

Abstract

The Greater Mekong Subregion is a transnational area bound together by the Mekong River basin and its immense hydropower resources, historically seen as the backbone of regional economic development. The basin is now punctuated by several dams, successful in attracting both international investors and fierce criticisms for their environmental and societal impacts. Surprisingly, no attention has been paid so far to the actual performance of these infrastructures: is hydropower supply robust with respect to the hydro-climatic variability characterizing Southeast Asia? When water availability is altered, what are the implications for power production costs and CO₂ emissions? To answer these questions, we focus on the Laotian–Thai grid—the first international power trade infrastructure developed in the region—and use a power system model driven by a spatially-distributed hydrological-water management model. Simulation results over a 30-year period show that production costs and carbon footprint are significantly affected by droughts, which reduce hydropower availability and increase reliance on thermoelectric resources. Regional droughts across the Mekong basin are of particular concern, as they reduce the export of cheap hydropower from Laos to Thailand. To put the analysis into a broader climate-water-energy context, we show that the El Niño Southern Oscillation modulates not only the summer monsoon, but also the power system behaviour, shaping the relationship between hydro-climatological conditions, power production costs, and CO₂ emissions. Overall, our results and models provide a knowledge basis for informing robust management strategies at the water-energy scale and designing more sustainable power plans in the Greater Mekong Subregion.

Plain Language Summary

The development of hydropower dams in the Mekong River basin has historically been seen as a means to support economic growth in Southeast Asia. Because water availability varies on both seasonal and interannual time scales, we hypothesized that an unstable supply of hydro-electricity may temporarily increase reliance on gas and coal, thereby affecting power production costs and carbon footprint. To verify this hypothesis, we developed a coupled water-energy model of the Laotian–Thai grid, the largest power infrastructure in the region. The model represents the relationship between hydro-climatological conditions, water availability, and power system behaviour. Simulation results show that prolonged droughts in the Mekong basin reduce hydropower production by about 4,000 GWh/year, increasing the annual production costs and CO₂ emissions by about US\$ 120 millions and 2.5 million metric tonnes, respectively. These events are largely explained by the periodic oscillations in the tropical eastern Pacific Ocean that modulate water availability in Southeast Asia. Our findings can help reduce the carbon footprint of power systems and inform the design of hydroelectric dams.

1 Introduction

Power systems provide the fundamental service of balancing electricity supply and demand. Ideally, the service should be reliable, affordable, and sustainable. But, in practice, generating units and transmission networks are often vulnerable to climate-induced disruptions. Changes in water availability, for instance, limit the generation of hydropower dams and steam-cycle thermoelectric plants, leading to higher risks of power shortfall (Turner et al., 2019). Higher ambient temperatures affect peak loads (for space cooling) and reduce the thermal capacity of transmission lines, further stressing the grid (Ke et al., 2016). Disruptions can also cause substantial economic and environmental impacts if temporary losses from renewables must be offset by more expensive and carbon-intensive sources of energy, such as coal or gas. During the the 2012–2016 drought in California, for example, utilities faced losses of about US\$ 2.0 billions, while CO₂ emissions increased by 10% compared to pre-drought conditions (Gleick, 2015; Kern et al., 2020). Other re-

67 cent examples can be drawn from Brazil (Prado Jr et al., 2016) or Europe (De Felice et
68 al., 2020). To design more sustainable grid operations, we need to quantify, understand,
69 and explain the relationship, or nexus, between climate, water, and energy.

70 Process-based hydrologic models are the bread and butter of studies addressing the
71 relationship between water availability and electricity generation. Since the dimensions
72 of the relationship are multiple, different aspects have been explored, including gener-
73 ation types—hydro and thermoelectric, taken individually or together (X. Liu et al., 2016;
74 Wang et al., 2019; Bartos & Chester, 2015)—spatial domains—national, regional, and
75 global (Stillwell & Webber, 2013; L. Liu et al., 2017; van Vliet et al., 2016)—and timeframes—
76 from seasonal to long-term (Ng et al., 2017; Turner, Ng, & Galelli, 2017). The major-
77 ity of impact metrics revolve around the effect of water availability on power supply, with
78 a few works considering cross-sectoral impacts, such as electricity prices (van Vliet et al.,
79 2013) or investment needs (Turner, Hejazi, et al., 2017). Something that all these stud-
80 ies have in common is a boundary drawn at the interconnection between water and power
81 systems. And yet, it is only by placing dams and thermoelectric plants in a broader water-
82 energy context that we can fully understand how water availability affects power systems
83 behaviour, especially during heat waves and droughts (Voisin et al., 2018). From a mod-
84 elling perspective, this means coupling hydrologic models with power system models rep-
85 resenting the broad spectrum of decisions made at the grid scale—e.g., commitment of
86 generating units, electricity generation and transmission. Multi-model multi-scale frame-
87 works represent the nuances in the links between water and energy systems, thereby of-
88 fering a tool for explaining how hydro-climatic extremes affect power systems operations
89 (Voisin et al., 2016; Turner et al., 2019; Su, Kern, Reed, & Characklis, 2020).

90 Notwithstanding these recent advances, a deeper understanding of the climate-water-
91 energy nexus is needed to support management and planning interventions at the grid
92 scale. A first complexity is the relation between power system performance and the dif-
93 ferential impact of climate across multiple basins within a region. Knowledge about such
94 relation is particularly important for systems that rely on long-distance, international
95 interconnections—examples are many, ranging from the Southern African Power Pool
96 to the ASEAN Power Grid (Wu et al., 2017; Ahmed et al., 2017). Interconnections are
97 meant to transfer electricity from unevenly distributed production sites to load centers,
98 but may accidentally expose them to unforeseen risks—for example, by connecting them
99 to temporarily water-scarce areas. Second, we need to understand whether the signa-
100 ture of large-scale climate features, such as the El Niño Southern Oscillation (ENSO),
101 is detected concurrently on both water and power systems. ENSO, for instance, affects
102 temperature, rainfall, and hydropower supply in several regions (Chiew & McMahon, 2002;
103 Ng et al., 2017), so one would expect ENSO-driven droughts to modify the energy gen-
104 eration mix or increase the risks of power shortfalls. With the only exception of Voisin
105 et al. (2018), this hypothesis has not been tested. Since *teleconnections* represent one
106 of the physical mechanisms upon which seasonal hydro-meteorological forecasts are is-
107 sued, verifying the hypothesis would allow us to predict grid operations and design con-
108 tingency measures. Finally, the existing literature on coupled water-power system mod-
109 els is biased towards developed countries (Kern & Characklis, 2017; Su et al., 2017; O’Connell
110 et al., 2019; Byers et al., 2020), and thus overlooks large regions where electricity infras-
111 tructures have, and will, experience a tumultuous growth (Zarfl et al., 2015; Shearer et
112 al., 2017; Wang et al., 2019)—possibly exacerbating the conflict with other water users
113 (Satoh et al., 2017). How these fast-growing systems respond to hydro-climatic variabil-
114 ity remains an open question.

115 Here, we focus on the Greater Mekong Subregion, a transnational area bound to-
116 gether by the Mekong River, whose immense hydropower potential has historically been
117 seen as a means to support economic growth and cooperation between countries (X. Yu,
118 2003). While China and Vietnam are using the available portions of the Mekong—the
119 Lancang and part of the 3S basins (Sekong, Sesan, and Sre Pok), respectively—for lo-

cal hydropower supply, Thailand and Laos have developed the first large-scale, cross-border, power-trade infrastructure (Watcharejyothin & Shrestha, 2009). Through this interconnection, Thailand imports almost 90% of Laos' electricity production, which depends heavily on hydropower dams in the Mekong. The Chao Phraya River basin is a second fundamental element of the Laotian–Thai water-energy system, as it provides water for both hydropower and thermoelectric plants. The electricity demand is almost constant throughout the year, while water availability follows a monsoon-like pattern, with prolonged dry spells in the period from November to April. Importantly, water availability in both rivers varies on an inter-annual time scale as well, in response to changes in the sea surface temperature over the tropical Pacific Ocean (Singhrattana et al., 2005; Räsänen et al., 2016). These pronounced changes in water availability—and their association with features of variability of the earth-atmosphere system—raise the prospect of a tight relation between hydro-climatic variability and energy generation mix. Prolonged shortfalls of hydropower production, for example, may be offset by increased electricity production from gas and coal, with a consequent increase of production costs and CO₂ emissions. The questions of interest are therefore the following: How do teleconnections between large-scale climate drivers and local hydro-meteorological processes affect the energy generation mix? When water availability is altered, what are the implications for power production costs and CO₂ emissions? Is the behaviour of the power system sensitive to the spatial footprint of droughts across the Mekong and Chao Phraya?

