Effects of increased droughts on hydropower plants production

Ruben Haalebos[1*], Florian Gallo[2], and Claire Hugo[3]

[1]Data Scientist, Sustainable Investment Research, LSEG.
[2]Senior Research Lead, Sustainable Investment Research, LSEG
[3]Senior Analyst, Sustainable Investment Research, LSEG
[*]Corresponding author. Email: ruben.haalebos@lseg.com

Abstract

Hydropower plants are key assets to produce decarbonized energy and limit Greenhouse Gas (GHG) emissions from the power sector industry. Hence, they are prominent in the fight against climate change. However, the generation of hydroelectricity relies heavily on climate conditions, water availability specifically. This work investigates the impact of climate change on water availability and on hydropower production around the world. We use localized drought conditions as a proxy for water availability. We find that hydropower production is linked to localized drought conditions, with low production events happening during periods with higher drought. We then use this relationship to forecast the electricity production of existing plants under various climate scenarios and we translate the variation of production into the Levelized Cost of Energy of the power plants. Finally, we aggregate the results at company level. A company's risk exposure is essentially influenced by two parameters: the localization of its hydropower plants and the share of hydropower plants in its portfolio. We find that in general, some companies in South America are most at risk as they are located in regions where drought occurrences likely will increase and their assets are often focused on hydropower.

1 Introduction

The impact of climate change on the economy is becoming more and more material. Morgan Stanley Research [14] estimates the global cost of climate related disasters between 2016 and 2018 at a total of 650$ billion. In a 2020 report, SwissRe [20] stated that the growing trend in economic losses from extreme weather events has two origins: (1) the accumulation of assets in more exposed regions (coastal areas, etc.) resulting from urbanization and economic growth and (2) the changing climate. Forward looking studies are necessary to track the effects of climate change to uncover the geographical areas and sectors most at risk. Physical risk is defined by the Task Force on Climate-related Financial Disclosures (TCFD) [21] as the risk related to the physical impact of climate change. It can be either event driven or related to long-term changes in climate patterns. The aim of this

study is to focus on the financial impact of climate change on hydropower plants, at a company level.

Hydroelectricity is a major provider of decarbonized electricity[1] and is a valued ally in the fight against climate change. It contributes to more than 15% of total generated electricity and currently is the largest source of renewable electricity generation. Any impact of climate change on the hydroelectricity production might lead to an uptake in the use of fossil-based electricity and interfere with decarbonization efforts. Investigating the role of climate change in future water availability and the related impact on hydroelectricity production is important to ensure that this key decarbonized capacity fulfills its role in the energy transition.

The occurrence of drought periods leads to reduced water availability and can impact power generation from hydropower and thermal plants[2]. This can lead to substantial financial damages for an asset, an operating company and the energy system as a whole, as illustrated by recent events. For example, between 2011 and 2014 in California, the increase in the cost of producing electricity from the droughts was estimated to $1.4 billion (Gleick [9]). These costs include the recourse to electricity from gas thermal plants, wind and solar production facilities as well as out-of-state electricity, all more expensive options used to make up for the loss of hydroelectricity[3], leading to a higher overall cost of producing electricity.

Several studies have explored the link between water availability and hydropower production. Van Vliet et al. [22] found that during drought years, global hydropower plant utilization rate was reduced by 5.2% compared to a 1981-2010 average. Moreover, major drought years produced statistically significant reductions in used capacities. A similar approach was used by Falchetta et al. [6] to assess the vulnerability of the power sector for the case of Malawi, using a combination of satellite data (precipitation, temperature, Standardised Precipitation Evapotranspiration Index (SPEI) and soil moisture) to model river discharge deviation and the hydroelectricity capacity factor. They found that extreme events impact both electricity production and its final use, allowing for better understanding of climate vulnerabilities. Similarly, Gleick [9] found a statistically relevant link between water runoff and hydropower generation in California, explaining the cause of the lower share of hydropower in the Californians electrical mix during drought years. Finally, Byers et al. [4] estimated that, with climate change under a RCP 8.5 scenario, almost 50% of total freshwater thermal capacities can become unavailable in an extreme day of drought. Moreover, the median impact of extreme days of drought in the UK exceeds £100 million per year. If this average impact seems limited, severe regional disparities exist and should be documented (Berga [3]).

We seek to estimate the effect of these regional disparities on hydropower production companies,

[1] The term of "decarbonized" for hydroelectricity is disputed on account of the lifecycle emissions of the cement needed to build the dams.

[2] We separate both effects as lower hydropower production is directly linked to lower water availability. For thermal power plants, the link is indirect: decrease in water availability reduces cooling capacity thus lowering production.

[3] Hydropower is generally considered one of the cheapest way to produce electricity, see for example `https://irena.org/-/media/Files/IRENA/Agency/Publication/2020/Jun/IRENA\_Power\_Generation\_Costs\_2019.pdf`. (Accessed: 22/03/2021.)

to uncover the regions most at risk from drought. The financial impact is derived using a classical IPCC framework [12], where the risk is a combination of physical hazards, exposure, and vulnerability. The Network for Greening the Financial System (NGFS) published a report [16] acknowledging the exposure of financial systems to the impacts of climate change. Based on the IPCC framework, it provides a four-step process to estimate climate risk to the economy, adapted to our context:

Step 1: Identify objective and exposure	The objective is to make projections on hydropower production, using the evolution of a drought index depending on different climate scenarios.
Step 2: Choose climate scenarios	Climate scenarios were selected from publicly available sources.
Step 3: Assess economic and financial impacts	Economic impact is derived in terms of changes in revenues and produced power cost.
Step 4: Communicate and use results	Our work provides a global analysis for utility companies which could use it for investment planning.

The risk is defined by two complementary metrics, allowing for an extensive analysis of the financial impact of climate change on hydropower plants:

- A long-term trend, focusing on long-term evolution of production and the consequences on the financial profitability of the company;
- The increase in occurrences of extreme events, where hydropower electricity production needs to be replaced by other sources.

Overall, this study constitutes a deep dive into understanding how climate change could affect the profitability and risk of power companies. It is complementary to the work of Lorans et al [13] that implemented a top-down approach to study the effect of climate change on sovereign bonds. Here, we adopt a sectoral view and look at how specific weather events impact a specific activity.

We aim to estimate a robust relationship that we can test at world level, without developing a complete hydroclimate model of water runoff which would require too much information for this study. Thus, we apply a more pragmatic approach and use the SPEI index to model the capacity factor of power plants. A complete hydroclimate model could be implemented in a subsequent analysis, should the result of this study prove useful to measure physical climate risk on companies.

2 Methodology

Two aspects are studied: (1) the impact of climate change on average production of hydropower plants and (2) the impact of climate change on the occurrences of extreme low production events. Figure 1 provides graphical insight on the information we extract from both the SPEI and capacity

factor[4] data.

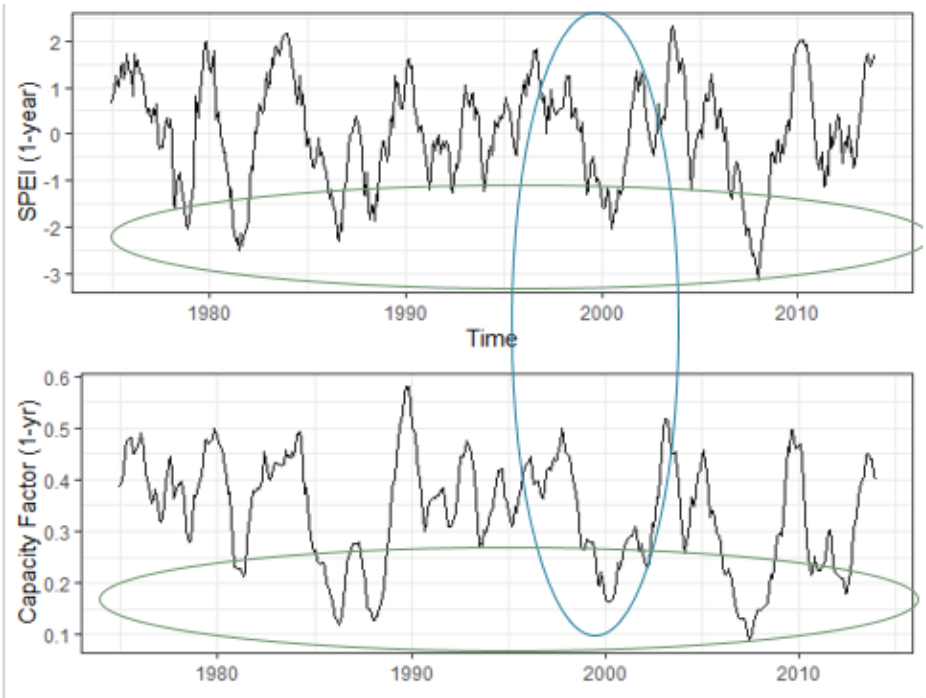

Figure 1: SPEI and yearly capacity factor for a single hydropower plant.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data.

