# Illuminating trade-offs: the socio-economic impacts of dam construction in the Global South

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Lucy Goodman


## ABSTRACT

Governments adapting to and mitigating climate change face trade-offs between the local impacts of infrastructure designed to address it and national action plans. Reservoir dams are one example of such infrastructure, having profound social and environmental impacts. The literature is inconsistent on the socio-economic impacts of dams and opinions vary widely. Thus, this study investigates the local socio-economic impact of large dam construction on surrounding areas in the Global South. It uses annual night time lights at a 1 km resolution, which correlates to GDP, to understand changes in socio-economic activity. It compares areas where dams have been built before and after construction to areas where dams will be built. The sample of 145 dam sites is drawn from reservoir dams constructed between 2005 and 2009, compared to control sites that were constructed from 2013 onwards. Results show that dams decrease socio-economic activity 15 km around the dam site, an effect that can be observed up to 50 km from the dam and that persists for at least three years. The effect decreases with distance and increases over time, patterns suggest that migration and inundation are drivers. Results show that dams fundamentally shift socio-economic dynamics, which should be considered when evaluating their trade-offs.

# 1. Introduction

The Anthropocene era requires urgent action for climate change adaptation and mitigation (Arsel, 2022; Biermann et al., 2012; Robbins & Moore, 2013). Energy, water, and food consumption continue to increase globally, posing significant environmental challenges (IPCC, 2023). Mitigating climate change will require further investment in infrastructure for adapting to and mitigating the impacts of climate change on water, energy, and food (Granoff et al., 2016; Shi et al., 2019). This infrastructure has and will involve significant trade-offs socially and environmentally (Howe et al., 2014) between food and power, free-flowing rivers and food security (Legese et al., 2018).

Reservoir dams were first built for irrigation and flood control, then energy and since the 20th Century, more ambiguously, for development (Biswas, 2012). In recent years they are increasingly developed as infrastructure to address climate change and have been experiencing a renaissance (Moran et al., 2018). One body of literature, particularly from political ecologists, critiques the power asymmetries between developers and impacted communities and the differentiated environmental and social impacts of dams (Huber et al., 2017; Jiménez-Inchima et al., 2021; Lavers & Dye, 2019; Nüsser, 2003). A second body of literature observes that large dams are the "best available option" to meet "water, food, and energy demands" (Shi et al., 2019). Reservoir dams are presented as the lesser of two evils compared to the pollution involved in battery manufacture for energy storage (Tahseen & Karney, 2016). Chen et al. (2016) argue that dams are vital for development, while Biswas (2004) suggests that there is no single solution for development but instead that reservoir dams should be considered as one possible option. However, both sides agree that dams may profoundly impact the environment and people (McCully, 2001; Petsch, 2016; L. Poff & Hart, 2002; N. L. Poff et al., 2007; T. Scudder, 2012). The debate remains whether hydropower is "worth it" (Mayer et al., 2021), with clear stances on both sides but significant nuance in understanding the varied opinions (Ansar et al., 2014; Baghel & Nüsser, 2010; Biswas & Tortajada, 2012; J. Chen et al., 2016; Schulz & Adams, 2019; T. T. Scudder, 2010; Tortajada, 2015; World Commission on Dams, 2000).

One area where there are divergent views is the socio-economic impacts of dams on project-affected people around the dam site (Ansar et al., 2014; Bhatia & Malik, 2007; Ghimire

& Kim, 2018; Tortajada, 2015). Literature which considers socio-economic impacts at the local scale is often based on an analysis of one or a small number of case studies (Fan et al., 2022; X. Zhao et al., 2020). In contrast, comparison studies of dams within or between countries are carried out at the national or regional scales (J. Chen et al., 2016; Sovacool and Walter, 2018).

This study describes the local socio-economic impact of large dam construction on the surrounding area in the Global South. It exploits the natural variation in timing when reservoir dams have been built, to compare the socio-economic activity around where dams have been built to the socio-economic activity in areas where dams will be built. It uses satellite imagery – Night Time Light (NTL) – to understand changes in socio-economic activities. NTL enables comparisons to be made across different countries and within countries without being dependent on economic assessments of different cadences and methodologies. The sample of 145 dam sites is drawn from the Global Reservoir and Dam (GRanD) database (Beames et al., 2019) in the Global South for dams constructed between 2005 and 2009 (treated sites) and those that will be constructed after 2013 (control sites).

This study contributes to previous literature in various ways. First, it describes a trend in socio-economic activity between 2004 and 2009 within 15 km of dam sites in the Global South. This is the first inter-country comparison on this topic made at a local scale in this timeframe. Second, it investigates the time and distance over which the effect attenuates, which adds robustness to the study. Finally, it makes a methodological contribution by addressing some critiques on using NTL as a panel dataset in economics. Locally impacted people's opinions are linked to the impacts they experience (Mayer et al., 2021; Wiejaczka et al., 2018); therefore, this study articulates the trade-offs around reservoir dams for better governance, making a policy contribution.

Results reveal that large dams decrease NTL activity in the dam site immediately after construction and, therefore, socio-economic activity. The impact attenuates over three years and with distance from the dam. The result contrasts with de Faria et al. (2017) in their study of Brazilian counties hosting large hydropower plants; they found ephemeral but positive impacts for 15 years or less. It is comparable to the notable Duflo and Pande (2007) study in India, which showed rural poverty increased in the districts that hosted dams but decreased in downstream districts.

## Theory

The landmark World Commission on Dams (2000) report - a multi-stakeholder report on large dams - said: "Poor accounting in economic terms for the social and environmental costs and benefits of large dams implies that the true economic efficiency and profitability of these schemes remains largely unknown." Despite twenty further years of research, the debate is still intense on this topic and "emotional" (Biswas, 2004), and ideological (Lavers & Dye, 2019). Ansar et al. (2014) asked, "Should we build more large dams?" in their study on 245 dams. They found dams are not economic due to cost overruns, even when not considering the social and environmental costs, drawing on project documentation. Another study by Chen et al. (J. Chen et al., 2016) published a year later asked, "Should the construction of large dams continue?" and used the correlation between over 32,000 dams (built between 1960 and 2010) and national-scale data on energy, water and food consumption to state that there was a "close association…between dams and socio-economic development". Contributing to the debate on reservoir dam's effectiveness is evidence that they may worsen water shortages (Di Baldassarre et al., 2018) and have not delivered on their irrigation objectives (Higginbottom et al., 2021).

Many individual papers focus on the local socio-economic impacts of large dams at the case study level, while some meta-analysis studies examine these case studies as a collective body of literature (Biswas, 2004; World Commission on Dams, 2000). However, there are limited studies (Castro-Diaz et al., 2022; de Faria et al., 2017; Duflo and Pande, 2007; Fan et al., 2022) that look at multiple dams at a local scale using the same metric of socio-economic performance as measures of socio-economic performance are not standardised globally (Fan et al., 2022).

