Grantham Research Institute on Climate Change and the Environment

Centre for Climate Change Economics and Policy

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February 2023

Centre for Climate Change Economics and Policy Working Paper No. 418
ISSN 2515-5709 (Online)

Grantham Research Institute on Climate Change and the Environment
Working Paper No. 394
ISSN 2515-5717 (Online)

Economic and Social Research Council

The Grantham Foundation
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Suggested citation:
Colesanti Senni C and von Jagow A (2023) *Water risks for hydroelectricity generation*. Centre for Climate Change Economics and Policy Working Paper 418/Grantham Research Institute on Climate Change and the Environment Working Paper 394. London: London School of Economics and Political Science

Water risks for hydroelectricity generation*

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February 2023

Abstract

This paper studies how reduced water availability affects hydroelectricity generation in Europe and the US. We build a novel dataset for the period 2015-2021 that matches information on hydropower plants with geospecific precipitation and water risk (a compound measure reflecting different aspects of water availability). The paper develops two complementary research designs. First, it uses a cross-sectional design that considers changes in hydroelectricity generation in 2021 - a low rainfall year - compared to its historical average. We find that plants located in riskier basins produced less electricity vis-a-vis the historical average compared to their counterparts located in less risky basins. Second, we use a panel design where we exploit changes in precipitation over time. Consistent with our cross-sectional results, we find a that an increase in precipitation is associated with higher levels of electricity generation. The empirical strategies adopted in this paper offer a framework that can be replicated for other sectors and environmental risks. The findings inform the design of the low-carbon transition and the management of environmental financial risks.

JEL classification: C21, C23, Q20, Q25, Q42, Q51.

Keywords: Hydroelectricity generation, water-related risks, energy security, geospatial data.

*The authors gratefully acknowledge Oliver Braunschweig, Rafael Camargo, Antoine Champetier, Yannis Dafermos, Ben Filewod, Skand Goel, Alain Naef, Mathilde Salin and Yoshihide Wada for the very useful comments and discussions. We are particularly grateful to Edwin Sutanudjaja for his help with water-related data and detailed comments. The authors also acknowledge support from the Grantham Foundation for the Protection of the Environment and the UK Economic and Social Research Council through the Centre for Climate Change Economics and Policy.

1 Introduction

In August 2022, intense droughts hit several locations of the globe. In Southwestern China, declining reservoir levels reduced the amount of energy produced by hydropower plants and the government of Sichuan issued a power rationing plan: Energy-intensive industry had to halt production for two weeks, affecting for instance Toyota and Apple supplier Foxconn (Yin, 2022; Langley et al., 2022). In the same summer, the European Drought Observatory reported significant economic impacts from water stress mixed with high temperatures. Nuclear reactors in France had to reduce capacity and hydroelectricity generation in Italy, France and Portugal fell by 11233 GWh in the first half of 2022 compared to previous years (Toreti et al., 2022). Despite these large and well known warning signs, the risks posed by water stress to the energy sector and in particular to hydroelectricity generation have received little attention in the academic literature.

Hydropower is a central piece in the low-carbon transition puzzle. Existing hydropower plants are the largest source of low-emission electricity globally and the International Energy Agency (IEA) estimates that hydropower capacity could double by 2050, representing about 15% of total electricity generation in its net zero scenario (IEA, 2021). The importance of hydropower is further compounded as it is needed as a flexible source of clean electricity to smooth over peaks in generation from solar and wind (Grady and Dennis, 2022). Changes in water availability that reduce the generating capacity of hydropower plants, might hinder the transition to a low-carbon economy. Failing to account for these risks in forward-looking risk assessments could lead to a rapid financial revaluation of the firms and economic activities exposed to such risks. Central banks and financial supervisors have highlighted that nature-related risks can transmit to the financial sector, creating risks for individual investors and the financial system (NGFS, 2022).

In this paper, we quantify the reduction in hydroelectricity generation depending on the exposure of a plant to changes in water availability. Thanks to progress in geo-spatial data generation and analysis, the availability of granular hydro-meteorological data has expanded. This has led to the development of various software, metrics and databases that rely on hydrogeological and economic models to translate water data into water-related risks. We rely on both on the WRI Aqueduct Water Risk Atlas, described by its designers as a tool to "understand water-related risks and assess exposure to water risk across multiple locations" and on raw hydro-meteorological data (as provided by TerraClimate). We show that the data warehouse tool and the raw data can be used to investigate changes in hydroelectricity generation at the plant level.

We combine location-specific information on water-related risks and hydro-meteorological data with hydropower plants location and build a novel dataset that we use to perform two complementary analyses: (1) a cross-sectional regression, in which we rely on the water risk metrics provided by WRI; (2) a panel regression in which we use the time series of location-specific precipitation as a proxy for changes water availability. The first regression allows us to investigate water-related reductions in electricity generation in the low-rainfall year 2021 compared to the historical average (2015-2020). The panel regression instead explores how the variation in location-specific water availability is associated with changes in electricity generation. We find that modeled estimates of water-related risks are associated with a reduction in hydroelectricity generation by 21%. In the panel setting, halving the amount of precipitation is associated with 2.75% less electricity generation generated at the plant level. Our results are robust to the use of alternative specifications and indicators, such as the Palmer Drought Severity Index (PDSI).

1.1 Relation to the literature

Our work links the literature on the impact of environmental risks on the economic and financial system with the literature on renewable energy security (Valentine, 2011; Allcott et al., 2016).

Among environmental risks, climate risks have recently been identified as a potential source of economic losses and financial instability (Stolbova and Battiston, 2020; Campiglio et al., 2022). There is increasing evidence of the economic costs due to natural disasters and environmental degradation (Hornbeck, 2012; Parker, 2018; Botzen et al., 2019; Coronese et al., 2019; Pankratz and Schiller, 2021; Johnson et al., 2021) and several attempts have been made to estimate appropriate damage functions (Nordhaus, 1993; Botzen and van den Bergh, 2012; Diaz and Moore, 2017; Bretschger and Pattakou, 2019; Neumann et al., 2020; Franzke, 2021; Dunyo, 2022; Russell et al., 2022).

A subset of this literature has focused on the negative impact of water-related risks. In the context of water-related risks, changes in water runoff significantly impact economic growth (Russ, 2020) and water-related risks can hinder the transition to a low-carbon economy by tilting the energy mix towards fossil fuels (see Eyer and Wichman (2018) for the US electricity sector). Recent research has highlighted the importance of identifying exposure to physical risks at the asset-level (Bressan et al., 2022). We follow this strand of the literature in that we employ plant-level information to provide an empirical estimate of the damage function of changes in water availability on hydroelectricity generation.

Hydropower also plays an important role in securing energy availability, both at the global level (IEA, 2021; Ramião et al., 2022; IRENA, 2023) and within hydropower-dependent states (Prado Jr et al., 2016). However, water-related risks have been shown to reduce hydropower availability, while climate change is set to exacerbate physical water risks (Pörtner et al., 2022). In an early example, Munoz and Sailor (1998) develop a model to predict the availability of hydroelectricity generation in Northern California under various climate scenarios. More recent literature finds that frequent droughts increase the variability and reduce the reliability of hydroelectricity generation, reducing total power generation (Beilfuss et al., 2012; Von Randow et al., 2019). With our results, we strengthen the evidence on the negative effects of water-related risks and changes in water availability on hydroelectricity generation, which is deemed to be an important source of renewable energy in the future. Van Vliet et al. (2016) project the impact of climate-driven changes in hydrology on the electricity generation of 24,500 hydropower projects globally. They find that between 61 to 74% of plants will see they energy input fall. Goodarzi et al. (2020) conduct a microstudy of Seimare Dam in Iran and find that climate change likely reduces both water inflow into the dam and electricity generation over a a 30-year horizon. Similarly, Zhao et al. (2023) study the impact of climate-induced droughts on hydroelectricity generation in China. They find that more than one-fourth of studied plants will experience a 20% reduction in electricity generation under both optimistic and pessimistic climate scenarios vis-a-vis the baseline. Finally, Opperman et al. (2022) show that existing and projected dams are predominantly located within river basins that currently have medium to very high values of water risk and that climate change will increase the risk for about one third of these plants by 2050.

