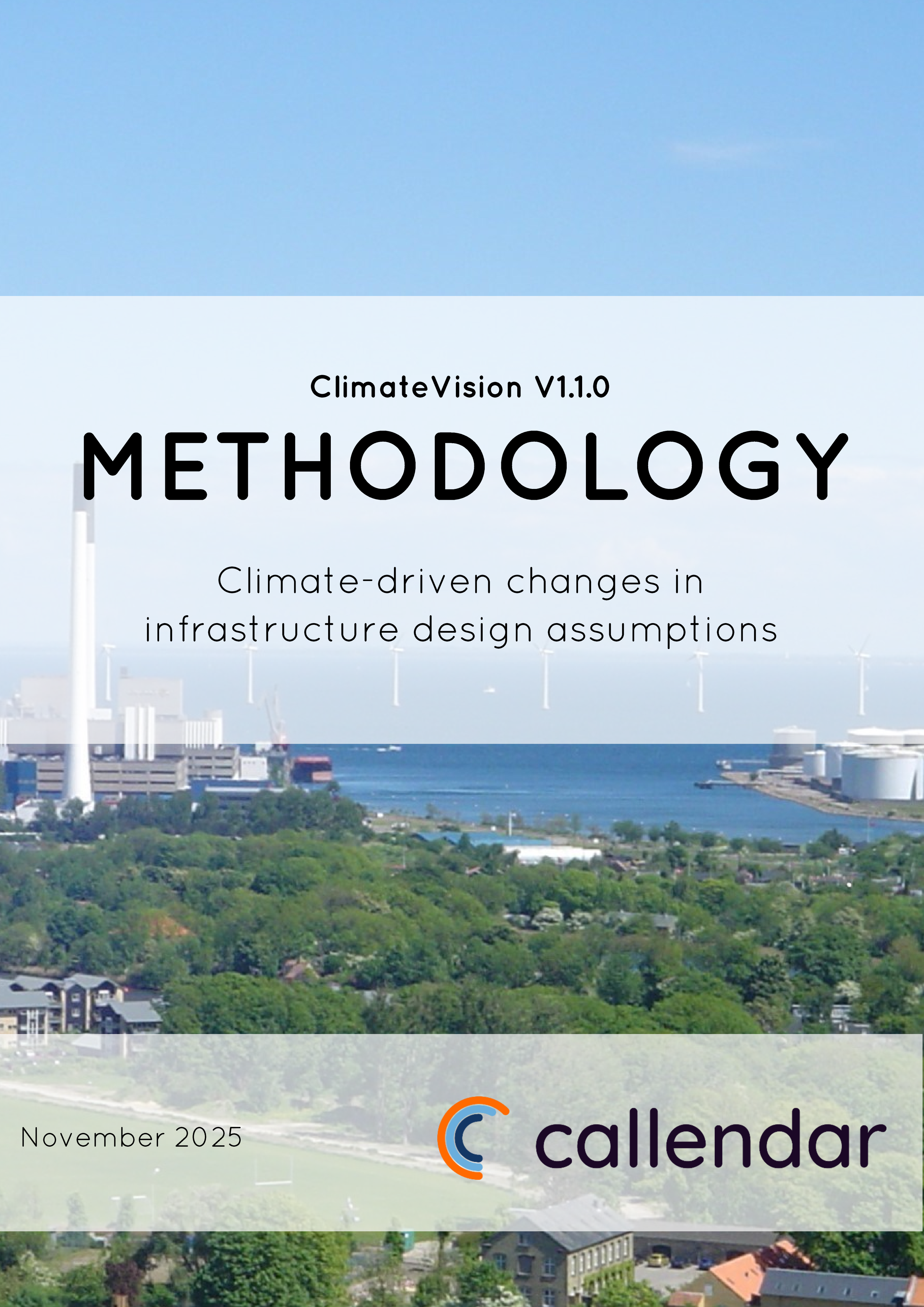

ClimateVision V1.1.0

METHODOLOGY

Climate-driven changes in infrastructure design assumptions

November 2025

callendar

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About ClimateVision

Companies engaged in the design and construction of both on- and off-shore infrastructures rely on meteorological and oceanographic assumptions. Variables such as temperature, wind, precipitation, wave height, and sea level play pivotal roles in project feasibility, design, and operation. However, these assumptions, typically grounded in a study of past weather records, may become inadequate over a project's lifetime, especially under the influence of climate change.

ClimateVision is an innovative and efficient solution for accessing future local climate projections crucial for designing resilient infrastructures. Leveraging Callendar's expertise in climatology and data automation, ClimateVision can generate precise local climate projections worldwide in a manner that is both convenient to users and compliant with the current scientific literature.

This document serves as a comprehensive guide to assist ClimateVision users in understanding how their projections are produced. The first chapter, "Overview of Data Sources and Processing", provides a short summary of data sources and processing methodologies for users seeking a broad understanding. The following chapters cover the various methodological elements in full detail for experts and users seeking more complete explanations.

Should you have any further questions on your results, feel free to contact us: contact@callendar.tech.

Overview of data sources and processing

General overview

ClimateVision uses automated data processing to generate climate indicators useful for infrastructure projects from global climate projections. The tool reproduces recognized methodologies using the latest scientific data to produce state-of-the-art local information about current and future climate.

This first part gives a short overview of the data source and methodology used for each indicator.

Average temperature and rainfall projections

Average temperature and rainfall projections are based on simulation of future climate by 12 climate models from the Coupled Model Intercomparison Project phase 6 (CMIP6). These projections are a subset of the projections used in the Intergovernmental Panel on Climate Change's 6th assessment report.
The simulation point closest to the location of interest is extracted and the results are downscaled and corrected for bias using historical data from European Centre for Medium-Range Weather Forecasts's reanalysis as reference. ERA5 Land is used for in-land or coastal locations and ERA5 is used on offshore projects.

INDICATOR	PROJECTION	REFERENCE
AVERAGE TEMPERATURE	CMIP6 tas (daily)	ERA5/ERA5 Land t2m (daily average computed from hourly data)
AVERAGE RAINFALL	CMIP6 pr (daily)	ERA5 pr (daily average computed from hourly data)

The impact of climate change for a given decade is then evaluated by averaging corrected projections over 30 years centered on the decade (e.g., average temperature for the decade 2050 is computed based on climate simulations from 2040 to 2069).

