Valuing Tropical Forests: Deforestation, Rainfall, and Hydropower

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Abstract

Tropical forests affect rainfall regimes in a continental scale. This paper develops an approach to value this important ecological service to the energy sector. I develop an econometric climate model that connects tropical deforestation with rainfall hundreds or even thousands of kilometers away from the forest. As an application, I estimate the impact that Amazon deforestation has on the power generation capacity of the Teles Pires hydropower plant in Brazil, a country that has hydropower as its main source of energy. The decrease on energy generation is higher in the wet season, with an average decrease of 10% and extreme scenarios of 17%, amounting to a potential loss for the hydroelectric operator of USD 21 million per year. I then map the regions of the Amazon that would have the highest values of preservation for the hydroelectric operator. The results provide evidence of the economic importance of ecological services of tropical forests to economic activities.

JEL: *Q57, L94, Q23, Q25, Q54*

Keywords: *Deforestation, Amazon, Energy, Climate, Land Use*

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1 Introduction

Tropical forests provide a range of positive externalities via ecological services, such as storing carbon (Baccini et al., 2012), controlling temperature (Lawrence et al., 2022), and maintaining rainfall regimes (Spracklen et al., 2012). The evaluation of these ecological services is part of an agenda of accounting for the natural capital in economic models and is an important step to design environmental protection policies (see Ferraro et al. (2020) for a review). Nonetheless, one difficulty of assessing the value of these externalities is the necessity of working with complex computationally demanding climate models and then to connect their results with models of other areas, such as hydrology, agriculture, and carbon sequestration.

In this paper, I develop an approach to estimate the impact that deforestation of tropical forests has on energy generation of hydropower plants (hereby HPs). This allows me to estimate the value of the forest for HP's operators. To do that I study a chain of effects: deforestation affects rainfall, rainfall affects river flow, and river flow affects energy generation. Tropical forests play a crucial role in continental rainfall, since trees' transpiration increases air's humidity contributing to rainfall downwind. Interestingly, this transpiration-rainfall mechanism has effect in locations that are hundreds and even thousand of kilometers away from the forest.

To model this mechanism, I develop a computationally light econometric climate model that connects a deforestation scenario with rainfall. In this model, I build atmospheric trajectories that cover the forest using data on wind speed and direction. Along the trajectories, I create a measure of how many pixels of forest each trajectory has "flown" over. I then estimate the effect that this measure of upwind forested pixels has on downwind rainfall with a linear regression. The estimated parameters allow me to build, for each possible scenario of deforestation, a counterfactual rainfall measure. In the next step, I estimate the effect of rainfall on the river flow with a linear model and the effect of river flow on the energy generation using a log-log specification from physics (Stickler et al., 2013). The cost of the loss in energy capacity can be seen as the willingness to pay for the conservation of the forest. Finally, I map the regions of the forest that would have the highest values of preservation for the HP, which are the regions that are most visited by the atmospheric trajectories upwind of the HP.

As an application for the methodology, I investigate the impact that the accumulated deforestation of Amazon Rainforest since the 1980's has on the energy generation capacity of the Teles Pires HP in Brazil. The electrical matrix in Brazil is vulnerable to rainfall changes since 59% of its installed capacity comes from hydropower. The Teles Pires HP is one of the ten biggest HPs in Brazil and the biggest one located in the State of Mato Grosso, a state in which the rainfall is heavily impacted by the proximity with the Amazon Rainforest.

I find that the accumulated Amazon deforestation generates an average decrease of rainfall of 13% and 8% of the historical average in the State of Mato Grosso in the dry and wet seasons, respectively. For the location of the Teles Pires HP this decrease is between 6% and 10%. The impact of this decrease in rainfall amounts to an average decrease in potential energy generation between 2.5% and 10%, with extreme scenarios of more than 17%. For the HP's operator, this loss in energy generation amounts to an average of USD 21 million per year.

This paper contributes to different areas of research. The methodology adds to an agenda of valuating ecological services (Ferraro et al., 2020), that for tropical forests are often constrained to valuating the forest as a carbon sink (Franklin Jr and Pindyck, 2018; Araujo et al., 2020). When assessing the cost-benefit of different policies to curb deforestation (Souza-Rodrigues, 2019; Assunção et al., 2022; Jung et al., 2022; Simonet et al., 2019), this externality effect of the forest on rainfall has not been accounted for.