Our paper makes contributions on several fronts. First, it presents statistical evidence that water-related risks are material to hydroelectricity generation. This direct statistical evidence is complementary to hydrological or physics-based models (Turner and Voisin, 2022) and can be used to validate simulations from process-based models. Second, as far as we know, this is the only study that provides estimates of the effect of water scarcity on hydroelectricity generation for *high-income* economies. This is important because much of the literature on economic impacts on natural resource scarcity is focused on developing economies, arguably because they have a higher dependence on their natural resource base. However, it is important to note that vulnerabilities to natural resource also exist in developed economies. Third, the paper provides a framework for understanding the impact of other forms natural capital risks on different sectors of economic activity. In particular, we merge novel granular geospatial data with asset-level data, which could set a benchmark for future studies. Moreover, we employ a variety of empirical approaches to develop confidence in their findings. This is important because it is difficult to clearly define and comprehensively measure a multidimensional concept such as natural capital risk - we can at best find proxies for it. Moreover, finding experimental, or quasi experimental, variation in these measures can be challenging. The empirical strategies adopted in this paper offer a framework that can be replicated across similar datasets. Fourth, hydropower will be crucial to the transition to renewable energy (Ramião et al., 2022). However, the effects of climate change on water scarcity will determine the effectiveness of hydropower projects.[1] Combined with these effects, the estimates in the paper can be used for planning, for instance in an exercise such as Sarzaeim et al. (2018), as well as for calibrating economy-wide models (CGE, IAM) that endogenize hydroelectricity generation, such as Zhang et al. (2022).

The remainder of the paper is organised as follows: Section 2 describes the sources of the data and the construction of the dataset. In Section 3 we lay out our empirical analysis. Section 4 discusses our findings and highlights limitations and future research needs. Section 5 concludes.

2 Data

For the empirical analysis, we rely on data sources listed in Table 1 and described below.

[1] The effect of climate change on water scarcity will depend on location. Some regions are likely to see increase in hydropower potential (Ali et al., 2018).

Table 1: Data sources

Data	Application	Source
Hydropower plant location and operating capacity	Location data (latitude, longitude), age and operating capacity of 9'498 active hydropower plants. The location is used to obtain generation, water risk and precipitation data. The operating capacity is used as a control variable.	S&P CapitalIQ Pro Asset Data
Hydroelectricity generation at the plant level	Hourly electricity generation data is aggregated at the monthly level. Total generation in each month is used as the dependent variable in the analysis.	European data comes from ENTSO-E and is downloaded from Fraunhofer Energy Charts. US data comes from the Energy Information Administration (EIA)
Water risk factors	For the cross-sectional analysis, we use indicators of water risk (water stress, drought risk and water depletion), which are based on a hydrological model validated on data from 1960 onwards (Sutanudjaja et al., 2018; Hofste et al., 2019).	WRI Aqueduct Water Risk Atlas (World Resource Institute)
Hydro-meteorological data	In the panel analysis, we use data about precipitation (rain and snow-water equivalent as explanatory variables), evapotranspiration and the Palmer Drought Severity Index. The data comes from the analysis of satellite imagery and is available at a resolution of 5 km with missing data taken from separate historical sources.	TerraClimate via Google Earth Engine
Reservoir data	Reservoir size is used as a control variable. The dataset contains the surface water area of 71,208 reservoirs/lakes derived from optical satellite imagery.	The data was compiled by Donchyts et al. (2022)

Hydropower plant location and operating capacity. We obtain global data on hydropower plants from S&P CapitalIQ Pro Asset Data (CIQ). We extract the location (latitude, longitude), operating capacity (in MWh) and first year in service for all active hydropower plants globally (for a total of 9'498 plants).

Hydroelectricity generation at the plant level. Hourly data on hydroelectricity generation in Europe is taken from the Energy Charts managed by the Frauenhofer Institute for Solar Energy Systems, which is based on hourly electricity generation data from the European association for the cooperation of transmission system operators for electricity (ENTSO-E). Monthly data on plant-level hydroelectricity generation in the US is taken from the Electricity Data Browser provided by the U.S. Energy Information Administration. For Europe, the plant names from ENTSO-E data do not correspond to the names in CIQ. To merge them, we manually construct a correspondence table. We use this data both in our cross-sectional and panel regressions. For the cross-sectional model, we compute the ratio of electricity generation in 2021 at the plant level over the average generation in the period 2015-2020. We can interpret this ratio as the deviation in electricity generation in a low-rainfall year such as 2021 compared to the average historical generation in our sample. For the panel model, we aggregate generated electricity (hourly data for the European plants) at monthly intervals to smooth over some of the variance in electricity generation due to operational reasons.

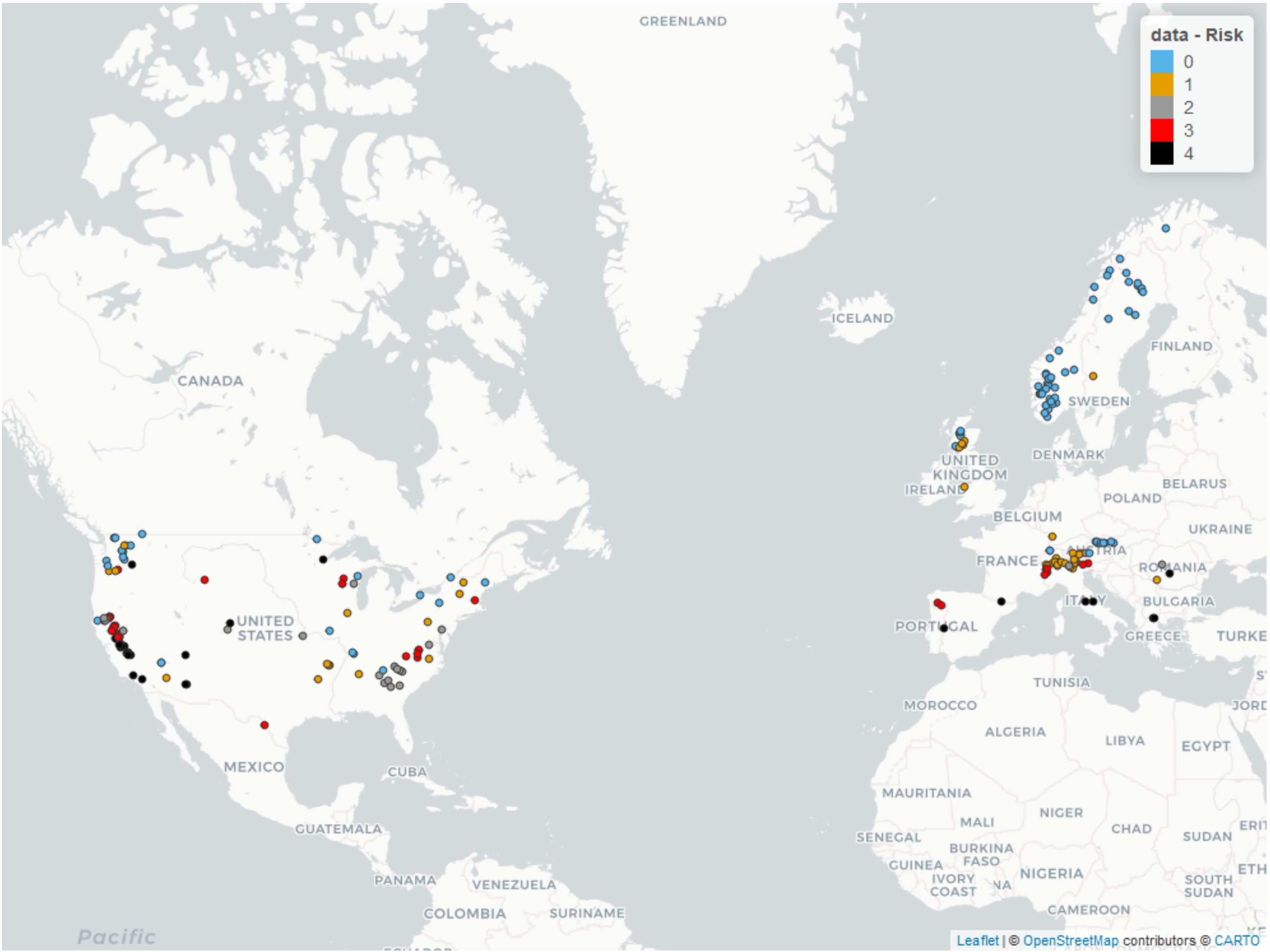
Power plant types. The European data includes information on generation from two types of hydropower plants, run of river (ROR) and water reservoir (WR) plants. ROR plants are located directly on or next to active rivers, using water channeled from the riverbed to the facility. Water pressure to operate the turbines is generated by the natural decline of the riverbed. WR plants are located at or below artificial dams or impoundment facilities, which collect the water from rivers and/or precipitation. The pressure to power the turbines is derived from the elevation of the reservoir's surface compared to the turbine. The distinction between ROR and WR plants is not directly available for US data. Instead, we construct a classification table based on the plant's water source ("river"/"rio"/"creek" vs. "reservoir"/"lake"/"dam"), as available from CIQ.

