Master Thesis

**How to Distribute New Solar Systems in Europe to Reduce Power Generation Variability**

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Summary

* Still from proposal

To reduce greenhouse gas emissions and combat climate change, the electrical power production sector is facing a fundamental transition from conventional fossil to renewable technologies. The transition has already started, which can be seen by the great effort and ambitious targets of many nations around the globe. Installed power production capacities of solar photovoltaics (PV) are increasing every year and are already capable of producing around 5.5% of the Europeans electricity demand. Since PV power output depends on weather and climate, it exhibits a highly variable production pattern. This variability challenges the electricity grids because the stability of the grids depends on balanced supply and demand. Further massive deployment of PV systems could lead to an increase of the variability and therefore add to this challenge. Different studies suggest strategies to reduce the PV power output variability on rather short (minutes to hours) or long (seasonal) timescales. However, weather regimes lasting several days influence the PV power output across Europe as well, and knowledge of its impact on multiday PV power output variability is still limited. In this thesis, we aim to identify spatial distributions of newly installed PV systems that minimize the multiday power output variability within Europe. To quantify the variability, we will perform empirical orthogonal function (EOF) analyses of solar downward radiation, which influences the PV power output directly, and geopotential height at 500hPa which reflects weather regimes and therefore has an indirect effect on the PV power output. Both fields will be taken from the ERA5 reanalysis dataset which covers the time period from 1979 to present. The resulting subspace spanned by the leading EOFs of our analysis will be grouped in different weather regimes with the k-mean clustering techniques. To assess the PV power output variability the resulting regimes will be related to country/region specific PV capacity factors, which are defined as the quotient of actual power output and installed PV capacities. We will use hourly PV capacity factors provided by the simulation of renewable.ninja from 1985-2019. Connecting the regimes with the PV capacity factors will lead to an overview of under- and overproduction (relative to the mean) per country/region and weather regime. The current installed capacity of PV systems in Europe will then be used together with our findings to assess the current multiday PV power output variability in Europe. Furthermore, an optimal distribution of additional PV systems will be proposed with the goal to minimize the multiday variability.

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# Introduction

* STILL FROM PROPOSAL

Many governments undertake ambitious climate mitigation efforts to reduce the adverse effect of global warming and thereby try to meet the 1.5°C goal from the Paris agreement (Hulme, 2016). To achieve this goal a transition from conventional fossil to renewable energy technologies is substantial. Solar power generating photovoltaic (PV) systems, as one of the major renewable technologies, has seen a tremendous growth in recent years. According to the PV status report (2019) by the European commission, there was a global installed capacity of 520GW by the end of 2018. By the end of 2019 the installed capacity is expected to reach 650GW, which allows the PV systems to produce roughly 4% of the global electricity demand. Europe's share of installed PV capacity at the end of 2018 was about 117GW, which allowed to produce 5.5% of Europeans electricity demand. Furthermore, recent scenarios for the necessary installed PV capacity if the world is to reach 100 % renewable electricity production in 2050, suggest that the PV installed capacity must rise to more than 4TW by 2025 and 21.9TW by 2050. For Europe this would imply an PV installed capacity of 630GW by 2025 and 1.94TW by 2050 (Jäger-Waldau, 2019).

PV power output depends on weather and climate and therefore challenges the current power grid by variable power input (Graabak and Korpås, 2016; Stram, 2016). Within minutes, the power production from a PV system can vary by as much as 80% due to passing broken cloud cover (Mills and Wiser, 2010). There is also a diurnal cycle with highest power production during the day and no production during night. By analysing multiday fluctuation, a relation between long lasting weather regimes and PV power production can be observed. During one weather regime the PV production pattern varies substantially to the next weather regime (Grams *et al.*, 2017). Furthermore, variability in the PV power production is caused by the seasonal cycle (Heide *et al.*, 2010). The efficiency of a PV panel is mainly dominated by the available surface solar radiation and the panel temperature (Huld *et al.*, 2010). Since the seasonal cycle affects both, a direct effect can be observed. Even decadal to multidecadal analyses suggest that global warming and solar brightening/dimming influences the PV power output. Solar brightening/dimming is often caused by air pollution patterns, which influences the available surface solar radiation and therefore affects the PV power output. Global warming leads to an increase of panel temperatures and reduces the efficiency of the panels (Wild *et al.*, 2015; Sweerts *et al.*, 2019).