The methodology can be applied in different regions with the presence of tropical forests, such as South America, Indonesia, and Africa. As the effect of deforestation on precipitation crosses country boundaries, this model can be used to measure externalities among countries, much in the same way of agreements over the use of rivers (Olmstead and Sigman, 2015; Ambec et al., 2013). It can also be applied in a range of different sectors, such as, agriculture and water supply for human consumption, and therefore be used to study allocation of scarce water resources across competing sectors (Olmstead, 2020).

Tropical forests are instruments to counteract rainfall changes caused by the rising global temperature (Seneviratne et al., 2012). Thus the forest can dampen the impacts of changes in rainfall studied in literature of adaptation to climate change, such as changes in the agricultural sector (Skidmore, 2022) and economic growth in general (Damania et al., 2020; Barrios et al., 2010). The literature of HPs has studied shifts of energy source (Crampes and Moreaux, 2001; Genc and Thille, 2011; Eyer and Wichman, 2018) and multiple entry of HPs in the same basin (Moita, 2008). On the intersection of deforestation and HPs, Stickler et al. (2013) studies local effects of deforestation on the flow of a basin and its effect on energy generation. This paper departs from this literature by uncovering another layer of externalities that must be taken into account when studying HPs in regions affected by ecological services.

In the remainder of this article, Section 2 describes the climate model; Section 3 describes the connection between rainfall and energy; Section 4 estimates the impact of deforestation on energy generation; Section 5 values the ecological service of the forest; Section 6 concludes.

2 Climate Model: Deforestation and Rainfall

Tropical forests are an important part of the water cycle. The evaporation of the water in the Oceans creates humid air parcels that are transported to continental lands. Along its trajectory the air parcel loses humidity via precipitation. But, on the ground, trees' transpiration recharges the air parcel's humidity contributing to rainfall downwind. Thus, trees affect rainfall. The presence of tropical forest can affect rainfall in locations that are hundreds and even thousands of kilometers away from the forest, a phenomenon known in the literature as flying rivers (Marengo et al., 2018). An implication of this mechanism is that deforestation decreases rainfall. To model this effect, I follow Spracklen et al. (2012) in creating a data set that connects upwind exposure to trees to downwind rainfall.

The first step is to generate trajectories through which these air parcels travel, or a model of atmospheric transportation. The trajectories is built with data on wind speed and direction. Suppose I have an air parcel over a location ℓ (latitude and longitude) for which I am interest in modelling rainfall, then I can use the data on wind speed and direction to move one step back, that is to find where this air parcel was one hour ago. If I keep doing this, eventually I will have traced the air parcel trajectory back to the Ocean[1]. Figure 1a shows an example of such back trajectory.

The second step is to create a measure of exposure of that back trajectory to the forest. This step requires forestation data for all the area covered by the back trajectory, such as a binary data indicating whether a location is forested or deforested. I then count the number of forest pixels crossed by a back trajectory. For example, the back trajectory in Figure 1A will have a measure of 12 pixels of forest. I can then repeat steps one and two for different periods for all locations that I want to. For example, in a different year I could have the second trajectory depicted in Figure 1B, with a measure of 11 pixels of forest. From Figure 1, it is likely that the back trajectory in scenario A will deliver more rainfall than the back trajectory in scenario B, since the exposure to forested pixels is higher in scenario A.

I model the effect of upwind exposure to the forest on downwind rainfall with a linear regression model. In this paper, I will model the effect of Amazon deforestation on the rainfall of the Brazilian State of Mato Grosso, shown in Figure 3A. I collect data on monthly wind speed and direction from Copernicus (2017) and use this data for all months of the year from 1985 to 2020 for the entirety of South America at its native resolution of 0.25°. I also collect yearly data of land use for the entire Amazon from 1985 to 2020 from Mapbiomas (2022). Figure 2A shows a sample of back trajectories for the State of Mato Grosso in

[1] I compute the back trajectories up to 5 days and set pressure level to 800 hPa following Spracklen et al. (2012). Each step and output has length of 1 hour.

February 2020.