Water-related risks. Water risk data is taken from the World Resources Institute's Aqueduct Water Risk Atlas. The Water Risk Atlas covers three sources of water-related risks: water quantity (made up of eight indicators), water quality (two indicators) and reputational/regulatory risks (three indicators). Weights can be adjusted to the user's needs. Our interest are water quantity risks, which are defined as "the exposure to changes in water quantity that may impact a company's direct operations, supply chains and/or logistics." Five types of quantity risk are based on the hydrological model PCR-GLOBWB 2: baseline water stress, baseline water depletion, interannual variability, seasonal variability, and groundwater table decline. In our analysis, we use an aggregated score of all of the physical quantity risks, which is computed directly within the Aqueduct Water Risk Atlas. This approach leads to risk factors that are geographically specific to water basins.[2] We obtain risk scores for the location of each hydropower plant by uploading the longitude and latitude of each plant into Aqueduct. As an example, Figure 1 shows the aggregate risk exposure expressed in categories of 0-4 (where 4 is higher risk) of a sample of hydropower plants. The map clearly shows some clustering of power plants in either high risk regions (e.g., Southern California) or low risk regions (e.g., Norway and Sweden). Low-risk and high-risk plants, however, can also fall close to each other, as in the Alps or the South Western US.

Hydro-meteorological data. As WRI Aqueduct only provides a cross-sectional risk value, we rely on hydro-meteorological data to obtain a time-variant proxy for water-related risks. We use geo-specific precipitation and evapotranspiration data in mm/month as well the Palmer Drought Severity Index (PDSI) from TerraClimate. The PDSI is a standardized index and uses readily available temperature and precipitation data to estimate relative dryness. Lower values are associated with drier locations.

[2]Basins are defined as land areas in which surface water converges

Figure 1: Hydropower plants location and water risks.



Reservoir data. Time-variant data on size of the reservoirs is obtained from Donchyts et al. (2022). The dataset includes reservoirs location (in latitude/longitude) and the reservoirs surface area (in ha) for the period 2000-2021. Based on the location, we match each power plant to the closest reservoir, counting a power plant as connected to a reservoir up to a maximum distance of 20km.

Our final sample includes 1141 power plants in 14 European countries and 47 US states. In our panel, electricity generation and precipitation data are aggregated at the monthly level over the period 2015-2021. We report the summary statistics in Table 4 in the Appendix.

3 Empirical analysis

In this section we investigate the relationship between hydroelectricity generation and changes in water availability. All the variables are expressed in logs and are winsorized at the 5% level, unless differently indicated.

3.1 Cross-sectional regression

We first estimate the relationship between water-related risks - as provided by WRI - and the ratio in hydroelectricity generation in 2021 (a low-rainfall year) over the historical average (2015-2020). Our ordinary least squares (OLS) regression reads

$$\tilde{y}_i = \beta risk_i + \gamma' x + \delta + \epsilon_i,$$

where i denotes the power plant, $\tilde{y}_i$ is the ratio in electricity generation in 2021 over the historical average (2015-2020) for each plant, $risk_i$ is the standardized WRI raw weighted aggregated physical quantity risk score in the location of plant i. The vector x includes the control variables age, the years since when the power plant is operating, its operating capacity and the surface area of the closest reservoir. We also include country and power plant type (run of river or water reservoir) fixed effects (δ). The fixed effects control for unobservables at the country level, such as country-specific demand for electricity. Errors are clustered at the country levels.

Table 2 displays our results. We find a significant negative relationship between the risk score and hydroelectricity generation. A one-standard deviation increase in the risk score is associated with a 20% lower electricity generation in 2021 compared to the historical average. To provide an intuition of what this number means in terms of generation reduction, notice that the mean ratio across all power plants is 1.03, that is, across all power plants, generation increased by 3% in 2021. [3] A reduction in the ratio by 20% thus results in a reduction in

[3] See Figure 2 in the Appendix, which displays plant and average electricity generation ratio by risk category.

electricity generation of about 21% for one standard deviation increase in the risk score.

WRI also provides the risk measure on a discrete scale of five categories, running from 0 to 4 (lowest to highest risk). Specification (2) in Table 2 provides our results when using the discrete risk categories. The coefficients have to be interpreted as the change in effects compared to the no-risk category (category 0). Higher risk categories (above 2) are associated with more significant and larger reductions in electricity generation in the low-rainfall year 2021 vis-a-vis the historical average.[4]

[4] In the cross-sectional approach, we consider the effect for the year 2021. This is because the water risk metrics are only available for a cross-section. However, it is unlikely that the risk ranking of plants changes from year-to-year. Under this assumption, and because the metric is ordinal, we could also adopt the following hybrid empirical strategy:

$$\tilde{y}_{i,t}\tilde{y}_{i,t} = \beta risk_i + controls + \epsilon_{i,t}$$

where i refers to a plant and t refers to the year. The regression can be estimated separately for each year. It can then be checked if β_t ¡ 0 for other years that were drier than average. Note that the assumption of non-changing ranks are consistent with the correlation between precipitation and water-related risks (See Figure 4 in the Appendix).

Table 2: Cross sectional regression of electricity generation change in 2021 compared to the historical average at the plant level. We use as regressors both the raw risk score and the risk categories, where the reference value is the risk category 0.

Dependent Variable:	$\tilde{y}$	
Model:	(1)	(2)
Variables		
Water risk	-0.2060***	
	(0.0313)	
Age	-0.0081	0.0342
	(0.0901)	(0.0969)
Operating capacity	-0.0245	-0.0294
	(0.0205)	(0.0271)
Reservoir size	0.0034	-0.0013
	(0.0227)	(0.0174)
Risk category 1		-0.2397*
		(0.1207)
Risk category 2		-0.2234***
		(0.0607)
Risk category 3		-0.5973***
		(0.1060)
Risk category 4		-0.6341***
		(0.0862)
Fixed-effects		
Country	Yes	Yes
Type	Yes	Yes
Fit statistics		
Observations	338	338
R^2	0.40091	0.40631
Within R^2	0.11140	0.11941

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

To contextualize our estimates, a back of the envelope calculation that translates these effects in GDP would multiply the effect of water-related risks on hydroelectricity generation times the effect of hydroelectricity generation on GDP as provided by Allcott et al. (2016). This would result in a 2% reduction of GDP.

The cross-sectional relationship between water-related risks and hydroelectricity generation represents an optimized outcome, including effects due to adaptation and endogenous location of plants (e.g. in the Ricardian approach to climate change (Mendelsohn et al., 1994)). This implies that to ameliorate these effects, any adaptation measures must be in addition to the ones that may have already been adopted in the past.

3.2 Panel regression

While the cross-sectional analysis shows that a region's water risk score is indicative of hydropower plants' performance in a specific year, it does not explore how the time variation in water-related risks affects the results. Unfortunately, no time-variant water risk scores are currently available in the Aqueduct database. To move to a panel setting, we assume that water-related risks are proxied by hydro-meteorological variables, such as precipitation and evapotranspiration.[5] Our panel regression reads

$$y_{i,t} = \beta prec_{i,t} + \phi' x_t + \delta_t + \epsilon_{i,t}$$

where i denotes the power plant, t is the time period (in our case, months between January 2015 and September 2021) and $y_{i,t}$ is the electricity generated by a plant in each period. The variable $prec_{i,t}$ is our main explanatory variable, location-specific precipitation at time t, as given by the sum of rain and snow-water equivalent. The vector x_t includes plant- and location-specific control variables (operating capacity [in MWh],[6] age, area of

[5]The validity of the proxies adopted in the panel regression is supported by the fact that water risk categories as defined by WRI are correlated with precipitation. This can be seen from Figure 4 for the correlation between precipitation and categories and Figure 6, which displays the average monthly precipitation by risk category, in the Appendix.

[6]Note that this value is constant over time. Even if this is not ideal, changes in the operating capacity of a power plant only occur to a limited extent. Most new turbines are counted as separate power plants.

closest reservoir [in ha], evapotranspiration [in mm/month]). The vector δ_t includes month, country and type fixed effects. The time fixed effect purges our estimates from unobservable global trends common to all countries and controls for seasonal effects. The country fixed effect eliminates country-specific patterns, such as water demand and management of the electricity grid. Errors are clustered at the country level as the generation residuals are likely to be correlated within a country, due, for instance, to their joint management in the electricity grid.