A stable power grid depends on balanced electrical supply and demand (Stram, 2016). Short time scale variability due to passing broken cloud cover can affect one PV system substantially. But wider geographical distribution of multiple interconnected PV systems can significantly smooth this short time PV power output variability (Delucchi and Jacobson, 2011; Graabak and Korpås, 2016). Co-deployment of renewable energy system (water, wind and solar) can counteract the variable power output caused by diurnal and seasonal cycles. The basis for these approaches is the different diurnal and seasonal production pattern of water, wind and solar power plants. For example, wind power output exhibits highest production rates during winter whereas solar power production is highest in summer. Co-deployment of wind and solar can therefore reduce the seasonal power production variability. Other combination are possible as well (Heide *et al.*, 2010; Santos-Alamillos *et al.*, 2015; Graabak and Korpås, 2016). To summarize, different studies already have proposed methods to reduce short, diurnal or seasonal solar power production variability.

Fewer studies have investigated in reduction of multiday solar power output variability from a meteorological standpoint. Grams *et al.* (2017) did but rejected the idea to further invest in it, based on their findings that it would need a tenfold increase of installed PV capacity in Europe to be comparable to the variability of wind power output. Therefore, they focused their study on wind and concluded, that spatial deployment of wind fleets based on information of different weather regimes can reduce the wind power output variability within Europe substantially. Nevertheless, they showed that connecting weather regime to PV power output variability is also possible. Even though the decision to focus on wind rather than solar power output variability is comprehendible, calculations of necessary future installed PV capacities gives reason to do the investigations anyway. Ram *et al.* (2017) estimated that the installed PV capacity for a 100% renewable scenario in Europe must rise to 1.94TW by 2050. This is roughly a twentyfold increase of installed PV capacity compared to the 87.19GW installed PV capacity used in Grams *et al.* (2017) study. Therefore, the impact of multiday PV power output variability caused by different weather regimes could also become substantial, which makes investigation of the optimal spatial deployment of future PV systems in Europe before further massive deployment of great interest. The results could support current planning activities and could help to reduce future grid balancing problems.

# Data & Methods

This section first describes the datasets which are the underlying sources of this thesis. Afterwards it illustrates how the datasets are used to achieve the goal of reducing PV power output variability.

## Data

### ERA5

The reanalyse dataset, ERA5, which is published by the European Centre for Medium-Range Weather Forecasts (ECMWF), is used as source for the weather regime definition. It provides atmospheric, land and oceanic variables from 1979 to present with a temporal resolution of an hour. The grid of ERA5 has a horizontal spatial resolution of 0.28 degrees (~31km) and 37 pressure levels in the vertical. A detailed documentation about ERA5 reanalyse dataset can be found on the ECMWF confluence web page (Hennermann and Yang, 2018).

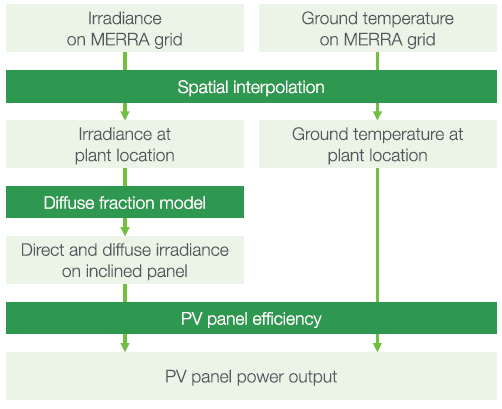
We use the 500hPa geopotential height variable from ERA5 in the domain 80°W to 40°E, 30°N to 90°N. Geopotential height is commonly used for weather regime definition (REF). The domain specification is reasonable for our meteorological field investigates since it captures the largescale circulation that affects Europe. The hourly dataset covers the time from 01.01.1979 until 31.05.2020, which yields in 363’048 datapoints. The following chapter describes the pre-processing of the raw ERA5 data which is needed before the weather regime definition can take place.

