1. Introduction

Climate change is putting global energy security at risk globally. Weather, water, and climate services are vital for the global energy transition to achieve net-zero. And downscaling techniques would be crucial in this regard.

Climate change poses a significant threat to global energy security, as extreme weather events and changes in precipitation patterns disrupt energy systems around the world. In order to achieve a successful transition to net-zero emissions, it is essential that we have access to accurate weather, water, and climate services. These services can help us anticipate and prepare for potential disruptions, as well as identify opportunities for renewable energy production. However, in order for these services to be effective at the local level, we also need downscaling techniques that can provide detailed information about conditions on the ground.

These essential climate variables (ECVs) are expected important for climate service:

- Wind speed (m/s)
- Solar radiation (W/m^2)
- Precipitation (mm)
- Temperature (°C)
- TMax (°C)
- TMin (°C)
- Sea level pressure (hPa)

This study will start with wind speed.

1.1. Challenges: spatial variability and representatives

The wind speed is a spatial-scale-dependent value (Figure 1.1 and 1.2). As wind turbines are deployed at favorable sites, such as top 10% windiest (Q10) area, it is important to be able to capture the distribution of wind power density due to terrain features, and this is only possible by consideration of high resolution dataset (Badger et al., 2015).

1.2. Challenges: temporal variability

In the assessment of wind power capacity, it is a widely accepted practice to rely on 10-year mean values, as did by the Global Wind Atlas. However, it is imperative to take into account extreme low or high values. For instance, the wind drought event observed in the United States (as shown in Figure) highlights how actual wind speeds can fall below historical levels by up to 90%. Similarly, wind speeds

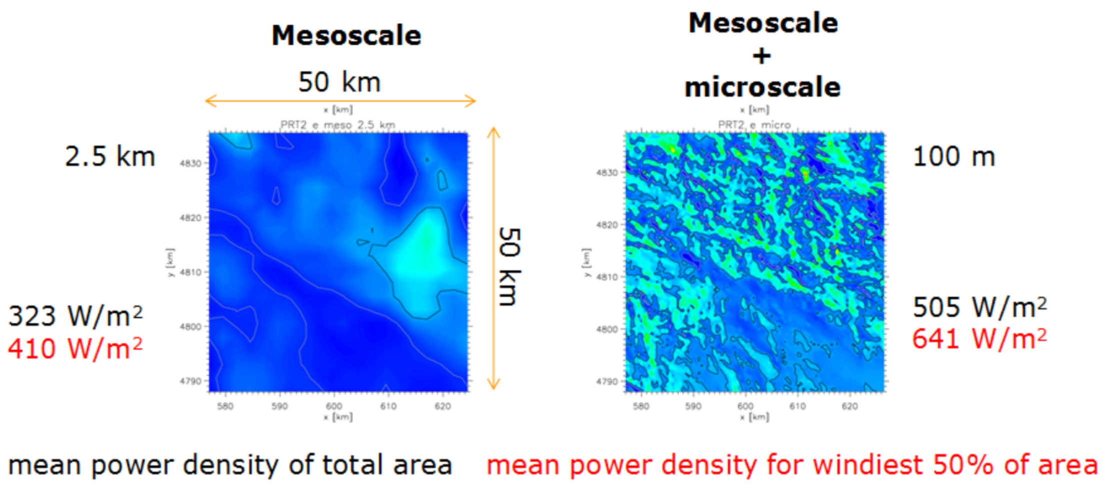

Figure 1.1 – Wind power density calculated at 50 m above the surface for a 50 km x 50 km area at two different resolutions, (left) 2.5 km and (right) 100 m. The colour scale used in each map is the same. Dark blue is low values and bright green and yellow are high values. The mean power density for the area is given in black. The mean power density for the windiest 50% area is given in red.

Figure 1: image.png

exceeding 20 m/s can result in wind farm closures due to safety concerns. It is worth noting that wind speed variability is not only dependent on spatial scale but also on time intervals. The instantaneous wind speed displays much higher variability than daily means. Therefore, for energy system modeling purposes, hourly inputs such as those obtained from climate reanalysis would be ideal for characterization of the variability on time-scales from hours to months (season and daily included).