Note: A low SPEI value indicates drought.

Schematically, the blue oval represents the first indicator: a period of increased drought is linked to an overall lower capacity factor. The green oval represents the second indicator: periods of extreme droughts correspond to periods of low production.

Average production is defined as the 1-year average of monthly production. An extreme low production event is defined as a 1-year average production 50% lower than the 10-year average production. These impacts are complementary, as focusing solely on the average production underestimates the overall impact of the increase of occurrences of extreme lows. Both impacts are compared over three periods:

- The historical period: 1970-2015;
- The medium-term period: 2020-2050;
- The long-term period: 2070-2100.

[4]The capacity factor is defined as $\frac{Production}{30*24*Capacity}$ and is used to normalize individual plant productions. Please note that here that we are considering a monthly production. In the following, the capacity is assumed constant over time, and the capacity factor is directly linked to production

The impact of climate change on average production can be translated into a variation in the Levelized Cost of Energy (LCOE) of the plants. The LCOE measures the lifetime cost of producing electricity and is commonly used to compare technologies or measure the viability of a project. It is the ratio between the discounted costs over a lifetime of a power plant divided by the discounted sum of actual energy produced (Lai & McCulloch [11]). Data for LCOE calibration are derived from the National Renewable Energy Laboratory (NREL) [17] [5]. The sum of actual energy produced is a function of the capacity factor of the plant: if it decreases, the LCOE increases. We measure the impact of drought on the capacity factor through the following model:

$$CF_{1-yr} = \alpha + \beta_0 * SPEI_{1-yr} + \beta_1 * CF_{10-yr} + \epsilon$$

where:

- CF_{1-yr} is the 1-year average capacity factor;
- $SPEI_{1-yr}$ is the 1-year average SPEI;
- CF_{10-yr} is the 10-year average capacity factor.

This specification expands the work of Gleick [9] and adapts it for drought conditions. Here, the 1-year capacity factor is a function of the 1-year average SPEI and an overall trend measured by the 10-year average capacity factor. The 1-yr moving average is used to smooth out the effect of exogenous parameters (seasonality, short-term management decisions, etc.) on hydropower production. Electricity production is then modelled as the combination between a long-term trend representing the different long-term parameters of the power plant (long-term climatic cycle, long-term management decisions, etc.) and a more immediate adjustment for the localized drought. Because long-term parameters are not observable, we use the 10-yr moving average of production as a proxy.

The impact of climate change on low-production extremes is modelled through a copula model. This method studies the nature of the link between periods of extreme droughts and extreme low-production. It builds upon the idea developed by Falchetta et al. [6]. We use the following method:

- We build the following variables: the capacity factor ratio, $T = \frac{CF_{1-yr}}{CF_{10-yr}}$, and the 1-year average SPEI, $S = SPEI_{1-yr}$
- We estimate the empirical copula between S and T
- We compute the new T following a change in S due to climate change

[5] In particular, we used the default calibration for the discounting factor. Expansion of this work should include sensitivity testing of this parameter

3 Data and calibration of the model

3.1 Data

Towards building projections of hydropower plants electricity production using a drought index, the following data are used:

- For model calibration:
  - Historical electricity production of multiple US hydropower plants, with several parameters such as location and nominal capacity;
  - Historical data on localized drought;
- For model application:
  - Locations and size of hydropower plants around the world;
  - Modelled data on localized drought;

Historical data of electricity production from power plants is retrieved from the US Energy Information Administration (EIA): the EIA-923 form [8] reports monthly and annual power production of different power plants throughout the United States; the EIA-860 form [7] provides supplementary information on those plants, including precise location, nominal capacity, type of plant and owner. The data spans from 1970 until 2018. To test the results at a global level, the model is applied to the plants listed in the Enerdata PowerPlant Tracker database [18], which gives information on capacities and locations of utilities worldwide. Company names are also given in that database, allowing for a corporate overview.

The drought index used is the Standardised Precipitation Evapotranspiration Index (SPEI) [1]. It is a measure of drought that accounts for both precipitation and potential evapotranspiration (PET). For historical SPEI, we used data from Beguería et al. [2]. For each plant, the local SPEI corresponds to the value of the SPEI geographically closest to the coordinates of the power-plant[6]. For projected SPEI, we use data from the European Commission Joint Research Center (JRC) [15]. This dataset provides projections forecasts for the SPEI in a RCP 8.5 scenario and for seven climate models. The results presented here are the aggregation between the results obtained for each model. More details on data characteristics can be found in Appendix B.

3.2 Model calibration

The model is calibrated using monthly production from hydropower plants located in the United States. The results obtained for both models are outlined below, with more details available in Appendix C.

[6]The historical SPEI has a spatial resolution of 0.5°, providing a good proxy of drought conditions in the hydropower plant surroundings

3.2.1 Impact of climate change on average production

In Section 2, we introduced the following model:

$$CF_{1-yr} = \alpha + \beta_0 * SPEI_{1-yr} + \beta_1 * CF_{10-yr} + \epsilon$$

Table 1 presents the coefficients estimated using a fixed-effect panel estimator.

	Coefficient value
SPEI (12 months)	0.057***
Capacity factor (10-yr)	0.884***
Adj R-square	0.49
F-test (p-value)	<2.22e-16

Table 1: Estimation results for the two models.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

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The quality of the models is acceptable, with an Adjusted R-Square equal to 0.49 and all coefficients statistically different from 0. The sign before the SPEI indicator is as expected: a higher level of SPEI leads to a higher level of production thus to a higher capacity factor.

3.2.2 Impact of climate change on the occurrences of low-production extremes

Observations from the model show that low values of the 1-year average SPEI S correspond to low values of the capacity factor ratio T, and that the same effect occurs with high values. This means that the distribution of T given a low value of S is different from the distribution of T given a medium or high value of S. To describe this dependency, we use a Frank copula with the following parameters (estimated based on the empirical data): $Par = 4.61$,$\tau = 0.43$ (see Appendix C for more details). Further work could be implemented to test other copulas.

We use the following steps to estimate the probability of an extreme low production[7], based on projected SPEI (adapted from Simard et al. [19]):

- Step 1: Estimate the copula between T and S, using empirical data;
- Step 2: Set the cumulative distribution function of S based on projected SPEI data;
- Step 3: Simulate observations using the estimated copula;
- Step 4: Compute the cumulative distribution of T, based on the observation simulated by the copula;
- Step 5: Estimate $P(\hat{T} < 0.5)$, the probability of having a capacity factor that is 50% lower than the long-term average.

[7]Defined in Section 2 as a yearly production 50% lower than the long-term production

Thus, for step 2 and step 4, we estimate cumulative distribution functions that remain constant over time. They are approximated by normal distributions, using the empirical data. Table 2 outlines the parameters:

		T	S
Distribution		Normal	Normal
Parameters	Mean	0.99	0.09
	Std	0.28	1.05

Table 2: Distribution estimation for T and S

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

A key assumption of our work is that estimations based on US data remain valid at global level. Because of the disparities in climate throughout the United States and the number of hydropower plants included in the estimation process, generalization of the relation is possible to some extent, and our models has good performance even on out-of-sample power plants (see Appendix D for in- and out-of-sample results benchmarking). However, work is currently undergoing to improve our model by adding hydropower plants located in other parts of the world.

4 Application to global assets

The methodology is applied to all plants with a capacity larger than 50MW from the Enerdata PowerPlant Tracker database[8]. For the two risks studied, results are given at asset and company level.