To answer these questions, we adopt a multi-model multi-scale approach hinged on the coupling between two spatially-distributed models. The hydrologic-hydraulic model simulates the relationship between hydro-meteorological forcings and water availability in the Mekong and Chao Phraya basins, while the power system model reproduces the operating decisions made in the Laotian–Thai grid (Section 2). By accounting explicitly for the constraints imposed by water availability on hydro and thermoelectric plants, the coupled models help us untangle the relationship between climate, water, and energy variables (Section 3). Building on this knowledge, we identify opportunities for the joint management of water and energy resources and discuss plans for future capacity expansions (Section 4 and 5).

2 Materials and methods

2.1 The Laotian–Thai water-energy system

Figure 1 shows the main infrastructure of the Laotian–Thai water-energy system operated in 2016, the most recent year with comprehensive and reliable data (EPPO, 2017). The plants located in Thailand have a total installed capacity of 42,531 MW, with the Laotian ones contributing an additional 5,362 MW. The annual system-wide generation of $\sim 198,100$ GWh relies, in order of importance, on gas-fired power plants (63.2% of the annual generation), coal (18.6%), biomass and waste heat (6.2%), hydropower (1.8%), oil, wind, and solar (below 1%) (EGAT, 2016; IRENA, 2017). The remaining 10% of electricity supply is provided by the Laotian plants. Specifically, Thailand imports almost the entire generation of nine hydropower dams (total installed capacity of 3,485 MW) and one coal power plant (Hongsa Lignite; 1,878 MW). This import is regulated by a long-term power purchase agreement between the Electricity Generating Authority of Thailand (EGAT) and Électricité Du Laos (EDL) (EDL, 2016; EGAT, 2016). To put the extent of this agreement into perspective, consider that Thailand has direct access to 5,362 of the 6,688 MW of capacity installed in Laos. In recent years, minor steps have been taken to create a liberalized electricity market, but the supplier side is still de facto controlled by EGAT, who benefits of a monopoly position (Dubash & Williams, 2017).

The Mekong and Chao Phraya river basins are two fundamental components of the water-energy system. Naturally, hydropower production depends on water availability: all Laotian dams exporting to Thailand are located in the Mekong basin; of the 14 Thai

171 dams, five are in the Mekong, two in the Chao Phraya (Bhumibol and Sirikit; total installed
 172 capacity of 1,279 MW), and seven in smaller basins. Additional details about all
 173 hydropower dams are provided in Table S1. Some thermoelectric plants depend on fresh-
 174 water availability (see Table S2). The Mekong provides cooling water for Hongsa Lig-
 175 nite coal power plant (HPCL, 2018), as well as a few smaller plants located in Thailand.
 176 The Chao Phraya supports the operation of five thermoelectric plants, including Mae
 177 Moh plant (2,400 MW capacity). The remaining plants, strategically located near Bangkok
 178 metropolitan area and its gas import facilities (DBS, 2017), do not depend on freshwa-
 179 ter supply.

180 A comparison between total installed capacity and system-wide peak hourly de-
 181 mand (29,892 MW, EGAT (2016)) indicates that the power system should be able to
 182 maintain a reserve capacity of about 30%, well-above the minimum requirement of 15%
 183 (EGAT, 2016)—this is a trait shared by other power systems in Southeast Asia, where
 184 shortfalls of electricity supply are often caused by the poor state of distribution networks
 185 rather than limited reserve capacity (ADB, 2012). Instead, its generation mix, carbon
 186 footprint, and production costs may largely depend on the state of the Mekong and Chao
 187 Phraya river basins. There are three aspects worth considering here. First, most of the
 188 annual rainfall is delivered by the Southwest Monsoon (roughly, from May to October),
 189 so streamflow shows a pronounced seasonal pattern. Second, ENSO modulates the sum-
 190 mer monsoon on an interannual time scale. Warm conditions in the tropical Pacific (El
 191 Niño) delay the monsoon onset and shorten the overall rain season, while cold conditions
 192 (La Niña) are associated to wetter conditions in mainland Southeast Asia (Singhrattna
 193 et al., 2005; Cook & Buckley, 2009). Third, streamflow in the Mekong and Chao Phraya
 194 river basins is spatially coherent, owing to common meteorological and climatological drivers
 195 (Nguyen et al., 2019). We thus expect water availability and dispatchable hydropower
 196 to show seasonal and interannual modes of variability in both basins.

197 2.2 Power system simulation

198 The dynamic behaviour of the Laotian–Thai power grid is simulated with PowNet
 199 (Chowdhury, Kern, et al., 2020). Similarly to other production cost models (e.g., PRO-
 200 MOD (ABB, 2020), PyPSA (Brown et al., 2018), CAPOW (Su, Kern, Denaro, et al., 2020)),
 201 PowNet simulates the decision-making problem of determining (1) which generating units
 202 to start-up and shutdown (Unit Commitment) and (2) the amount of power supplied by
 203 each unit (Economic Dispatch). Importantly, PowNet simulates the power flow through
 204 the grid, thereby explicitly representing the high-voltage transmission lines. This is a fun-
 205 damental, yet often overlooked, aspect of rapidly-evolving power systems, where the de-
 206 ployment of new generation facilities—particularly variable renewable resources—can lead
 207 to transmission congestion (Sharpe, 2019; Chowdhury, Dang, et al., 2020). From a math-
 208 ematical modelling perspective, the model solves a network-constrained Mixed-Integer
 209 Linear Program that minimizes the production costs while meeting the electricity de-
 210 mand at all sub-stations. PowNet works with an hourly time step and a planning hori-
 211 zon of 24 hours.

212 Since the electricity supply is controlled by a single authority, the total power pro-
 213 duction costs (in US\$) are well estimated by accounting for the use of thermoelectric gen-
 214 erating units and amount of electricity imported from Laos. The relative production costs
 215 of the Thai variable renewable resources (i.e., hydro, solar, and wind) are considerably
 216 smaller, and hence negligible for the Unit Commitment/Economic Dispatch process (Kern
 217 & Characklis, 2017). As illustrated in Figure 2, the scheduling and dispatch of hourly
 218 electricity depends on several other factors, including the design features of the thermo-
 219 electric plants, derated capacity of individual plants, amount of power available from the
 220 variable renewable resources, minimum requirements of reserves, capacity and suscep-
 221 tance of the transmission lines, and transmission losses.