2. Dataset

2.1. Global Wind Atlas

Wind Atlas provide tailored, long-term mean wind energy information at a high spatial resolution. The Global Wind Atlas (GWA) provided by the Technical University of Denmark (DTU) used WAsP module spatially downscale the reanalysis data into a resolution of 250 m, by taking account the orography, roughness and roughness change characteristics. The current version, GWA 3.0, was derived from the ERA5 reanalysis and provides mean wind speeds and mean power densities at five different heights (10, 50, 100, 150 and 200 m), as well as mean capacity factors for three different turbine classes according to the International Electrotechnical Commission (IEC) for the period 2008 to 2017.

GWA is mean value for static analysis, does not provide the extreme value.

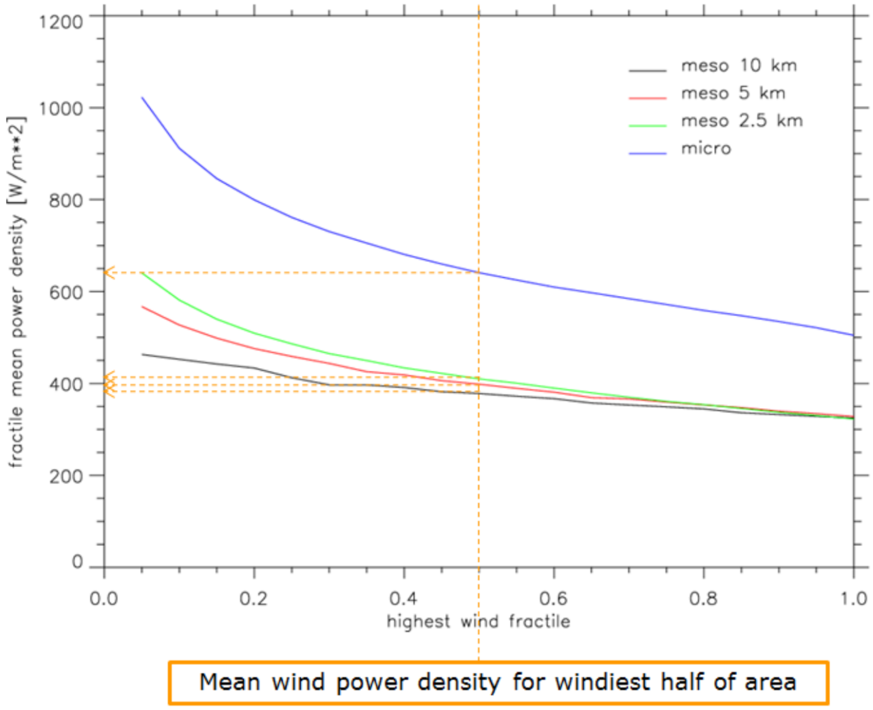

Figure 1.2 – Graph showing the mean wind power density (y-axis) for the windiest fractile area (x-axis) of the 50 km x 50 km area in Fig. 1.1, calculated from modelling using different resolutions, namely, 10, 5, 2.5, and 0.1 km. A guiding line is drawn at fractile 0.5, which gives power density values corresponding to those in Fig. 1.1. Note that when modelled at high resolution we see that the windiest areas are significantly windier than the average for the whole area.

Figure 2: image.png

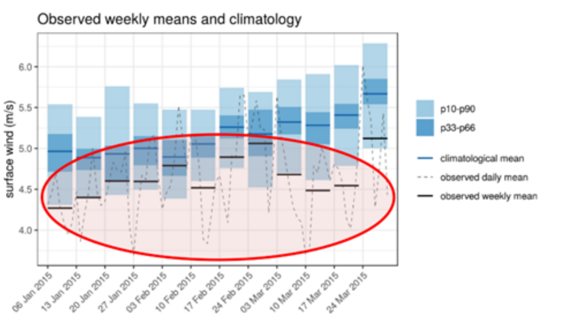

Figure 16: Observed weekly means and climatology, surface wind, USA, January to March 2015