Our results are displayed in Table 3. A 1% increase in precipitation is associated with 0.055% higher electricity generation on average. Halving the amount of precipitation (a decrease of 50%), would thus be associated with 2.75% lower electricity generation.[7]

Under the assumption of classical measurement in the water risk metric and measurements of precipitation, the estimated effects likely suffer from an attenuation bias. Therefore, in combination with the endogenous location of plants highlighted in the previous section, these estimates are a lower bound of the partial equilibrium effect of water-related risks.

[7]Note that the coefficient for operating capacity is significant, unlike in the cross-sectional regression. A possible explanation is that a ratio is not affected by the operating capacity, whereas when we want to explain changes to the overall generation, operating capacity plays a more important role.

Table 3: Panel regression of electricity generation at the plant level on location-specific precipitation.

Dependent Variable:	y
Variables	
Precipitation	0.0554***
	(0.0076)
Age	0.1609***
	(0.0153)
Reservoir size	0.0047
	(0.0030)
Operating capacity	0.9273***
	(0.0141)
Evapotranspiration	-0.0562***
	(0.0182)
Fixed-effects	
Month	Yes
Country	Yes
Type	Yes
Fit statistics	
Observations	57,280
R^2	0.79134
Within R^2	0.71257

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

We conduct several robustness checks. First of all, we run the model without winsorizing the variables to account for the effects of extreme values in the variables of interest. We also run the model with an interaction term between plant type and precipitation to explicitly capture the different effect of water availability depending on the technology adopted at the plant level. All these model variants return similar results. We further run a version with a one month lag in our precipitation variable with the following rationale: a utility company's decision on how much energy to generate might depend on past water levels in reservoirs and rivers. The results under this specification are reported in Table 9 in the Appendix, but they are qualitatively not affected.[8]

Although precipitation seems to be a good proxy for water risk scores given the correlation of the two variables, we also conduct a robustness test using an alternative measure of water availability, the Palmer Drought Severity Index (PDSI). Table 8 in the Appendix displays our findings when using the PDSI as explanatory variable[9]. A higher value of the index implies more wet locations and is associated with significantly higher electricity generation. In particular, a standard deviation increase in the PDSI is associated with 14.4% more electricity generation. In order to identify the dynamic response of hydroelectricity generation to water availability, we also report our results when using a local projections approach à la Jordà (2005) (see Figure 8 in the Appendix). Finally, we introduce country by month and country by year fixed effects to better control for demand effects.

4 Discussion and further analysis

In our cross-sectional analysis, we examine the relationship between water risk scores and the ratio of hydroelectricity generation in the low-rainfall year 2021 over the historical average (2015-2021). With this analysis, we aim to better understand how water risks affect hydroelectricity generation, an important source of renewable energy. We use a sample period of

[8]The results using larger order of the lags are available upon request.

[9]See Figure 7 in the Appendix, which displays the average monthly PDSI.

2015-2021 to capture the trends and patterns in hydroelectricity generation and water risks over time. We show that being located in higher water risk basins is associated with a decline of hydroelectricity generation. The effect is stronger in high-risk regions. Analyzing the effect of hydro-meteorological variables on hydroelectricity generation in a panel setting, we find that reductions in precipitation are associated with lower hydroelectricity generation. These findings are robust to several specifications and to alternative explanatory variables.

Our findings help identify research needs in three important areas: (1) understanding the future risks to hydroelectricity generation from changing water availability and how they could be addressed; (2) exploring how these risks spill over into other sectors and the financial system; and (3) extending the understanding of the relationship between nature and the economy to include further ecosystem services.

First, our study provides evidence that water-related risks pose a threat to hydroelectricity generation. While it does not predict the evolution of these risks in the future, the estimated relationship could inform future analysis, assuming unprecedented water-related risks do not render our model inaccurate by reducing its out-of-sample predictive power. This data-driven approach should be complemented by the development of models, which could provide an alternative to predict future impacts given the unprecedented character of changes in water availability. Future research should focus on evaluating the external validity of existing case studies and assessing the impact of water-related risks on hydroelectricity generation in regions different from the one covered in this study. In particular, a deeper understanding of the vulnerability of individual hydropower plants and how adaptation measures can reduce it, is crucial. Similarly, additional insights on the economic impact of changes in water availability could come from modeling how hydro power plant managers might react to water-related risks. Managers make production decisions based on expectations about future demand and water availability. They also have regulatory constraints and contractual requirements to provide water for irrigation. These limit their ability to smooth over changes in water availability. Sustainable finance could play a key role in mitigating the negative effects of changes in water availability by directing funding towards mitigation and adaptation measures. Further analysis is needed to identify the most effective levers for reducing vulnerability, such as measures to prevent water evaporation or improve water efficiency in electricity generation, as well as policies which could reduce the amount of water used across all sectors of the economy.

Second, the impact of water-related risks on hydroelectricity generation spill over to other sectors and regions (Allcott et al., 2016). Water-related risks can lead to higher production costs. If the higher costs cannot be passed on to consumers, profit margins for producers shrink, potentially stranding their assets.[10] If the increased costs of electricity generation are passed on to consumers, higher prices or lower availability of clean electricity can have repercussion on the entire economy (Power et al., 2022). This happened, for instance, in the summer of 2022, where a heatwave in China's Sichuan province led to a reduction in hydropower capacity and increased demand for air conditioning, resulting in temporary closures of some companies. In Norway, low reservoir levels also put pressure on electricity exports and prices. The higher energy prices can also translate into inflationary pressures. These events highlight the need to study cascading effects beyond reduced hydroelectricity generation to understand the full impact of water availability on the economy. One approach could be to examine production network linkages using input-output tables and firm-level supply chain information. Including information about the ownership of the power plants would also provide valuable insights into how water risks propagate into financial markets.

Third, our study is a first building block to understand the complex relationship between water and economic activities. This framework needs to be expanded to by integrating additional data sources and to cover other ecosystem services. Conducting robustness checks by exploring alternative sources of data and proxies for variables is crucial. And even more so in

[10]Clearly, this will be the case for some producers, others might see an increase in their profit, for instance, as more water becomes available from ice melting.

the context of nature degradation as it is difficult to clearly define and comprehensively measure a multidimensional concept such as natural capital. Future research should, for instance, incorporate information such as altitude and reservoir capacity, as well as time-varying measure of water-related risks. Our focus on hydropower is just one example of the many sectors that are exposed to water-related risks. And many other ecosystems provide important services to the economy. These include, amongst others, forests, soil and biodiversity. Further research should examine the impact of water-related risks on other water-dependent industries, such as mining and also apply a similar framework to investigate the impacts of other ecosystem services loss or degradation.

5 Conclusion

The past summer has revealed the critical dependence of economic activities on water and the risks they face in case of reduced water availability. This is especially true for water-dependent sectors such as hydroelectricity generation, which plays a crucial role in ensuring a clean energy future.

In this paper, we examine the relationship between hydroelectricity generation and water availability. Water-related risks are locally specific, so that any analysis of such risks has to account for the geo-specific character of the risks. We build a novel dataset containing information on hydropower plant locations, their electricity generation, the size of the closest reservoir as well as measures of water risk and hydro-meteorological variables in the corresponding water basins. We develop two complementary research designs. First, we use a cross-sectional design that considers changes in hydroelectricity generation in 2021 - a low rainfall year - compared to its historical average. We find that plants located in riskier basins produced less electricity over their historical average compared to their counterparts located in less risky basins. Second, we use panel design where we exploit changes in precipitation over time. Consistent with our cross-sectional results, we find a positive elasticity of electricity production with respect to precipitation. The paper provides a framework for understanding the impact of other forms natural capital risks on different sectors of economic activity. Cross-sectional water risk measures are obtained from the World Resource Institute. Our analysis of this data reveals a significant negative correlation between precipitation and hydroelectricity generation, robust to different model specifications and variable choices.

Hydropower will be crucial to the transition to renewable energy. However, the effects of climate change on water scarcity will determine the effectiveness of hydropower projects. To the best of our knowledge, this is the first paper to provide a multi-country analysis of the impact of changes in water availability on hydroelectricity generation at the plant level in high-income economies and using location-specific information on water-related risks and hydro-meteorological data. Our asset-level analysis of the exposure of economic activities to water availability contributes to the increasing evidence of the risks posed by environmental degradation on economic activities and the empirical strategies adopted in this paper can be replicated across similar datasets. The findings of the paper can be used for planning as well as for calibrating economy-wide models that endogenize hydroelectricity generation. Thus, they can have important consequences for the design of the low-carbon transition and for the role of hydroelectricity in it.