Extreme temperature and rainfall projections

Extreme temperature and rainfall projections are based on simulation of future climate by 12 climate models from the Coupled Model

Intercomparison Project phase 6 (CMIP6). These projections are a subset of the projections used in the Intergovernmental Panel on Climate Change's 6th assessment report.
The simulation point closest to the location of interest is extracted and the results are downscaled and corrected for bias using historical data from European Centre for Medium-Range Weather Forecasts's reanalysis as reference. ERA5 Land is used for in-land or coastal locations and ERA5 is used on offshore projects.

INDICATOR	PROJECTION	REFERENCE
MINIMUM TEMPERATURE	CMIP6 tasmin (daily)	ERA5/ERA5 Land t2m (daily minimum computed from hourly data)
MINIMUM DAILY TEMPERATURE	CMIP6 tas (daily)	ERA5/ERA5 Land t2m (daily average computed from hourly data)
MAXIMUM TEMPERATURE	CMIP6 tasmax (daily)	ERA5/ERA5 Land t2m (daily maximum computed from hourly data)
MAXIMUM DAILY TEMPERATURE	CMIP6 tas (daily)	ERA5/ERA5 Land t2m (daily average computed from hourly data)
MAXIMUM DAILY RAINFALL	CMIP6 pr (daily)	ERA5/ERA5 Land pr (daily average computed from hourly data)

Return levels for a selection of return periods are then computed using extreme value analysis.

Extreme wind projections

Extreme wind projections are based on simulation of future climate by 12 climate models from the Coupled Model Intercomparison Project phase 6 (CMIP6). These projections are a subset of the projections used in the Intergovernmental Panel on Climate Change's 6th assessment report.
Since extreme wind speeds must be computed on shorter time steps than those of the climate models, an extrapolation method is used.

The simulation point closest to the location of interest is extracted and the results are downscaled and corrected for bias using historical data from European Centre for Medium-Range Weather Forecasts's reanalysis as reference. ERA5 Land is used for in-land or coastal locations and ERA5 is used on offshore projects.

INDICATOR	PROJECTION	REFERENCE
WIND SPEED	CMIP6 SfcWindmax (daily)	ERA5/ERA5 Land u10 and v10 (daily maximum total wind computed from hourly u and v component of wind at 10 meters)

Return levels for a selection of return periods are then computed using extreme value analysis.
Extremes wind speeds on shorter time steps (from 10 minutes to 3 seconds) are then evaluated using an empiric model.

Sea level rise

Sea level projections are from the Intergovernmental Panel on Climate Change's 6th assessment report retrieved from NASA's Physical Oceanography Distributed Active Archive Center.

The results are displayed for the valid data point closest to the location of interest.

Extreme wind wave height

Extreme waves projections are based on WAVEWATCH III simulations forced by future climate from 8 climate models of the Coupled Model Intercomparison Project phase 6, retrieved from the Australian CSIRO. These significant wave height projections use a 3-hour time step that are aggregated into daily maximum significant wave height series.

The SPP2-4.5 scenario is not available. Only the 2071 to 2100 period is available for the projections. The valid data point closest to the location of interest is extracted.

INDICATOR	PROJECTION	REFERENCE
SIGNIFICANT WAVE HEIGHT	CMIP6 hs (daily significant wave height maximum computed from 3-hourly hs)	ERA5 swh (daily significant wave height maximum computed from hourly swh *significant height of combined wind waves and swell*)

Return levels for a selection of return periods are then computed using extreme value analysis.

Climate models

Climate models, also known as general circulation models or GCMs, use mathematical equations to characterize how energy and matter interact in different parts of the ocean, atmosphere, land. They are closely related to meteorological models used for weather-forecast.

Approximately 100 global circulations models participate in the Coupled Model Intercomparison Project phase 6 (CMIP6). To limit the resources required for the studies, especially in terms of time needed for data access and computing power, ClimateVision uses a subset of models.

Models for atmospheric indicators

To ensure consistency and comparability, the same climate models are used for all atmospheric indicators. In ClimateVision V1.1.0, these indicators include mean temperature, maximum temperature, minimum temperature, mean precipitation, maximum precipitation, maximum wind speed, sea level rise, and maximum significant wave height.

Models were selected based on 3 criteria:

- Data availability
- Equilibrium climate sensitivity
- Model independence

Due to the recent publication of model data, studies on their regional performance are still scarce and usually only consider a subset of the models currently available. As a result, this criterion was not considered in ClimateVision V1.1.0 but will be added in later versions.

Data availability

The models were selected primarily based on data availability, as some projections are unavailable. Climate models were prioritized based on the range of climate parameters they provide. To maximize the number of models available, only three emissions scenarios are considered in the current version:

- SSP1-2.6: low emission scenario, representative of an emission trajectory that keeps global warming below 2°C
- SSP2-4.5: intermediate emissions scenario, close to current emission trajectory
- SSP5-8.5: very high emissions scenario that can be used as a worst case

Other scenarios not included are: SSP1-1.9, SSP3-7.0 and SSP4-6.0. Both SSP1-1.9 and SSP4-6.0 are "tier 2" (or low priority) SSP[i]. And SSP3-7.0 is a high emissions scenario intermediary between SSP2-4.5 et SSP5-8.5.

Equilibrium climate sensitivity

Equilibrium climate sensitivity (ECS) is the long-term warming that would occur if the concentration of CO_2 in the atmosphere were to double. According to the IPCC 6th Assessment Report the best estimate for equilibrium climate sensitivity is 3°C with a likely range of 2.5 to 4°C and a very likely range of 2 to 5°C.[ii]