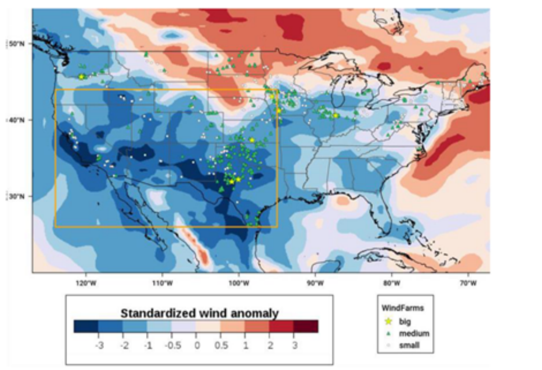

Figure 17: Wind speed anomalies reflecting the wind drought over the United States for the first trimester of 2015. The US wind farm fleet is also shown.

Figure 3: image.png

2.2. Climate Reanalysis

McKenna et al. (2022) has a good review on using climate reanalysis in onshore wind power assessment

Reanalyses combine a numerical weather prediction model of the atmosphere with observations using a technique called data assimilation. They provide meteorological data on a global regular grid, with information considered representative for the entire grid cell. This differs from observational data which provides point-based information.

Over flat terrain in Northern Germany and the Netherlands, global reanalysis results are relatively well correlated to measured date. Temporal variability in general is underrepresented in reanalysis , which is confirmed by Cannon et al. particularly for individual locations. Ramon et al. find important discrepancies with regard to interannual variability and decadal trends in satellite-era reanalysis, yet report that ERA5 agrees reasonably well with tall tower measurements, except in areas of complex terrain where the subgrid orographic drag artificially lowers the simulated wind speeds.

2.3. Climate Modes

While reanalyses and observations are only available in hindsight, climate model projections can be used to investigate impacts of future climate change on wind power generation. Climate model simulations are fundamentally different from reanalyses and observations giving rise to different sources of uncertainty. Large ensembles of climate model simulations are available from the Climate Model Intercomparison Project (CMIP) and downscaled projections are available from the Coordinated Downscaling experiment (CORDEX) initiative. These datasets have been used in different assessments related to future wind energy potentials.

3. Method

3.1. Downscaling

Downscaling is a transfer function that translate coarse resolution climate data into higher resolution climate data. **Statistical downscaling** (SD) involves “training” a model on the statistical relationship between a GCM and an observational dataset over a historical period, and then applying that model to generate future predictions.

The statistical downscaling approach assumes that there exists a stationary empirical relationship between large-scale and local observations, which is commonly referred to as “perfect prognosis (PP)” by climatologists. The downscaling can be applied not only to climate reanalysis but also to model-based atmospheric variables, referred to model output statistics (MOS). MOS focuses on downscaling model-based predictors that are often biased from historical observations with additional post-processing called bias correction. Hence, this approach is known as bias correction statistical downscaling (BCSD)(Maraun & Widmann, 2018).

IPCC AR6 has reviewed these different methods in Chapter 10.3.3.1, 10.3.3.7 (Doblas-Reyes et al., 2021, p. 10).