To estimate the relation between forest and rainfall, denote by $r_{\ell,m,y}$ the rainfall in location ℓ, month m, and year y; $f_{\ell,m,y}$ the count of forested pixels along the back trajectory started in ℓ, or the upwind exposure to the forest; $x_{\ell,m,y}$ the length of the back trajectory on land, to control for the fact that longer trajectories mechanically present a higher count of upwind exposure to the forest. The effect of deforestation on rainfall is given in Expression 1

$$r_{\ell,m,y} = \alpha + \beta_m f_{\ell,m,y} + \gamma x_{\ell,m,y} + \epsilon_{\ell,m,y} \tag{1}$$

As the back trajectories are long, the $f_{\ell,m,y}$ measure is dominated by forest pixels that are far away from location ℓ. Therefore, it is unlikely that local shocks to ℓ can affect the count $f_{\ell,m,y}$. The pixel-month fixed effect eliminate concerns of seasonal local shocks. It is important not to include bad controls (Wooldridge, 2005), such as temperature, since the upwind exposure to the forest can affect temperature at ℓ. Essentially, the identification of the model relies on the variation of the back trajectories and therefore on the variation of the wind data. Furthermore, the mechanisms behind the link between transpiration and humidity transport (Spracklen et al., 2012) provide further evidence of the causal interpretation of Expression 1. On alternative models, the economics literature of pollution make use of atmospheric models with greater temporal resolution (Hernandez-Cortes and Meng, 2020; Miller et al., 2017). This is necessary since the pollution source, such as fires, is usually short-lived. But, the transportation of humidity from the ocean is a continuous process, which allows me to leverage monthly trajectories patterns.

Figure 2B shows the results of this estimation for different sets of fixed effects with stable results across specifications: month; month and year; month, year, and pixel; month-pixel and year (Table 1). As expected the estimated β_m coefficients are all positive, meaning that upwind exposure to the forest increases downwind rainfall. It is easier to understand the magnitude of the estimated effects with a counterfactual. I explore in this paper a counterfactual where there would not have been deforestation in the Amazon since 1985, the first year I have data on land use. Figures 2C and 2D shows the impact that the accumulated deforestation of the Amazon since 1985 has on the total rainfall of the dry season - April to August - and the wet season - September to March - measured as a proportion of the historical average. The accumulated Amazon deforestation generates an decrease of rainfall of 13% and 8% of the historical average in the State of Mato Grosso in the dry and wet seasons, respectively. Some regions face an effect of more than 25% in the dry season and other regions face an effect of more than 14% in the wet season.

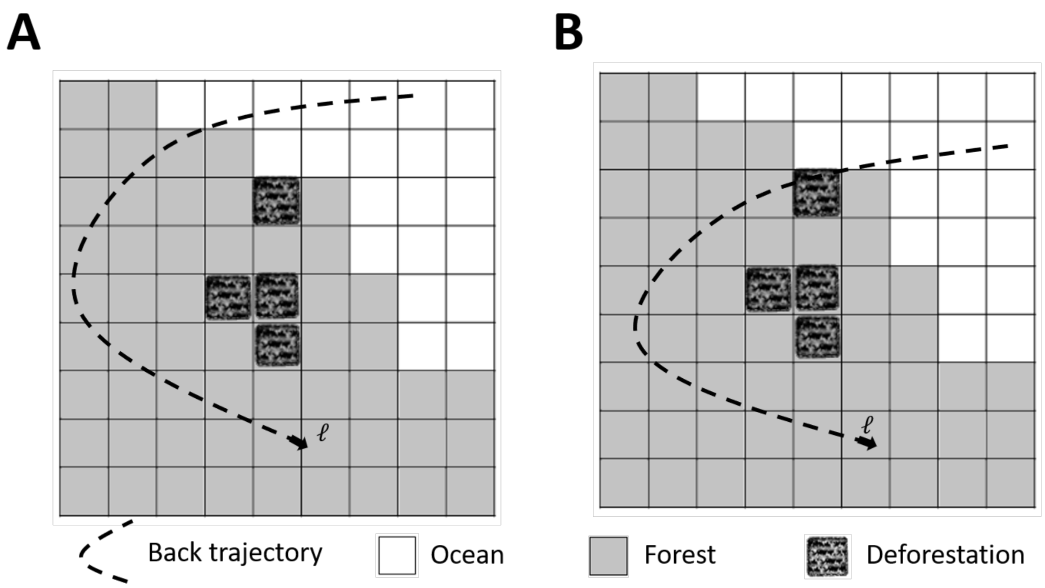

Figure 1: This figure illustrates the construction of the upwind exposure to forested pixels. Consider a location ℓ, in which we are interested in modelling the rainfall. In A and B, the dashed black line represents a back trajectory of atmospheric transport from ℓ to the Ocean. Each trajectory visited different pixels along the way. Specifically, in A the back trajectory visited 12 pixels of forest and in B the back trajectory visited pixels 11 of forest. These numbers are what I denoted by $f_{\ell,m,y}$ in Expression 1

