broad picture remains policy-relevant. The evidence suggests that islands might need to prepare for a gradual transition: from climates where winter precipitation and storms dominate toward climates where extremes, particularly heat, summer gain prominence. For decision-makers, this underlines the importance of strengthening monitoring and impact-tracking systems, so that future adaptation policies are guided not only by probabilistic projections but also by consistent and comparable evidence of how hazards are evolving on the ground.

Beyond the physical results, the work exposes several critical methodological and data challenges that limit the robustness of regional assessments. The current fragmentation of alert data across European territories makes systematic comparison difficult. Only for the Canary Islands—after an exceptionally laborious process of compiling and cleaning unstructured historical records, including scanned documents—and for the Central Group of the Azores was it possible to access structured long-term alert histories. For Madeira and Cape Verde, modeling had to substitute for missing observational alert datasets. Furthermore, there is currently

no systematic follow-up of alerts: it remains extremely difficult to trace whether a given warning corresponded to an actual damaging event affecting populations, infrastructure, or ecosystems. This lack of linkage between warnings and impacts represents a major gap for both science and policy.

Equally problematic is the inconsistency in which extreme events are tracked across regions. Dust, storms, or visibility are recorded in some territories but absent in others, breaking continuity. The European Severe Storms Laboratory (ESSL) dataset (40), which could in principle serve as a harmonized continental reference, proved incomplete and insufficient for operational use in this analysis. This indicates that greater EU-level effort is needed to strengthen coordination between European institutions, national meteorological services, and regional authorities, to improve the coverage, comparability, and reliability of extreme event datasets.

The lessons from Macaronesia therefore go beyond the islands themselves. They show that Europe requires a unified methodology to define hazard zones and to standardize alert records. Without this, comparative climate-risk assessments will remain fragmented, and adaptation policy will lack the evidence base it needs. Improving data accessibility and ensuring systematic documentation of both hazards and impacts are essential to transform the information into actionable knowledge for resilience planning.

In short, the results confirm that climate hazards in Europe's island regions are intensifying, diversifying, and shifting in seasonality, while the ability to monitor and compare them remains constrained by fragmented and incomplete datasets. Closing this gap is as critical as the physical adaptation measures themselves.



## Annex I – Risk Categories

Risk categories convert continuous projections into discrete classes that are easier to use in planning, communication, and platform logic.

- Operational decisions: the simulation platform triggers actions by category, not by raw scores.
- Communication & mapping: green / yellow / red classes are clearer for non-technical readers.
- Comparability: using tertiles standardizes interpretation across zones with different ranges.

These categories are designed to be integrated into an existing online platform that simulates how extreme events could affect the functioning of critical infrastructure in the Canary Islands. This is why they have been only calculated for this territory.

For each zone, use the projected annual count of alert days for three anchor years:

- $A(2025)$  — expected alert days in 2025
- $A(2050)$  — expected alert days in 2050
- $A(2100)$  — expected alert days in 2100

Categories are event-agnostic in this version, the same steps can be repeated per hazard if needed.

Calculation steps:

- Step 1 — Magnitude:

$$M = A(2050)$$

Equation 7 – Risk Categories Magnitude

- Step 2 — Trend:

$$T = A(2100) - A(2025)$$

Equation 8 – Risk Categories Trend

- Step 3 — Normalize  $M$  and  $T$  to  $[0,1]$  across all zones using min–max scaling. If max = min, set all normalized values to 0.5.
- Step 4 — Risk score:

$$R = 0.7 \cdot M + 0.3 \cdot T$$

Equation 9 – Risk Categories Score

- Step 5 — Categories (tertiles of  $R$  across all zones):
  - Category 1 (Low)  $\leq q33$
  - Category 2 (Medium) between  $q33$  and  $q66$
  - Category 3 (High)  $> q66$ .

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