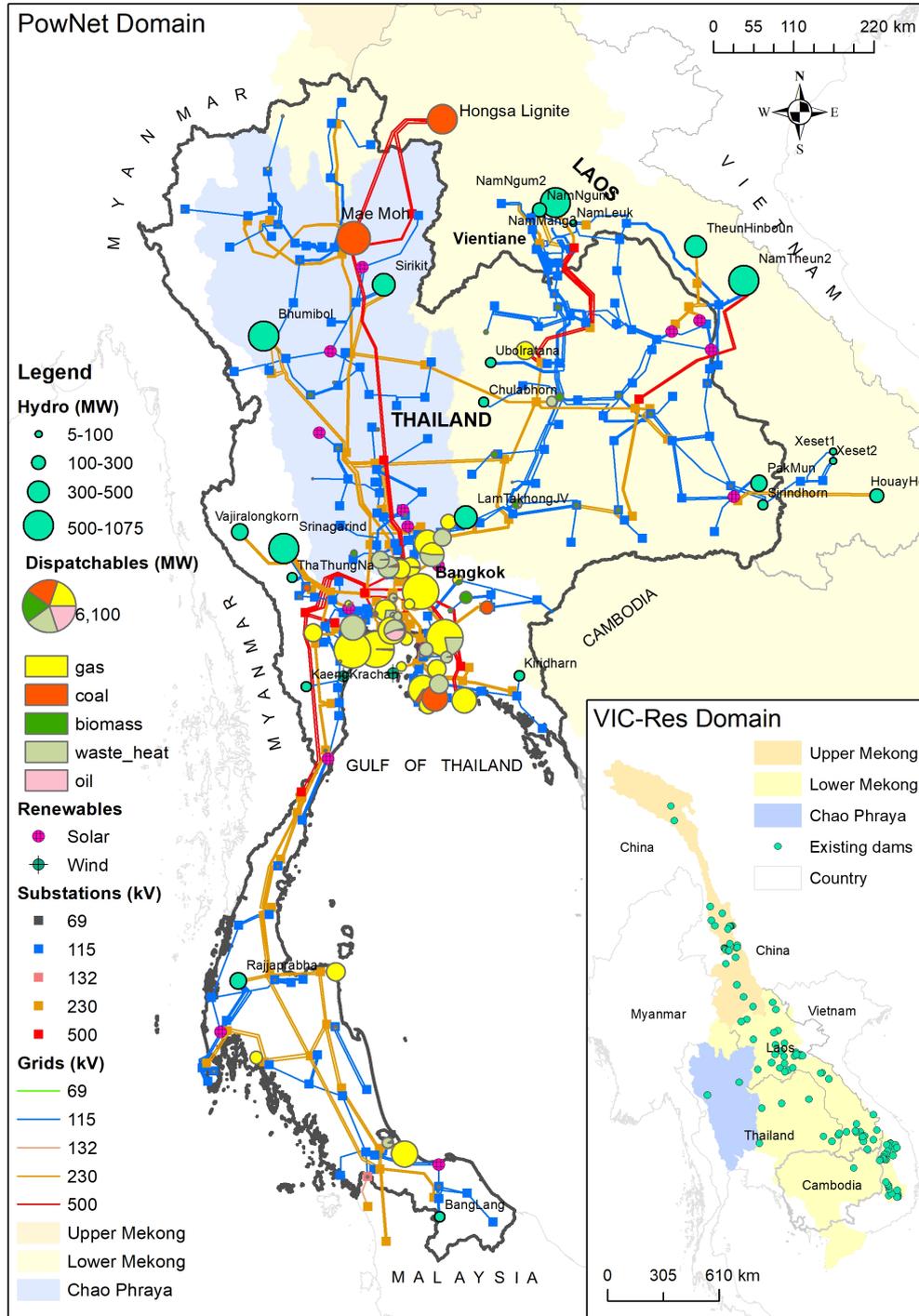


Figure 1. Main components of the Laotian–Thai water-energy system. The areas shaded in blue and yellow denote the Chao Phraya and Lower Mekong basins, while circles, squares, and segments indicate power plants, sub-stations, and high-voltage transmission lines. All components of the power grid were operational in 2016. In the inset, we report the full spatial extent of the Chao Phraya and Mekong basins, together with the dams operated by all riparian countries. These dams are modelled by the hydrologic-hydraulic model VIC-Res.

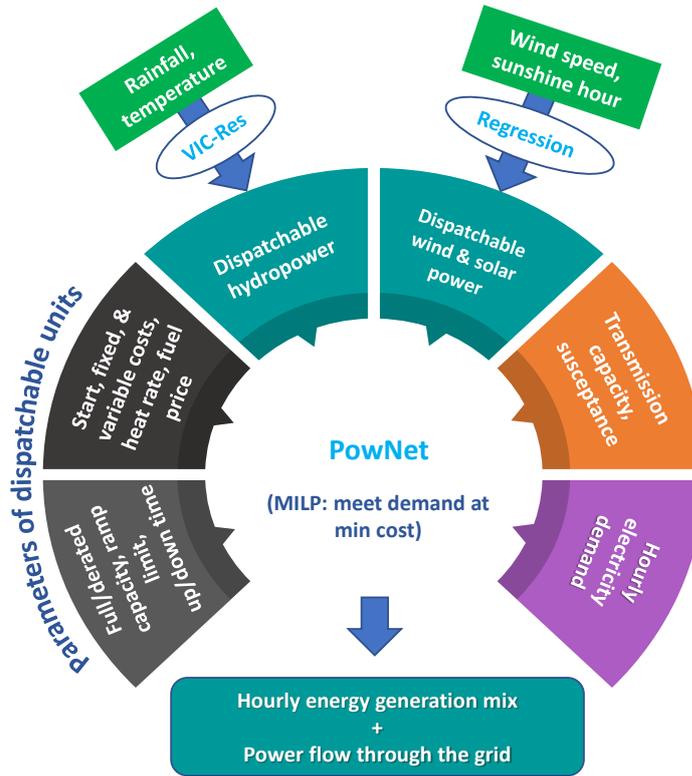


Figure 2. Graphical representation of PowNet’s input-output data. The term MILP refers to the Mixed-Integer Linear Program solved by PowNet.

222 PowNet is implemented to mimic the 2016 configuration of the Laotian–Thai power
 223 grid. The design features of the dispatchable units are collected from technical reports
 224 (EGAT, 2016; EPPO, 2017), while the techno-economic parameters are gathered from
 225 either global databases (EPA, 2015; EIA, 2016) or previous studies (Kern & Charack-
 226 lis, 2017); see Table S3 for additional details. Load shedding is modelled by adding hy-
 227 pothetical ‘slack’ generators (with high capacity and cost, but low ramping time) to some
 228 nodes with high demand. As for the high-voltage transmission lines, we used data on length,
 229 size, number of circuits, and voltage level (EPPO, 2015, 2018) to estimate their capaci-
 230 ty and susceptance. The hourly electricity demand at each sub-station is estimated start-
 231 ing from province-wise, monthly-varied peak electricity demand, collected from EPPO
 232 (2017). Both spatial and temporal disaggregation rely on a common approach in power
 233 system modelling (see Chowdhury, Kern, et al. (2020), and references therein). The for-
 234 mer depends on the voltage level of the sub-stations, the latter is based on weekday-weekend
 235 and peak-off-peak demand profiles to account for the variation among days in a week
 236 and hours in a day. The minimum hourly reserve is set to 15% of the system-wide de-
 237 mand (cfr. Guerra et al. (2016)), while generation is discounted by 7.5% to account for
 238 the transmission losses (EGAT, 2016). 25% of the transmission lines’ capacity is kept
 239 unused as safety margin (cfr. Schlecht and Weigt (2014)).

240 The amount of power available from the variable renewable resources is modelled
 241 separately. The production of wind and solar farms is modelled with a regression
 242 model, using wind-speed and sunshine-hour data (as in Papavasiliou et al. (2015) and Blair et
 243 al. (2014)), collected from the Thai Meteorological Department’s website (TMD, 2020).
 244 The hourly availability of hydro-electricity is simulated with the hydrologic-hydraulic model
 245 VIC-Res, as explained in the next section. VIC-Res is also used to estimate the amount

of water available at the freshwater-dependant thermoelectric plants, an information needed to calculate the adjustment factor of their generation capacity during the driest months. Following the same approach of O’Connell et al. (2019), we calculate these factors by comparing the simulated flow deviations with respect to the long-term flow conditions in the stream closest to each plant. With this set-up, PowNet is validated against 2016 data on generation mix, production costs, and CO₂ emissions (see Section S1).

2.3 Water availability simulation

To capture the relationship between hydro-meteorological processes and water availability over large domains, such as the Chao Phraya and Mekong basins, it is best to adopt a spatially-distributed, hydrologic-hydraulic model. Here, we rely on VIC-Res (Dang, Vu, et al., 2020), a variant of the flow routing model commonly used as a post-processor with the Variable Infiltration Capacity (VIC) hydrologic model (Liang et al., 1994; Lohmann et al., 1996, 1998). Both VIC and VIC-Res proceed by first organizing the spatial domain into a number of computational cells, where baseflow, runoff, infiltration, and evapotranspiration are estimated as a function of various hydro-meteorological forcings. The simulated runoff is then routed through the river network. In VIC-Res, the river routing process includes an explicit representation of storage and release dynamics of all reservoirs. This is achieved by determining the dam locations, implementing a number of cells in which the storage dynamics are calculated, and adopting bespoke rule curves that determine the release as a function of water level and dam design specifications. Using the information on release through turbines and hydraulic head, VIC-Res finally calculates the hydropower available at each dam. The explicit representation of the operating rules yields two advantages with respect to more traditional approaches that estimate available hydropower based on the post-processing of simulated discharge. First, VIC-Res accounts for the cascading effect of hydropower operations—a feature particularly important in the Lower Mekong, whose flows are affected by dams located in upper reaches of the basin (Hecht et al., 2019). Second, we ensure that both model parameterization and representation of key hydrological processes are not flawed by the misrepresentation of dam operations (Dang, Chowdhury, & Galelli, 2020).