3 Teles Pires: Rainfall and Energy Capacity

The Teles Pires HP started operating in 2015 and is one of the 10 largest plants in Brazil. It is part of a new batch of HPs known as run-of-the-river plants, which are characterized by a limited capacity of water storage and thus rely heavily on the river flow. This type of HP can change environmental costs associated with HPs (Assunção et al., 2017), since its does not require the flooding of large portions of land for the construction of a reservoir. Teles Pires started its operation in 2015 with an installed capacity of 1,820 MW, sufficient to supply a population of 5 million inhabitants. It is part of a complex of HPs in the Teles Pires river, where other smaller plants are located. Figure 3A shows the location of the HP and of the Teles Pires' basin. The effect of deforestation on rainfall calculated in Section 2 for the location of Teles Pires generates an average decrease of rainfall of 6% and 10% of the historical average in the dry and wet seasons, respectively.

There are two steps to measure the impact that changes in rainfall have on energy generation: first, map how rainfall affects the river flow; second, map how the river flow affects potential energy generation.

I use river flow data from the National System Operator (ONS, 2022) from 2015 to 2020 and the same monthly data on rainfall that was used for the climate model, but selecting data only at the location of the plant. The model is a linear regression of the log of river flow on a month (d_m) on the accumulated 4 months rainfall (r_m), as described in Expression 2. Figure 3B shows that both variables are strongly correlated and Table 2 in the Appendix shows a R^2 of 94% for the linear regression model.

$$\log d_m = \alpha + \beta \left(\sum_{t=m-3}^{m} r_t \right) + \epsilon_m \tag{2}$$

To map how river flow (d_m) affects monthly potential energy generation (p_m), I follow the formula described in Stickler et al. (2013), given in Expression 3. This expression is not estimated since the elasticity of river flow on potential energy generation is known.

$$\log p_m = \log d_m + \psi_m \tag{3}$$

Once the β parameter is recovered from Expression 2, I can compute the effect of rainfall changes on potential energy generation in a reduced form Expression 4

$$\frac{\Delta p_m}{p_m} = \beta \Delta \left(\sum_{t=m-3}^{m} r_t \right) \tag{4}$$