4.1 Impact of climate change on average production

For some hydropower plants, an estimate of the yearly capacity factor is given by the PowerPlant Tracker database. When available, it is used in our model. For plants where this information is missing, the global mean is taken as input. To reduce the bias effect of this imputation method, results can only be interpreted compared to the baseline value.

There is an inverse relationship between the capacity factor (and production) and the LCOE: all things being equal, a lower production implies lower capacity factor and lower electricity flows to sell, thus increasing the overall cost of the plant. As the theoretical cost of producing electricity increases, the plant becomes less competitive. Plants where the capacity factor is expected to decline show a rising LCOE.

[8]It should be noted that the existence of the dams is not guaranteed until 2100. However, given current needs for electricity and given that hydropower plants are a major source of low-carbon electricity, current locations are assumed to be a good proxy of future dam locations.

In Figure 2, hydropower plants located in southern Europe, central Brazil and the central United States appear to be most at risk. South-East Asia seems relatively preserved: in this region, droughts are expected to decrease, thus the capacity factor of power plants increases. However, this result is only theoretical, as other negative impacts in the RCP8.5 scenario, such as floods, are not accounted for in the model.

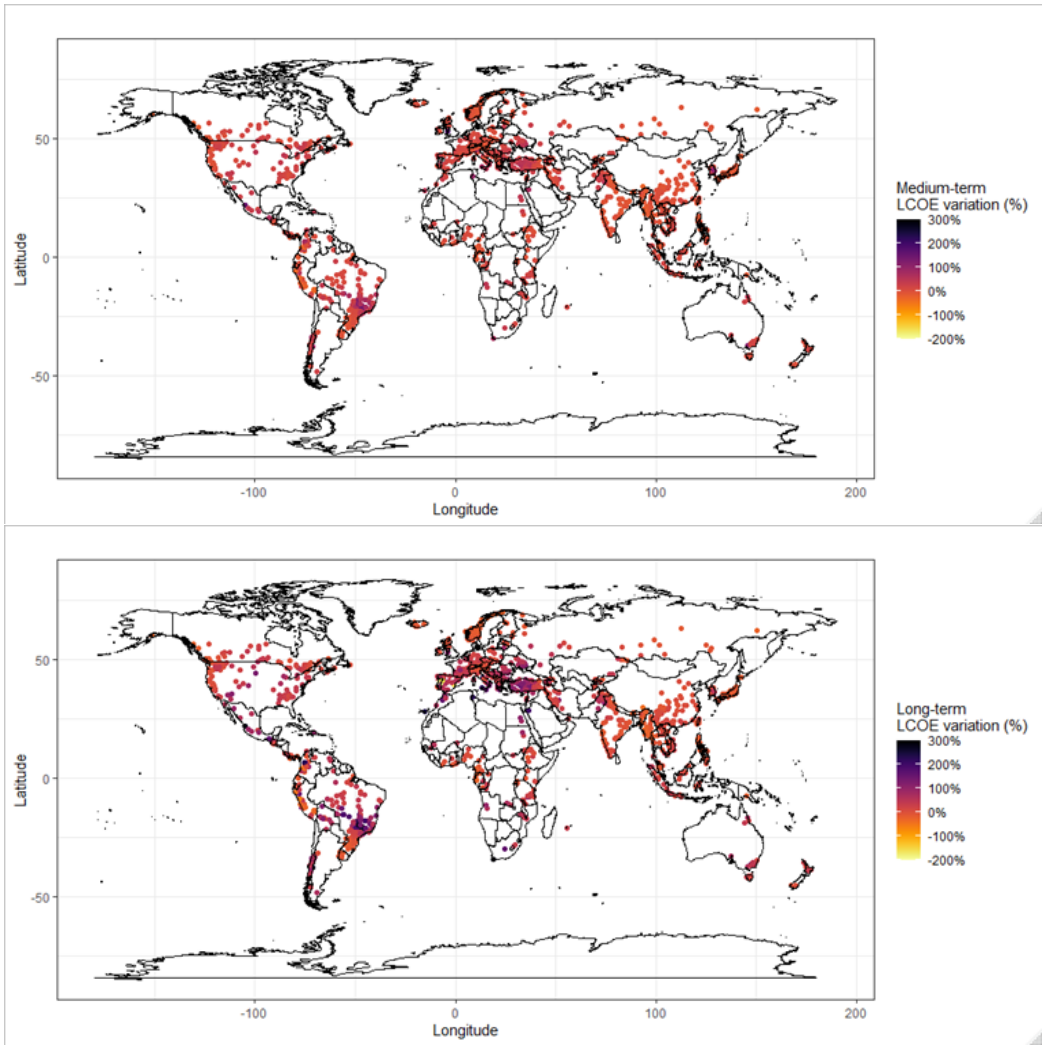

Figure 2: Variation of the theoretical LCOE medium (upper) and long-term (lower) periods - RCP 8.5 scenario

Source: LSEG SI Research, based on JRC data. Note: A positive LCOE variation reflects an unfavourable impact: production prices increases, thus profitability decreases.

Surprisingly, the Nile basin seems relatively spared. This illustrates one caveat of our model: the flow of the Nile essentially depends on rainfalls in the Upper Nile Basin (covering Ethiopia, South Sudan and Uganda) and the localized SPEI, based on the location of the power plant, may

not be the most relevant indicator [5]. Using the SPEI from the Upper Nile Basin could help with this issue[9]. More generally, using a water runoff model would probably yield more robust results. Moreover, our model does not account for river basins that cover multiple countries and make water availability subject also to political choices.

Figure 3 shows the results for the twenty companies with the largest hydropower capacities in the RCP8.5 scenario. In the long-term, some companies face an LCOE higher than 300 USD 2015/MWh. This hypothetical value is probably overestimated since, at company level, steps would be implemented to limit the LCOE increase. Nonetheless, it indicates that these companies own assets in regions where drought is expected to increase and could put their business model at risk.

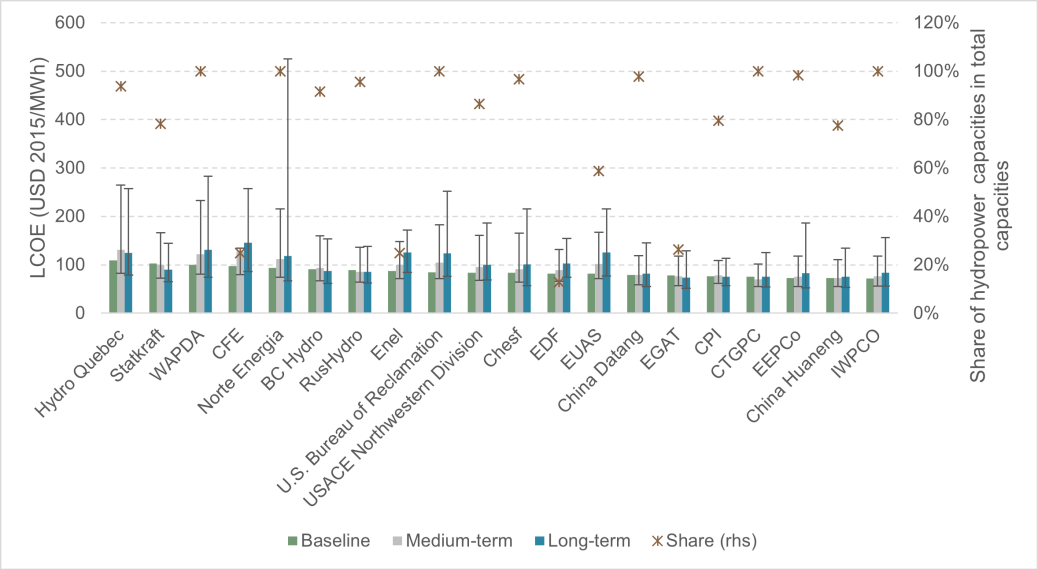

Figure 3: Variation of the theoretical LCOE for the medium-term and the long-term for companies with the largest hydropower capacities.

Source: LSEG SI Research, based on JRC data.

Overall, the evolution of droughts due to climate change could have slightly positive effects for South-East Asian companies, while companies located in Europe or Brazil are the most at risk. This risk can be translated into financial terms, with for example an expected 25% increase in hydropower LCOE for Electricité de France (EDF). However, this increase in cost should be analysed in relation to other business segments of the company. A small increase in LCOE for companies with only hydropower capacity may be more detrimental than a larger increase for a company where hydropower plant capacities is a small proportion of total managed capacity.