Here I outline the literature on how large dams might create local socio-economic impacts in general, with reference to case studies, meta-analysis and cross-site analysis.

The first consideration is forced or voluntary migration when an area is inundated (Cernea, 2004b; Kirchherr & Charles, 2016; T. Scudder, 2012). An oft-quoted figure from the World Commission on Dams (2000) is that dams have displaced 40-80 million people worldwide. Although displacement numbers are intensely political (Kirchherr et al., 2019) – and variable – for India alone, estimates range from 16-39 million people (World Commission on Dams, 2000) – it is clear that displacement is a major consequence of reservoir dams.

Inundation when a reservoir is filled will cause displacement, but out-migration from the area will not be limited to those whose homes are flooded (Iyer, 2007, p. 165). Push factors include environmental issues, such as a reduction in biodiversity from the destruction of fish habitats, changing river hydrology and sediment regimes (Hall et al., 2011; N. L. Poff et al., 2007; Soukhaphon et al., 2021), and new diseases from the reservoir (Hunter, 2003; Jobin, 1999). A loss of natural wealth can severely impact the economy (P. Dasgupta, 2021, p. 84). Further, the uncertain investment conditions surrounding dam construction and the potential inundation of other infrastructure and services may bring a "planning blight" (World Commission on Dams, 2000, p. 99). This phenomenon can cause people to be hesitant about investing in an area if it may ultimately be flooded and may be especially acute if the construction is delayed (Braeckman & Guthrie, 2016).

While many studies report negative socio-economic impacts at a local scale, there are also evidence and theories that impacts are positive or differentiated dependent on context. Fan et al. (2022) demonstrate a correspondence between dam construction and economic and environmental change, employing NTLs, GDP measures (Kummu et al., 2018) and land cover change satellite imagery. In their site-level study on 631 dams from 2001 to 2015, examining the correlation between dams and their impacts on population, economy, and the environment they found broadly negative impacts in the Global South, including on the environment, but broadly positive relationships between the economy and population in the Global North.

De Faria et al. (2016) use an event-study to investigate whether GDP within Brazil's counties is related to the construction of 56 hydropower plants in those counties. The authors also use an econometric approach to evaluate the post-construction outcomes on socio-economic conditions such as income and education. They find ephemeral but positive socio-economic impacts in counties with dams for 15 years or less.

With new infrastructure, such as dams, comes further infrastructure for construction and maintenance. New access roads and services may surround the new dam; thus, one expectation is that these additional services may increase socio-economic activity (Bhatia & Malik, 2007; Hartmann, 2015).

New employment opportunities, especially during construction, bring thousands of new jobs (Reddy, 2016; World Commission on Dams, 2000, p. 99) and increase local GDP

(Bhatia & Malik, 2007; Cai et al., 2011). Renewable energy installations have been shown to create almost three times as many short to medium-term employment opportunities as conventional fossil fuel ones (Garrett-Peltier, 2017). Reservoir tourism may increase the number of visitors to an otherwise remote area (Naithani & Saha, 2018).

The famous Duflo and Pande (2007) paper showed that agricultural production increased downstream of dams in India, alongside decreased rural poverty. Therefore, one might expect agricultural production and economic activity to increase. However, there are opposing views on this in the literature, through a comparison of project documents and satellite imagery in sub-Saharan Africa, Higginbottom (2021) found that actual irrigation services from dams were only 16% of expectations. The Duflo and Pande (2007) paper also showed an increase in rural poverty in the district that hosted the dam, suggesting that proximity is important to realise whether affected stakeholders are "stake-gainers" or "stake-losers" (Iyer, 2007).

In summary, there are several mechanisms by which socio-economic outcomes will be shaped by large dam construction. These mechanisms pull in different directions and have long been contested (World Commission on Dams, 2000, p. 99). Castro-Diaz et al. (2022), who investigate trade-offs between different sorts of capital (natural, physical and social) in their analysis, argue that no one pathway shapes social outcomes in dams. It is, therefore, unclear what the impact might be at a local scale of large dams in general, contributing to the contested debate. However, the literature does suggest that duration since construction and distance from construction are significant factors influencing socio-economic experiences.

# 2. Data And Methods

What is the local economic impact of large dam construction on the surrounding area? To address this question, I employ the Differences in Differences (DiD) approach. As a response variable, I use Night Time Lights between 2004 and 2009, combined with dam locations and construction dates, to generate treatment and control sites. This section will outline my data sources, provide a rationale for my method choice, and detail my empirical model.

## 2.1 Socio-economic data

This study uses the Night Time Lights (NTL) from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) satellite imagery to understand socio-economic activity (C. D. Elvidge et al., 2012; Huang et al., 2014). Multiple authors have connected NTLs to socio-economic activity (Doll et al., 2000; Gibson et al., 2020; Henderson et al., 2012; Michalopoulos & Papaioannou, 2017). NTLs have been used as a substitute for GDP when there are temporal or spatial gaps (Kocornik-Mina et al., 2020), correlated with traditional measures of socio-economic development at a country scale (Proville et al., 2017) and in India at the district scale (Singhal et al., 2020). The dataset is also valuable for investigating electrification (Bargain et al., 2023), well-being (Ghosh et al., 2013) and poverty (C. Elvidge et al., 2009; Smith & Wills, 2018). Previous scholars (Sigman & Olmstead, 2015) have measured the socio-economic impact of drought using NTL and how impacts are and are not mitigated by proximity to dams.

The DMSP NTL data is derived from six non-consecutive satellites available between 1992 and 2013 (see Figure 4 in Appendix 6.2). Images have been pre-processed into annual cloud-free composites with a 30 arc-second resolution (930 $m^2$ at the equator) downscaled from an onboard sensor spatial resolution of 2.7 km x 2.7 km at the nadir[1] (Gibson et al., 2020). NTL DMSP was originally used and analysed for meteorological purposes and requires further processing for use as socio-economic data. First, the phenomenon of overglow - where NTL from one pixel may spread into an adjacent pixel – should be addressed, especially when working at fine scale (Gibson et al., 2020). I applied the Abrahams et al. (2018) approach to deblur the data to address this issue (details are in Appendix **Error! Reference source not found.**). Second, there is an issue with using data as a time-series, as data between satellites do not have standardised light measures, such as lumens (Hsu et al., 2015; Wu et al., 2013). I chose to use one satellite of the available six – F16 – (see Appendix 6.9) rather than calibrating between satellites, as the deblurring step rendered the calibration method available in the literature inappropriate. This restricted the time period of my investigation to 2004-2009.