As shown in Figure 1 (inset), water and hydropower availability are simulated over a large spatial domain comprising both Mekong and Chao Phraya River basins. For the Mekong, we consider a domain of $\sim 635,000$ km² ranging from the upper reaches of the Lancang to the station of Kratie (Cambodia). In this domain, we represent the operations of 108 dams operational in 2016 (across China, Laos, Thailand, Cambodia and Vietnam), including the 14 dams feeding the Laotian–Thai power system (see Section 2.1). For the Chao Phraya, we model an area of $\sim 110,000$ km², which is partially controlled by Bhumibol and Sirikit dams. To keep the model implementation consistent across the two basins, we adopted the same setup and input data: the spatial resolution is 1/16th of a degree, with which we accurately represent the location of each dam, while rainfall and temperature data are retrieved from APHRODITE (Yatagai et al., 2012) and CFSR (Saha et al., 2014), which were found to be reliable for the region of interest (Lauri et al., 2014). As for the hydropower reservoirs, we gathered data on dam design specifications and operating rules from the Mekong River Commission, the International Commission On Large Dams, and the Global Reservoir and Dam Database. Further details on the model setup and validation are provided in Section S2. For the handful of dams and freshwater-dependant thermoelectric stations falling outside the Mekong and Chao Phraya basins, we resorted to a simpler representation of the hydrological processes (Section S3).

2.4 Experimental setup and Analysis

Since our goal is to understand how water availability affects power system performance, we proceeded by isolating changes in the infrastructure while emphasizing the

effect of hydro-climatic variability—a common choice in power system modelling (e.g., Pereira-Cardenal et al. (2014); Voisin et al. (2016); De Felice et al. (2020)). We achieved this by keeping the setup on power plants, transmission facilities, and power demand for the year 2016 and forcing VIC-Res with 30 years of precipitation and temperature data spanning the period 1976–2005. There are two reasons behind the choice of this period. First, the teleconnection between ENSO and the summer monsoon in continental Southeast Asia started to strengthen in the 1970s (Singhrattna et al., 2005). Second, the period includes two particularly strong El Niño events, observed in 1982–1983 and 1997–1998 (Capotondi & Sardeshmukh, 2017). The period 1976–2005 therefore offers an ideal scenario for evaluating the exposure of the Laotian–Thai power grid to hydro-climatic variability.

To characterize the behaviour of the water-energy system, we consider a few explanatory variables for each sub-system. For the Mekong and Chao Phraya, we use the Streamflow Drought Index (SDI, Nalbantis and Tsakiris (2009)), whose calculation follows two steps. First we post-process—with a Box-Cox transformation and standardization—the discharge data simulated at hydropower and freshwater-dependant thermoelectric plants; then, we spatially aggregate the data to produce one index for each basin. For power supply, we analyze the available hydropower (calculated by VIC-Res), the unavailable capacity of freshwater-dependant thermoelectric plants, the electricity generation mix, production costs, and CO₂ emissions. (Reliability metrics, such as the reserve margin, are reported only in the Supplement, since grid reliability is not an issue.) All variables are aggregated at monthly and annual time steps—for the latter, we use the calendar year, instead of the hydrological year, following a standard practice in energy statistics.

To test the hypothesis that grid operations are sensitive to ENSO, we classify each year in the study period as either El Niño, Neutral, or La Niña. We adopt the classification provided by the Japan Meteorological Agency (<https://www.coaps.fsu.edu/jma>), but tailor it to our study site by shifting the years back by one, so as to account for the time that ENSO takes to affect Southeast Asia—for example, we classify 1998, instead of 1997, as an El Niño year. In our 30-year dataset, we isolate seven El Niño and four La Niña years, with the remainder classified as Neutral (Table S4). The resulting classification is used in a composite analysis with which we explore how the water-energy variables vary during the ENSO phases.

3 Results

This section moves along three phases. First, we quantify the exposure of hydropower and thermoelectric plants to climate variability. Then, we use this information to understand how generation mix, production costs, and carbon dioxide emissions vary in response to droughts, pluvials, and ENSO phases. Finally, we carry out a probabilistic assessment aimed at determining the likelihood of the most extreme events.

3.1 Impact of hydro-climatic variability on hydropower and thermoelectric plants availability

The scatter plots in Figure 3 illustrate the impact of droughts and pluvials on the availability of hydropower, coal-fired, biomass, and waste heat plants. To put these results in a broad hydro-climatological context, we begin by analyzing the annual values of the SDI in the Mekong and Chao Phraya (SDI_{MK} and SDI_{CPO}), reported on the horizontal and vertical axes, respectively (see, for example, Figure 3(a)). The first, fundamental, pattern to notice is that both basins exhibit a similar behaviour over time, meaning that the majority of pluvials and droughts are synchronized (first and third quadrants). The depth, or intensity, of these events is comparable across the two basins, as shown by the SDI range of variability. A second pattern is the response to ENSO. All

347 El Niño events are associated to dry conditions in either or both basins; La Niña events
 348 tend to increase water availability throughout the spatial domain. A notable exception
 349 is the 1989 La Niña, when positive rainfall anomalies were limited to central Vietnam,
 350 leaving the Mekong and Chao Phraya basins drier than average (Räsänen et al., 2016).

351 The impact of hydro-climatic variability on the hydropower budget is profound:
 352 as shown by the colour bar of Figure 3(a), the anomalies of available hydropower vary
 353 between $\pm 4,000$ GWh; a range equivalent to about one-third of the annual hydropower
 354 availability. Since most of the hydropower potential is realized by dams in the Mekong,
 355 droughts affecting this basin (second and third quadrants) have a bigger impact on hy-
 356 dropower availability than droughts affecting the Chao Phraya alone (fourth quadrant).
 357 As we shall see later, the unavailability of cheap hydropower from Laos limits the effec-
 358 tiveness of long-distance power transfers to Thailand, with a consequent impact on the
 359 overall generation mix and associated production costs. Another important point revealed
 360 by Figure 3(a) is that deeper droughts do not necessarily lead to larger anomalies of hy-
 361 dropower availability; see, for example, the years 1977 and 1983, which present similar
 362 anomalies (about -4,000 GWh) but different drought intensities. This result is explained
 363 by the drought spatial patterns: as shown in Figure 4, different patterns can result in
 364 similar effects if the main impacted units (Nam Theun 2 and Nam Ngum 2, in this case)
 365 are exposed to events of comparable depth. (The reader is referred to Figure S4 for an
 366 additional analysis of drought spatial patterns and impacted units.)

367 The exposure of freshwater-dependant thermoelectric plants to hydro-climatic vari-
 368 ability is quantified by calculating the total annual unavailable, or derated, capacity. Be-
 369 ginning with coal (Figure 3(b)), we find that the largest value of derated capacity is $\sim 1,500$
 370 MW in Thailand and ~ 750 MW in Laos (Table S2, Figure S5), corresponding to about
 371 27% and 40% of the installed capacity—a result in line with the one reported by Wang
 372 et al. (2019). Since coal-fired plants are located in both Mekong and Chao Phraya basins
 373 (Section 2.1), the most impactful droughts are the ones affecting both basins concurrently.
 374 Similarly to the case of hydropower, the overall impact of droughts depends not only on
 375 severity, but also on geographical extent. This concept is exemplified by the 1979 and
 376 1993 events, whose spatial patterns are illustrated in Figure 4. Similar conclusions can
 377 be drawn for the biomass and waste heat plants (Figure 3(c)), whose role in the Laotian–
 378 Thai water-energy system is more marginal.