[9]In this case, the assumption to use only US data to build our model seems inappropriate: it does not (or not enough) account for cases where local water availability is dictated by upstream drought severity.

4.2 Impact of climate change on the occurrences of low production extremes

This section focuses on the impact of climate change on the probability of extreme low production events. Our model computes the difference between the baseline (historical) and projected probability that the yearly capacity factor will be halved compared to its long-term value. As an example, a 0.1pp increase means that there are every year 1.2 additional months (in the RCP8.5 scenario) where plants produce less than 50% of their long-term value.

Figure 4 provides a geographical overview of plants and regions most at risk. The same locations are highlighted as in Section 4.1: central Brazil and Southern Europe.

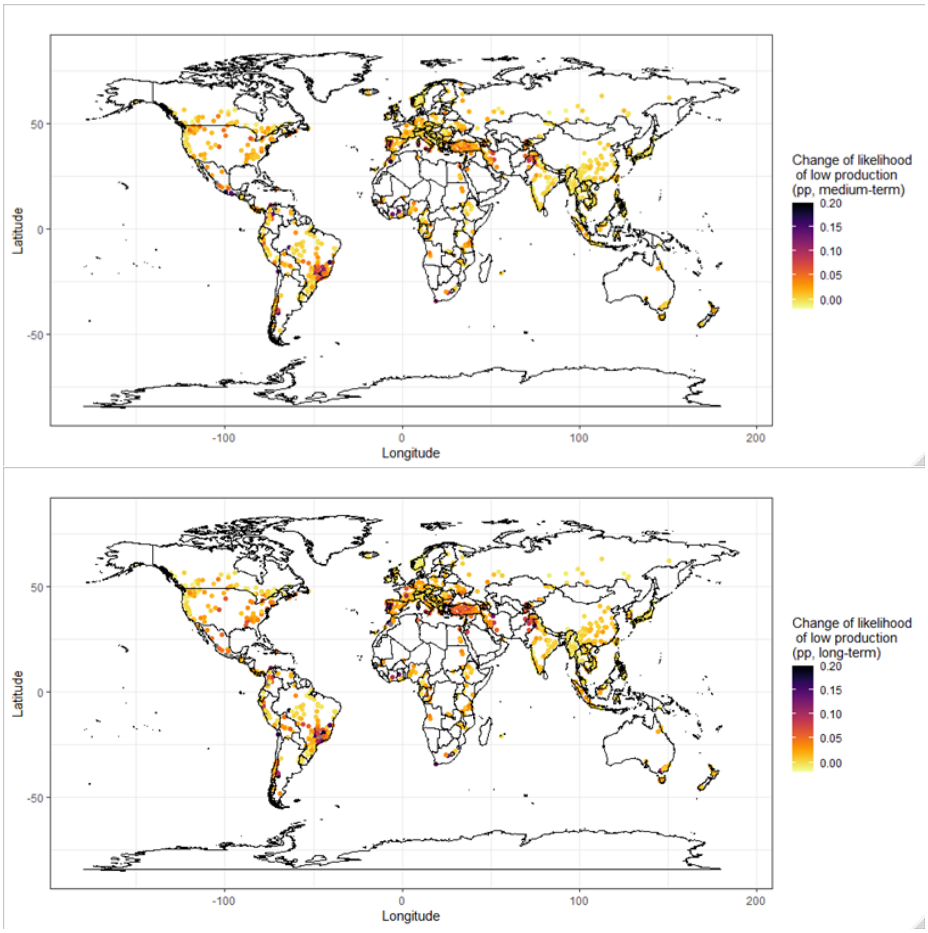

Figure 4: Increase of the likelihood of extreme low production for medium (upper) and long-term (lower) periods - RCP8.5 scenario.

Source: LSEG SI Research, based on JRC data. Note: : pp refers to percentage points. An increase of 0.1pp means that the probability increases by 10 points compared to the baseline value, or 1.2 supplementary months per year.

However, not all plants in these regions face the same risk. Figure 5 shows the aggregated

probabilities of having an extreme low production for the 20 largest companies[10]. Interestingly, the baseline probability is approximately the same for all companies. However, some companies main hydroelectric assets are located in regions where the occurrence of extreme drought is expected to increase, impacting the probability of having low production.

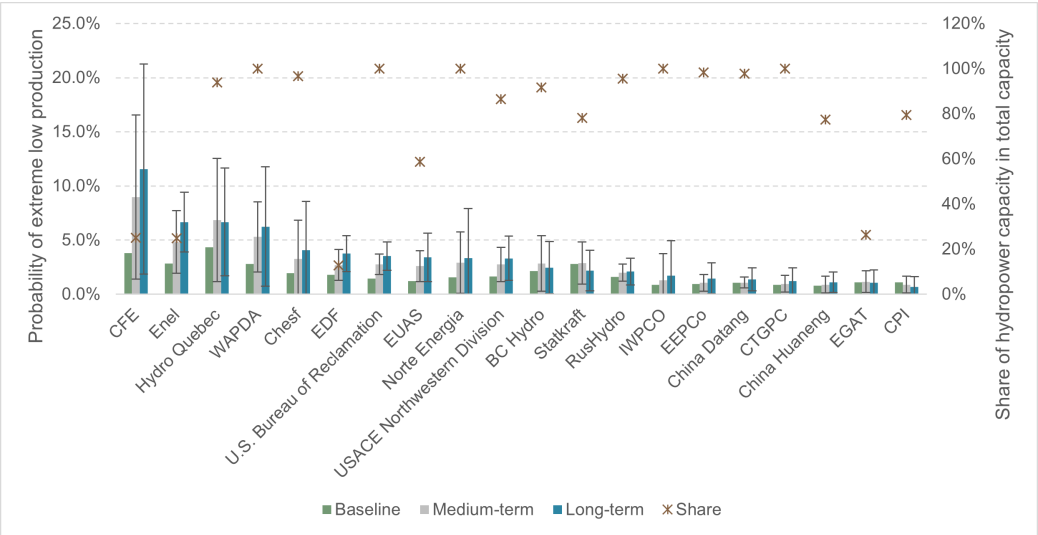

Figure 5: Comparison between the baseline, medium- and long-term probability of extreme low production.

Source: LSEG SI Research, based on JRC data.

Overall, this risk correlates with the long-term production decrease, showing the twofold effect of climate change and drought modification: it lowers overall production while also increasing the probability of having extreme low productions. The interesting feature of this work is that it allows better comparability through a large-scale computation of these metrics. Nonetheless, a plant-by-plant analysis would certainly yield more precise results.

5 Discussion and conclusion

In this study, US data is used to calibrate a damage function linking a drought index to hydropower plant production. The estimated model is then used on a worldwide database to identify the areas, plants and companies most exposed to climate change, with the construction of two indicators: (1) the LCOE variation and (2) a risk for critically reduced production.

Quite naturally, areas where drought will increase are the most exposed. This allows for company-level analysis, favouring companies that own plants in various regions rather than concentrated in

[10] All values are based on simulated data and results should be interpreted with caution, as these results have not been benchmarked against observed values for individual companies.

one area. From a financial perspective, this model gives an insight into how physical climate risk impact on companies' activities can be integrated into corporate analysis:

- Through the estimation of losses (increase in LCOE can be linked to decrease in profitability);
- Through the construction of a risk-assessment tool for companies.

However, even though the results are interesting, the sectoral focus constrains immediate adoption in global investment strategies. Beforehand, this study should be complemented with the same approach on all utilities and other sectors. The computation of a probability of impaired activity could be reproduced on other types of utilities (all thermal power plants need a stable access to water to function) or other sectors (agricultural yields, impact of climate extremes on different industries, supply chains, etc.).

This work also illustrates how geolocalized data (the SPEI index) can be used along with asset-level data to uncover specificities and differentiated impacts depending on location. This is true for example in large countries such as Brazil or the United States.

Finally, here we only consider impact on plants' activity. Further analysis could be done to also include the physical infrastructure damage impact (flooding, destruction of the dam, etc.).

Appendix A: Detailed methodology

In this appendix, we detail the methodology that is used to model the impact of drought condition change on both the long-term power capacity factor and the occurrence of capacity factor extremes.