Yet, future research is needed to overcome some of the limitations of this paper. Future research should focus on exploring heterogeneity across regions to better project future impacts due to environmental, as well as developing water availability scenarios. An analysis of spillover effects and ownership relationships would help translating water-related risks into financial losses. Finally, alternative data sources and econometric specifications should be used to better define and comprehensively measure the multidimensional

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A Summary statistics

Our sample includes 14 European countries, 47 US states, 1140 power plants of two types (run-of-the-river and reservoir) and span over the period 2015-2021.

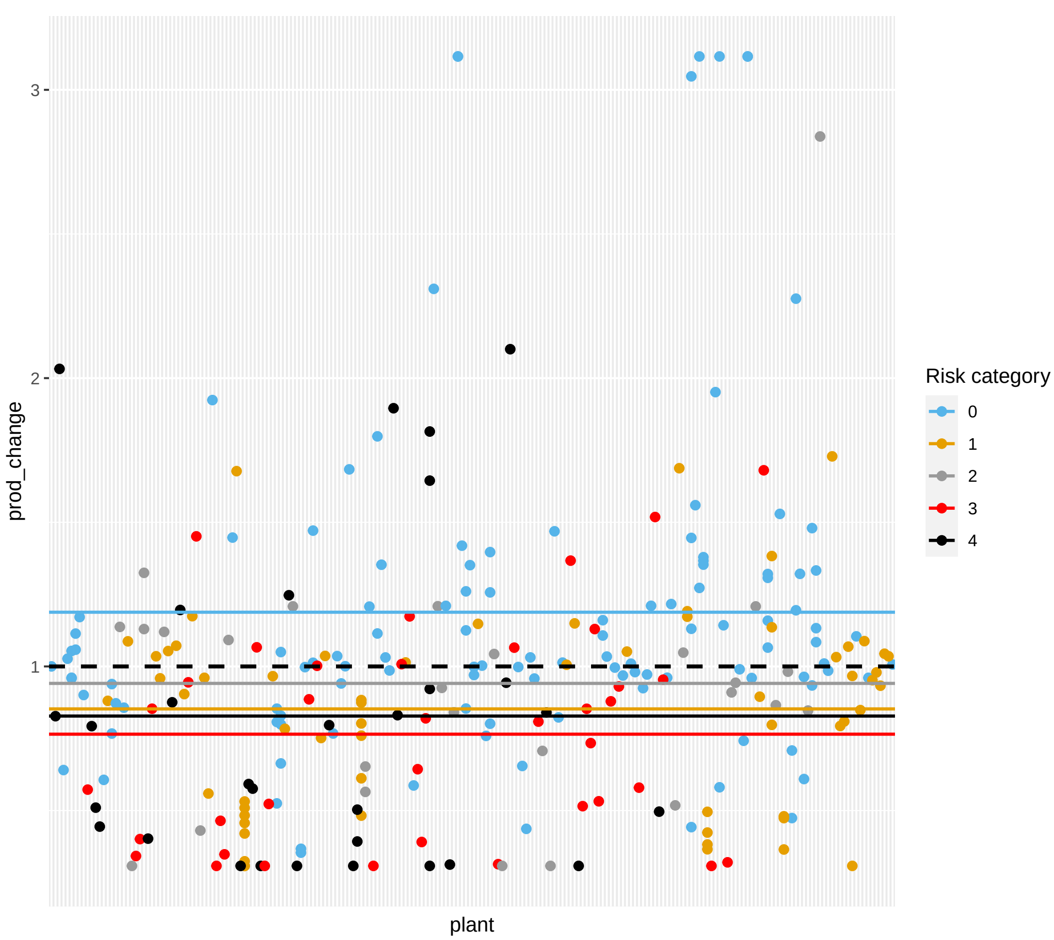
Table 4: Summary statistics

Variable	Unit	Obs.	Min.	Max.	Mean	Standard deviation
Cross section						
Generation change	*ratio*	599	0.2445	3.1729	1.0365	0.6744547
Age	*numeric*	599	28	94	53.07	17.09649
Operating capacity	*MW/h*	480	5.4	960.0	304.7	277.0865
Risk	*numeric*	483	0.3618	3.6041	1.0630	0.706435
Panel regression						
Generation	*MW/month*	75485	0	75039	10250	18985.06
Operating capacity	*MW/h*	72981	0.4	328.50	52.66	87.06316
Age	*years*	75485	1	112	69.42	29.09638
Precipitation and snow-water equivalent	*mm/month*	75485	0.00	322.63	105.56	86.56558
Evapotranspiration	*mm/month*	75485	0.00	1224.4	511.9	403.2654
Palmer Drought Severity Index	*numeric index*	75485	-781.52	589.82	76.51	298.5261
Reservoirs' size	*ha*	71315	919	41099169	5284713	10530783

B Generation ratio

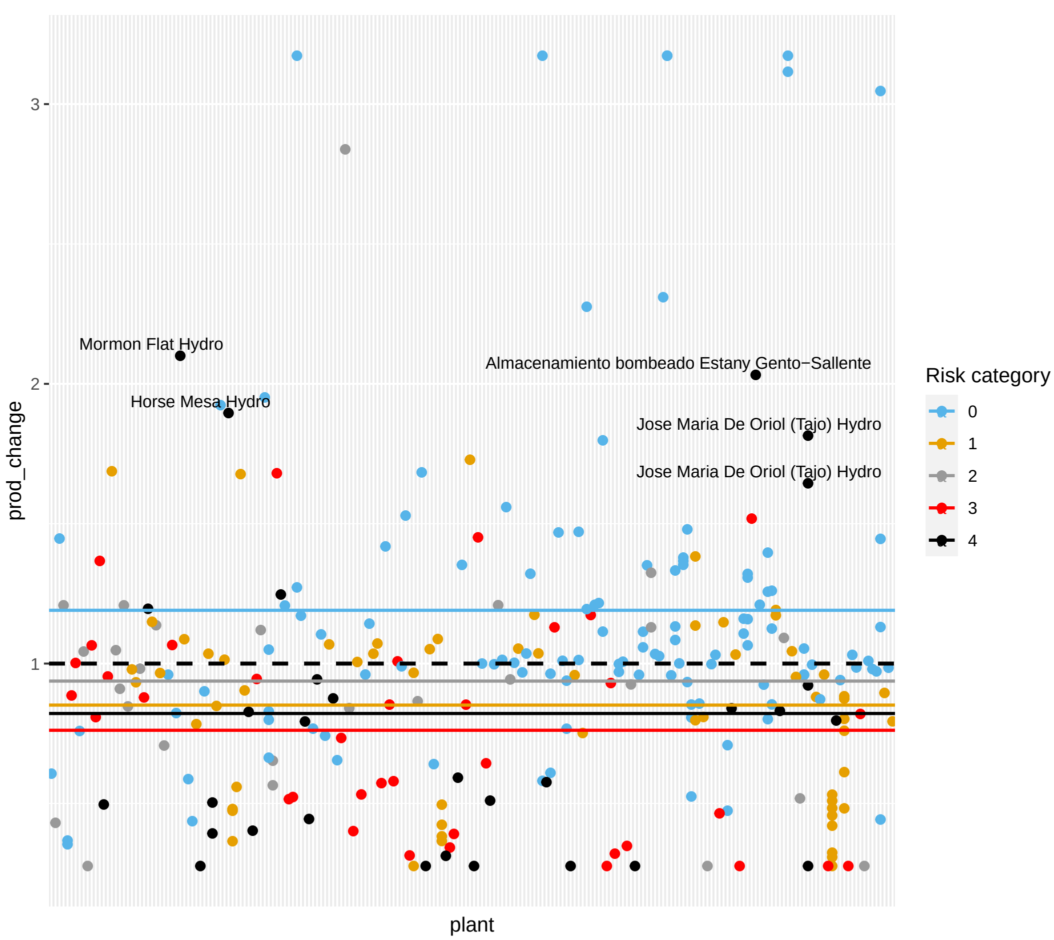
Figure 2 displays the ratio of electricity generation in 2021 (a low-rainfall year) over the historical average by plant. The different colours reflect the different water risk categories. Some of the plants located in high risk category generate more electricity in 2021 compared to the historical average in face of the high temperature. These plants are, in order, Mormon Flat Hydro (US), Almacenamiento bombeado Estany Gento-Sallente (ES), Horse Mesa Hydro (US) and Jose Maria De Oriol (Tajo) Hydro (ES), which appear twice. First, notice that all these plants are water reservoir plants, which are automatically more insulated from water stress compared to run of river hydropower plants.