379 We consolidate the results from the previous steps in Figure 3(d), where colours
 380 represent the annual anomalies of hydropower budget and size represents the unavail-
 381 able capacity of thermoelectric plants (aggregated across coal, biomass, and waste heat
 382 plants). The plot reveals the overall exposure of the Laotian–Thai water-energy system
 383 to hydro-climatic variability. When both basins are in normal or wet conditions (pos-
 384 itive values of SDI), we observe large, positive, anomalies of hydropower availability. When
 385 the Mekong, or both basins, are in dry conditions, we find events affecting the hydropower
 386 dams (e.g., 1977, 1983), thermoelectric plants (e.g., 1979, 1993), and a combination thereof
 387 (e.g., 1982, 1992). As explained above, the reason behind these ‘different droughts’ has
 388 to be sought in the position of impacted units—a critical factor in determining the sys-
 389 tem’s exposure.

390 **3.2 Cumulative impact of water availability on generation mix, produc-** 391 **tion costs, and CO₂ emissions**

392 How does the exposure of hydropower and thermoelectric plants to hydro-climatic
 393 variability affect the power system’s performance? To answer this question, we study the
 394 annual anomalies of hydropower, coal, gas, and biomass supply, productions costs, and
 395 CO₂ emissions—all simulated by PowNet. These variables are illustrated in Figure 5,
 396 together with the hydro-climatological conditions characterizing the study period. The
 397 figure highlights the fundamental role played by the Mekong’s dams: when their produc-

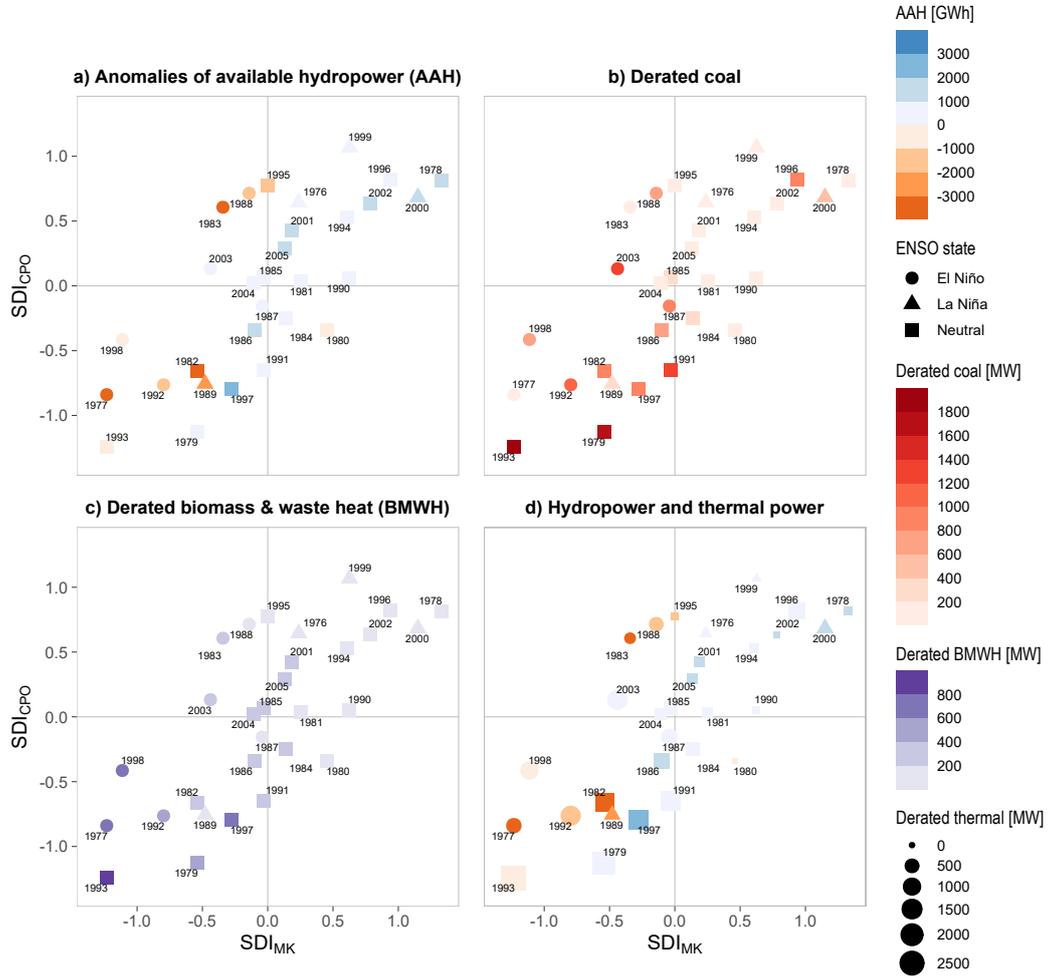


Figure 3. Scatter plots illustrating the impact of hydro-climatic variability on hydropower plants (a), coal-fired plants (b), and biomass and waste heat plants (c). (Note that in panel (c) we included the only freshwater-dependant gas-fired plant.) For hydropower, we calculate the annual anomalies of available hydropower, while for the freshwater-dependant thermoelectric plants we calculate, on annual basis, the derated capacity. In each scatter plot, the horizontal and vertical axes correspond to the Streamflow Drought Index of the Mekong and Chao Phraya (SDI_{MK} and SDI_{CPO}), while points correspond to the annual values of the aforementioned variables. The ENSO state is represented with three symbols, indicating El Niño (circle), Neutral (square), and La Niña (triangle) conditions. In panel (d), we aggregate the impact of hydro-climatic variability on all plants: anomalies of hydropower budgets are represented by colours, while the derated capacity of thermoelectric plants is represented by the size of the symbols.