Impact of climate change on average production

Our assumption is that localized drought is linked to the capacity factor of hydropowerplants. To control for the individual capacities of the power plants, we use the capacity factor (or load factor): $CF = \frac{P}{30*24*C}$, expressed in percentage, where P is the monthly production and C the nominal capacity.

Thus, the following generic model is used:

$$\widehat{CF}_{1-yr} = \alpha + \beta_0 * SPEI_{1-yr} + \beta_1 * CF_{10-yr} + \epsilon$$

Our aim is to compute the 1-year average of capacity factor for future periods, where CF_{10-yr} is missing. For those periods, it is approximated using the following equation:

$$\widehat{CF}_{10-yr} = \alpha' + \beta' * CF_{10-yr} + \epsilon'$$

The method accounts for both the short- and long-term factors influencing the 1-yr average of production. The final estimate for out-of-sample observations is[11] :

$$\widetilde{CF}_{1-yr} = \alpha + \beta_0 * SPEI_{1-yr} + \beta_1 * \widehat{CF}_{10-yr}$$

The intention is not to give a precise 1-year forecast of the production. The drought index used is inadequate for such a study, as is this method of estimation. Rather, our aim is to compare average capacity factors between periods. The following metrics are used:

- The historical capacity factor, or average historical factor of the power plant: $CF_{historical} = mean_{1970-2015}(CF_{1-yr})$, $CF_{1-yr} = \frac{P_{1-yr}}{30*24*C}$ with C the nominal capacity.
- The medium-term estimated capacity factor of the power plant: $CF_{mediumterm} = mean_{2020-2030}(\widetilde{CF}_{1-yr})$, $\widetilde{CF}_{1-yr} = \frac{P_{1-yr}}{30*24*C}$
- The long-term estimated capacity factor of the power plant: $CF_{longterm} = mean_{2070-2100}(\widetilde{CF}_{1-yr})$, $\widetilde{CF}_{1-yr} = \frac{P_{1-yr}}{30*24*C}$

The metrics are averaged over these different periods, allowing to consider the overall impact of drought regime chance. The capacity factor is used to compute the Levelized Cost of Energy (LCOE) of the powerplants. The comparison between the LCOE's for different time-periods gives the impact of drought.

Impact of climate change on the occurrences of low production extremes

The method described above is adequate to account for average trend changes in the SPEI. However, an effect of climate change on the SPEI will be the multiplication of drought periods. Thus, we build another model to analyze the change in occurrence and severity of extreme values of SPEI.

We use a copula framework: we estimate the relationship between the deviation of the capacity factor from its long-term value and the 12-months SPEI (called S for simplicity stake). Two new variables are introduced; T, the capacity factor ratio and S, the 1-year average SPEI defined as:

$$T = \frac{CF_{1-yr}}{CF_{10-yr}}$$

And

$$S = SPEI_{1-yr}$$

Then, the empirical copula C linking both variables is:

$$C(u_1, u_2) = P(T \leq F_T^{-1}(u_1), S \leq F_S^{-1}(u_2))$$

With:

- u_1 and u_2 are realizations from U_1 and U_2, two continuous uniform variables;

[11] In the following, $\hat{X}$ is the estimation of X and $\widetilde{X}$ is the estimation of X where the estimation process uses estimated data.

- F_T and F_S are the cumulative distribution functions for T and S respectively.

Copulas are used to describe the dependence between random variables and account for non-linear dependencies[12]. They are used here to model the fact that low values of SPEI are often correlated with low values of capacity factors. The future distribution of the SPEI is exogenous and we use it along with the estimated copula to simulate an expected distribution of T, called $\tilde{T}$. This future distribution is estimated, following Simard et al. [19], and we compute $P(\tilde{T} < 0.5)$. Then, we compare it to $P(T < 0.5)$ to see if the probability increases of having a capacity factor that is 50% lower than the long-term average.

The following metrics are used:

- The historical yearly probability of occurrences of extreme low production $POELP_{historical} = P(T_{1970-2015} < 0.5)$
- The medium-term yearly probability of occurrences of extreme low production $POELP_{mediumterm} = P(\tilde{T}_{2020-2050} < 0.5)$
- The long-term yearly probability of occurrences of extreme low production $POELP_{longterm} = P(\tilde{T}_{2070-2100} < 0.5)$

The comparison between historical, medium- and long-term probabilities gives a risk measure for each plant, that can be aggregated at company level. The difference is computed as the difference between the baseline probability and the medium- or long-term probability of having an extreme low production, and is expressed in percentage point difference.

Appendix B: Data characteristics

Table 3 below presents the different characteristics of both the SPEI and the capacity factor data.

	Capacity factor	SPEI (12 months)
N	83 849	89424
Mean	0.37	0.13
Median (IQR)	0.36 (0.22;0.51)	0.14 (-0.66;0.92)
Range	0.00; 1.00	-3.61; 3.38
Missing	5 575	0

Table 3: Univariate characteristics of Capacity factor and SPEI data.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

The capacity factor is located between 0 and 1, with a mean at 0.37. The SPEI follows a normal distribution, between -3.61 and 3.38. A low SPEI value indicates drought.

[12]For more details on copulas, see the introduction by Haugh[10] for example.

Figure 6 shows the result from the bivariate analysis of our variables. The 1-year capacity factor is heavily correlated with the long-term capacity factor. It shows a correlation of 0.3 with the short term SPEI. This correlation decreases between the long-term capacity factor and SPEI. Short term SPEI and long-term capacity factor are uncorrelated, and are usable in the same model.

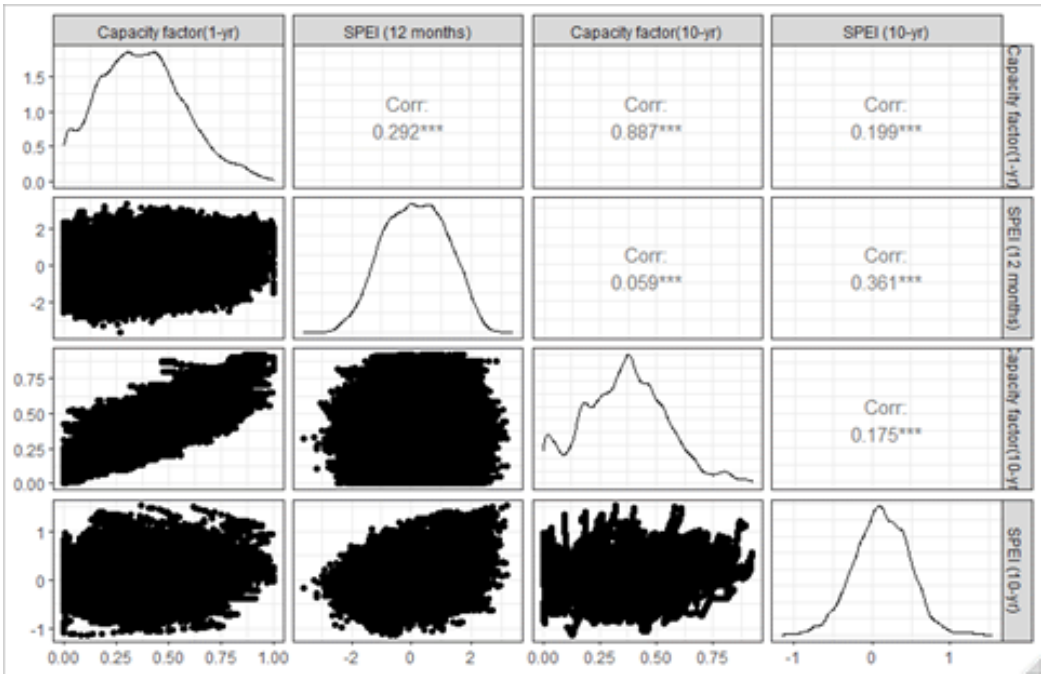

Figure 6: Bivariate analysis of the variables.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Appendix C: Calibration details

The appendix below details the results of our calibration.