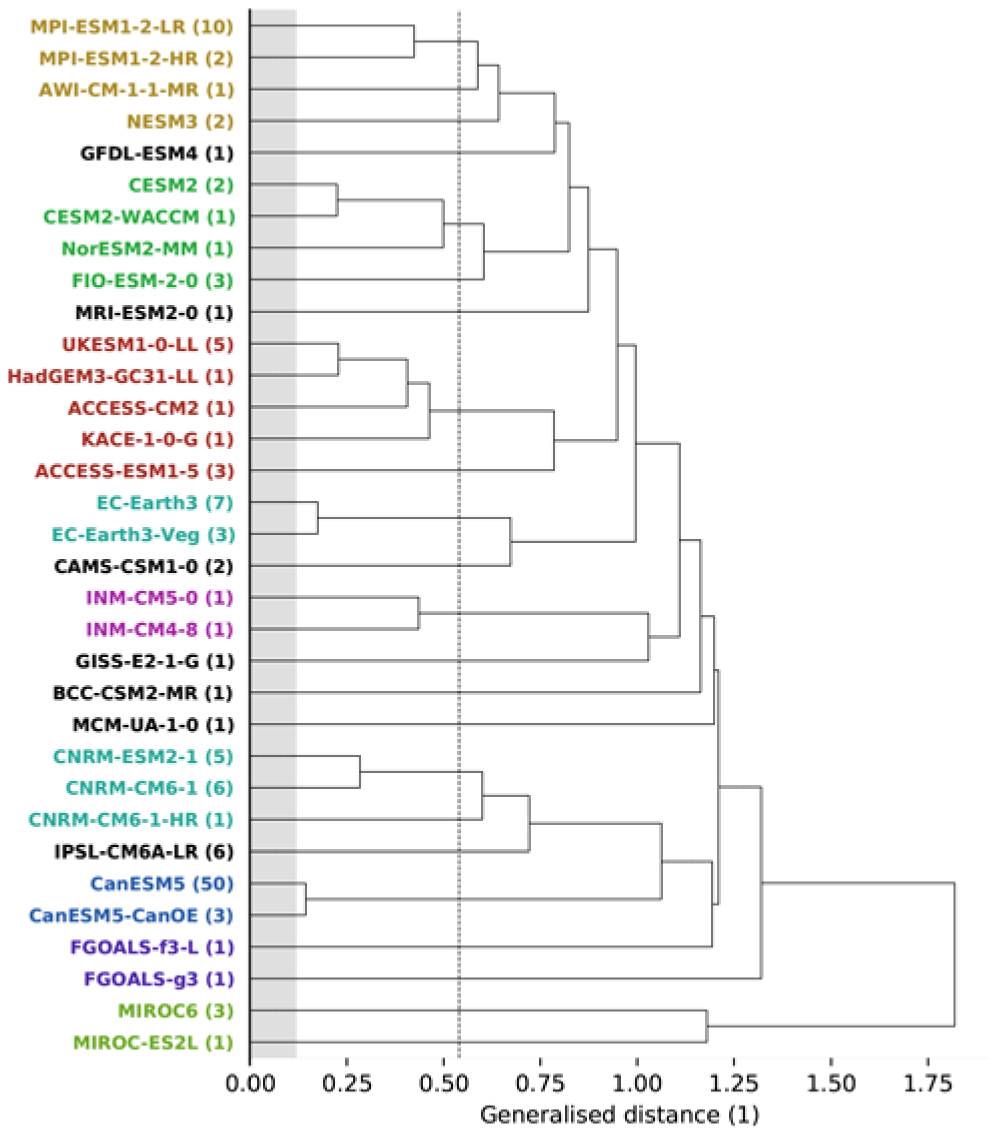
Several GCMs of CMIP6 have ECS that fall outside this range either below (low-likelihood, low warming) or above (low-likelihood, high warming). Because one of those models can significantly alter the results on a small ensemble, an increasingly common practice in the scientific literature is to downweigh models with ECS values outside the assessed range or simply exclude them from ensembles[iii,iv].

In practice, this criterion leads to the exclusion of the Russian model (INM-CM5-0) from our list of candidates[v]. The latter is left on the list and is used until new models are added. It will be removed shortly.

Model's independence

Even when they are exploited by different institutions, climate models are not necessarily independent of each other: they can use similar assumptions or common modules. The use of several closely related models in an ensemble could therefore result in an overweighting of the corresponding trajectory.

The studies on the correlations between models are still significantly less complete than for the CMIP5 generation[vi]. One publication investigating 33 CMIP6 model suggests the following dependency tree[vii]:



Models branching further to the left are more dependent, and models branching further to the right are more independent. An estimate of climate natural variability is indicated using gray shading, models that have a distance similar to this value (for instance CanESM5 and CanESM5-CanOE) are statistically indistinguishable. Models branching after the dotted line are reasonably independent.

Models set

The ideal models' ensemble should meet the following conditions:

1. It includes enough models (at least 10),
2. It provides projections for all desired variables,
3. It provides projections for all scenarios,
4. It does not include models with ECS outside the IPCC's very likely range,
5. It prioritizes models that perform well on the study area, and ideally on the whole planet,

6. If possible with respect to the previous conditions, it does not include closely related models.

The ensemble of models that best fit these objectives is the following:

Model	ripf
AWI-CM-1-1-MR*	r1i1p1f1
FGOALS-g3*	r1i1p1f1
CanESM5	r1i1p2f1
CMCC-ESM2	r1i1p1f1
CNRM-CM6-1	r1i1p1f2
CNRM-ESM2-1	r1i1p1f2
ACCESS-ESM1-5	r5i1p1f1
EC-Earth3*	r4i1p1f1
INM-CM5-0	r1i1p1f1
IPSL-CM6A-LR	r2i1p1f1
MIROC6	r2i1p1f1
MIROC-ES2L	r1i1p1f2
UKESM1-0-LL	r4i1p1f2
MPI-ESM1-2-LR	r5i1p1f1
MRI-ESM2-0	r1i1p1f1

*not used in V1.1.0 but available

Statistical downscaling

Methodology

Global and regional climate models' resolution is often lower than desired and they are in general biased. As a result, bias correction and downscaling are widely used in climate impact modelling.

Bias correction is the process of adjusting climate model outputs to account for their systematic errors. Numerous statistical bias correction methods exist. The essence of these methods is to build a transformation that fits the simulations on a past reference period to the observations on this same period, then apply the same transformation to future climate simulations with the fundamental assumption that it will remain valid in the future.

No method can be considered as entirely reliable[viii], the choice of a suitable method depends on the use case but also on the needs and technical constraints of each project (e. g.: explicability, computational efficiency…).

At this stage, ClimateVision employs one method: the Cumulative Distribution Function transform (CDF-t) for all the variables.

The CDF-t method[ix], a well-established variation of the quantile-quantile method. It effectively corrects biases while preserving trends in future scenarios. It has been used in numerous research and adaptation projects.