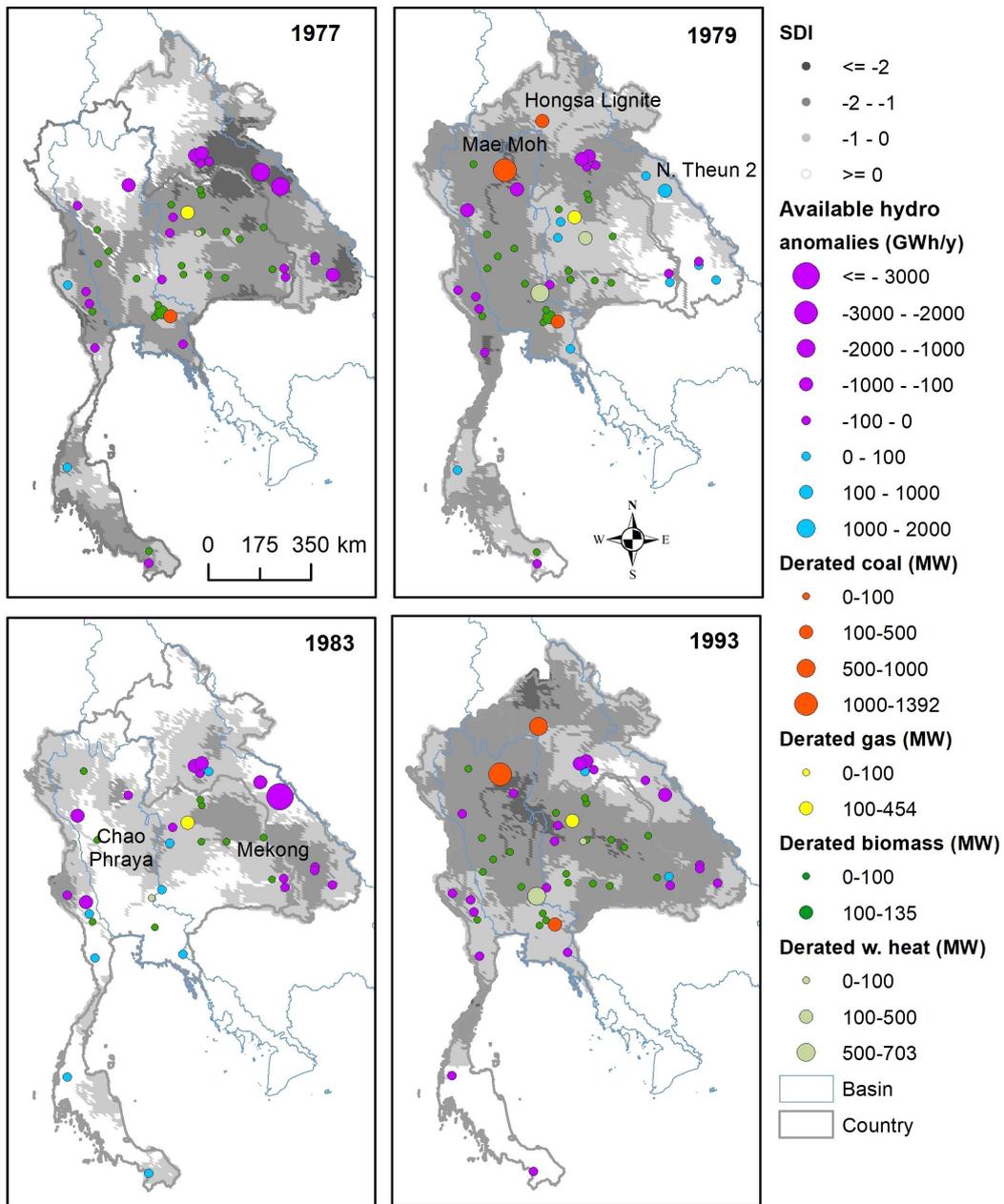


Figure 4. Spatial distribution of the SDI for four selected years. The impact of hydro-climatic variability on the power system is quantified with the same variables used in Figure 3: annual anomalies of available hydropower (in GWh) and derated capacity of freshwater-dependant thermolectric plants (in MW).

tion drops (Figure 5(a), second and third quadrants), the power system responds by increasing its reliance on thermoelectric plants (Figure 5(b-d)). In turn, this largely affects production costs and CO₂ emissions. ‘Hydropower droughts’—like those experienced in 1977 or 1983—increase production costs and emissions by more than 100 M\$ and 2 Mt per year, respectively. Pluvials have the opposite effect: by increasing water availability and hydropower supply, they dwindle the carbon footprint. Overall, we find that hydroclimatic variability alone makes annual production costs and CO₂ emissions vary in a range of about 250 M\$ and 5 Mt. The signature of ENSO is clear: during El Niño years, costs and emissions increase, on average, by 50 M\$ and 1 Mt (Figure S6). In other words, the teleconnection between Pacific Ocean sea surface temperatures and the Mekong’s hydrological processes permeates through the power grid, influencing the operations of the thermoelectric sector and its carbon footprint.

To better understand the role played by thermoelectric stations, we visualize the annual values of ten water-energy variables in a parallel-coordinate plot (Figure 6). The variables are shown in ten parallel axes, so each line connecting the axes represents a different year. The figure illustrates three important behaviours. First, coal, gas, biomass, and waste heat plants are never used at full capacity, even when the Mekong’s dams hit the lowest production levels—note the diagonal lines crossing the axes Coal_{LA}, Coal_{TH}, Gas, and BMWH. This behaviour is explained by the large reserve capacity (see Figure S7). Second, there is a dichotomy between the Thai coal plants and the Hongsa coal-fired power plant in Laos; a result that provides fertile grounds for criticisms about the hidden costs, and real benefits, of this infrastructure (Deetes, 2015). Third, coal-fired (in Thailand), biomass, and waste heat plants tend to be the preferred options, because they are the cheapest alternative. Yet, when their capacity is affected (as in 1979 or 1993), gas plants are run at higher capacity. When this happens, production costs and CO₂ emissions are decoupled, with the former increasing and the latter reaching the lowest levels. In other words, there can be instances in which droughts lead to a decrease of CO₂ emissions.

3.3 A probabilistic assessment

The analyses in Section 3.1 and 3.2 show that droughts affect the availability of hydropower and thermoelectric resources and, by extension, production costs and CO₂ emissions. To determine the likelihood of the most extreme instances, we use monthly values of SDI at each hydropower and (freshwater-dependant) thermoelectric station and calculate the percentage of installed capacity under severe drought—using a threshold of SDI equal to -1. In Figure 7, each dot represents a month in the study period while the colour represents the corresponding anomaly of cost (upper panel) and carbon dioxide emissions (bottom panel). Using kernel density estimation, we also calculate the univariate and bi-variate probability distributions of hydropower and thermoelectric capacity impacted by extreme droughts. Beginning with the hydropower sector, the probability distribution indicates that it is more likely to have some dams (about 5% of the total installed capacity) under drought conditions than none—note that the median is larger than zero. The plot also shows that when about 25% of the capacity is under extreme droughts, the power grid experiences large monthly anomalies of both costs and emissions; a result of the increased reliance on thermoelectric resources. As indicated by the probability distribution, such instances are not unlikely—the 25% threshold falls within the interquartile range. The thermoelectric sector has slightly higher chances of not experiencing extreme droughts. And yet, the exposure of just a small fraction of the cumulative capacity (from 10 to 25%) is sufficient to trigger a system’s response, manifested by an increase in costs and decrease in emissions—recall that gas, the alternative to coal, is more expensive, but has a smaller carbon footprint than coal. Similarly to the case of hydropower, these instances fall within the interquartile range. In synthesis, both sectors are likely to be affected individually by short and intense droughts that disrupt the entire system’s operations. Bringing the two sectors together under the bi-variate dis-

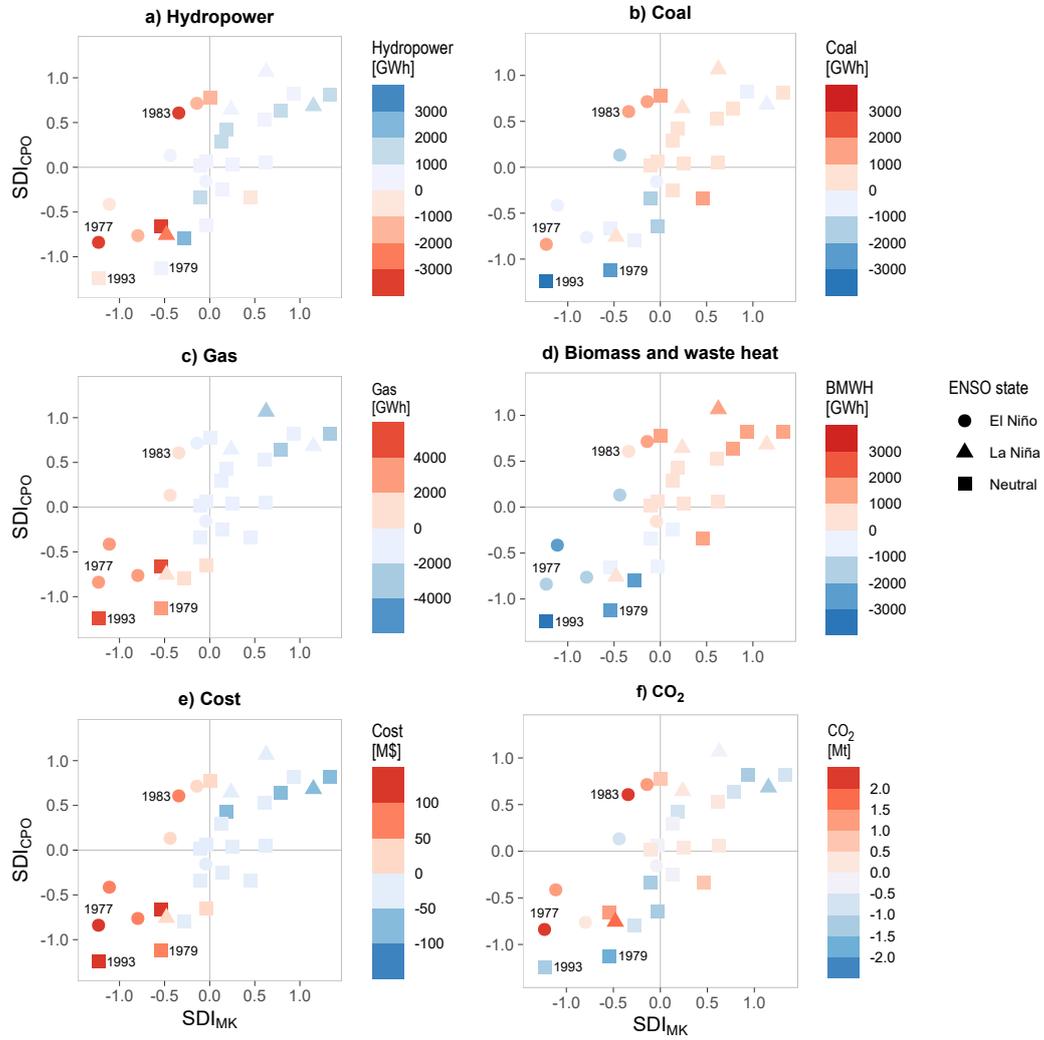


Figure 5. Scatter plots illustrating the relation between climate, water, and energy variables. The ENSO state is represented with three symbols, indicating El Niño (circle), Neutral (square), and La Niña (triangle) conditions. The state of Mekong and Chao Phraya basins is measured with the Streamflow Drought Index (SDI_{MK} and SDI_{CPO}), reported on the horizontal and vertical axes, respectively. The behaviour of the power system is quantified with the annual anomalies of hydropower, coal, gas, and biomass supply (panels (a-d)), productions costs, and CO_2 emissions (panels (e-f)).