Figure 2: Ratio of electricity generation by plant in 2021 over historical average by risk category.



Second, when reordering that plants by their operation capacity, we obtain Figure 3, which hints to the fact that even if located in high water risk regions large power plants might be less vulnerable to water availability. Jose Maria De Oriol (Tajo) Hydro (ES) with its two turbines is connected to the massive Alcantara/José Maria de Oriol reservoir, the second largest reservoir in Europe. The hydropower plant also has a very large operating capacity, which contributes to explain why it was able to increase generation despite the adverse conditions when other plants reduced or halted electricity generation. The other plants, i.e. Almacenamiento bombeado Estany Gento-Sallente (ES), Horse Mesa Hydro (US) and Mormon Flat Hydro (US), are located at reservoirs, as well.

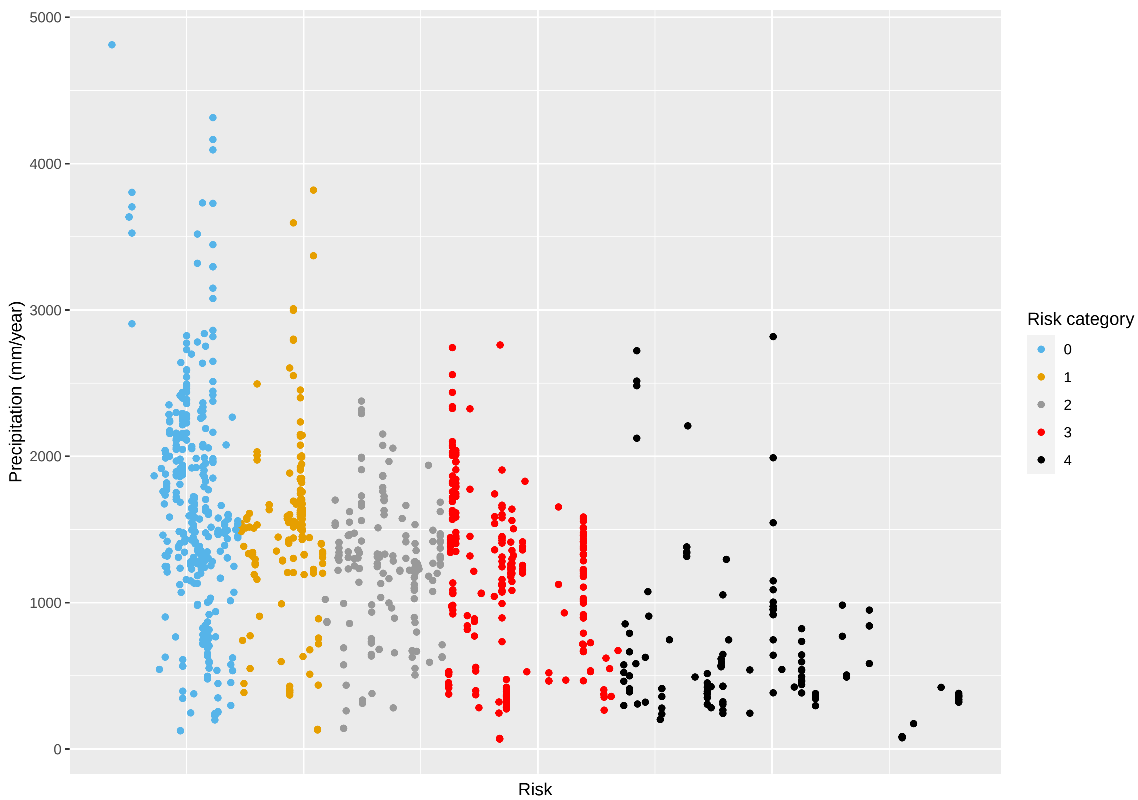
Figure 3: Ratio of electricity generation by plant in 2021 ordered by operating capacity of the plant over historical average by risk category



C Correlation between precipitation and water risk scores

Figure 4 shows average yearly precipitation at the plant level and water risk categories. Higher water risk is associated with lower precipitation (the correlation is -.48). In each water risk category, variation within the water risk category (across the x-axis) is explained by regional variation in water demand.

Figure 4: Correlation between precipitation and water risk, by risk category



D Precipitation

Figure 5 shows the average monthly precipitation across locations. The seasonal is clearly evident and explains our choice of introducing monthly fixed effects in the panel regression.

Figure 5: Average monthly precipitation across locations.

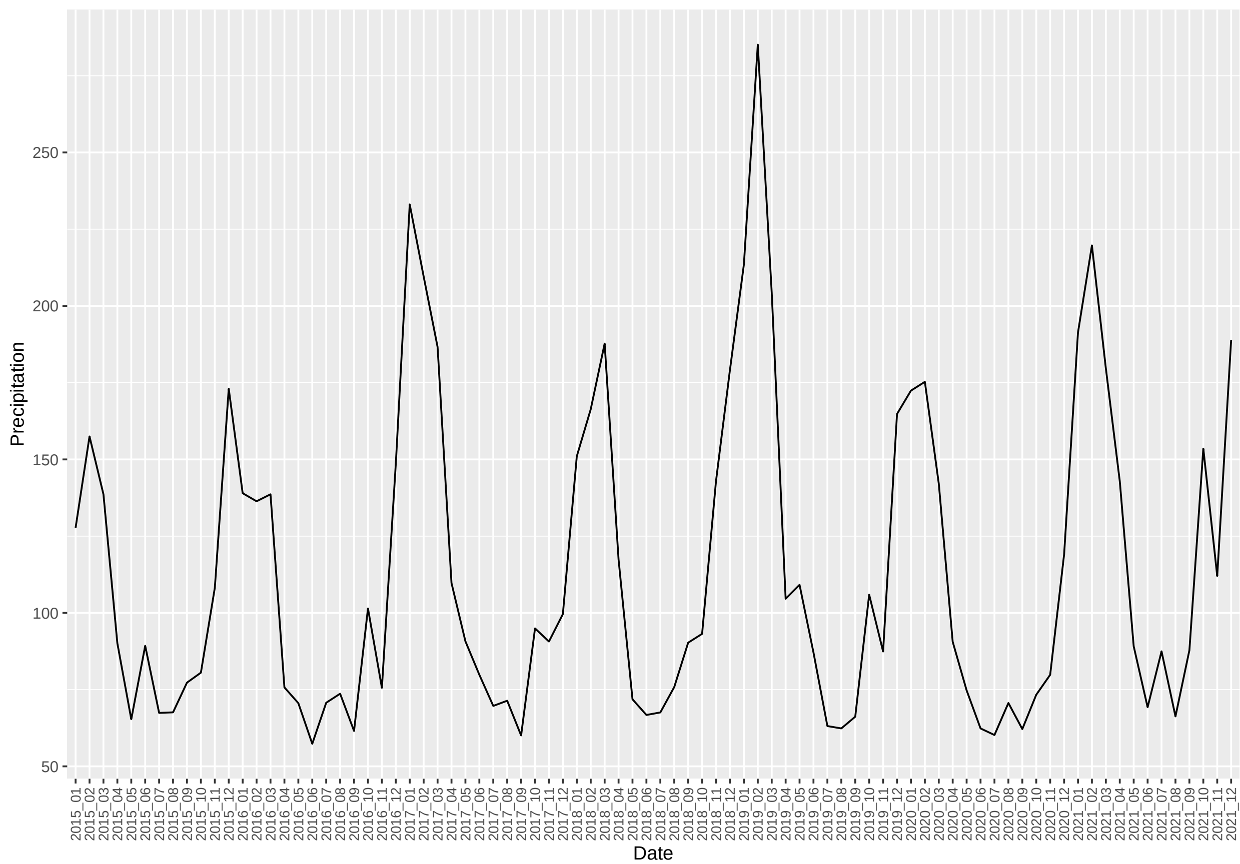
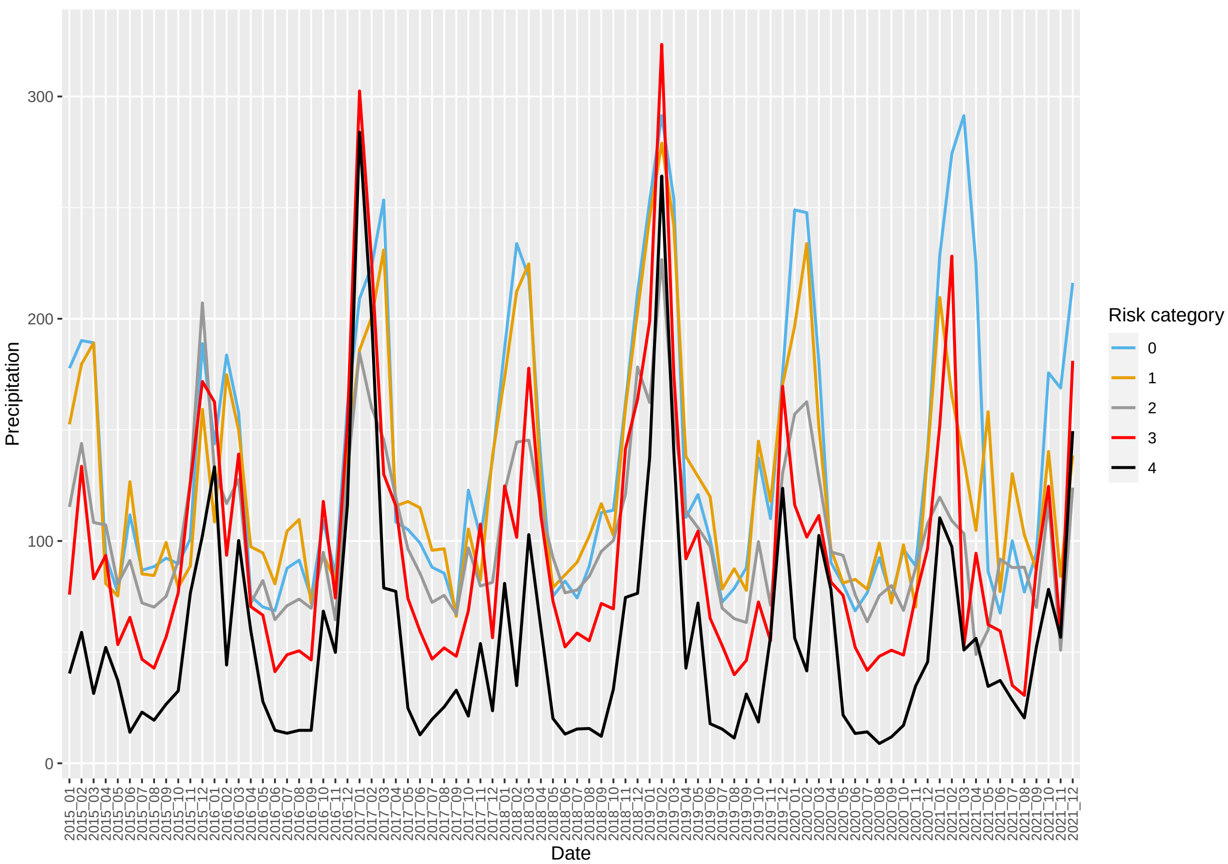