Changes from the previous version

The previous version V0.2.0 was using the Asynchronous Regional Regression Model (ARRM) for precipitation and has been left aside due to poor correction efficiency for extremely arid areas, following an internal study. The ARRM uses multiple linear transformations to correct the precipitation data and due to the scarcity of precipitation in dry areas, the ARRM method was not reliable with an inability to process a very few data points (the method do not correct the 0 in the series). Since the ARRM was chosen because it shows slightly better results (mostly more stable results across a variety of locations) than with the CDF-t, we enhanced the latter in ClimateVision V1.1.0. Now, to correct the precipitation the CDF-t method is combined with the Singularity Stochastic Removal (SSR) approach[x]. In addition, a security barrier has been implemented for the precipitation extremums. To limit the effects of an overestimation of extreme precipitation, sometimes introduced, by the CDF-t method, an adaptive smoothing approach for the distribution tails was implemented. It is based on the definition of a maximum precipitation threshold S, determined as follows:

$$S = \max\{\text{ERA5}\} \times \min\left(1{,}5,\ \frac{Q95(\text{GCM}_{\text{proj}})}{Q95(\text{GCM}_{\text{calib}})}\right)$$

This threshold helps to constrain the excessive amplification of extremes during the projection phase. It depends on the evolution of the 95th percentile of the GCM between the calibration and projection periods, with an upper bound set at +50% relative to observations (ERA5).

In practical terms, for each corrected time series, if the maximum corrected precipitation value M obtained from ARRM exceeds this threshold (M > S), the upper tail of the distribution is adjusted. The interval [Q95([Equation]), M] is then reprojected onto [Q95([Equation]), S], ensuring a smooth transition while preventing unrealistic extreme values.

Hence, the ARRM method has been removed from ClimateVision V1.1.0 and will not be used to correct the climate parameters available in the version.

CDF-t principle

The CDF-transformation method shares the same philosophy of quantile-quantile bias correction methods. CDF-t differs from typical quantile-quantile methods by considering the change in the large-scale CDFs between the training and the future period. These transfer functions between past and future CDFs correspond to a change in the distribution of the variable of interest over time. The CDF-t method is based on the assumption that the evolution over time of the distribution of the global scale variable is identical to the evolution of this local scale variable.

Let V be the number of variables and N be the number of time steps. X_{M_p} is the VxN matrix containing projections. $X_{M_p}^d(n)$ is the value of the model simulation for the variable d and the nth time step of the projection period. Similarly, X_{M_c} and X_{R_c} are the matrixes containing the model simulation and observation records, respectively, for the calibration period.

Let $F_{M_p}^d$, $F_{M_c}^d$ and $F_{R_c}^d$ be the univariate cumulative distribution functions of the model projections, model calibration and records calibration data for the variable d. These distributions can be estimated from the data.

The objective is to calculate $F_{R_p}^d$, the cumulative distribution of observations in the future.

	Calibration (Past reference period)	Projection (Future period)
Model (Simulated weather)	$F_{M_c}^d$	$F_{M_p}^d$
Records (Actual weather)	$F_{R_c}^d$	$F_{R_p}^d$?

Let T be the transfer function between the cumulative distribution function of the observations and projections during the reference period. For any quantile q:

$$F_{R_c}^d(q) = T\left(F_{M_c}^d(q)\right)$$

By inversing this relation, we get:

$$T(u) = F_{R_c}^d\left({F_{M_c}^d}^{-1}(u)\right) \qquad \text{for u in [0, 1]}$$

Assuming time stationarity of the transfer function, the first relation can be applied to the projection period as well:

$$F_{R_p}^d(q) = T\left(F_{M_p}^d(q)\right)$$

By combining the two previous equations, we get:

$$F_{R_p}^d(q) = F_{R_c}^d\left({F_{M_c}^d}^{-1}\left(F_{M_p}^d(q)\right)\right)$$

Once $F_{R_p}^d$ has been estimated, a simple quantile-quantile method is performed to calculate the bias corrected series $\widehat{X_{M_p}^d}$, i.e.:

$$\widehat{X_{M_p}^d}(n) = {F_{R_p}^d}^{-1}\left(F_{M_p}^d\left(X_{M_p}^d(n)\right)\right)$$

The method is applied on a month-by-month basis to avoid processing seasonal data.

Extrapolation of extreme values

Methodological approach and reference

Climatology is generally based on 30-year periods during which the climate is assumed to be stationary. As low probabilities events (typically with a return period of 10 years or more) cannot be computed empirically from a 30 years sample they must be extrapolated. Many extrapolation methods are used, and none is universally accepted in the industrial field[xi].

In this project we used a statistical method based on Extreme Value Theory[xii]. The idea of this method is to take extremes values from a weather data sample and fit the tail of the probability distribution with an appropriate extreme value distribution. More specifically, we use the block-maxima approach to select extrema and the maximum likelihood estimation to fit their distribution to a generalized extreme value (GEV) distribution.

This method is similar to the "historical method" recommended in the ISO19901, except that input data are derived from bias-corrected climate projections instead of in-situ measurements or model hindcasts. It is frequently used in climate research[xiii].

A key advantage of extreme value analysis is that it is highly flexible as it is based on the mathematical proprieties of extreme distribution and not on a knowledge of the underlying physical process. Therefore, the same method can be used to study heatwaves, cold spells, extreme rainfall, etc.
The definition of the blocks is adapted to the variable and location, e.g.: for maximum temperature the block is a calendar year (January-December) in the northern hemisphere and July-June in the southern hemisphere.

Illustration

The extrapolation is based on a sample of 30 years, either from reanalysis for current and past climate or from bias-corrected projections for future climate.

The first step is to select the extreme values from the sample using the block-maxima method: we divide the sample in blocks of similar duration (1 year) and take the highest value in each block:

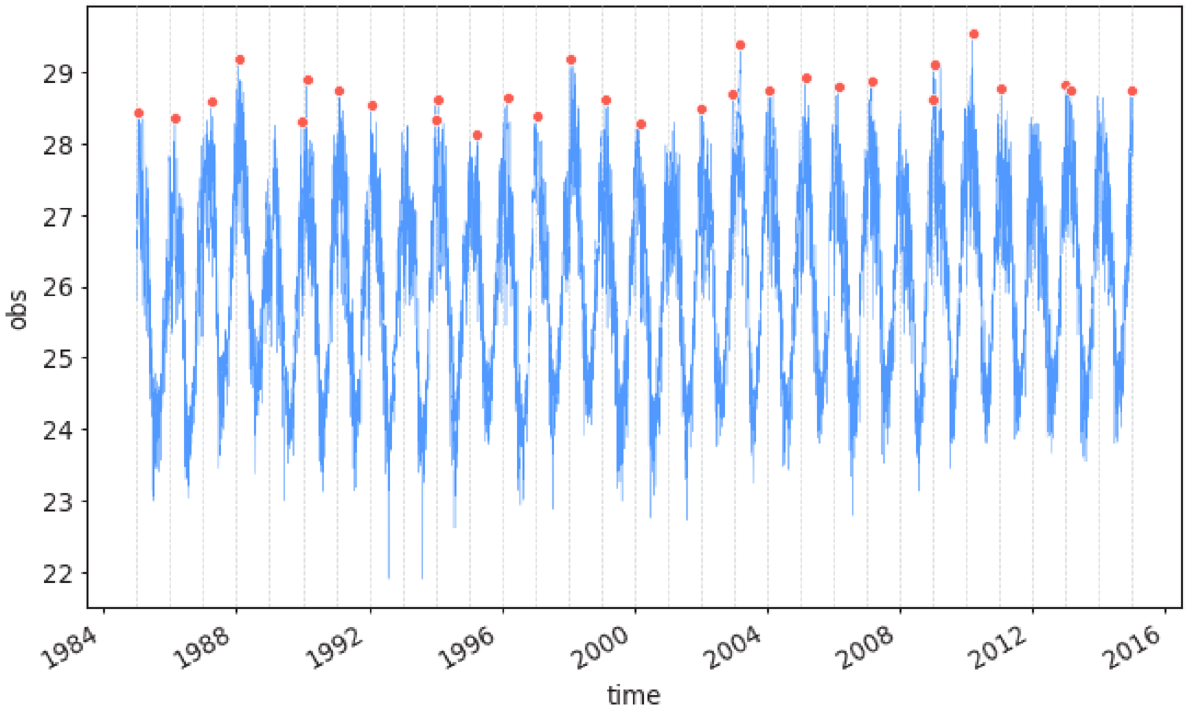


Figure 1: Extreme selection using the block maxima method

Assuming that the selected values are independent and identically distributed, the normalized distribution of block maxima must converge to a generalized extreme value (GEV) distribution:

$$f(x) = \frac{1}{\sigma}\left(1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{\xi}-1} e^{-\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{\xi}}}$$

This mathematical property is known as the Fisher-Tippett theorem. Other distributions can be used, such as the Fréchet, Gumbel or Weibull distributions, but they are in facts special cases of the more general GEV distributions. ClimateVision uses the more general form as it does not require assumptions on the physical properties of the extremes.

The trade-off is that the GEV as three parameters, μ (location), σ (scale) and ξ (shape), while other distributions may have less degree of liberty. This means that fitting our maxima to the GEV (i.e.: choosing value of the parameters that minimize the distance between the empirical and theoretical distributions) will be more complex. Various methods exist and can yield slightly different results, especially for long return periods and/or small samples[xiv,xv].

ClimateVision uses maximum likelihood method. The idea is to define the probability to get the observed data as a function of the parameters, then numerically choose the set of parameters that maximize this function. This is a flexible method, widely adopted in statistics as it can be used to adjust any theorical distribution to observed data, and it usually performs well for extreme value analysis.

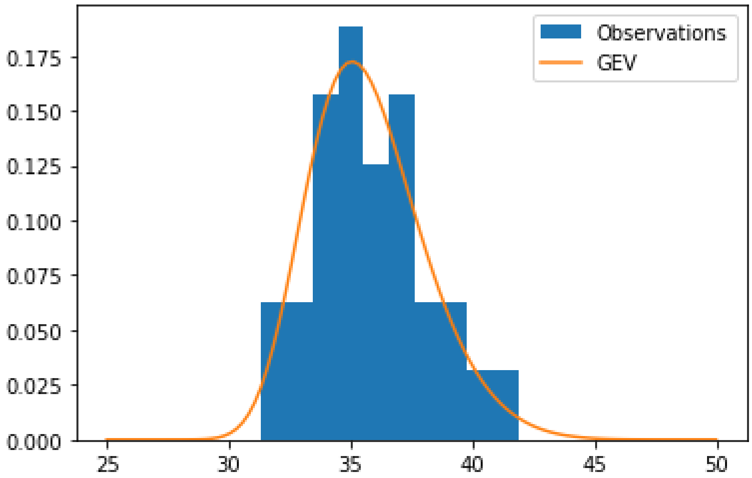


Figure 2: GEV fitted to an empirical distribution of block maxima

The cumulative density function of the fitted GEV can be interpreted as the probability that a value is not exceeded, in other words the long-term frequency of the event "the value x is exceeded" is:

$$\mathrm{f}(x) = P(X \geq x) = 1 - F(x)$$

With:

$$F(x) = \int_{-\infty}^{x} f(u)\, du$$

Conversely, the return period of a given x value is:

$$T(x) = \frac{1}{\mathrm{f}(x)} = \frac{1}{1 - F(x)}$$

This formula and the fitted GEV distribution can be used to estimate the return level associated with any specified return period:

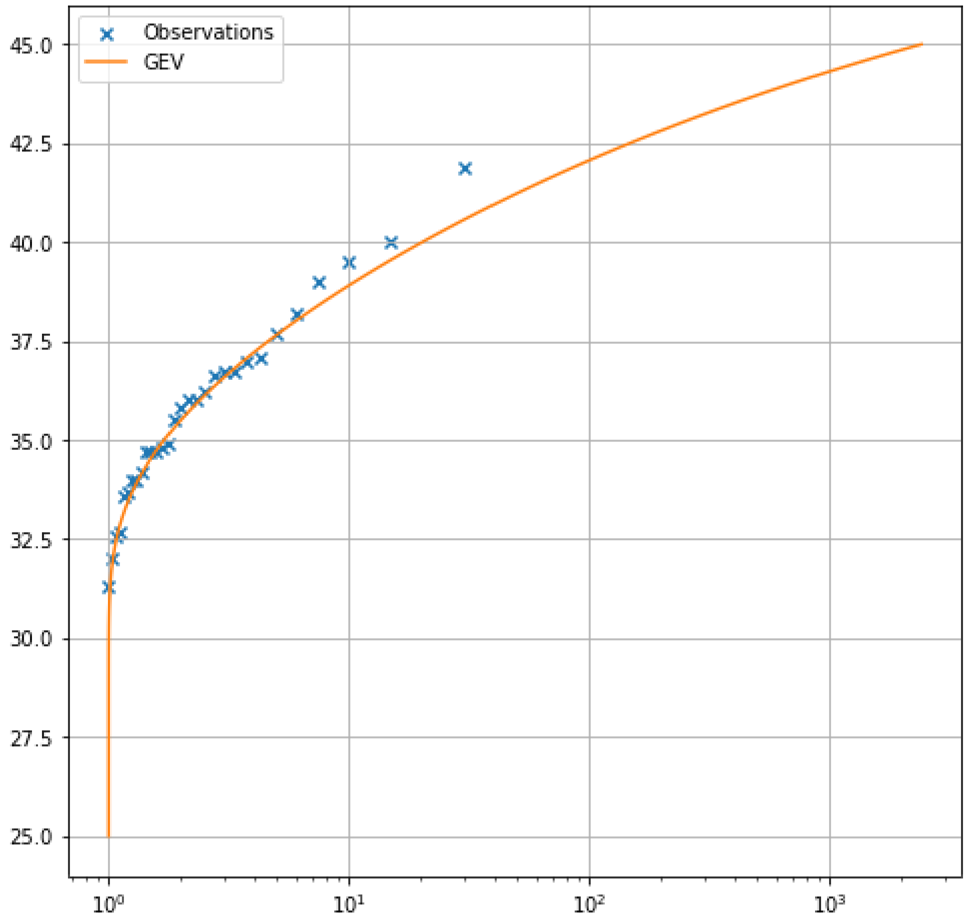


Figure 3: Theoretical and empirical return levels a function of return periods

Minima are computed using the same method simply by inversing the sample data and results:

$$Min(f) = -Max(-f)$$

Extreme wind

Context and issue

ClimateVision provides an evaluation of the local evolution of maximum wind speed over 10 minutes, 1 minute and 3 seconds throughout the 21st century.

Most climate projections are available with monthly, daily, 6-hour or 3-hour time steps. As a result, an extrapolation is necessary to calculate wind speed on a time step of a few minutes to a few seconds from much coarser data. The maximum wind speed for a given return time is then calculated from the downscaled data using the extreme value analysis methods detailed in the previous chapter.

In addition, these projections are typically for sustained wind speeds and do not consider short term phenomena, like gusts. Extreme gusts occur due to a variety of short-lived phenomena that climate models are not designed to capture[xvi]. The ratio of maximum gust wind speed to mean wind speed can be large[xvii].

Extrapolation methodology

Industrial standards, both ISO[xviii] and API[xix], provide a method for estimating the wind speed from measurements taken at different heights and/or time steps.

Knowing the wind speed at height z_r and time step t_0, first the mean wind speed for the same time step t_0 at a different height z is evaluated with the following formula:

$$U(z) = U(z_r)\left(1 + 0.0573\sqrt{1 + 0.15U(z_r)}\ln\left(\frac{z}{z_r}\right)\right)$$

Then the wind speed corresponding to an average wind period $t \leq t_0$ is given by:

$$U(z,t) = U(z)\left(1 - 0.41 I_n(z)\ln\left(\frac{t}{t_0}\right)\right)$$

Where I_n is the turbulence intensity at level z given by:

$$I_n(z) = 0.06\big(1 + 0.043U(z_r)\big)\left(\frac{z}{z_r}\right)^{-0.22}$$

Projections used

To improve the quality of the results, the evaluation of extreme winds is based on projections with a daily step. The projections used are the daily maximum wind speeds, corrected to the daily maximum wind speeds from the ERA5/ERA5-Land reanalysis. The instantaneous projections of maximum wind speeds are, after correction, homogeneous with hourly wind speeds.

The subset of models employed is consistent with that used for the other climate parameters.

Sea level rise

Sea level projections are from the IPCC AR6 Assessment Report[xx] retrieved from NASA's Physical Oceanography Distributed Active Archive Center.

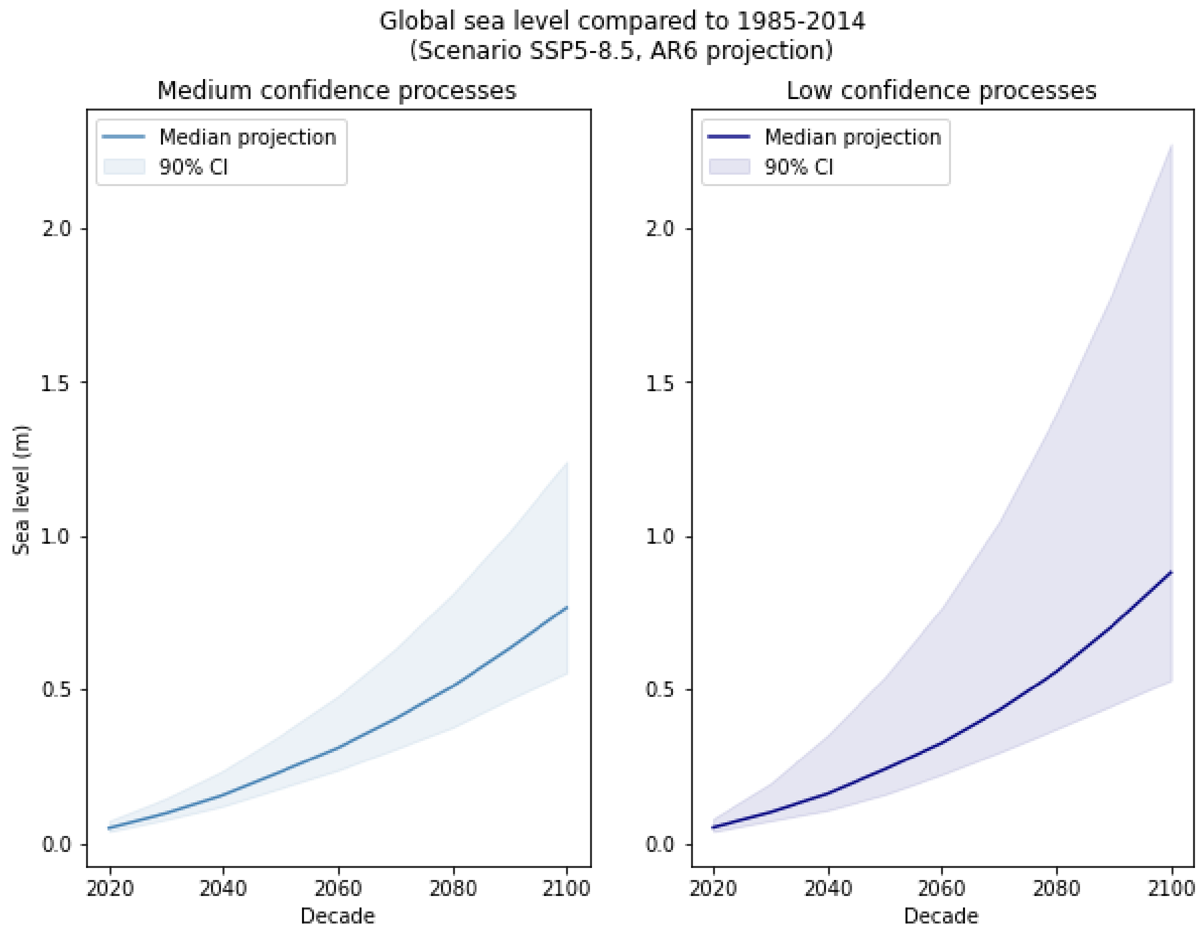
Medium and low confidence projections

The AR6 features two sets of projections for sea level:

- "Medium confidence" projections include only processes that can be projected skillfully with at least medium confidence,
- "Low confidence" projections consider processes whose quantification is highly uncertain regarding the timing of their possible onset and/or their potential to accelerate sea level rise.