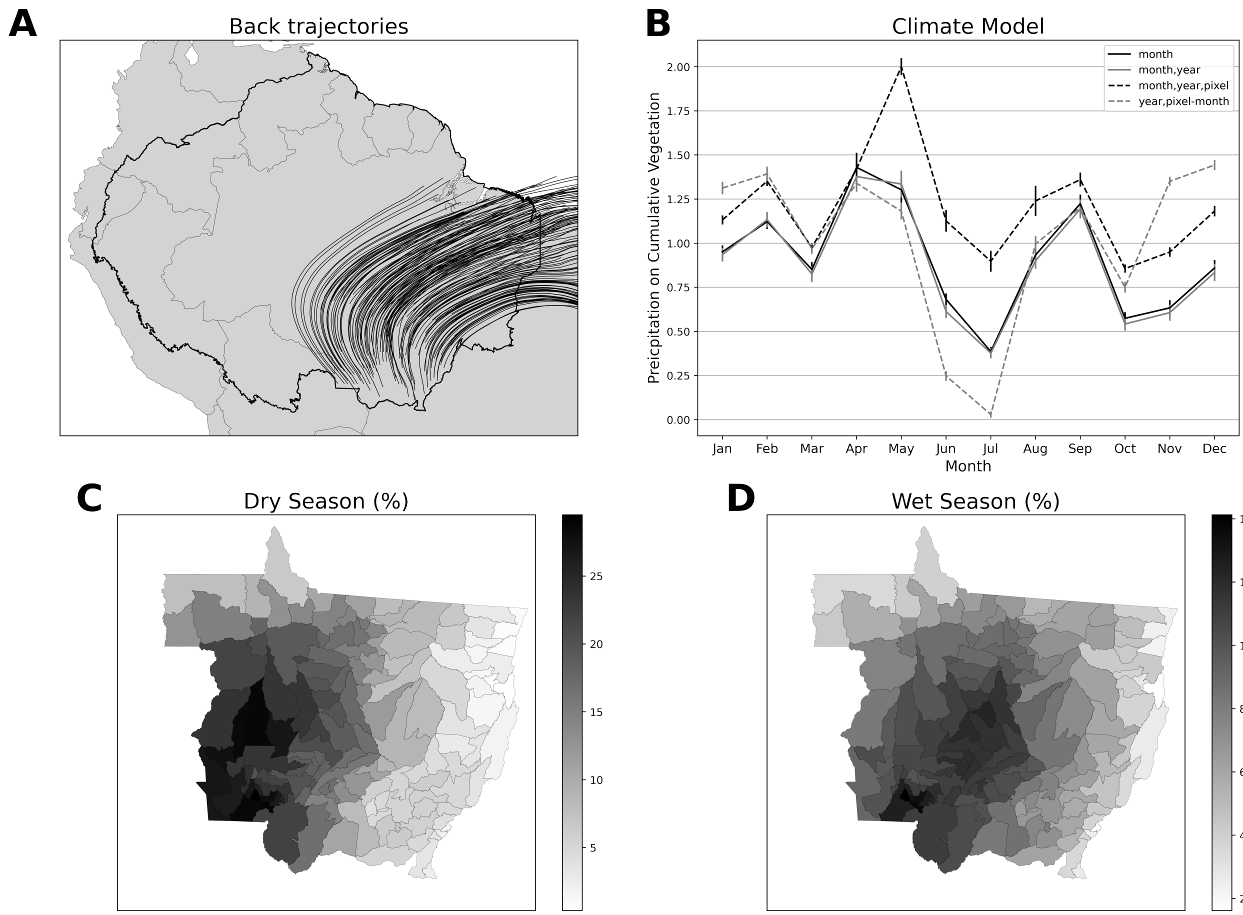

Figure 2: (A) the black lines show a sample of the atmospheric back trajectories for February 2015. (B) shows the result of estimating Expression 1 for different sets of Fixed Effects. This regression captures the effect that upwind exposure to the forest has on downwind rainfall. The values of this graph is shown in Table 1 in the Appendix. (C) and (D) shows the decrease in rainfall as the result of Amazon deforestation for the dry season and wet season, respectively, measured as a proportion of the historical average.

4 Teles Pires: Deforestation and Energy Capacity

To compute the impact that the Amazon deforestation has on the energy capacity of the HP, I combine in Expression 4 the difference between observed and counterfactual rainfall, computed in Section 2, with the estimated parameter β of Table 2. I generate a difference between observed and counterfactual rainfall for each month of year since 1985 up to 2020. The idea is that all the atmospheric trajectories of the last four decades offer a good approximation of the support of the distribution of possible atmospheric trajectories. Then, for each month and year I compute $\frac{\Delta p_m}{p_m}$, the percentage change in energy capacity, as described by Expression 4. Figure 3C shows the result of this exercise. The gray lines show the loss in potential capacity for each year of atmospheric trajectory and the black line shows the average across the years. The average effect across years indicates a loss of capacity between 10% and 2.5% due to the Amazon deforestation. The average effect, nonetheless, is far from the extreme scenarios in which the effect can be as large as 17.5%.

5 The Value of the Forest for Teles Pires

What is the value of the forest for the operator of Teles Pires? To answer this question I use a partial equilibrium analysis where the average loss of energy capacity is multiplied by a monthly average of the price of energy from 2015 to 2020 (CCEE, 2022)[2]. To do this I multiply the estimated effects of Figure 3C (the gray lines) by the monthly potential energy generation and take the average[3]. The resulted expected loss is of USD 21 million per year, which can be seen as the HP's willingness to pay for conservation policies. This calculated loss, which is essentially price times quantity, is suitable for my application because the marginal cost of the HP operation is negligible and Teles Pires is a price taker, since Teles Pires HP accounts for a little more than 1% of the installed capacity in Brazil. Nonetheless, a counterfactual scenario without deforestation could impact other HPs and other sectors, changing the overall demand and supply of energy in Brazil. That would require a general equilibrium model which is not the goal of this paper.