### Renewables.ninja and the Global Solar Energy Estimator (GSEE)

Renewables.ninja ([www.renewables.ninja](http://www.renewables.ninja/)) is an interactive web platform that simulates hourly power output of wind and solar power plants all over the world. To calculate the PV power output, it uses the so-called Global Solar Energy Estimator (GSEE). The source code of the GSEE is freely available on [GitHub](https://github.com/renewables-ninja/gsee) and a detailed description of the GSEE can be found in Pfenninger and Staffell (2016). The theoretical background of the GSEE is based on Huld *et al.* (2010). The following variables are the key input parameter of this method to estimate the energy yield of PV modules:

1. Direct and diffuse irradiance at the PV panel
2. Panel temperature

Pfenninger and Staffell (2016) used two data sources to estimate these variables: First the reanalysis dataset Modern-Era Retrospective analysis for Research and Applications (MERRA and MERRA-2) and second the Surface Solar Radiation Data Set - Heliosat (SARAH). Figure 1 shows the general approach of GSEE.



**Figure 1:** Overview of the approach used to model PV power output (Pfenninger and Staffell, 2016).

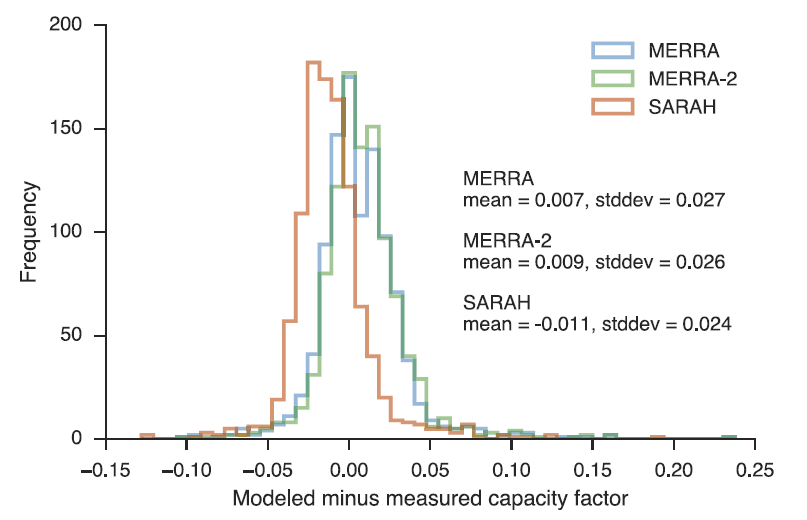
Both data sources provide the variables in hourly intervals. The spatial resolution of MERRA-2 is 0.5° latitude and 0.625° longitude. SARAH has a higher spatial resolution of 0.05° × 0.05°. MERRA only provides direct irradiance, but diffuse irradiance is needed as well. Therefore, they used the Boland-Ridley-Lauret model to estimate the diffuse irradiance (Ridley *et al.* 2010; Lauret *et al.* 2013). Since SARAH provides direct and global irradiance no further estimates were needed. Additionally, they use T2M (temperature at 2m above ground level) from MERRA-2 as estimates for the ambient temperature. To get the panel temperature they used the ambient temperature of MERRA-2 and additionally considered the effect of the irradiance on the panel temperature. This relation was estimated with site measurements of one of their sources (DTI see below). This dataset provides ambient and panel temperature for each site with which they derived an empirical relationship.