The dataset is geographically and temporarily available for the entire area under investigation – the Global South – at the local scale. This made it preferable to national scale

[1] the area directly below the satellite position when it captures the image.

measures such as those available form the World Bank, often employed in socio-economic development investigations (Azevedo, 2020). By using NTL, I believe I make a first inter-country fine-scale analysis of the relative impact of dams on local socio-economic activity within this timescale. Descriptive statistics of the NTL dataset by dam location and construction dates are in Table 2, and by calendar year in Table 13 in Appendix 6.1.

## 2.2 Dam locations and construction dates

For dam geolocations and construction dates, I use the Global Reservoir and Dam Database (GRanD 1.3) (Lehner et al., 2011). The dataset has metadata on data quality, reservoir size, dam height, construction date, and spatial polygons representing reservoir boundaries (Beames et al., 2019). Only dams with over 0.1 cubic kilometre reservoir storage capacity are included, meaning large run-of-river schemes are excluded from this study. The social, environmental, and economic dynamics of large dams have been shown to differ from those of smaller infrastructure (Vedachalam and Riha, 2014; Harlan, Xu and He, 2020). Large dams dominate in terms of the services dams provide. In India, 1% of large dams provide 63% of effective water storage (National Register of Large Dams, 2018 quoted in Palmer-Jones, 2021).

GranD 1.3 provides a quality index for all the dam sites. I excluded "fair," "poor," or "unreliable" records. Only "good" or "verified" records were included, indicating that the location and data were deemed reliable or better (Beames et al., 2019). While this resulted in a smaller working sample, it ensured confidence in the location of the dams and reservoir area size, which is critical to the analysis. The study follows a similar approach to Fan et al. (2022), but those authors used the WRI Global Database of Power Plants, which did not have the necessary metadata for this study (Byers et al., 2021).

A country comparison is in Table 10; China dominates the sample, with 62 of the 145 dam sites. Table 8 and 9 (Appendix 6.1) give characteristics of the treated and untreated groups. Numeric time-invariant characteristics, reservoir size and dam height will be used to adjust for pre-treatment and treatment group outcomes. Summary statistics of lit cells within 15 km of the dam site for both treatment and control groups are provided in Table 2.

My identification strategy (Table 1) exploits the different years in which large dams are constructed. I use dam sites that have yet to be constructed during the investigation period but will be constructed from 2013 up to 2017 as controls. I use dam sites constructed between 2005 and 2009 as treatment sites, corresponding to the available NTL time-period. I exclude dam sites constructed in 2004, even though they overlap with the time period, as I cannot observe their untreated state.

**Table 1. Identification strategy based on dam site construction years, NTL – Night Time Lights – will be used to assess socio-economic impacts.**

| Construction year | Number of potential dam sites | Consideration in model set-up | Justification |
|---|---|---|---|
| 2004 | 13 | Excluded | Untreated status unobserved |
| 2005-2009 | 102 | Treated | Constructed when NTL available |
| 2010-2012 | 58 | Excluded | Excluded in case there is an unobserved anticipation effect of construction. |
| 2013-2017 | 43 | Never-treated controls | Sites where dams have been constructed, therefore location is known. |

**Table 2. Descriptive statistics of NTL response variable - natural log of the number of lit cells within a 15 km radius of a dam by dam site construction year. Construction year is the identification strategy of the empirical approach used.**

| Construction year | Never-treated | | | Post-treated | | | Pre-treatment | | |
|---|---|---|---|---|---|---|---|---|---|
| | mean (SD) | min | max | mean (SD) | min | max | mean (SD) | min | max |
| 0[i] | 2.13 (1.56) | - | 5.48 | | | | | | |
| 2005 | | | | 2.76 (1.25) | 0 | 5.44 | 3.02 (0.89) | 2.20 | 5.44 |
| 2006 | | | | 2.13 (1.39) | 0 | 5.08 | 2.62 (1.00) | 0.69 | 5.05 |
| 2007 | | | | 1.91 (1.15) | 0 | 3.81 | 2.01 (1.04) | - | 3.89 |
| 2008 | | | | 1.59 (1.30) | 0 | 4.62 | 1.59 (1.23) | - | 4.60 |
| 2009 | | | | 2.70 (1.47) | 0 | 4.82 | 2.65 (1.22) | - | 4.89 |

[i] indicates construction year of 2013 – 2017, set to 0 for all never-treated groups.

To adopt a conservative approach, I have excluded dam sites from 2010 to 2012 as potential untreated sites. This is to mitigate the risk of potential anticipation effects that may have impacted the never treated group. As dams might attract change before construction, I allow three years before dam sites are constructed before they might be considered control sites. I expect sites constructed between 2005-2009 to be similar to those constructed in 2013-2017, which is the basis of this natural experiment and DiD setup.

## 2.3 Measuring economic activity around dams

To combine dam location with NTL data, I defined an area of interest around each dam site, informed by my pilot interviews with engineers and affected people in 2018 and 2019. The area of interest is a fifteen NTL pixel buffer (each pixel is approximately 1km at the equator) around the dam site. Following Papaioannou and Michalopoulos (2013), Smith and Wills (2018), Proville and Zavala-Araiza (2017) and Gibson (2019; 2017), I identify the number of "lit" pixels in my area of interest above a threshold[2] and use the sum of the lit pixels in my area of interest[3] as my response variable. A fuller discussion of how I derive the response variable is in Appendix 6.3.

## 2.4 Analytical strategy

To investigate if large dams in the Global South are linked to economic change, I use the quasi-experimental, natural experiment method Differences-in-Differences - DiD (Angrist & Pischke, 2008). The concept of DiD is straightforward. For a particular treatment or policy change, a group of treated units is compared to a group of similar non-treated units, a control group (Wing et al., 2018; Wooldridge, 2016, 2023). The treatment and control groups must have "parallel trends"; that is, the response variable for both groups should move in tandem without treatment (Callaway & Sant'Anna, 2018; Gipper et al., 2015; Strezhnev, 2017). The two groups must also have "common shocks"; shocks must impact both groups in time, impacting both groups in the same way (Ryan et al., 2015). If both of these assumptions hold, a difference in the difference between the treatment group's trend after treatment and the control group trend can be considered the treatment effect. This treatment effect is the change in trend between treated and control units over two or more time periods, before and after treatment and is known in the DiD literature as the Average Treatment effect on the Treated (ATT).

The attraction of the ATT is that if the confounding factors are the same between the treatment and control groups and change at the same rate over time, then the DiD approach

[2] The researcher needs to choose a threshold NTL intensity to determine which pixels are "lit". I choose 5 as my threshold. Prior to deblurring NTL intensity ranges from 0-63 "digital numbers", but processing deblurring increases the range from 0-239, as NTL from overglow is reassigned (stacked) from adjacent pixels to the pixels from which the light came see Abrahams et al. (2018) for a discussion.