The differences between the two projections lie primarily in the methodology used to assess the contribution of the Antarctic and Greenland ice sheets to sea level rise.

Both projections are usually similar on the short term, but low confidence projections tend to be higher starting from the second half of the 21st century:



For example, by 2100 in a high emission scenario (SSP5-8.5) the median projection for global sea level rise compared to 1985-2014 level is 0.766 meters in the medium confidence projection and 0.88 m in the low confidence projection.
Uncertainties are also significantly higher: under the same assumptions, the upper bound of the 90% confidence interval is 1.242 m in the medium confidence projection but 2.274 m in the low confidence projection.

The most appropriate projection depends on the lifespan of the project, on its ability to adapt to a faster-than-expected sea level rise, and on the level of risk that is deemed acceptable.
According to the IPCC[xxi,xxii], stakeholders that are risk tolerant (e.g., those planning for investments that can be easily adapted to unforeseen conditions) may prefer to use projections in the medium confidence range while those with a low risk tolerance (e.g., those planning for long-term investment in critical infrastructure) may wish to consider sea level rise that falls within the high-end scenario.

Since both cases can occur, ClimateVision provides projections from the two sets.

Methodology

The original dataset contains sea level projections relative to 1985-2014 level on a 1x1 degree global grid and on 1016 tide gauge locations.

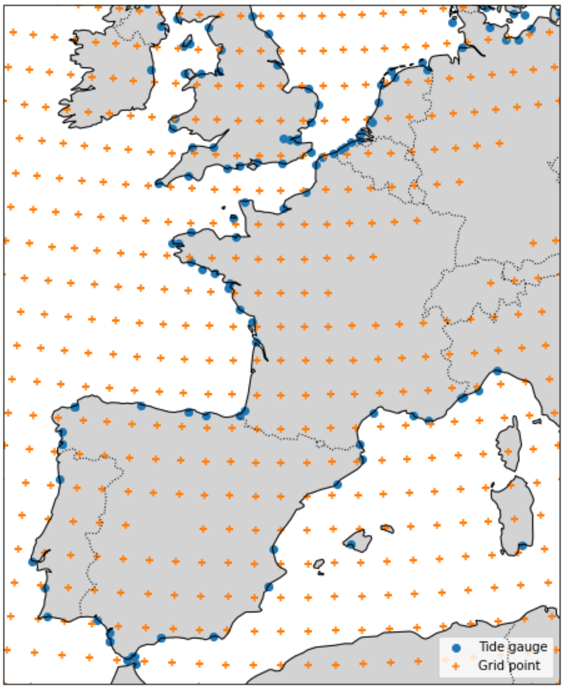


Figure 4: Data points available for west Europe

The results reported correspond to the closest data point to the location of interest.

To remain consistent with the other indicators in the report, the median projection and 90% confidence interval are presented between 2020 and 2080.

Waves

Context and issue

ClimateVision provides an estimate the local evolution of wind waves with climate change, including their period, the significant wave height and the maximum wave height.

The significant wave height (H_s) is a statistical measure of the height of waves during a given period of time. It was originally defined as the average height of the highest one-third of waves. Currently, significant wave height is often taken as 4 times the standard deviation of the water surface elevation series, typically over a period of approximately 30 min[xxiii,xxiv].

The maximum wave height (H_{max}) is the maximum height of an individual wave for a given return period.

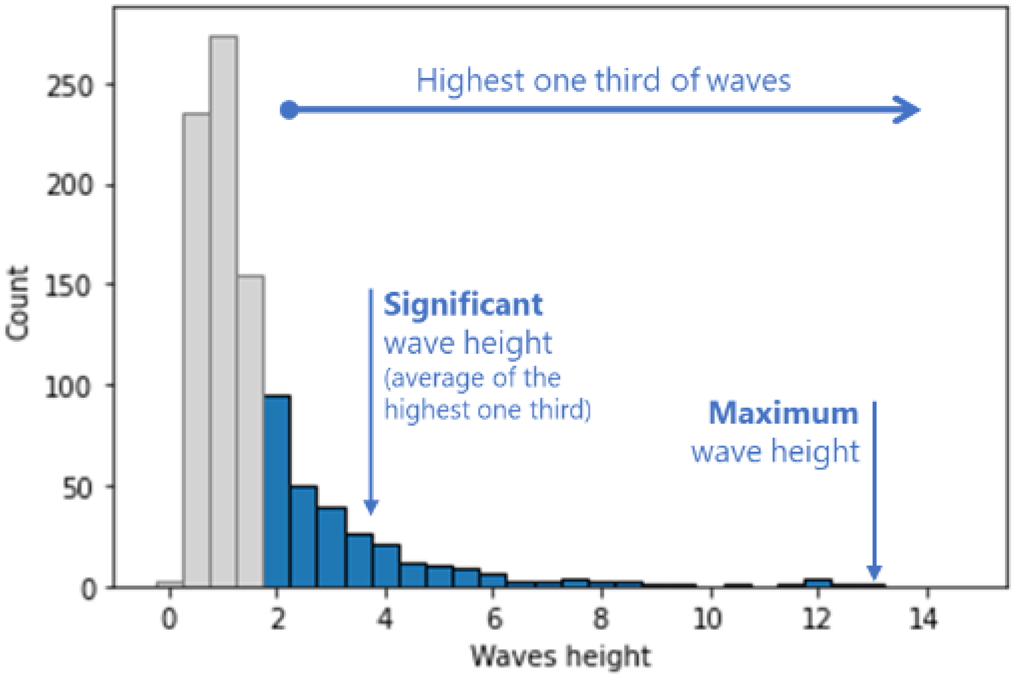


Figure 5: Significant and maximum wave height for a sample of 1000 waves generated using the Pierson-Moskowitz spectrum

The wave period can be evaluated in different ways. The most common definitions are:

- Spectrum peak period (T_p) : the period corresponding to the peak of the spectrum[xxv],
- Mean wave period (T_{m01}): the wave period corresponding to the mean frequency of the spectrum[xxvi],

- Mean zero crossing wave period (T_{m02}): the time obtained by dividing the record length by the number of down crossings (or up crossings) in the record[xxvii,xxviii],

Other existing definitions include the significant wave period (approximately equal to the spectrum peak period) and the wave energy period (corresponding to the weighted average of the wave energy).