It is more common and easier to make comparison and analyses of PV power output with capacity factors rather than with absolute power output and we will use this approach as well. The unit-less capacity factor CF is defined as:

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 1 |

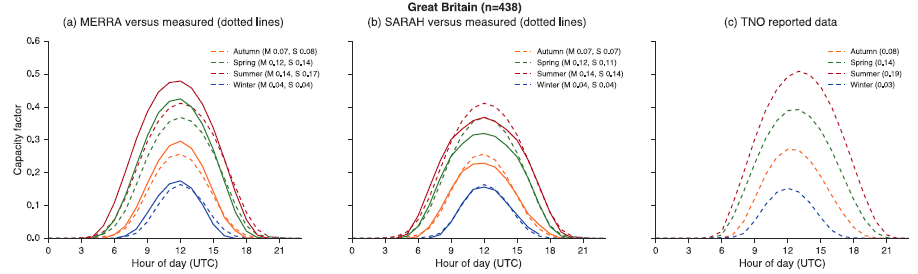
where P is power output [W] and IC is the installed capacity [W].

To evaluate the results obtained with the method described above, Pfenninger and Staffell (2016) compared it with capacity factors based on site measurements. To obtain the measured capacity factors they used three sources: DTI, PVLog.de and PVOutput.org. Over 1000 site data (measurements from PV systems) were collected from these three sources. Figure 2 shows a histogram of the difference between measured capacity factors and capacity factors simulated with the GSEE.

**Figure 2**: Histogram of the difference between the three modelled and measured capacity factors. Negative values infer underestimates of the capacity factor and positive values overestimates. The blue graph corresponds to modelled data with MERRA, the green graph to MERRA-2 and the red graph to SARAH. (Pfenninger and Staffell, 2016)

The mean of this differences is taken by Pfenninger and Staffell (2016) as basis for a bias correction. They used it to calculate one correction factor for each simulation (MERRA, MERRA-2 and SARAH).

Additionally to the power output simulation of a wind or solar plant at a specific location, renewables.ninja also provides capacity factors per country. Pfenninger and Staffell (2016) have performed randomized (tilt and azimuth angel) national-scale simulations with MERRA and SARAH data to estimate averaged capacity factors per country. Also, these data were analysed against the measured site data. To do so only countries with a least 10 available measurement sites were used. The measured capacity factor per country was then calculated as the mean of all capacity factors per site in one country. Transmission Network Operator (TNO) reports were used as a further data source of the national aggregated capacity factors. Figure 3 shows an example of the results for Great Britain.



**Figure 3:** Capacity factors per season for Great Britain from aggregated measurements site data (solid line, a and b), from simulation with MERRA and SARAH (dotted line, a and b) and from Transmission Network Operator (TNO) reports (c).

### Installed PV capacities

The following datasets will be used to gather the installed PV capacities for each country in Europe, which is necessary to calculate the absolute PV power output:

1. IRENA: International Renewable Energy Agency
2. EVTL. EUROSTAT!!??

TABLE WITH IC COUNTRY FROM IRENA

## Method

### ERA5 data pre-processing

Since we investigate in weather regime which last several days, the ERA5 dataset is resampled by calculating daily means of the geopotential heights. Furthermore, a 10-day lowpass filter is applied to smooth the data. Fig

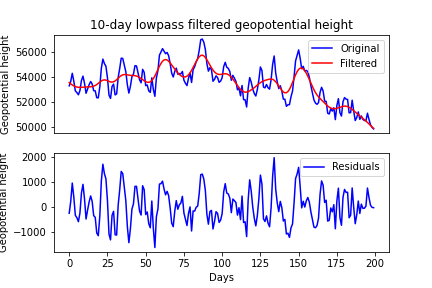


Figure 10-day lowpass filter applied on one grid point and 200 days as sample

The input data for the EOF analysis are standardized anomalies (EQ1):