[3] The response variable is transformed with a natural logarithm. Some sites have zero lit cells in a year. A constant of 1 is added to the whole dataset as the natural log of 0 is an undefined number, following Baskaran (2015).

will not produce biased results, even if these factors are not directly observed (Cowger et al., 2022). However, Ryan et al. (2015) note that not all specifications of DiD are equally robust, and careful model selection, which includes matching and clustered standard errors improves accuracy of estimates.

In my model, I exploit the different timing of dam construction to determine the control group –dam sites that have not yet been constructed in the period of interest – and treatment group – dam sites that have been constructed (Table 1). This means that my approach has multiple treatment timings and time-periods. Several authors have recently criticised using the canonical Two-Way Fixed Effects (TWFE) model for DiD, calculated using a regression estimator, when the model has multiple time-periods and treatment timings (Baker et al., 2021; Callaway & Sant'Anna, 2020; Goodman-Bacon, 2018; Sun & Abraham, 2020). Criticisms include that the TWFE model puts unjustified weight on the middle of the panel and that recently treated units are compared to treated units as controls - adversely impacting and even reversing measures of ATT (Cunningham, 2020). New estimators have been developed to address these critiques in a fast-moving literature (Cunningham, 2020; Dube et al., 2022; Wooldridge, 2023). I will follow Callaway and Sant'Anna's (2022; 2020) approach to DiD. While the estimator addresses recent critiques, it does sacrifice control units (Wooldridge, 2023) but for a more robust outcome.

The Callaway and Sant'Anna's approach identifies the "group-time average treatment effect", which is the average treatment effect for treated units that were treated in a specific time-period, called a group by the authors, within a time-period. In the context of my study, this would mean there would be a different group-time average treatment effect for a dam treated in 2005 in 2009 when compared to the group-time average treatment effect of a dam constructed in 2006 in 2009. Another way to consider this is to imagine units treated in each period as a cohort. The "group-time average treatment effect" is then the specific effect of the cohort in a time-period for that cohort's specific pathway. This allows investigation of heterogenous effects between years and treatment groups. Another attractive component of the Callaway and Sant'Anna's estimator (hereafter CS estimator) is its propensity score matching of controls to treated units based on independent time-invariant covariates (Callaway and Sant'Anna, 2021).

## 2.5 Empirical approach

To investigate dynamic effects of large dams on socioeconomic activity, I employ Callaway and Sant'Anna's (2021) event-study style estimates for each time period pre and post commissioning:

Equation 1

$$\theta_{es}(e) := \sum_{g \in G} 1\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e).$$

$G$ is the multiple treatment timings year the dam site is first treated (commissioned), $g$ is the year of treament for a cohort. $T$ is the time period and e is the number of years since the treatment event i.e. $e = g - t$. $\theta_{es}(e)$ is the parameter of interest, describing the average effect of being treated after $e$ numbers of time periods (years in this study), across all groups $g$ that were treated for this number of time periods. $\theta_{es}(e)$ sums the $ATT$ of groups exposed to the treatment at event time e, weighted by the probability $P$ that the $ATT$ belongs to that group, for each group $g$. The assumption, as for other event studies, is that the term $ATT(g, g + e)$ is homogenous for all groups across all numbers of treatment years post-treatment.

Building the estimator with Callaway and Sant'Anna's approach requires the calculation of the group-time average treatment effect building block (Equation 2). This has two features 1) it only makes comparisons between never-treated units and treated units[4], 2) it uses propensity score matching to improve comparisons between treatment and controls.

Equation 2

$$ATT(g, t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1 - \hat{p}(X)}}{E[\frac{\hat{p}(X)C}{1 - \hat{p}(X)}]}\right)(Y_t - Y_{g-1})\right]$$

Equation 2 calculates the semiparametric CS estimand via the weighted average of the outcomes (Caetano & Callaway, 2023, p. 8; Callaway & Sant'Anna, 2018, p. 3; Le, 2022, p. 12; Zeldow et al., 2023, p. 22). Where t is time period of treatment, in my case the year, and $g$ is the time the unit is first treated i.e., when the dam is commissioned – see Table 1. $G_g$ is 0 or 1, and equal to 1 if cohort g is first treated in time $G$. $C$ is also 0 or 1, and defines the comparison groups or control groups which equal 1 if never treated. $\hat{p}(X)$ gives the propensity score

[4] This can be relaxed in the R package, with yet-to-be-treated units used as the control group. However, I used the never-treated group in my primary specification.

matching based on co-variates[5]. Specifications for aggregating the group-time treatment effect into meaningful estimates of overall impact and underlying assumptions are in Appendix 6.7. This approach has four assumptions. First, units may not be treated in the first time-period. In my setting, this means I exclude dams constructed in 2004 – they have no available untreated comparison (see also Table 1). Second, the anticipation of treatment is not allowed. Anticipation would result in invalid comparisons between the control and treatment groups, as controls would not be unaffected by the upcoming treatment[6]. Third, once instigated, treatment cannot be reversed. I should exclude any dams which are decommissioned having been commissioned in the time period of investigation. Fourth, the parallel trends assumption needs to hold, conditioning on covariates.

For further equations detailing the doubly robust[7] estimator, parallel trends assumptions and aggregation equations for the group-time average treatment effect, see Appendix 6.7. These steps are all automated in the CS DiD R package (Callaway & Sant'Anna, 2022).

# 3. Results

## 3.1 Socio-economic activity appears to decrease after dam construction for three years

I present a first attempt to examine the local socio-economic impacts of dams in the Global South, at a 15 km radius around the dam, using a Night Time Light dataset as a proxy for socio-economic activity between 2004 and 2009. I find that large dams decrease the number of lit pixels near the dam site immediately after construction and thus socio-economic activity. This impact persists for 3 years. This result is shown visually in the event-study in Figure 1.

[5] $\hat{p}(X) = Pr(Gg = 1|X, Gc + C = 1)$

[6] The DiD package allows for relaxing this assumption at the cost of some replicates, I do this as a robustness check.

[7] Callaway and Sant'Anna (2020) allow for three potential specifications of their model, outcome regression modelling (Heckman et al., 1997), inverse probability weighting (Abadie, 2005) and their own doubly robust method which combines these. I choose to use the doubly robust method, as it is consistent even with a degree of misspecification.