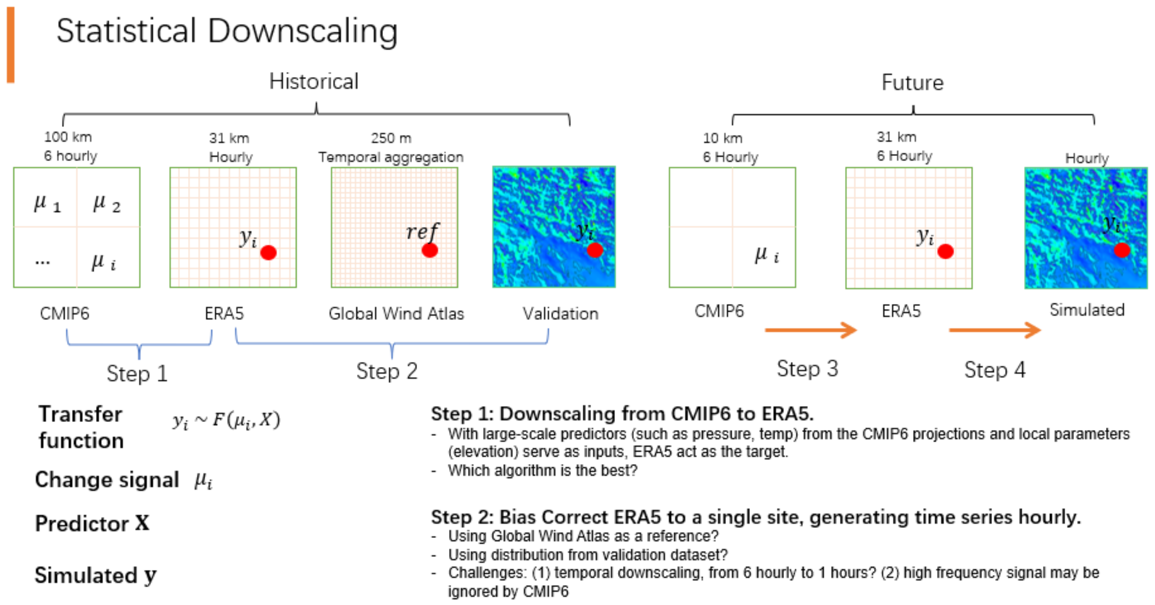

Figure 4: image.png

In this transfer function, the μ is the change signal, and predictor X contribute the subgrid variability, which could be large-scale predictor from GCM and local parameters such as elevation, terrain roughness (may need).

> **!** Assumptions of statistical downscaling: - Stationary assumptions. The transfer function can be used in the past, and in the future. - Explainable predictors. The results can only describe the variability that can be explained by predictors.

3.2. Bias correction, or bias adjustment

Quantile mapping (QM) is a bias correction algorithms are commonly used to correct systematic distributional biases in precipitation outputs from climate models. QM correct the dataset to reference distribution, change the values but keep the ranking of original dataset. For example, if there is a nice teacher, give all students points from 90 to 100, instead of 0 to 100. The grades will follow the different distribution to historical statistics. Applying quantile mapping can reverse it to fit the historical distribution but the ranking order remains.

This technique enables us to calibrate simulated results using observations, even if the downscaling/-model output only provides ranking information. Bias correction does not upscale spatial resolution; instead, it is used for single site time series data (Tobin et al., 2015). They obtain values from larger-scale datasets and fit them to empirical distributions from observations through quantile mapping. I would not call it "downscaling," but rather "bias correction."

Some ideas we talked:

(1) Scaling method (or delta method)

Using the scaling (or ratio) of mean value ERA5 and Global Wind Atlas to 'bias correct' ERA5 data (Gruber et al., 2022; Murcia et al., 2022).

> The delta method assumes a stationary delta. It works for e.g. 10-years mean of ERA5. But the hourly data has totally different variability..

(2) Quantile mapping

Acquire the distribution from wind park observation time series and match ERA5 time series to this distribution. In the future scenario, using the same distribution to correct ERA5 time series.

> Assumption of Quantile mapping: - Each 'distribution' works for a single site. - The bias ('target distribution') may not be true in the future. - Although effective at removing biases relative to observations, it has been found that quantile mapping can artificially corrupt future model-projected trends (Doblas-Reyes et al., 2021, p. 10 Chapter box 10.2).

The possible implement and questions :

- Get timeseries from ERA5

- Get timeseries from observations
- Bias correct ERA5 to observation by QM (QM describing the bias by quantiles, but the key is bias may be different in various conditions. For example, winter? summer? flow direction?)
- How to used combine the information from GWA?
- Need more discussion on this step.

3.3. Temporal disaggregation

There are some examples (Fiddes et al., 2022; Tobin et al., 2015)

3.4. Wind speed to wind power

Wind energy density (WED)

$$WED = \frac{1}{2}.\rho.U^3$$

where U is the near-surface wind speed and ρ the air density taken equal to 1.2 kg.m−3.