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 2 |

where zd are the daily means of the geopotential height, zd,mean is the climatological mean with a running window of 30 days, and zd,std is the standard deviation of the geopotential height with a running window of 30 days. The running window is defined such as the respective day acts as centre of the window. For instance, to derive the reference climatology for the 15th of January the mean of the first to the 30th January is calculated for every year. This results in 41 means since our dataset covers 41 years. These 41 means are taken to calculate a mean again, so that we finally have one reference climatology for the 15th of January. This is done analogous for every day of the year, which yields in 366 sperate reference climatology and standard deviations. The standardized anomaly is used because we want to define weather regimes year around. Since the standardized anomaly includes normalization with the standard deviation, the amplitude in the anomaly caused by the seasonal cycle is removed (GRAMS) prior to the weather regime classification. We here use 30-days for our reference climatology and standard deviation calculation which differs to other studies. Often, investigations are only made for weather regime in winter where a correction for the seasonality is not needed (REF). Others (GRAMS) are using 90-day but since our interest focus on multiday timescale this is rather long and increase the probability that the signal of the seasonal cycle is included.

EVTL PICTURES WITH COMPARISON

### Weather regime classification

For the weather regime classification, the well-known method of empirical orthogonal function analysis and k-means clustering is used (Michelangeli, Vautard and Legras, 1995; Cassou, 2008). An EOF analyses decomposes a dataset into statistically orthogonal modes that describe the variability of the data. For metrological datasets, a few modes are often sufficient to explain a large fraction of the total variability in the data, which is helpful to assess the key patterns of the variability and to further analyse them. We perform the EOF analysis on our pre-processed data with the eofs python package by Dawson (2016).

The resulting first 16 principal components of our EOF analyses which explained ~90% of the variance are used to cluster the data into weather regimes. We use the clustering method k-means which is implemented in the python package sklearn.cluster by Pedregosa *et al.* (2011). Generally, clustering techniques are used to group data with similar characteristics by minimizing the variance within the clusters. The difficulty lies in the definition of the number of clusters. For the Euro-Atlantic region often four clusters are used to define the weather regimes (Michelangeli, Vautard and Legras, 1995; Cassou, 2008; Van Der Wiel *et al.*, 2019). The well-studied four weather regimes which are received with the approach are the negative and positive phase of the North Atlantic Oscillation, the Scandinavia high and the Atlantic ridge (EVTL FIG). But these studies focus only on wintertime weather regime classification. According to Grams *et al.* (2017) the optimal number of clusters to define weather regime year around is seven which seems to be plausible by a simple check with the elbow and silhouette method (EVTL FIG). Therefore, we use 7 clusters as well which additionally make a comparison to the study by Grams *et al.* (2017) easier. Furthermore, we sort all days out where the weather regime does not last for at least 3 days and assign these days to a separate weather regime hereafter called “no-regime”.

To summaries, we use EOF analyses and k mean clustering to derive an assignment for each day of the ERA5 dataset to one of 7 weather regime or to no-regime.

### Capacity factors

We use the national aggregated CF by renewable.ninja, which are provided in hourly intervals. The advantage of this dataset is the included bias correction described above. But one must consider that this is strongly depended on the amount and position of measurement sites in a country. For example, for Spain they only have 14 available measurement sites that are mostly located at the northern coast. This leads to a statistically unrepresentative sample (Pfenninger and Staffell, 2016). Nevertheless, a further advantage of this approach is that we would be in line with the study of Grams *et al.* (2017) which makes further comparison or combination analyses of wind and solar power output variability easier.

We resample the dataset analogously to the ERA5 dataset to get daily means. Since the CF are highly influenced by the seasonal cycle, we analyse them separately for each season (winter, spring, summer, autumn). EVTLFIG. With the weather regime classification method we now can attribute the capacity factor to the different weather regimes. We use the attributed capacity factors to calculate a mean capacity factor per weather regime, season, and country. The difference between this mean capacity factors and the mean capacity factors for the whole season of a country determines whether the impact of the weather regime exhibits over- or underproduction (Eq. 3).