Impact of climate change on average production

With the notation from Section 2, we define Model 1:

$$CF_{1-yr} = \alpha + \beta_0 * SPEI_{1-yr} + \beta_1 * CF_{10-yr} + \epsilon$$

As described in Appendix A, for some plants, CF_{10-yr} is missing, either because they are not in the training sample, or because we are using projected data. In that case, it is estimated using Model 2:

$$\widehat{CF}_{10-yr} = \alpha' + \beta' * SPEI_{10-yr} + \epsilon'$$

The coefficients for both models are estimated using panel regressors. Table 4 shows the results of the different tests justifying these choices.

p-value	Model 1	Model 2
Chow Test	<2.2e-16	<2.2e-16
Breusch Pagan test	<2.2e-16	<2.2e-16
Hausman Test	0.8302	<2.2e-16
Lagrange FF Multiplier Tests for Panel Models	<2.2e-16	
F test for individual effects		<2.2e-16
Breusch-Pagan test (heteroscedasticity)	<2.2e-16	<2.2e-16

Table 4: Results of the different panel tests

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

The Chow test indicates that the pooled model is rejected at level 5% and that the panel model seems more appropriate. The Breusch-Pagan rejects the null-hypothesis of no cross-sectional dependence, which was expected since some plants from our sample are in the same area. For Model 1, a random effect model seems more appropriate according to the Hausman test. This is confirmed with the Lagrange F-test that rejects the null-hypothesis of a pooled model versus a random effect model. For model 2, the Hausman test rejects the null-hypothesis and a fixed effect model is preferred. Both models reject the null-hypothesis of homoscedasticity. Next, we test if variables are stationary. Results are presented in Table 5.

Variable	p-value	Result
Capacity factor (1-yr)	1.821E-14	The variable is stationary
SPEI (12 months)	<2.2e-16	The variable is stationary
Capacity factor (10-yr)	1	The variable is non-stationary
SPEI (10-yr)	1	The variable is non-stationary

Table 5: Panel test results for the different indicators.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

The long-term averages of the variables (capacity factor and SPEI) are non-stationary, as expected. Given the length of our panel data, we include them, keeping in mind that the regression for Model 1 might not be consistent.

For Model 1, we use a random-effect panel estimator, while for Model 2 we use a fixed-effect panel estimator. These estimators normally assume the variables to be stationary, an assumption that is not met here. However, we are more interested in the long-term relationship between these variables than in the explanatory power of the SPEI and we keep this estimation technique. Nevertheless, these estimators might not be consistent and further modelling is required to enhance this relationship. The results are presented in Table 6. The quality of both models is acceptable, with Adjusted R-Squares equal to respectively 0.38 and 0.49. All coefficients are statistically different

from 0. The sign before the SPEI indicator is as expected: a higher level of SPEI leads to a higher level of production thus to a higher capacity factor.

	Model 2	Model 1
Constant	0.355***	
SPEI (1-year)		0.057***
Capacity factor (10-yr)		0.884***
SPEI (10-yr)	0.084***	
Adj R-square	0.38	0.49
F-test (p-value)	<2.22e-16	<2.22e-16

Table 6: Estimation results for the two models.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Impact of climate change on the occurrences of low production extremes

We use the following steps to estimate the impact of drought on future production extremes :

- Step 1: Estimate the copula between T and S (using the same notation as in Section 3);
- Step 2: Set $v = F_S(S)$, where F_S is the cumulative distribution function of $\hat{S}$ (computed using forecasted SPEI), estimated on historical data;
- Step 3: Simulate observations from the conditional copula:

$$U \sim C(., v)$$

  Where $C(., v)$ is the conditional copula $C(., v) = C_{U|V}(u, v)$
- Step 4: Compute $\hat{T} = F_T^{-1}(U)$, where F_T is the cumulative distribution of T, estimated using historical data;
- Step 5: Estimate $P(\hat{T} < 0.5)$

Figure 7 plots the distributions of T and S. The SPEI follows a normal distribution, while the capacity factor ratio is logically strictly greater than 0 with a heavy right-tail. A T value of 1 has a higher probability of occurrence than in a normal distribution. The left-tail, however, is closer to normally distributed curve.

Table 7 provides the parameters used to estimate T and S. Both distributions are approximated by normal distributions. This approximation is satisfactory here though further work should be conducted to find distributions with a better fit.

Figure 8 shows the relationship between the normalized ranks of the two distributions (left). This dependence is modelled using a Frank copula, with estimated parameters $Par = 4.61$,$\tau = 0.43$.

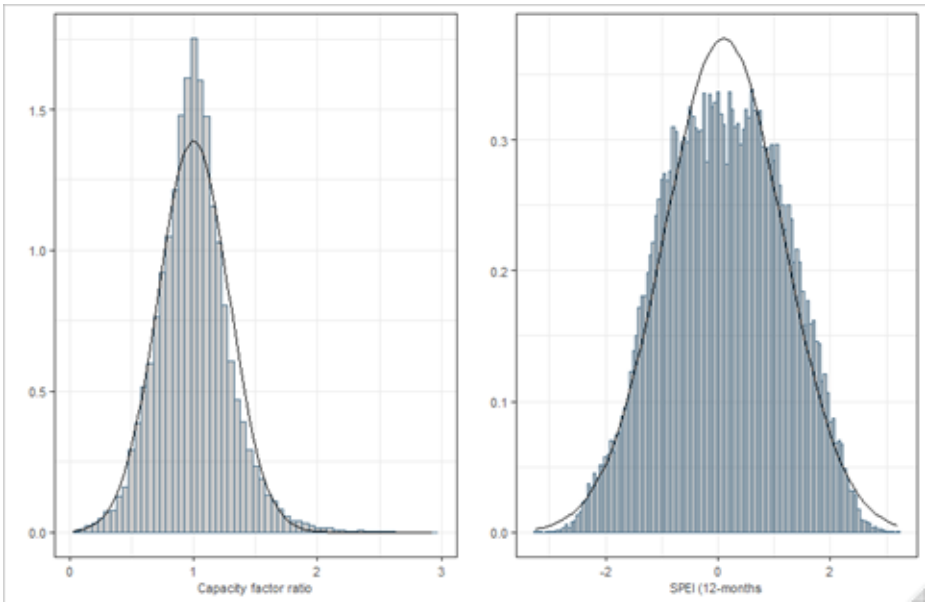

Figure 7: Distribution for the capacity factor ratio T (left) and the 1-year average SPEI S (right)

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

		T	S
Distribution		Normal	Normal
Parameters	Mean	0.99	0.09
	Std	0.28	1.05

Table 7: Distribution estimation for T and S

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Further work could be implemented to test other copulas. The graphic on the right shows this dependence modelled through the chosen copula.

Using the simulated distribution and copula, Figure 9 presents the empirical and simulated distribution. The empirical distribution is the same as the left-hand side graph in Figure 7. The simulated distribution is obtained using the steps describe at the beginning of this section. Following observations made on Figure 7, the distribution does not fit well on central values and estimation of the median are expected to be of poor quality. However, the left tail (where the short-term capacity factor is lower than its long-term value) seems well simulated.The historical value of $P(T < 0.5)$ is 3.5% and the estimated value is 3.5%. Overall the model quality is satisfactory.

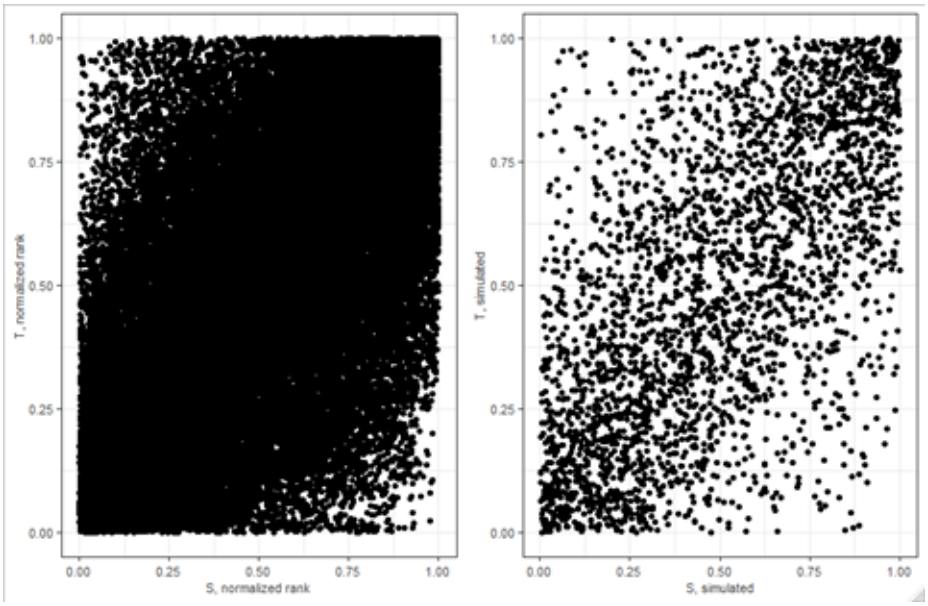

Figure 8: Normalized ranks of T given normalized ranks of S (left) and same relationship estimated through a copula (right).