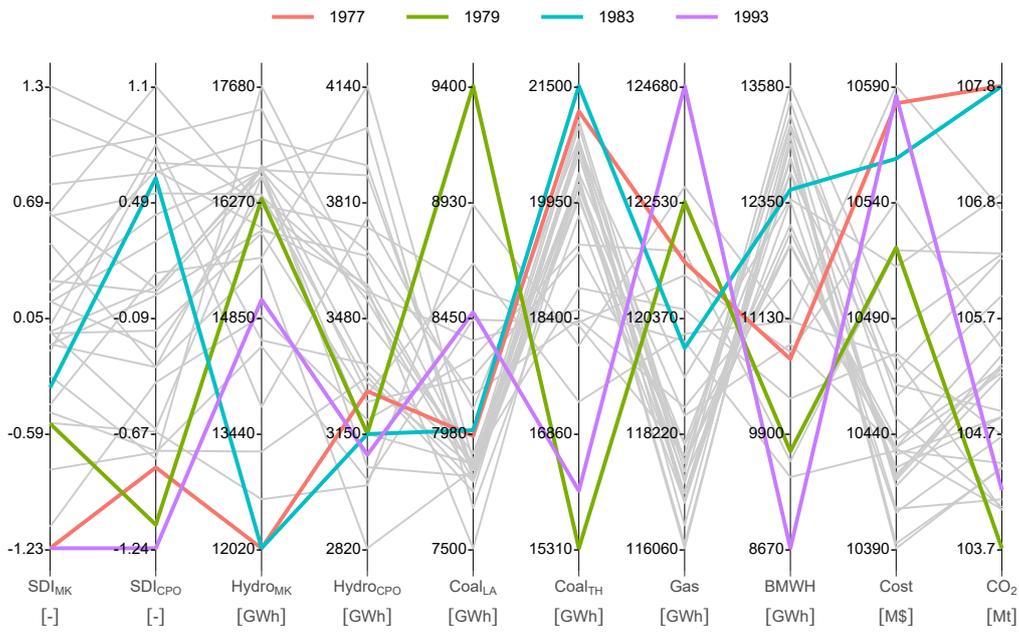


Figure 6. Parallel coordinate plot illustrating the relation between the state of Mekong and Chao Phraya basins (SDI_{MK} and SDI_{CPO}), energy generation mix, production costs and CO_2 emissions. Variables are aggregated on an annual basis, so each line corresponds to a year. For the energy generation mix, we report the electricity dispatched from: hydropower plants located in the Mekong and Chao Phraya ($Hydro_{MK}$ and $Hydro_{CPO}$), coal plants located in Laos and Thailand ($Coal_{LA}$ and $Coal_{TH}$), gas plants (Gas), biomass and waste heat plants (BMWH). Note that the years highlighted here correspond to those illustrated in Figure 4.

451 tribution, we note that the probability of extreme droughts affecting hydropower and
452 thermoelectric resources decreases sharply, especially for events impacting more than 50%
453 of the installed capacity. As expected, these are the instances resulting in the largest im-
454 pact on production costs and emissions.

455 4 Discussion

456 Our results reveal a cyclic pattern underpinning the relationship between climate,
457 water, and energy variables in the Laotian–Thai power grid: as water availability in the
458 Mekong and Chao Phraya River basins fluctuates between dry and wet conditions, in
459 response to El Niño and La Niña conditions, so too does the power system behaviour,
460 whose generation mix must periodically lean towards thermoelectric and hydropower re-
461 sources. The periodic fluctuations extend to annual production costs and CO₂ emissions,
462 for which we observe a possible range of variability of ~250 M\$ and 5 Mt per year. Taken
463 from another perspective, water availability alone controls about 5% of the annual CO₂
464 emissions. The trickle-down effect of ENSO on power system performance is likely a con-
465 sequence of the sensitivity of regulated streamflow regimes to seasonal and inter-annual
466 hydro-climatic variability (Ferrazzi et al., 2019). In theory, one would expect dams to
467 smoothen inflow variability, thereby providing a steady electricity supply. But, in prac-
468 tice, the capability of a dam to buffer inflow variability depends on its design specifica-
469 tions and operating rules (Ng et al., 2017). Run-of-the-river hydropower dams, for in-
470 stance, have limited storage capacity, so they cannot fully disconnect electricity gener-
471 ation from local hydrological conditions. The vulnerabilities we identified could be turned,
472 however, into opportunities for better operations, because the teleconnection between
473 ENSO and local hydrological conditions is one of the physical mechanisms on which sub-
474 seasonal to seasonal forecasts rely. The range of variables that can be predicted is broad—
475 e.g., electricity demand or wind, solar, and hydropower availability—and so is the num-
476 ber of actionable decisions at the water-energy scale (Orlov et al., 2020). For example,
477 operators could plan demand management strategies, modify hydropower rule curves,
478 or purchase financial instruments, such as power futures, to hedge financial risks and pro-
479 tect end-users (ibidem). All these opportunities will become even more important in the
480 coming years as the Laotian–Thai grid will integrate more renewables and long-distance
481 interconnections; a point on which we return later.

482 In accordance with previous studies (e.g., Byers et al. (2020)), our work also shows
483 that the response of a power system to droughts depends not only on their severity, but
484 also on their spatial footprint. Because hydropower and thermoelectric plants are het-
485 erogeneously scattered across two river basins, the position of impacted units determines
486 whether the power system must rely on coal, gas, or a combination thereof to offset the
487 detrimental impacts of droughts. Yet, conclusions drawn on the grid’s exposure and re-
488 sponse to hydro-climatic variability should be taken with caution, owing to the non-stationarity
489 in the ENSO–monsoon teleconnection. Analyses conducted over the period 1650–2004—
490 combining observed and paleo-reconstructed data—revealed that the strength of the tele-
491 connection varied over space and time, alternating decades of weaker and stronger ef-
492 fects (Räsänen et al., 2016). An explanation for this behaviour may be sought in the am-
493 plitude, temporal evolution, and spatial patterns of ENSO events. Recent decades, in-
494 cluded in our study period, witnessed a change in ENSO dynamics, with warm events
495 stronger than cold events in the eastern Pacific (Capotondi & Sardeshmukh, 2017). In
496 turn, these eastern Pacific-centered events tend to constrain the descending branch of
497 the Walker circulation within the Pacific domain, thereby modulating the summer mon-
498 soon in continental Southeast Asia (Singhrattna et al., 2005). If anthropogenic influence
499 will exacerbate such phenomena—an hypothesis still debated (Cai et al., 2014; Perry et
500 al., 2017)—we must then prepare for a drier summer monsoon, with less water available
501 for power systems.