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 3 |

where CFwr,country,season is the mean capacity factor of a specific weather regime, country and season [unitless] and CFcountry,season is the mean capacity factor of a country for the whole season [unitless].

Multiplication of capacity factors with installed capacities yields power output (Eq. 1). This can be used to expand Eq. 3 which gives us the total deviation of solar power output of Europe per weather regime and season.

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 4 |

where ICcountry is the installed capacity per country [W] and is the deviation of CF per weather regime, country and season to the seasonal mean [unitless].

We will use (Eq. 3 and) Eq. 4 as an expression for the variability. If the result of this equation is zero, the PV power production of the respective weather regime and season is equal to the mean PV power production of the respective weather regime and season and therefore the variability is maximally reduced.

The only unknown we still have is the installed capacity per country.

### Current and planned situation (2030)

To meet the EU’s energy and climate targets for 2030, EU Member States need to establish a 10-year integrated national energy and climate plan (NECP) for the period from 2021 to 2030. I

2030 data 🡪 IRENA 🡪 plus missing countries!!?? 🡪 CH, UK

### Variability reduction with optimal IC distribution

To determine an IC distribution which distinctive reduces the PV power generation variability, EQXY is used as a linear least-square problem and is solved with an upper and lower bound on the variables. This is done with the scipy.optimize.lsq\_linear python package which solves the following optimization problem:

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 4 |

where A is the coefficient matrix, x is the solution found, b is the target vector, lb is the lower bound of the solution x and ub is the upper bound of the solution x.

The coefficient matrix A is defined with from EQXY the following:

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 5 |

Where the first element of the matrix is the capacity factor anomaly of weather regime 0, in the Albanian winter. The country stays the same per column, but it goes through all weather regimes (0-6) and seasons, which gives a total of 28 rows. In one row the matrix goes through all countries, from Albania to Slovakia, which results in 34 columns with our considered countries (🡪 define somewhere above).

The target vector is set to zero to reduce the variability within one weather regime and season as much as possible and so also reduces the variability from one weather regime to other:

|  |  |  |
| --- | --- | --- |
|  |  | Eq. 6 |

where has the same length as the number of rows of matrix A, 28.

The result of this method is the vector which contains then the IC for each country:

The method to perform the minimization is the Trust Region Reflective (TRF) algorithm   
(Branch, Coleman and Li, 1999)

### Scenarios

1. Minimize PV power production variability but the PV IC and PV production must equal to the plan for 2030 which are projected in the 10-year integrated national energy and climate plan (NECP)
2. Cost minimization: Minimize PV power production variability and IC but the PV production must equal to the plan for 2030
3. Consumption: Minimize PV power production variability but each country must generate XY% of its electricity consumption with PV systems
4. REGIONAL AGGREGATED???
5. Minimize PV power production variability but the PV power production must equal the projected need for a netto null emission 2050
   * Solar PV could cover a quarter of global electricity needs by mid-century, becoming the second largest generation source after wind.
   * Global capacity must reach 18 times current levels, or more than 8 000 gigawatts by 2050.
   * Asia would continue to dominate solar PV use, with over 50% of installed capacity, followed by North America (20%) and Europe (10%).
   * 8000gigawatts\*0.1 = 800gigawatts 🡪 in excel from IRENA 891

# Results

First WR then CF then Distribution for scenarios

## Weather regimes

Figure : Weather regimes 0- 6 and no regime. The countours correspons to standardized anomalies of geopotential heigth at 500hPa

Figure 5 shows the derived seven weather regime and the separately defined no regime. The relation between the weather regime number and the ordinary names, which are often used in literature, can be found in table XY. Weather regime 0, 2, 3 and 6 which are known as the positive and negative phase of the North Atlantic Oscillation (NAO), the Atlantic ridge and the Scandinavian blocking are the typical weather regimes which are found in many studies that focus on wintertime weather regime classification (CASSOU, VAUTARD EVTL MEHR ANGEBEN). And in line with that the seasonal frequency (FIG XY) of theses weather regimes shows us that they occur more in winter than in the other seasons (nicht 100% NOAs schon aber andere nicht so).