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

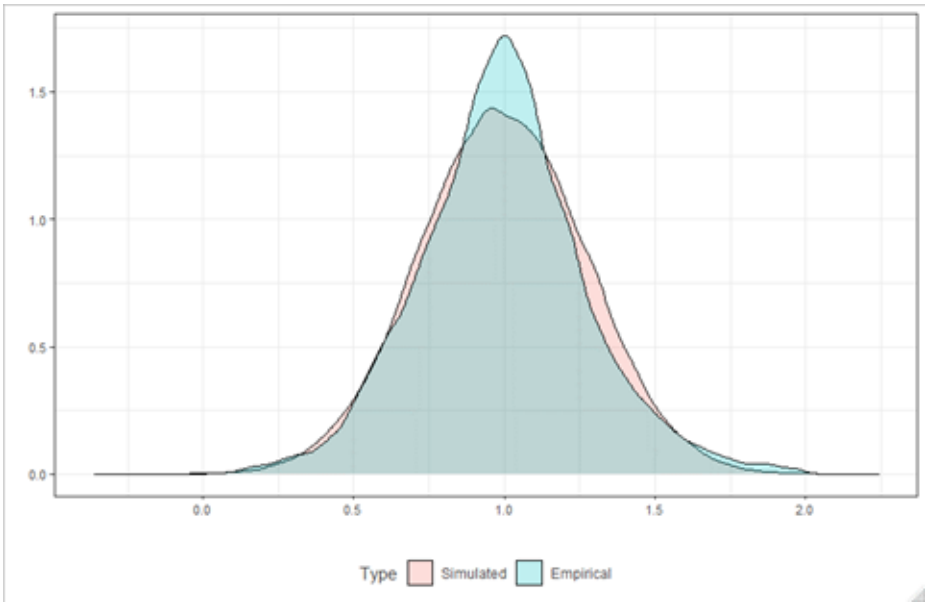

Figure 9: Empirical and simulated distribution for T.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Appendix D: Robustness analysis

This appendix describes the in- and out-of-sample performances of our method. In this analysis, forecasted data is not included and out-of-sample refers to plants that have not been included in the

construction of our model.

Impact of climate change on average production

Our goal is to compare the real and estimated capacity factors over the period 1970-2015.

Figure 10 shows the real and estimated values for a single plant. Both 1-year and 10-year estimations are of reasonable quality. For the 1-year estimation, both low and high capacity factor periods are underestimated[13]. This confirms the need for the short-term approach, where we link drought extremes to production extremes.

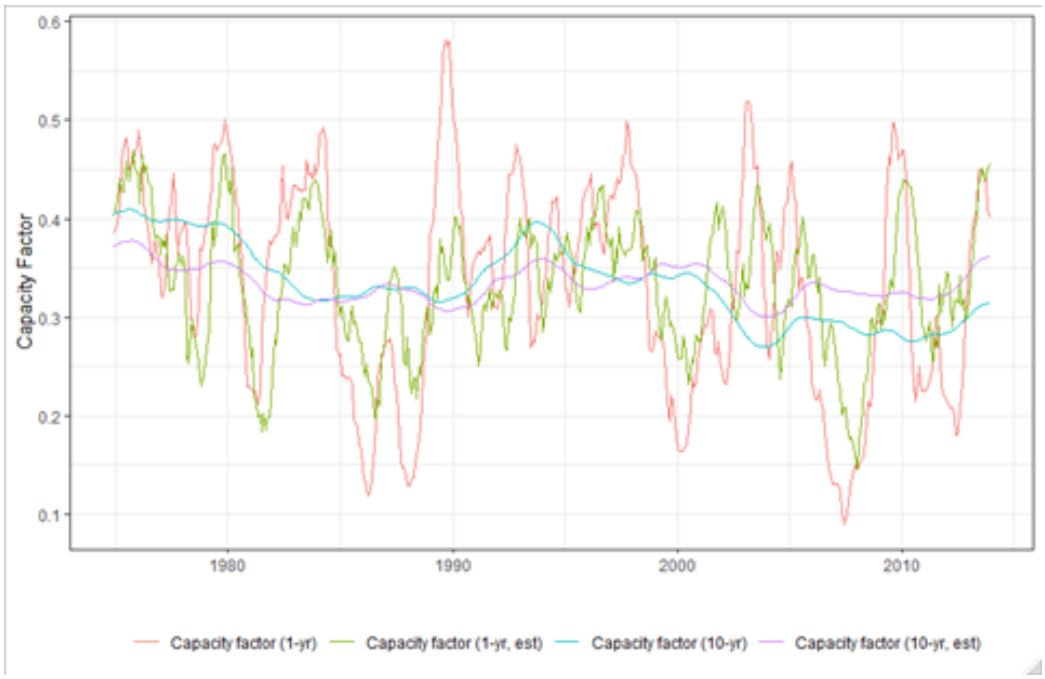

Figure 10: Real and estimated capacity factor for a single power plant.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Figure 11 shows the performance of our model at estimating average capacity factors over the period 1970 – 2015. The results are satisfactory. The bar chart represents the absolute median error, computed as the median over 1970-2015 of absolute error for the 1-year capacity factor estimation. The maximum median error is around 0.10, meaning that the capacity factor is over/under estimated by 10 percentage points. However, the overall mean error is around 0, meaning that underestimations are compensated by overestimations.

[13]Interestingly, there is an inversion for the 10-year capacity factor: the model underestimates the real value before 1995 and overestimates it afterwards. An external factor forcing the plant to run at sub-optimal level after 1995 may explain this.