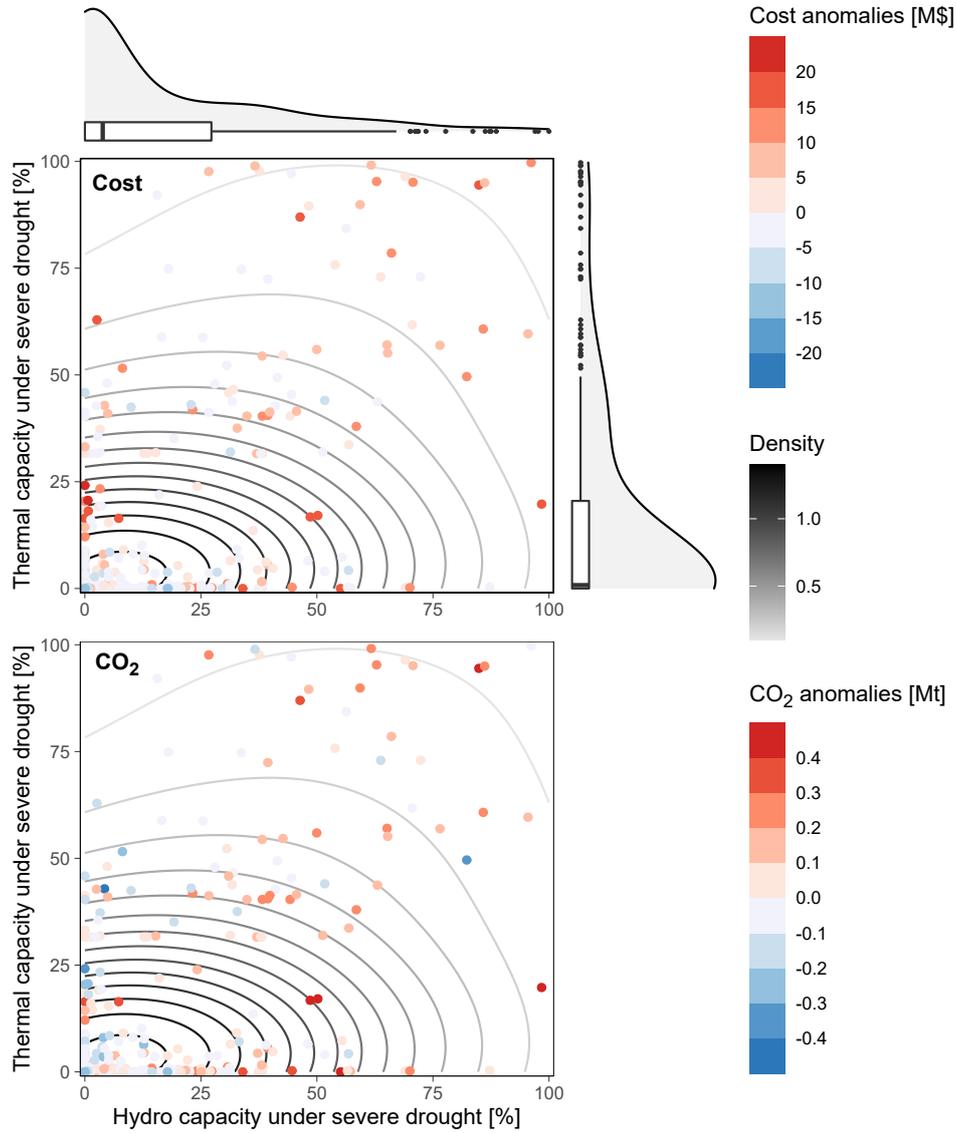


Figure 7. In the upper panel, the horizontal and vertical axes report the percentage of hydropower and (freshwater-dependant) thermoelectric capacity under severe drought, defined as $\text{SDI} < -1$. (Note that the SDI is calculated at each specific station.) Each dot represents a month in the study period, while its color the corresponding (monthly) cost anomaly. The probability distribution (of being under severe drought) is estimated with a Gaussian kernel and illustrated on the top and top-right, for hydropower and thermoelectric resources, respectively. In the box-plots, the median is marked by a line inside the box, which represents the inter-quartile range. The whisker extends to 95th percentile, while outliers are outside this range. The bi-variate distribution is represented by the isolines inside the plot. The bottom panel reports the same analysis, this time focussed on carbon dioxide emissions.

502 Future operating costs and CO₂ emissions will not only depend on joint water-energy
503 management strategies and climatic conditions. They will also depend on Thailand's fu-
504 ture Power Development Plans (PDP). According to the latest plan (EPPO, 2018), Thai-
505 land's electricity demand is expected to increase roughly 3% annually from 2018 to 2037.
506 To meet it, Thailand is planning to reach in 2037 an installed capacity of 77,211 MW.
507 This includes 56,431 MW of added capacity, since 25,310 MW are expected to be retired.
508 If all moves as per plan, coal will be slightly sidelined (to 13% of the power generation),
509 with gas, renewables, and energy efficiency contributing 53%, 28%, and 6% of power sup-
510 ply. As for the renewables, solar is expected to take a big leap forward, while wind tar-
511 gets, despite having reasonably good potential, are low (WoodMac, 2019). Hydropower
512 will be further expanded, both locally and internationally. The two basins of particu-
513 lar interest are the Mekong and Irrawaddy. Our results for the existing Laotian–Thai
514 interconnection suggest that the further reliance on monsoon rainfalls may undermine
515 the expected benefits of these plans. For example, regional droughts could hinder the
516 ambitious goal of cutting the CO₂ emissions intensity to 283 kg/MWh (EPPO, 2018).
517 The issue gains further importance if El Niño-like conditions will become more frequent.
518 Another point of potential concern is the heavy reliance on natural gas. Gas fields in the
519 southern Gulf of Thailand are depleting, forcing Thailand to import gas from other countries—
520 mostly Myanmar and Qatar (DBS, 2017). In turn, this may expose the grid to gas price
521 volatility, warranting more research on the compound impacts of droughts and fuel price
522 variability on grid operations (O'Connell et al., 2019).

523 Setting aside for a moment grid operations, what is also worth discussing here is
524 the fate of the Mekong and Irrawaddy River basins. The Mekong has already paid a sub-
525 stantial toll: dams built by Thailand, Laos, Vietnam, and China have affected the river-
526 ine ecosystems and altered hydrological processes (Arias et al., 2014; Kondolf et al., 2018;
527 Hecht et al., 2019), impacting entire economic sectors on which the livelihood of millions
528 depends (Sabo et al., 2017). In some cases, dam constructions have also increased green-
529 house gas emissions (Räsänen et al., 2018) and forcibly displaced large indigenous com-
530 munities (Scudder, 2020). If Thailand, and other countries, were to expand their hydropower
531 fleet, we may expect further environmental impacts and tighter conflicts between eco-
532 nomic sectors (Y. Yu et al., 2019; Do et al., 2020). The Irrawaddy River basin may be
533 next in line (Kattelus et al., 2015). The opportunities for a partial change of course are
534 many. A first option would be to deploy more solar and wind plants (Schmitt et al., 2019).
535 Eastern Thailand and central Myanmar, for example, have abundant theoretical poten-
536 tial of solar PV (Siala & Stich, 2016), offering a chance to make the 2018 PDP more sus-
537 tainable. Likewise, wind targets could be further pushed. A potential game changer is
538 the ASEAN Power Grid (APG): at this stage, Thailand and Laos are the only two coun-
539 tries largely relying on a cross-border power trade infrastructure, but things could change
540 if more ASEAN countries were to have access to the same transmission infrastructure
541 (Ahmed et al., 2017). The APG could connect load centers to more production sites, re-
542 ducing both pressure on river basins and power systems exposure to hydro-climatic vari-
543 ability.

544 5 Conclusions

545 In conclusion, our results indicate that the Laotian–Thai power system is vulner-
546 able to hydro-climatic variability. Electricity supply reliability does not seem to be at
547 risk, while operating costs and CO₂ emissions vary in response to the hydrological con-
548 ditions in the Mekong and Chao Phraya River basins. The two mechanisms controlling
549 such response are reduced hydropower generation, mostly in the Mekong, and capacity
550 derating at individual thermoelectric plants. Of particular concern is the spatial coher-
551 ence of the two basins: regional droughts are frequent, forcing the power system to rely
552 on gas and coal. In turn, these results suggest that long-distance power transfers may
553 be doomed to temporary failures, especially if their design stems from a limited under-

554 standing of the interplay between global climate phenomena, such as ENSO, and local
 555 water-energy processes. Multi-model multi-scale frameworks provide a methodological
 556 basis for characterizing this nexus, supporting operational decisions at the water-energy
 557 scale, and informing long-term capacity expansions.

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 562 results at <https://github.com/kama10013/PowNet-Thailand> (DOI: 10.5281/zenodo.4040851).
 563 Due to restrictions, the only exceptions are the observed discharge in the Mekong and
 564 the dam design specifications.

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