Wave characteristics are largely dependent on atmospheric parameters and evolve with climate change. For example, the IPCC's AR6 reports an increase in wave heights of order 0.5 cm per year, most pronounced in the Southern Ocean. But this trend is affected by significant uncertainties and rated only "medium confidence"[xxix].

While they evolve with climate change, waves are not among the variables simulated by global circulation models. In particular, they are not included in the variables reported in the CMIP5 and 6 projects. The study of the wave evolution in the future typically requires an additional simulation stage to compute heights, periods and directions from climate model outputs, such as wind projections.

Data and methodologies available

Wave projections are available from several sources, for example: COWCLIP[1], CSIRO[2] or Copernicus[3]. These projections have been used in many studies to quantify the impact of climate change on sea state, including studies of extreme waves [xxx] . Such publications regularly highlight significant uncertainties[xxxi], often greater than the projected evolution[xxxii].

Wave projections using the new climate models and emission scenarios from the 6th IPCC report are less common and do not yet seem to have been consolidated at the international level.

ClimateVision provides local waves data extracted from the first CMIP6 projections available and acquired directly through their producers:

- The Australian CSIRO [xxxiii] recently published global wind-wave projections[4] for a small subset of 2 scenarios (SSP1-2.6 and SSP5-85) and 8 models. The spatial resolution of this set of projections is 0.5° with a 3-hour time step. Projections are available for only one value of

[1] https://catalogue.aodn.org.au/geonetwork/srv/eng/catalog.search#/metadata/1de0e8b1-4777-4526-b3d7-805938b8e6bc?uuid=1de0e8b1-4777-4526-b3d7-805938b8e6bc
[2] https://data.csiro.au/collection/csiro:13500v2
[3] https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-ocean-wave-timeseries
[4] https://data.csiro.au/collection/csiro:53176

the wind-drag coefficient (CDFAC): 1[5]. The projections used in this report are based on a coefficient of 1.

A frequent review of publications is carried out in order to progressively integrate other projections based on the CMIP6 models and scenarios once they are published.

Evaluation of the maximum wave height

In addition to the significant wave height derived from models' outputs, the maximum wave height is evaluated using the Rayleigh distribution[xxxiv].

Assuming that the elevation of sea surface has a gaussian distribution, the maximum values of the elevation (i.e.: the maximum wave height) should follow a Rayleigh distribution. In that case the probability that waves reach a height H is:

$$Q(H) = e^{-2\left(\frac{H}{H_s}\right)^2}$$

Where H_s is the significant wave height.

As a result, the wave height associated with the probability Q is:

$$H = H_s\sqrt{-\frac{1}{2}\ln Q}$$

For instance, the value of the last centile of wave height is:

$$H = H_s\sqrt{-\frac{1}{2}\ln(0.01)} \approx 1.52H_s$$

A simplified version of this formula is frequently used for off-shore structure calculation:

$$H = 1.86H_s$$

This formula matches to the Rayleigh distribution with an exceedance probability of 0.1%.

Evaluation of the spectrum peak period associated with extreme wave height

[5] The wind-drag coefficient is a dimensionless value quantifying the aerodynamic friction between air and sea.

As the extremes of significant wave heights are calculated from a statistical model, waves of this height do not necessarily exist in observations or projections. As a result, the period associated with these extremes must be estimated theoretically.

The wave period associated with significant wave height extremes is calculated using the following formula:

$$T_p = a + b\sqrt{H_s}$$

Where H_s is the significant wave height and coefficients a and b are adjusted using the observed extremes.

However, the fit can sometimes be considered inconclusive with a low the coefficient of determination (R^2 close to 0). In such cases, the approach based on Goda's formula[xxxv] has been used to calculate the peak wave period, but shows no improvement compared to a poor fit on the local data.

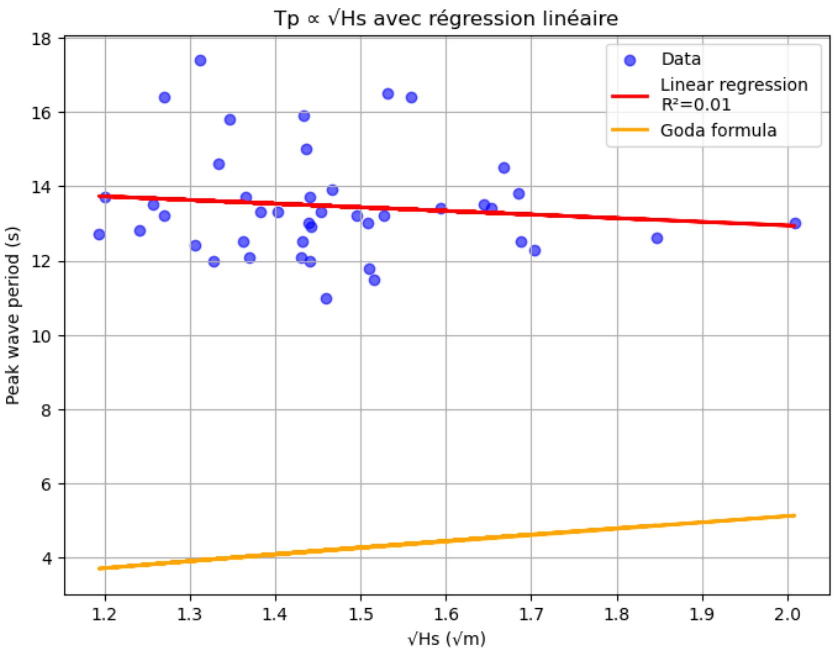


Figure 6 : Peak wave period expressed with the square root of yearly maximum significant wave height. In red the adjusted formula with a poor fit, and in orang the Goda formula.

A more detailed investigation will be conducted in future versions.

Appendix A: legal notices

ERA5/ERA5 Land

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