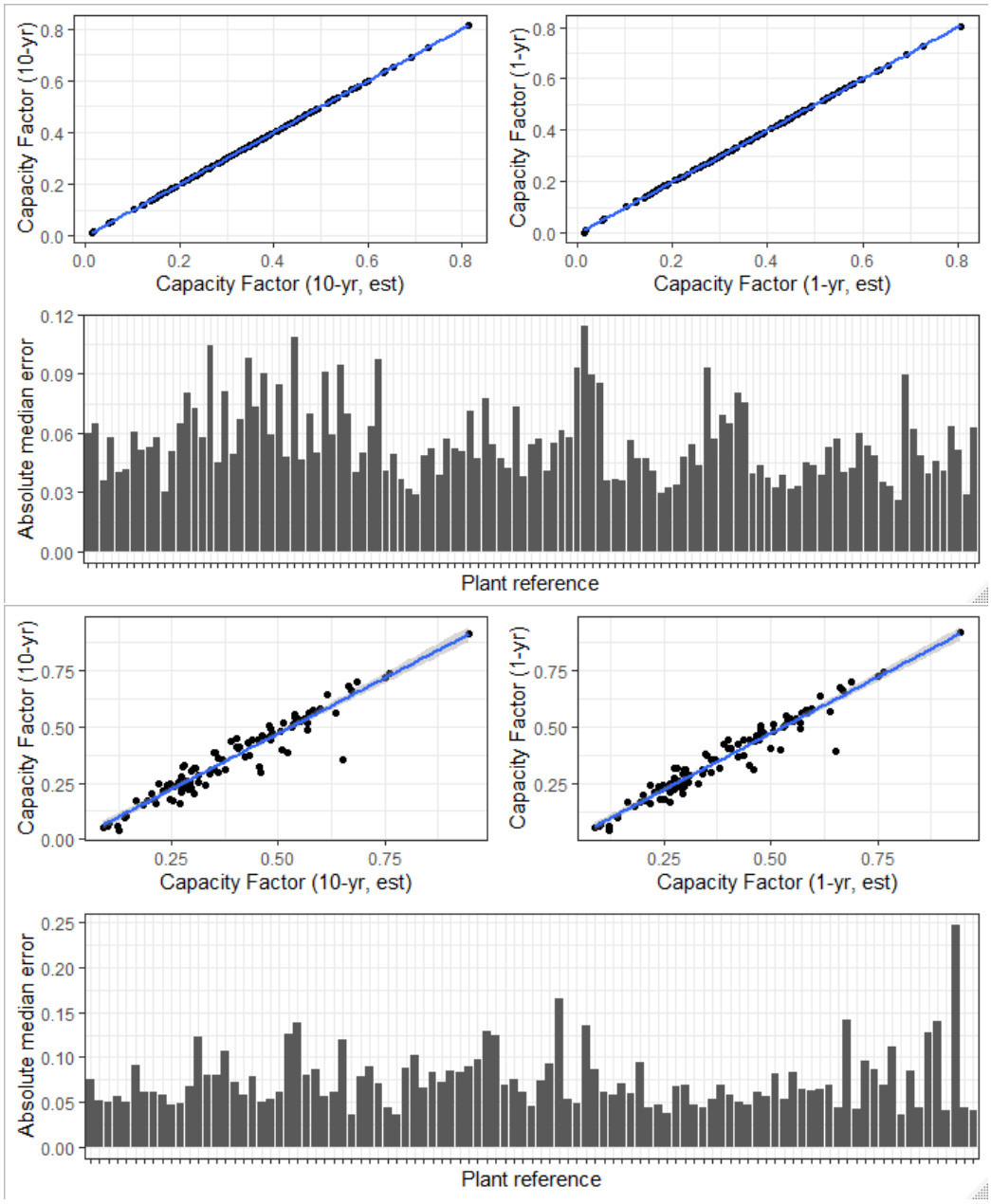

Figure 11: Comparison of average real and estimated capacity factors for in-sample (upper) and out-of-sample (lower) data.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Results are of similar quality for out-of-sample plants: the average capacity factor (both 1-year and 10-year) is correctly estimated. The absolute median error is slightly higher, with maximums at 25 percentage points, though the overall average error remains satisfactory at around 2%. This proves that our model correctly predicts capacity factors on a long-term average. This is not surprising:

because we take the average over a very long interval, we neutralize the effect of short-time changes.

Impact of climate change on the occurrences of production extremes

Again, we apply our methodology to two set of in-sample and out-of-sample plants. Three situations are simulated:

- For each individual plant, we compare $P(T < 0.5)$ with its estimate $P(\hat{T} < 0.5)$, where each plant has its own distribution function for T, based on historical data;
- For each individual plant, we compare $P(T < 0.5)$ with its estimate $P(\hat{T} < 0.5)$, where each plant has its own distribution function for T, based on estimated data;
- For a random sample of 20 plants, we compare $P(T < 0.5)$ with its estimate $P(\hat{T} < 0.5)$, where the distribution is estimated using the estimation for the capacity factors. This case simulates the fact that, at company-level, results are computed over a set of plants.

Results are presented in Figure 12. The graph in the upper right corner shows the comparison for the first situation. Using each plant historical distribution, we correctly estimate $P(T < 0.5)$. However, this is only usable in the case where we have historical data on T, which is rarely the case. In the second situation, the estimates of the short- and long-term capacity factors are used to build T. Based on empirical data, it is adjusted to account for the lower variance of the estimates versus the real values. For a single plant, results are of poorer quality because the number of data points per plant is insufficient (upper left corner). However, if we aggregate the data for 20 plants (for example, at company level), results are more satisfactory (bottom graph). Overall, we could significantly enhance the quality of our models by using the observed distribution of T. However, this would require to gather that information at world level and this data is not available. The lower graphs show similar results for out-of-sample data, with satisfactory results in the case where we aggregate 20 plants.

Table 8 provides R-square for each model, allowing to measure how simulated probabilities explain observed ones.

	In-sample	Out-of-sample
Situation 1: historical distribution for T	0.74	0.88
Situation 2: estimated distribution for T	0.19	0.22
Situation 3: estimated distribution for T and aggregation	0.21	0.24

Table 8: R-squared value for each case.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

Surprisingly, the model has better performance on out-of-sample data. The fact that the historical distribution will be unknown for most plants is an issue. Nevertheless, we reduce the bias by comparing estimated values to estimated historical ones. Hence, increase in risk due to lower SPEI should be computed regarding a baseline and cannot be interpreted in absolute value, if historical data is not reported.

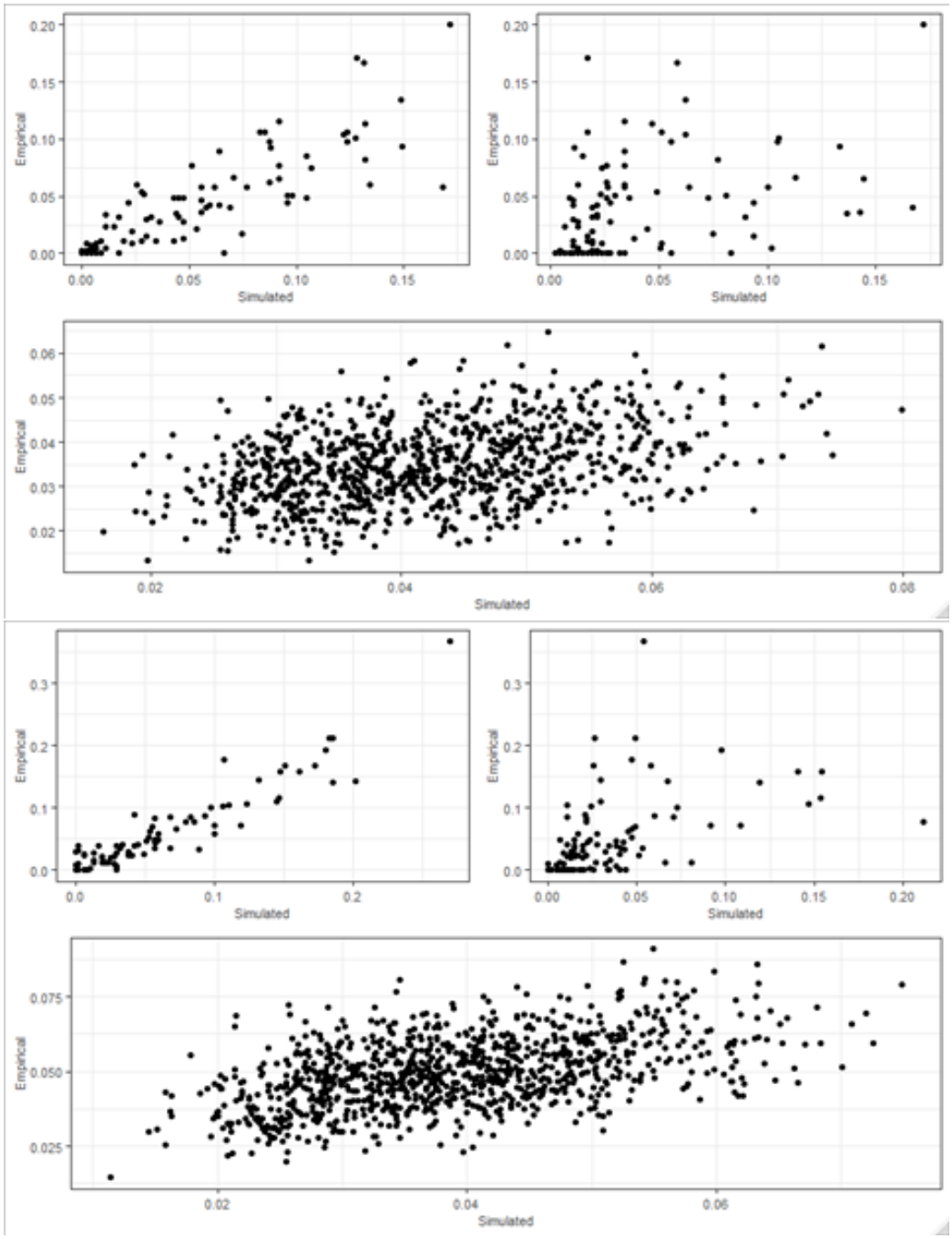

Figure 12: Real and estimated values for $P(T < 0.5)$ for the three scenarios for in-sample (upper) and out-of-sample (lower) data.

Source: LSEG SI Research, based on EIA and SPEI (from Beguería et al.) data

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