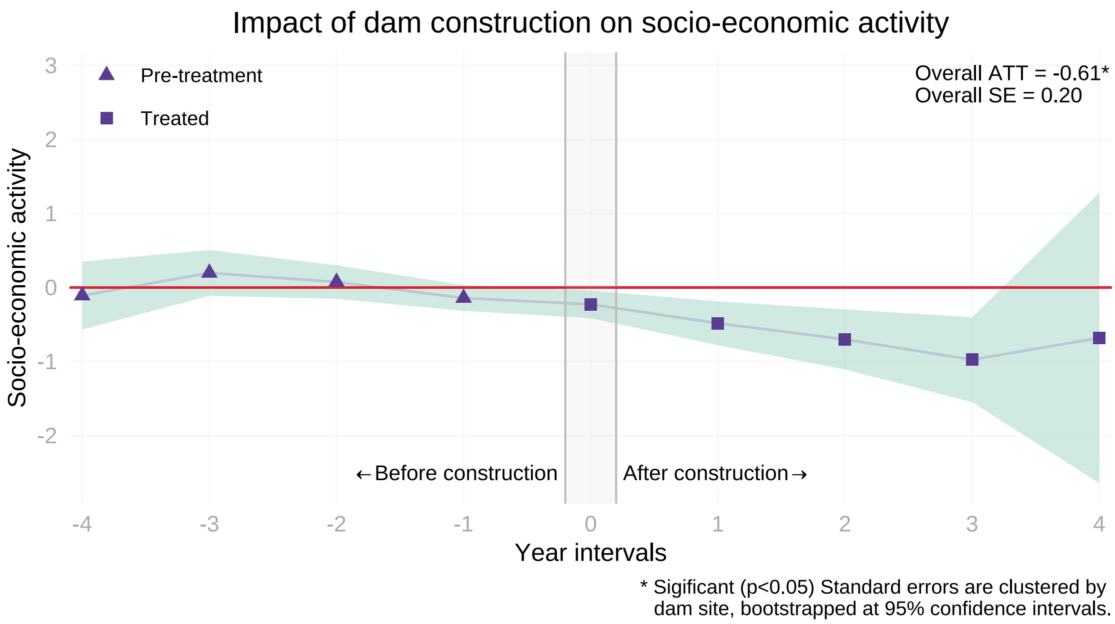



**Figure 1. Event study estimates of ATT – average treatment effects on the treated - following the Callaway and Sant'Anna (2020) approach. The outcome variable is the ln number of lit pixels in annual night time light images in a 15 km buffer around a dam site, 145 dam sites were investigated in the Global South. Results show a decrease in night lights around the dam sites post-treatment. Pre-treatment group corresponds to dam sites that have not yet been constructed, but will be constructed after 2013. Pre-treatment, there is no significant deviation from zero, evidence that the assumption of pre-treatment and treatment parallel trends being met, a condition of determining the ATT. Standard errors are clustered by dam site, bootstrapped at 95% confidence intervals. Control and treatment groups are matched on covariates, latitude, reservoir size and dam height**.

## 3.2 The extent of the decrease in socio-economic activity after dam construction varies depending on the year of construction

The group-time treatment effects, aggregated by year of construction, are presented in Table 3, as is the overall ATT -0.44 ($p < 0.05$), which can be considered the main result of this study. The ATT represents a decrease in lit pixels in a 15 km buffer around the dam site after construction, a portion of which is likely to be due to inundation, investigated in the next section.

There are two important aspects to note about the effect size. First, there is a great deal of heterogeneity between years investigated and years of construction (visible in Figure 10 in Appendix 6.8), and the event study also shows a temporal variability which is significant. Together they suggest that time variant context and time since construction are important in shaping the socio-economic outcome of the dam. Second, while the effect size is negative, Gibson et al. (2020, p. 962) caution that the absolute values in digital numbers vary between years and locations and cannot be considered as consistent measures of the same light and economic effect. A portion heterogeneity in each calendar year could result from this inconsistency between digital number measures, but can not be estimated due to unrecorded measures on-board the satellite[8]. This error is expected to be consistent between dam sites and treatment groups, but highlights the limitations of using the response variable to interpret the exact number of lumens or economic activity.

I believe the negative trend is the more important aspect of the results, instead of absolute numbers for light and economic activity after dam construction.

While the aggregate ATT is significant, only two of the five investigated construction years show a significant ATT (Table 3).

Given the tight relationship between NTL and electrification (Bargain et al., 2023), and the relationship between NTL and socio-economic activity, it suggests communities hosting dams experience a decrease in local socio-economic activity.

**Table 3. Average Treatment Effect on the Treated (ATT) of large dams on socio-economic activity for different construction years and aggregated overall.**

| Aggregation level | ATT (socio-economic activity) | Lower CI | Upper CI |
|---|---|---|---|
| 2005 | -0.41 | -1.21 | 0.38 |
| 2006 | -0.75* | -1.13 | -0.36 |
| 2007 | -0.44* | -0.87 | -0.01 |
| 2008 | -0.32 | -0.78 | 0.14 |
| 2009 | -0.28 | -0.65 | 0.08 |
| Overall aggregate ATT | -0.44* | -0.62 | -0.26 |

*Notes: S*ocio-economic activity is measured as the natural log of the number of lit cells in a 15km radius around a dam site. Conditioning on covariates using doubly robust estimation methods. Co-variates are latitude, area of reservoir and dam height. Standard errors are calculated by bootstrap as discussed in the text and are clustered at the dam site level, 95% confidence. * indicates a significant effect (p>0.05).

[8] Day to day adjustments to the gain of the sensor were made for DSMP data dependent on the moon cycle. On a full moon, the tops of the clouds (the original purpose of the data collection) were brighter than in a sickle phase (Gibson, Olivia and Boe-Gibson, 2020), the gain settings were not recorded on-board.

## 3.3 Investigating inundation and socio-economic activity

The size of the investigation is approximately 706 $km^2$, I therefore, consider whether the effect is driven – simply – by the local area being inundated by the reservoir during construction[9]. Given the linear nature of reservoirs that track the original river line, there is no standard area overlap between the buffer around the dam and the reservoirs. In Table 4, I compare the year of construction (treatment group and treatment timing) to the percentage overlap between the area under investigation and the reservoir outline. This analysis shows that the inundated area is moderate but substantive compared to the area investigated.

I conducted two robustness checks to test the impact of inundation on the treatment effect. First, I slice the dataset into two groups – one where the reservoirs are greater than 12 $km^2$, and one when they are less than 12 $km^2$. This gives 72 "small" reservoir dams and 73 "big" reservoir dams, divided at 12 $km^2$ as this is the median reservoir size. If inundation is alone in reducing the socioeconomic activity, I would expect no significant effect or a smaller significant effect corresponding to the small reservoir group. The investigation gives an inconclusive result (Table 5). The large reservoir size model (dam sites with the top 50th centile reservoir area) does not meet the required parallel trends assumption[10]. There is a significant effect for the small reservoir group – and the effect size is smaller than that for the main model (Table 3), which is suggestive but inconclusive that reservoir size is a factor.