Given an expected loss of USD 21 million per year and a total accumulated deforestation of 690,000 km^2 between 1985 and 2020, one could compute that the present value of the forest for Teles Pires would be of USD 612 per km^2[4]. Nonetheless, this computation does not consider that only some parts of the forest affects Teles Pires via the atmospheric transport mechanism.

To distribute the willingness to pay for conservation only among those pixels that affect Teles Pires I map which pixels in the Amazon has been visited (or flown over) by a trajectory arriving at Teles Pires. These are the colored pixels in Figure 3D. This Amazon area that influences rainfall in Teles Pires has 177,500 km^2 of deforestation and thus the present value of the forest for Teles Pires would be of USD 2,382 per km^2, if the willingness to pay were to be evenly distributed.

[2]For this exercise I use the Price for Settlement of Differences (PLD)

[3]When the flow of the river is already at the plant's full capacity, the benefit of more rainfall is zero. For Teles Pires, I take full capacity to be achieved with a river flow of 4,778 m^3/s, the maximum monthly average river flow. I then cap the value of rainfall to the maximum that Expression 2 predicts a flow of 4,778. The monthly potential generation is computed as the maximum energy capacity times the proportion of average monthly river flow to maximum capacity.

[4]Using a discount rate of 0.05: (USD 21 million/ km^2 690,000)/0.05

It is possible to further refine this distribution with two additional steps. First, I map how many times the visited pixels have been visited, which measures how much exposure Teles Pires has to each upwind pixel. Second, I divide the willingness to pay in proportion to how many times each deforested pixel is visited. The result is shown in Figure 3D. In this last step, the mean forest value is of USD 2,037 per km^2. With 10% of them getting more than USD 4,100 and 5% of them more than USD 6,000. The average land price in the Northeast of the Brazilian Amazon is USD 100,500 km^2 (Markit, 2021), that is, the externality cost of only one HP could buy off 2% of the private benefits of deforestation.

6 Conclusion

In this paper, I developed an approach to estimate the value for HPs of the ecological service provided by tropical forests of maintaining rainfall regimes. I presented an econometric climate model that connects a deforestation scenario with changes in rainfall. I then coupled these results with models of how rainfall affects river flow and of how river flow affects potential energy generation. With these results I can estimate the loss that a HP's operator faces in potential energy generation due to deforestation. Finally, I showed how it is possible to use the climate model to determine which specific locations in the forest the HP is more exposed to and therefore which specific locations the forest has a higher value for the HP's operator.

As an application, I studied the effect of the Amazon deforestation on the energy capacity of the Teles Pires HP, one of the biggest in Brazil. I first showed that, in the State of Mato Grosso, where Teles Pires is located, Amazon deforestation has had an average effect of decreasing rainfall by 13% in the dry season and 8% in the wet season. This effect amounts to an average decrease in potential energy generation of 10% in some months with extreme scenarios of 17%, or USD 21 million per year, which can be seen as a willingness to pay for conservation policies. Distributing this value proportionally among the locations in the Amazon that Teles Pires is most exposed to renders an average present value for the forest of USD 2,037 per km^2.