Extractable wind power (EWP)

$$U_H = U_S \cdot \left(\frac{H}{10}\right)^{\frac{1}{7}}$$

where U H is the wind speed at the turbine hub height H and U S is the wind speed at 10 m.

4. References

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A. Appendix

A.1. S2S4E

DST | S2S4E (bsc.es)

A.1.1. Dataset

Sub-seasonal forecasts are downloaded every week and seasonal forecasts are downloaded every month. From these forecasts, the different products of the essential climate variables and derived energy indicators are computed. The data acquisition procedure is done according to the origin and type of the data retrieved, as are detailed below.

dataset	resolution
ERA5 Reanalysis (ERA5)	31 km, hourly
Seasonal forecast (SEAS5)	0.25°, 6 hourly
Sub-seasonal Forecast (ECMWF-Ext-ENS)	0.25°, 6 hourly

A.1.2. Bias correction

The climate predictions of the ECV included in the DST have been bias-adjusted with the variance inflation method (or calibration) and the reference dataset is the ERA5 reanalysis. The variance inflation method produces predictions that will have interannual variance that is equivalent to that of the reference dataset. The method is described in Doblas-Reyes et al. (2005), and has been tested against a simple bias correction for the case of wind speed in Torralba et al. (2017) and with five more methods for temperature and precipitation in Manzanas et al. (2019). The main advantage of this method is the inflation of the ensemble spread, which ensures that predictions have reliable probabilities.

The bias adjustment parameters are determined by comparing the past forecasts with the same observational reference that is used for verification (ERA5 reanalysis in this case). The bias adjustment has been applied in cross-validation. Cross-validation adjusts a forecast for a particular year without using the information corresponding to that specific year. For example, when bias-adjusting a collection of 20 hindcasts runs (e.g. 2000-2019), the parameters used to calibrate a single year (e.g. 2005) are extracted from the other 19 years. This procedure is useful to emulate as closely as possible real-time forecast situations in which the observational reference is not available. The real-time forecast is calibrated with the full available hindcast period. The calibrated hindcasts are used to evaluate the skill of the forecast products.

A.1.3. Energy indicators

Tailored energy-relevant climate information is provided through energy indicators derived from the ECVs listed in the table above. These indicators provide robust information on the future variability in wind, solar and hydropower energy generation, as well as electricity demand, both at grid point level, and country or basin scale.

A.1.3.1. Wind and solar energy generation Capacity factor (CF) is a widespread indicator in the energy sector that allows fair comparisons between plants of different sizes. It is a typical way of assessing the relative performance or usage of any power-generating plant. For a given period of time, it is calculated by dividing the produced generation by the maximum production that would be achieved if the plant was operating at full capacity during all the time. The generation in wind and solar plants depends almost exclusively on meteorological factors such as wind (wind energy) or solar radiation (solar energy).

Wind CFs: Three capacity factors are computed for three turbine types (IEC 1, 2 and 3) suitable for high, medium and low mean wind speed conditions, respectively, as defined in the IEC-61400-1 standard. **The wind CF is derived from 6-hourly surface winds, extrapolated at 100m and employing power curves that relate wind speed at hub height to power output**. These CF estimates do not consider any kind of losses (electrical, curtailments, maintenance, etc.) that any wind farm experiences. See complete details in Lledó et al. (2019) .

Solar CF: This factor is computed as the ratio of actual power to power under standard conditions (i.e. an incoming surface radiation of 1000 W/m² and a temperature of 25°C). In practice, this is computed as the incoming surface radiation divided by 1000 and multiplied by an efficiency coefficient, which represents the panel efficiency. The efficiency varies with the panel cell temperature, which is estimated based on the 2m temperature and incoming radiation (Jerez et al., 2015; Bett and Thornton, 2016).