**Table 4. What percentage of the area investigated is inundated by reservoir?**

| Treatment group | Pixels per dam | Mean pixel number for each reservoir | % overlap |
|---|---|---|---|
| Controls | 697 | 27.6 | 4.0 |
| 2005 | 697 | 33.8 | 4.8 |
| 2006 | 697 | 35.6 | 5.1 |
| 2007 | 697 | 20.6 | 3.0 |
| 2008 | 697 | 15.4 | 2.2 |
| 2009 | 697 | 13.8 | 2.0 |

[9] A time-invariant characteristic I use for matching in the first step of the Callaway Sant'Anna estimator is reservoir size, however, as reservoirs in control sites are yet to be created, including this covariate does not control for variation caused by reservoir size, rather it helps to match related sites which have received and will receive dams.

[10] This unlikely to be due to the investigation, but because of the small sample size - there are only 29 dams in the never-treated group for large reservoirs. The authors of the DID Callaway package state that small group sizes make the statistical inferences unstable (Callaway & Sant'Anna, 2021), which is indeed true of many econometric investigations.

As a second test I repeat the analysis but mask out those areas which are inundated by reservoirs. The expectation is if inundation is the sole factor, the resulting ATT would stop being significant when the reservoir areas are excluded. This analysis required me to change the response variable from the sum of lit cells within 15 km of the dam to the mean number of lit cells within 15 km of the dam so that the response variable was dimensionless[11] with respect to the area considered (see Appendix 6.4). Excluding the reservoir areas after dam construction meant that overall a smaller number of pixels were considered, depending on the reservoir size. I excluded reservoir size as a co-variate in the DiD set up. This somewhat crude analysis complements sub-setting the data into large and small reservoirs, as in Table 5, to give further evidence as to whether reservoirs are driving the decrease in economic activity around dams. The group average treatment effect of the treated in this set up gives a negative result of -0.18 ($p<0.05$), and is suggestive that the decrease in socioeconomic activity is not merely due to reservoir size.

**Table 5. Investigating inundation gives an inconclusive result. The large reservoir size model (dam sites with the top 50th centile reservoir area) does not meet the required parallel trends assumption. The small reservoir size model meets the parallel trends assumption and has a similar but smaller effect than the main model. Excluding reservoir areas through a GIS mask from the analysis gives a significant negative impact on socio-economic activity, using a response variable which is unchanged by the size of the spatial area considered. Standard errors are clustered on the dam site level and calculated via bootstrap – 95% Confidence Intervals (CI) are given.**

| Group | Aggregate Group-Time ATT (socio-economic activity) | Lower CI | Upper CI | Number of sites (never treated number) |
|---|---|---|---|---|
| Dams bottom 50$^{th}$ centile reservoir size | -0.36* | -0.64 | -0.07 | 72 (14) |
| Dams top 50$^{th}$ centile reservoir size | -0.63*<br>Parallel trends not met | -0.89 | -0.38 | 73 (29) |
| Reservoirs excluded from the GIS analysis [i] | -0.18* | -0.28 | -0.09 | 102 (43) |

[I] ln mean lit cells rather than ln sum lit cells used as a response variable – therefore, coefficients are not directly comparable to the other models where the response variables use sum – see Appendix 6.4.
* indicates significance ($p < 0.05$).

[11] When I included all areas within 15 km, I had the same number of pixels for the zonal statistics per site. However, when I exclude the reservoir areas after dam construction a smaller and variable number of pixels were included, depending on the reservoir size, which is why I took the mean lit number of cells, not the sum. I excluded reservoir size as a co-variate in the DiD set up.

The impact of dam construction on socio-economic activity strengthens over time, as inferred from the decreasing coefficients obtained through the event-study analysis (Figure 1). This observation challenges the assumption that inundation alone is the sole cause of the observed effect. If inundation were the only factor, one would expect a significant decline in socio-economic activity in the first year after construction, followed by a stabilisation once the reservoir reached its operational capacity. However, given the limited duration of the analysed time period and the variability in reservoir filling time, influenced by factors such as rainfall, downstream water demands, and the purpose of the dam (ASDSO, 2014; Wheeler et al., 2016), it is problematic to assert categorically that the data supports or refutes this trend.

Collectively, based on these robustness checks and the event study, I cautiously reject the notion that simple inundation is the sole driver of socio-economic activity decreasing in the area around the dam, but suggest it is part of the reason, based on smaller reservoir group having a smaller effect. This is further supported by the next section, which investigates the attenuation of the effect over distance.

### *3.3.1 How does the effect change with distance from the dam?*

Based on interviews with engineers and affected communities in 2018 and 2019, I selected 15 km around the dam to explore socio-economic activity. However, a sensitivity test is to adjust the buffer size around the dam site to investigate how this changes the outcome. Therefore, I investigate 5 pixels, 10 pixels, 20 pixels, 30 pixels and 50 pixels around the dam site in Table 6. Pixel buffers of 5, 10, 20, 30 and 50 all have significant aggregate group-time average treatment effects, the size of the effect decreases as the distance from the dam site under consideration increases.

Interpretation of this effect should be cautious. The resolution of the night lights data is assumed to be 25 $km^2$ based on Gibson (2020, p. 20); buffering by 5 pixels around the dam site gives an area of approximately 79 $km^2$ - at the lower end of what is valid to investigate. When considering a 79 $km^2$ area, the impact of reservoir inundation is expected to be significant, given the size of the average reservoir in the sample is 44 $km^2$ (see Table 12 in Appendix 6.1). The small sample size (n=97) caused by having to remove dam sites that overlap with each other (Figure 6) at the 50 km radius means this result should be interpreted with caution, but it is within the trend.

**Table 6. The group-time average treatment effect of different radii around the dam, conditioned on co-variates. The main model is 15 pixels, as in Table 3, repeated here for comparison. The number of sites changes, as those which overlap are discarded, and more overlaps exist the wider the area considered around the dam - see appendix 0.**

| Radius in pixels[i] | Area ($km^2$) at the equator | Aggregate Group-Time ATT (socio-economic activity) | Lower CI | Upper CI | Number of sites (never treated number) |
|---|---|---|---|---|---|
| 5 | 79 | -0.63* | -0.81 | -0.44 | 176 (57) |
| 10 | 314 | -0.56* | -0.73 | -0.39 | 164 (51) |
| 15 | 707 | -0.44* | -0.62 | -0.26 | 145 (43) |
| 20 | 1,256 | -0.44* | -0.60 | -0.28 | 151 (47) |
| 30 | 2,827 | -0.33* | -0.51 | -0.15 | 138 (42) |
| 50 | 7,853 | -0.28* | -0.46 | -0.11 | 97 (33) |

* significant ($p<0.05$)

[I] a pixel is equivalent to 30-arc seconds, approximately a kilometre at the equator.