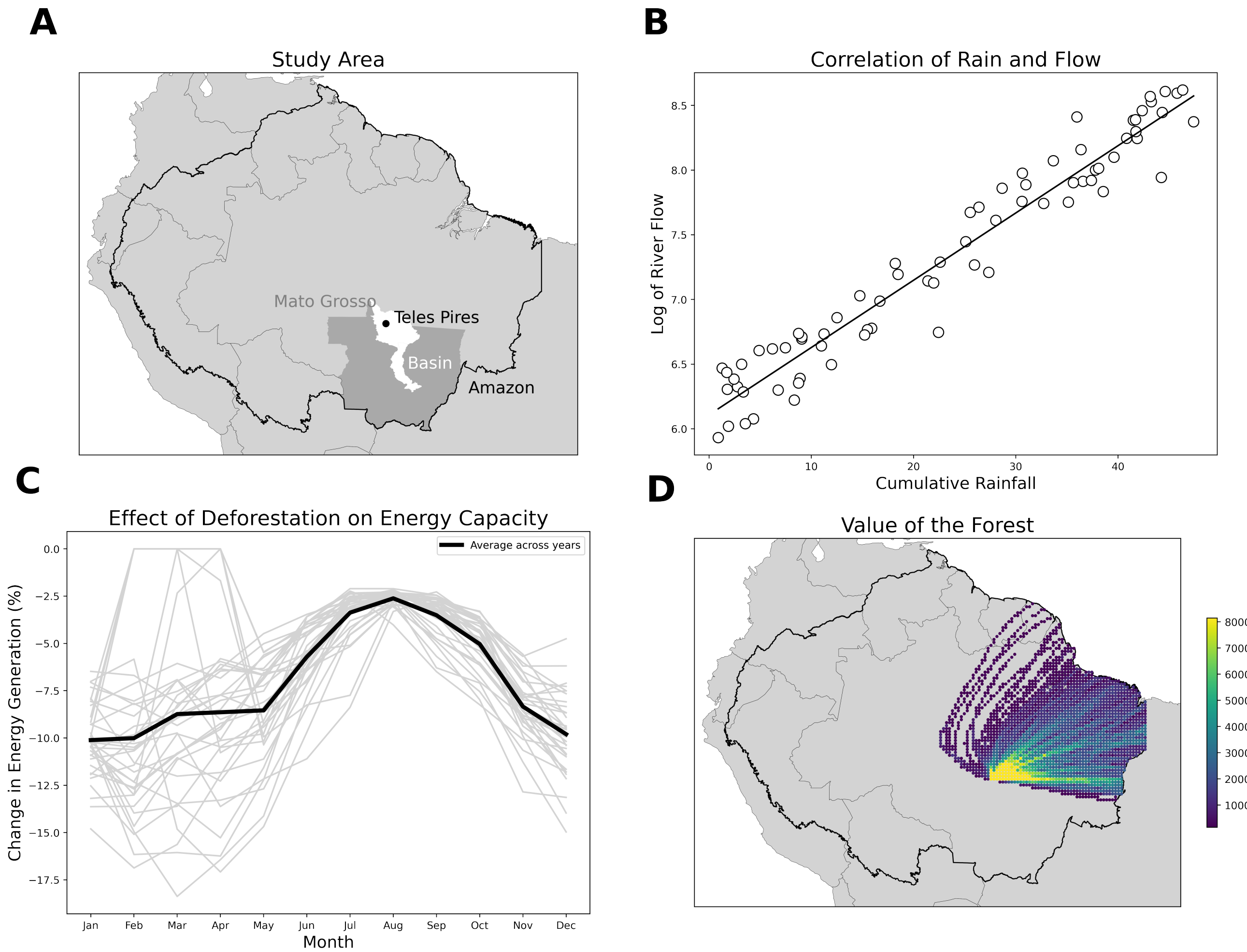

Figure 3: (A) shows the location of the Mato Grosso State, the Teles Pires hydropower plant, the Teles Pires river basin, and the Amazon Rainforest. (B) shows the correlation between the four months cumulative rainfall and the log of the river flow. (C) shows the effect of Amazon deforestation on the energy capacity of Teles Pires. Each gray line corresponds to the counterfactual energy capacity using atmospheric trajectories of a different year from 1985 to 2020. The black line shows the average effect of the gray lines. A zero effect occurs when the observed river flow already gives the plant full operation capacity. (D) shows the value of the forest as described in Section 5, measured in USD as the present value of 1 km^2 of forest.