Weather regime 1 and 4 are more difficult to assign wo well known weather regime. Weather regime 1 a mostly similar to the Scandinavian blocking also fined by GRAMS. But the low pressure field located a bit more southwar over the western coast of Europe. Weather regime 4 is most likely comparable with the Atlantic through. But one can clearly identify an high pressure filed in the Southern par of Europe which would be more typical fo a blocking situation. Finally, weather regime 5 is the European blocking situation which is often associated with warmen than seasonal average temperature over central Europe

Weather regime 5 is characterized by a blocking high pressure field like weather regime 5.

### WR0 – NOA+

The positive phase of the NOA (WR0) exhibit a negative geopotential height anomaly over the Northern part of the Atlantic, Easterly to the Greenland coast and a positive geopotential height anomaly over the Atlantic/Mediterranean sector. During this conditions, the Atlantic storm tracks are displaced polewards and the zonal flow is enhanced which increases the strength of the westerlies and brings maritime air (warm and moist) to central and northern Europe (ROGERS 1997, HURRELL 2003, Buch Wallace). Wetter condition in these regions also implies larger cloud clover fraction and therefore less available surface solar radiation. Studies by Pozo-Vázquez *et al.* (2004; 2011) indeed have shown that that the NOA index is negatively correlated with the solar irradiance in northern Europe and positive correlated with solar irradiance in southern Europe, what would have to manifest itself in the PV power generation. 🡪 disupted by Colantuono 2014 and francois 2016 🡪 nachlesen!

### WR1 - EVTL European trough

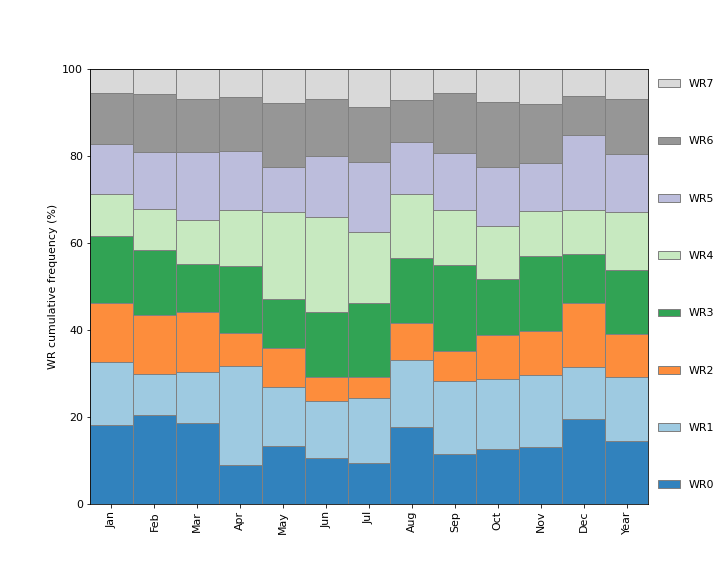
### WR2 – NOA-

### WR3 - Atlantic ridge

### WR4 - Atlantic trough ??

### WR5 - European blocking

### WR6 - Scandinavian blocking

probably the best studied regimes in this domain since most of

Frequency

|  |  |
| --- | --- |
| WR0 | Zonal Regime (ZO) NOA+ |
| WR1 | Scandinavian through or AT? |
| WR2 | Greenland blocking (GL) 🡪 NAO- |
| WR3 | Atlantic ridge (AR) |
| WR4 | AT? |
| WR5 | European blocking |
| WR6 | Scandinavian blocking |

## Capacity factor anomalies

## Situation with current PV IC

## Scenarios for IC distribution

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