Standard errors are clustered by dam sites and calculated via bootstrap for 95% Confidence Intervals (CI).

## 3.4 Robustness checks

### *3.4.1 Excluding an out-of-trend year*

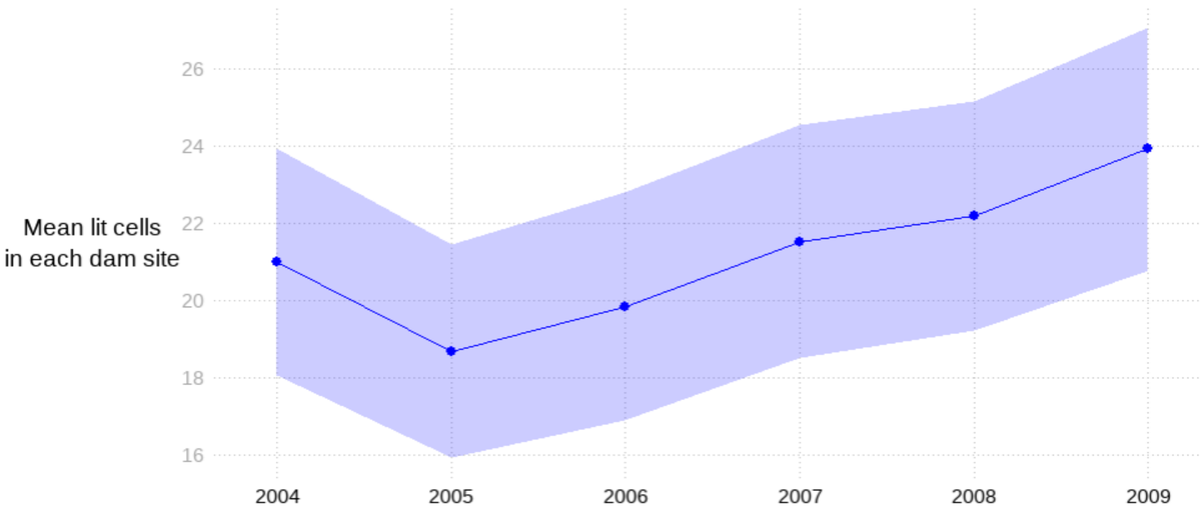



**Figure 2. Number of lit cells in 2004 is higher on average than in other years.**

Over the 20th Century, the world has become brighter as light sources increase. However, Figure 2 shows 2004 is unusually bright across all dam sites. To understand if this drives the trends, I report the calendar year effects with and without 2004 in Table 7. In both scenarios, the effects in 2007, 2008 and 2009 are significant, and the overall trend is downward in lit areas. Given the small sample size, this effect could bias the result if it impacted on the never-treated group differently to the treated one. However, there does not appear to be evidence of this in Table 7.

**Table 7. Calendar effects with and without the year 2004, conditioned on co-variates. * indicates the significance of the effect at p<0.05, standard errors are bootstrapped and clustered at the level of dam site. ATT is the average treatment effect on the treated, socio-economic activity is the response variable.**

| Year | Calendar ATT with year 2004 | Calendar ATT without year 2004 |
|---|---|---|
| 2005 | -0.40 (0.22) | |
| 2006 | -0.18 (0.15) | -0.16 (0.18) |
| 2007 | -0.44* (0.15) | -0.44* (0.14) |
| 2008 | -0.47* (0.13) | -0.50* (0.15) |
| 2009 | -0.68* (0.15) | -0.68* (0.14) |

### *3.4.2 Including an anticipation effect*

One might expect an increase in socio-economic activity and light sources prior to a dam's construction associated with the construction activity itself. This could be the building of roads or the equipment, as well as working at night to construct the dam. The data already suggests that there is not an anticipation effect - the confidence bands of the pre-treatment periods in Figure 1 cross zero, but investigating anticipation is a worthwhile robustness check. I investigate adding two years of anticipation to the model. The outcome of this is an aggregate group ATT of -0.39 ($p<0.05$), the downward trend in socio-economic activity is not altered, nor is it clear that there is an anticipation effect.

## 3.5 Limitations

### *3.5.1 Sample size*

One hundred forty-five dam sites is a comparatively small sample size in econometrics, however, the nature of natural experiments is that you cannot control the number of replicates.

Chinese dams dominate the sample, with over one-third of the dam sites (Table 10). Therefore, Chinese policies may have a disproportionate impact on the results. A future study might include the Global North, excluded as the dam-related economic issues to differ between the Global North and Global South (Fan et al., 2022).

Wooldridge (2023) criticises the Callaway approach for being imprecise, given that it restricts the potential controls to never-treated. However, in my model, precision is not as important as the investigation of a trend, and being sparing in selecting my controls to avoid artefacts adds robustness.

### *3.5.2 Short time period of investigation*

To focus my study on just one satellite from the available six (as shown in appendix 6.9), I only draw inferences about the period from 2004 to 2009, resulting in a limited time frame for my event-study. It is not possible to determine if the impact of dam construction is temporary due to the limited investigative period, and there may have been some trend within it, such as the sensitivity of the NTL to the Global Financial Crisis (GFC) of 2008 (W. Chen et al., 2019; Jiang et al., 2021) that could bias my results. An idiosyncratic event such as the GFC may have biased my results if the absence of dam construction during the crisis conferred a socio-economic advantage or disadvantage to the area. A future study and robustness check could use the Suomi National Polar-orbiting Partnership satellite VIIRS NTL data (Li et al., 2013), which is available from 2011, to investigate more recent trends, following Fan et al. (2022).

### *3.5.3 Policy interpretation*

In this study, a challenge with analysing the response variable is its policy interpretation. The response variable is not intuitively interpreted – it is the natural logarithm of the sum of lit pixels in an area around the dam, where lit is above a threshold of 5 digital numbers out of a potential 63. Gibson's papers (2015, 2020) caution that the absolute values in digital numbers (the metric used onboard the satellite to measure night light) vary between years and locations and cannot be considered consistent measures of the same light and economic effect. This error is expected to be consistent between dam sites and treatments, but the response variable does not correspond to an exact number of lumens or economic activity. Further, Papaioannou and Michalopoulos (2013) found corresponding conclusions but different effect coefficients for the two response variables in their investigation employing both NTL intensity and NTL lit/unlit pixels. NTL are therefore a less suitable measure of socio-economic activity than GDP for this investigation as they do not correspond to a precise value of economic vigour.