Figure 6 shows the average monthly precipitation disentangled by water risk categories. It shows that while the pattern of low risk regions remained stable across time, regions in high risk basins (category 4, black line) experience more variation across years, with a stronger reduction in precipitation in the last years.

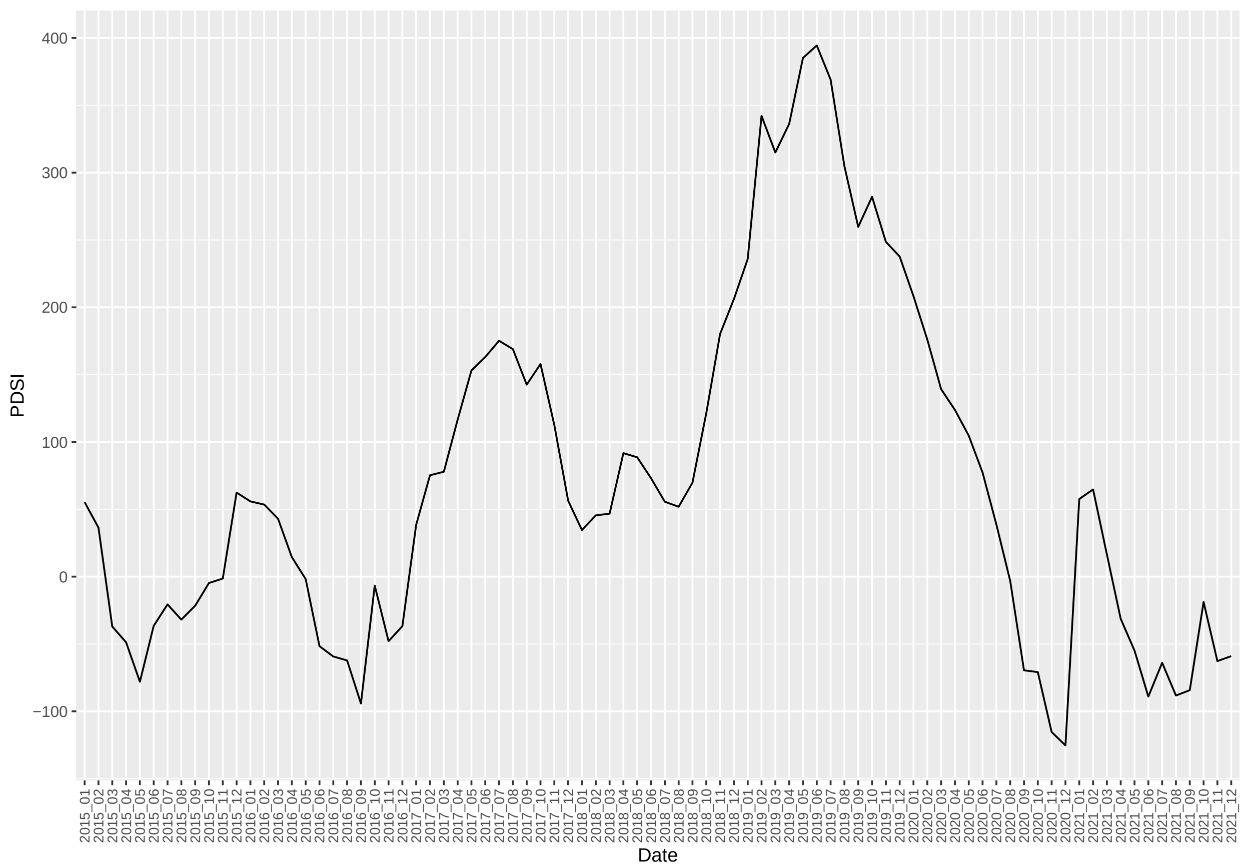
Figure 6: Average monthly precipitation by risk category



E Palmer Drought Severity Index

As a robustness check, we run our baseline panel regression using the geo-specific values of the Palmer Drought Severity Index as dependent variable (see Section F.4). The PDSI is a standardized index and uses readily available temperature and precipitation data to estimate relative dryness. Lower values are associated with drier locations. Figure 7 shows a drop in the average monthly PDSI after 2020.

Figure 7: Average monthly PDSI



F Robustness checks

In this section, we report some of the robustness checks that we performed.[11] Our results are robust to different specifications.

F.1 Panel regression without winsorizing

As a robustness check we rerun our baseline regression using non-winsorized variables. We chose this specification as we are interested in tail risks. However, this specification might suffer from measurement error. Table 5 shows that our results are not affected.

Table 5: Regression without winsorization

Dependent Variable:	y
Variables	
Precipitation	0.0538***
	(0.0092)
Age	0.1569***
	(0.0166)
Reservoir size	0.0060*
	(0.0033)
Operating capacity	0.9387***
	(0.0160)
Evapotranspiration	-0.0582***
	(0.0188)
Fixed-effects	
Month	Yes
Country	Yes
Type	Yes
Fit statistics	
Observations	57,280
R^2	0.79608
Within R^2	0.72238

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

[11] Additional robustness checks are available upon request.

F.2 Panel regression with type interaction

In our baseline regression we control for the type of plants (river or reservoir). Our intuition is that droughts are more serious for river plants than for reservoirs for which hydropower can be better managed in the short term. To test this hypothesis we introduce an interaction term between precipitation and type of reservoir. Our results show that run of river plants are more sensitive to precipitation: for a given increase in precipitation, run of river plants see a significantly larger increase in electricity generation.