A.1.3.2. Hydropower indicators Hydropower generation relies on water availability and river inflows to produce electricity. This depends largely on precipitation, but also on evaporation, runoff and snowpack. Therefore a whole hydrological model is used for understanding large-scale changes in river basin water resources. The service is based on the E-HYPE model (Donnelly et al., 2016; Hundecha et al., 2016).

Inflow anomaly: This indicates anomalous inflows in relation to a reference period. This information is of particular interest in basins where other characteristics are favourable for hydropower, such as high inflow, large elevation differences and good storage capacity.

Snow max anomaly: This reflects the maximum amount of water stored as snow. It is a measure of the natural storage and the temporal redistribution of precipitation and inflow. A change in the snow storage may affect the need for storage capacity in reservoirs.

A.1.3.3. Electricity consumption Electricity demand or load is the amount of electrical power needed in a transmission or distribution grid to meet the consumption from all sectors (industrial, residential, etc.). Electricity demand can be affected by several factors, such as economic growth, the price of energy or energy efficiency measures. Climatic variables can also influence the demand. In fact, the use of cooling and heating equipment is directly related to temperature and other variables that influence how we perceive temperature (e.g. wind speed). The daily-mean demand for each european country is estimated using a multiple linear regression model that relies on both weather-dependent and non-weather dependent terms (Bloomfield et al., 2020). First, a long-term trend allows for the representation of changes due to energy efficiency improvements, changes in GDP or changes in embedded renewable generation. A dummy weekday term allows to differentiate different loads throughout the week. Then, the heating degree (HD) and cooling degree (CD) terms represent the demand for either heating or cooling needs, respectively. HD is computed as the sum of all negative temperature departures from 15.5°C, while CD is the sum of all positive departures from 22°C.

A.2. Solargis

Solar radiation takes a long journey until it reaches Earth's surface. So when modelling solar radiation, various interactions of extra-terrestrial solar radiation with the Earth's atmosphere, surface and objects are to be taken into account.

The component that is neither reflected nor scattered, and which directly reaches the surface, is called direct radiation; this is the component that produces shadows. The component that is scattered by the atmosphere, and which reaches the ground is called diffuse radiation. The small part of the radiation reflected by the surface and reaching an inclined plane is called the reflected radiation. These three components together create global radiation.

In solar energy applications, the following parameters are commonly used in practice: - Direct Normal Irradiation/Irradiance (DNI) is the component that is involved in thermal (concentrating solar power, CSP) and photovoltaic concentration technology (concentrated photovoltaic, CPV). - Global Horizontal Irradiation/Irradiance (GHI) is the sum of direct and diffuse radiation received on a horizontal plane. GHI is a reference radiation for the comparison of climatic zones; it is also essential parameter for calculation of radiation on a tilted plane. - Global Tilted Irradiation/Irradiance (GTI), or total radiation received on a surface with defined tilt and azimuth, fixed or sun-tracking. This is the sum of the scattered radiation, direct and reflected. It is a reference for photovoltaic (PV) applications, and can be occasionally affected by shadow.

A.2.1. Satellite-based models

State-of-art solar irradiance models as Solargis make use of the most modern input data (satellite and atmospheric), which are systematically quality-controlled and validated. Models and input data are integrated and regionally adapted to perform reliably at a wide range of geographical conditions.

This process is based on sound theoretical grounds and shows consistent and computationally stable results. Old approaches are typically less elaborated, thus cannot reach the accuracy of the modern models. Even if the models are based on similar principles, differences in implementation may result in different outputs.

Satellite-based irradiance models are able to estimate the solar radiation levels (historic, recent and future levels) without the need of installing ground sensors at the location of interest. Satellite-based irradiance models range from physically rigorous to purely empirical:

- Physical models attempt to explain observed earth's radiance by solving radiative-transfer equations. These models require precise information on the composition of the atmosphere and also depend on accurate calibration from the satellite sensors.

- Empirical models consist of a simple regression between the satellite visible channel's recorded intensity and a measuring station at the earth's surface.
- Semi-empirical models use a simple radiative-transfer approach and some degree of fitting to observations. Today, all operational approaches are based on the use of this.