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7 Appendix

Month	(0)	(1)	(2)	(3)
Jan	0.950***	0.934***	1.131***	1.312***
	(0.018)	(0.019)	(0.013)	(0.018)
Feb	1.122***	1.133***	1.351***	1.392***
	(0.021)	(0.022)	(0.013)	(0.020)
Mar	0.850***	0.825***	0.975***	0.968***
	(0.021)	(0.023)	(0.012)	(0.015)
Apr	1.429***	1.377***	1.421***	1.339***
	(0.042)	(0.044)	(0.023)	(0.018)
May	1.302***	1.335***	2.000***	1.181***
	(0.037)	(0.038)	(0.024)	(0.023)
Jun	0.681***	0.612***	1.126***	0.247***
	(0.017)	(0.018)	(0.031)	(0.014)
Jul	0.385***	0.376***	0.897***	0.028***
	(0.013)	(0.015)	(0.030)	(0.009)
Aug	0.933***	0.901***	1.239***	0.995***
	(0.022)	(0.023)	(0.043)	(0.022)
Sep	1.223***	1.193***	1.360***	1.201***
	(0.025)	(0.027)	(0.020)	(0.018)
Oct	0.574***	0.542***	0.855***	0.750***
	(0.018)	(0.019)	(0.011)	(0.016)
Nov	0.633***	0.606***	0.949***	1.350***
	(0.022)	(0.023)	(0.013)	(0.013)
Dec	0.859***	0.833***	1.181***	1.442***
	(0.023)	(0.025)	(0.015)	(0.014)
N.obs	516,240	516,240	516,240	516,240
Month FE	Yes	Yes	Yes	No
Year FE	No	Yes	Yes	Yes
Pixel FE	No	No	Yes	No
Pixel-Month FE	No	No	No	Yes
Distance	Yes	Yes	Yes	Yes
R^2	0.82	0.83	0.86	0.88
R^2 (within)	0.21	0.21	0.26	0.17
R^2 (between)	-0.42	0.32	-0.30	0.47

Table 1: This table shows the estimates of Expression 1, a regression of monthly rainfall on the upwind exposure to the forest. Each column presents a different specification with a different set of Fixed Effects. Every specification includes total distance of the back trajectory on land as a control. Number of observations: 516,240. *** means p-value < 0.01.

Parameter	(1)	(2)
β	0.052***	0.049***
	(0.002)	(0.007)
α	6.109***	6.196***
	(0.042)	(0.154)
Month FE	No	Yes
N.obs	72	72
R^2	0.94	0.48

Table 2: This table shows the estimates for Expression 2, the regression of the log of the monthly river flow on the 4 months cumulative rainfall. The effect of rainfall on river flow is captured by the parameter β. In column (2), I add a month Fixed Effect. Number of observations: 72. *** means p-value < 0.01.

Data	Description	Source
Wind speed and direction	Three dimensional (latitude, longitude, pressure) monthly data on wind speed and direction from 1985 to 2020 for the entire South America continent at the resolution of 0.25°	Copernicus (2017)
Rainfall	Monthly data on precipitation from 1985 to 2020 for the entire South America continent at the resolution of 0.25°	Copernicus (2017)
Land use	Yearly data on land use for the entire Amazon Rainforest. Original resolution is of approximately 30 meters. It is then filtered (taking the average) to match the wind data resolution	Mapbiomas (2022)
River flow	Monthly data on river flow from 2015 to 2020 for the Teles Pires HP	ONS (2022)
Energy price	Monthly average of the price of energy – Price for Settlement of Differences (PLD) – from 2015 to 2020	CCEE (2022)

Table 3: This table describes the data used in the paper and their sources.

Month	Rainfall (mm)	River flow (m^3/s)	Energy price (USD/MW.h)
Jan	9.37	2669.33	36.21
	(2.53)	(436.33)	(21.87)
Feb	9.43	3796.5	38.97
	(2.67)	(977.54)	(27.79)
Mar	7.97	4778.5	33.96
	(2.25)	(807.73)	(19.39)
Apr	4.74	4282.17	32.68
	(2.04)	(804.28)	(25.36)
May	1.63	2505.0	40.86
	(1.19)	(695.16)	(26.32)
Jun	0.34	1360.0	35.81
	(0.51)	(290.74)	(30.04)
Jul	0.2	850.83	41.4
	(0.36)	(179.42)	(28.76)
Aug	0.46	604.33	48.14
	(0.73)	(105.37)	(35.33)
Sep	1.96	503.83	50.76
	(1.52)	(97.47)	(31.62)
Oct	4.8	661.33	54.04
	(1.69)	(155.11)	(22.29)
Nov	7.13	989.0	53.7
	(2.05)	(290.78)	(30.67)
Dec	8.85	1893.0	32.48
	(2.42)	(846.45)	(16.13)

Table 4: This table shows descriptive statistics (mean and standard deviation) of the data used in the paper by month.