Table 6: Panel regression with type interaction

Dependent Variable:	y
Variables	
Age	0.1584***
	(0.0171)
Reservoir size	0.0055
	(0.0034)
Operating capacity	0.9396***
	(0.0159)
Evapotranspiration	-0.0602***
	(0.0177)
Precipitation × Type_{ror}	0.0625***
	(0.0068)
Precipitation × Type_{wr}	0.0044
	(0.0169)
Fixed-effects	
Month	Yes
Country	Yes
Fit statistics	
Observations	57,280
R^2	0.79745
Within R^2	0.72541

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

F.3 Lagged panel regression

As a robustness check we rerun our baseline regression using the one month lagged values for precipitation. As in the baseline, precipitation includes both rain and snow-water equivalent. Table 9 shows that results are not affected. We also run specifications with additional lags: the coefficient on the lagged precipitation increases up to 4 lags and decreases afterwards. With 11 lags it becomes insignificant. The results under this specification have to be

Table 7: Panel regression with lagged precipitation

Dependent Variable:	y
Variables	
Lagged precipitation	0.0709***
	(0.0081)
Age	0.1583***
	(0.0153)
Reservoir size	0.0041
	(0.0027)
Operating capacity	0.9273***
	(0.0136)
Evapotranspiration	-0.0476**
	(0.0190)
Fixed-effects	
Month	Yes
Country	Yes
Type	Yes
Fit statistics	
Observations	56,465
R^2	0.79242
Within R^2	0.71576

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

interpreted with caution as given the presence of lagged values of the dependent variable as regressors, OLS estimation will yield biased coefficient estimates. Moreover, if the disturbance term is autocorrelated, the OLS will also be an inconsistent estimator.

F.4 PDSI

To test the robustness of our results we look at how results change when using the standardized Palmer Drought Severity Index, as a proxy for water availability. Results are qualitatively consistent with our baseline, with a standard deviation increase in the PDSI (a location becoming wetter) associated with higher electricity generation.

Table 8: Panel regression with Palmer Drought Severity Index

Dependent Variable:	y
Variables	
Age	0.1441***
	(0.0157)
Reservoir size	0.0034
	(0.0026)
Operating capacity	0.9277***
	(0.0113)
PDSI	0.2039***
	(0.0038)
Fixed-effects	
Month	Yes
Country	Yes
Type	Yes
Fit statistics	
Observations	64,812
R^2	0.80021
Within R^2	0.72986

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

F.5 Precipitation shock

Following Russ (2020) and Faccia et al. (2021) we build precipitation shocks computed as z-scores for the precipitation level. Shocks are define as large deviations in precipitation from the mean precipitation in our dataset. In particular, we define a "negative precipitation" shock as an incidence when precipitation is more than two standard deviations below the country- and month-specific mean. When looking at the effect of negative precipitation shocks on electricity generation, the variable *Shock* is set to be equal to 1 when the precipitation recorded in that month is below the country's long-run mean temperature calculated over the period 2015-2021 by at least 2 standard deviations; it is set to 0 otherwise.

Table 9: Panel regression with negative precipitation shock

Dependent Variable:	y
Variables	
Shock	-0.1036***
	(0.0093)
Age	0.1790***
	(0.0171)
Reservoir size	0.0049
	(0.0028)
Operating capacity	0.9243***
	(0.0132)
Evapotranspiration	-0.0319**
	(0.0135)
Fixed-effects	
Month	Yes
Country	Yes
Type	Yes
Fit statistics	
Observations	58,162
R^2	0.78988
Within R^2	0.71201

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

F.6 Local projections

In order to identify the dynamic response of hydroelectricity generation to a negative precipitation shock, we use a local projections approach à la Jordà (2005), with lags of the control variables as suggested by Plagborg-Møller and Wolf (2021). The least-squares local projection estimator β_h is obtained from the OLS regression at each horizon h

$$\Delta y_{i,t+h} = \beta_h shock_{i,t} + \phi_h' x_{t-1} + \delta_t + \epsilon_{i,t}^h$$

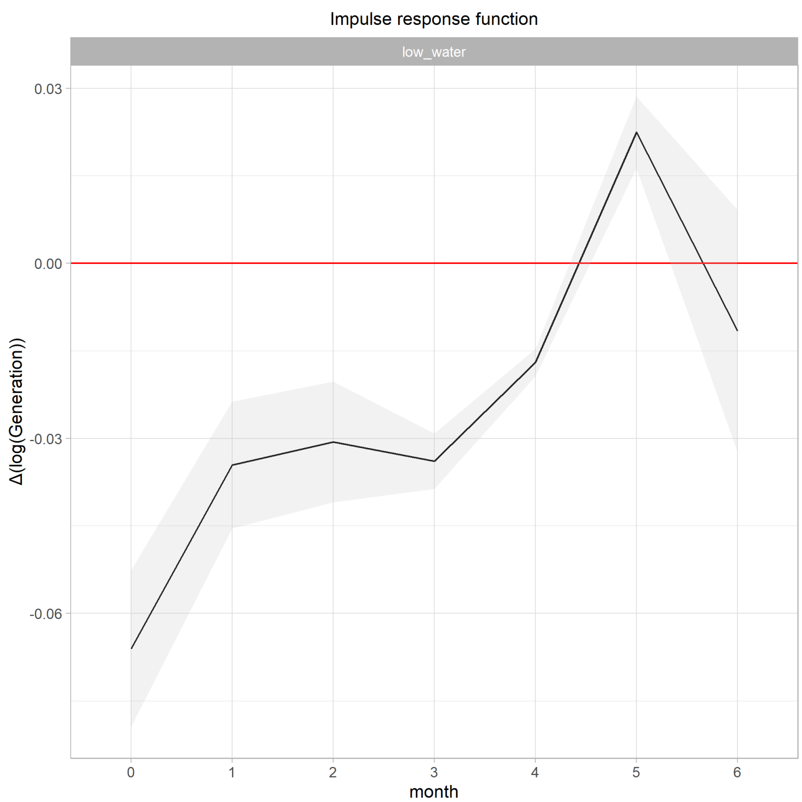
where x_{t-1} is a vector of control variables, and $prec_{i,t}$ is the identified variable in location i. Notice that this LP specification controls for one lag of the data. The coefficient β_h corresponds to the response of y at time $t+h$ to the shock at time t. We consider a 6 month horizon as the shocks are correlated over time so that a longer time horizon would pick up compounded effects due the serial correlation. Our results show that the effect of a negative precipitation shock disappears after 5 months. The impulse response function in Figure 8 represents the sequence of all estimated β_h.

Table 10: Local projections

Dep Variables:	Δy_t	Δy_{t+1}	Δy_{t+2}	Δy_{t+3}	Δy_{t+4}	Δy_{t+5}
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shock	-0.0661***	-0.0346***	-0.0306***	-0.0339***	-0.0170***	0.0224***
	(0.0081)	(0.0066)	(0.0063)	(0.0029)	(0.0014)	(0.0037)
Age	0.0015	0.0013	0.0011	0.0030***	0.0038**	0.0011*
	(0.0022)	(0.0020)	(0.0014)	(0.0003)	(0.0015)	(0.0005)
Operating capacity	-0.0026***	-0.0023***	-0.0023***	-0.0012***	0.0002	0.0021***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Reservoir size	0.0002	-9.73×10^{-6}	-0.0007***	-0.0003	-0.0007***	-0.0011***
	(0.0002)	(7.01×10^{-5})	(9.65×10^{-5})	(0.0002)	(0.0002)	(0.0002)
Evapotransporation	0.0236***	0.0138***	0.0136***	0.0052**	-0.0099***	-0.0120***
	(0.0010)	(0.0011)	(0.0021)	(0.0020)	(0.0012)	(0.0008)
Fixed-effects						
Month	Yes	Yes	Yes	Yes	Yes	Yes
Type	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	56,625	55,835	54,899	53,961	53,031	52,073
R^2	0.01717	0.01742	0.01897	0.01830	0.01831	0.01797
Within R^2	0.00222	0.00077	0.00075	0.00021	0.00033	0.00053

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 8: Impulse response function of electricity generation to a negative shock to precipitation



F.7 Panel regression with country by month and country by year fixed effects

To address additional concerns about the results being driven by electricity demand instead of supply shocks, we also run a regression with country by month and country by year fixed effects.

Table 11: Panel regression with country by month and country by year FE

Dependent Variable:	y	
Model:	(1)	(2)
Variables		
Precipitation	0.0544***	0.0503***
	(0.0083)	(0.0072)
Age	0.1611***	0.1616***
	(0.0149)	(0.0155)
Reservoir size	0.0047	0.0046
	(0.0030)	(0.0030)
Operating capacity	0.9281***	0.9285***
	(0.0132)	(0.0141)
Evapotranspiration	-0.0606***	-0.0550***
	(0.0140)	(0.0178)
Fixed-effects		
Month	Yes	Yes
Country by month	Yes	
Type	Yes	Yes
Country by year		Yes
Fit statistics		
Observations	57,280	57,280
R^2	0.79415	0.79434
Within R^2	0.71553	0.71464

Clustered (at the country level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*