In this study I compare only one type of dam, and one type of energy production and water-management infrastructure to one alternative – no dam. It is worth noting that this is not a realistic counterfactual for my natural experiment geographically or politically for all dam sites. Alternative options include but are not limited to fossil fuel energy infrastructure and ground water provision. I also investigate only one sort of dam – one with a significant reservoir – when alternatives will have different socio-economic and ecological impacts such as pumped-storage hydropower (Richter et al., 2020), smaller cascading dams (Nguyen-Tien et al., 2018) and run-of-river dams (Kuriqi et al., 2021).

### *3.5.4 Wellbeing impacts*

Through a narrow lens, this study shows that large dams may have small local negative impacts on socio-economic activity. Given that lens used to analyse the dam sites is literally far removed from the source, it is limited in its ability to understand the lived experience and causes of the changes captured. Tortajada (2015) talks about dams for meeting basic human needs, she asserts they are essential for development. This study does not investigate human needs or causes. Investigating how and why there is a decrease in local socio-economic activity around dam construction, and the impacts that this might have on the lived experience of people and livelihoods on the ground, is a logical next step of this study.

# 4. Discussion

My study contributes to the contradictory literature on the impact of dams on socio-economic activity. Some literature is positive, with authors demonstrating that socio-economic activity increases when dams are built in general through direct and indirect benefits through employment (Cestti & Malik, 2012; Tortajada, 2015), in one country (de Faria et al., 2017) and in specific dams (Bhatia & Malik, 2007; World Commission on Dams, 2000, p. 121). On the other hand, others state that socio-economic activity decreases once a dam has been built in the local area, for example, poverty increases in host districts in India (Duflo and Pande, 2007) or at the inter-country level (Sovacool and Walter, 2018).

My study found a local decrease in socio-economic activity that persists three years after construction. This contrasts with de Faria et al. (2017) in their study of Brazilian counties hosting large hydropower plants who found ephemeral but positive impacts for 15 years or less. My finding is comparable to the Duflo and Pande (2007) study in India, which showed rural poverty increased in the districts that hosted dams but decreased in downstream districts. It corresponds with Castro-Diaz et al. (2022) who discuss how different sorts of capital (physical, financial, natural and human) trade-off with negative and positive impacts after 33 dams have been built in the Global South. This study captures the physical capital (for example roads) and aspects of financial capital (as NTLs measure GDP) - Castro-Diaz found 37% positive impacts on financial capital and 63% negative in their 33 case studies, using a fuzzy-set qualitative comparative analysis.

I also found that inundation partially explains the decrease in socio-economic activity, dams' impact on socio-economic activity decreases with distance, and the effect increases with time. This is relevant for the displacement literature (Cernea, 2004a; Hay et al., 2020) and the literature on perceptions of locally unwanted infrastructure (Diduck et al., 2013; Safford et al., 2012; Wiejaczka et al., 2018).

## 4.1 Reflections on the scale of investigation and the dam site buffer shape

My investigation does not use a similar scale to those used by previous econometric investigations of the local impact of dams, which should be considered when comparing it to others. The de Faria (2017) and Duflo and Pande (2007) studies use administrative areas for their analysis, which vary in size. Brazilian counties considered by De Faria average around 1,200 km$^2$ and while Indian districts around 5,000 km$^2$ (MoHA, 2011), both have a large range. Bom Jesus, the smallest county considered by de Faria in Brazil has an area of 122 km$^2$, and the median county area considered was 500 km$^2$. Thus, while some units considered by these two studies were analogous to my own investigation, others were not. Differing results could be explained by the scale considered.

In addition to scale, the shape of the investigated area may be important in interpreting differences between my study and others. For example, administrative boundaries frequently follow rivers; thus, when administrative areas are used to aggregate socio-economic data as has happened in Sovacool and Walter (2018), De Faria (2016) and Duflo and Pande (2007), dams may lie within two jurisdictions compromising analysis. However, the disadvantage of my approach is that by not using jurisdictional boundaries my area of investigation around each dam site could cut across multiple significant policies and regulations administered at the jurisdictional level.

Studies interpreting socio-economic activity have also used variable response variables and sources, which may explain different results to my own. De Faria et al. (2017) used GDP figures taken from the Instituto Brasileiro de Geografia e Estatística (IBGE), a Brazilian government institution for each county in the analysis (de Faria et al., 2017). Cestti & Malik (2012) investigate the multiplier effect of three dams in India, Egypt and Brazil: the number of units of currency produced for every unit invested in the infrastructure. They estimate changes in productivity in related industries, such as agriculture and electricity, in with project and without project scenarios in the host region, at the state level. They report positive socio-economic outcomes. In contrast, Sovacool and Walter (2018) who found negative "development" impacts when comparing hydropower and non-hydropower countries, used World Bank GDP data as a response variable and investigated a different scale, the country level.

While the relationship between NTL and socio-economic activity is confirmed by many sources in the literature (Bhandari & Roychowdhury, 2011; Gibson et al., 2020; Mveyange, 2015), NTL may detect something other than conventional GDP. Authors have proposed that NTLs capture the shadow economy, including informal businesses not recorded by official government surveys (Tanaka & Keola, 2017). The shadow economy of informal businesses may be important in rural areas where dams are often located; if this economy is eroded by dam construction, that would be significant. Energy consumption has been used by Basbay et al. (2016) to detect the informal economy when not captured by GDP measures, and there is evidence that night-time lights have a close relationship with electricity consumption in the Global South (N. Dasgupta, 2022; Zhu et al., 2019). The decrease I detect using NTLs after construction might represent a decrease in the informal economy.

## 4.2 Socio-economic activity – reducing or moving?

Rather than a depression in socio-economic activity – the change in the area around the dam I observe could instead be a movement of socio-economic activity away from my investigation zone. The most obvious mechanism for this movement would be forced displacement by the dam or voluntary migration to a new site for those whose homes have been inundated. Whether or not resettled people will be captured within the 15 km radius around the dam site will be determined on a case-by-case basis.

Project-affected people might migrate to urban centres or to other countries, given the opportunity of compensation payments or the push of impoverishment at home (World Commission on Dams, 2000, p. 115). The socio-economic impact on the migrating people is uncertain and cannot be determined by my methodology, nor can my method determine if this is the cause. Scholar Del Bene (Del Bene et al., 2018) discusses the "complex social distress" which happens in space and time from dams, which my method cannot derive. A great deal of tools do exist to determine the impacts of migration (Cernea, 2004b, 2004a; Kibler et al., 2012; Kirchherr & Charles, 2016; T. Scudder, 2012). An area of further study would be to determine the role of migration in shaping the results.

## 4.3 Is the effect temporary?

Figure 1 shows that the longer period since dam construction, the greater the decrease is in socioeconomic activity. However, given the investigation was only for four years after construction, further examination is impossible, and the last year is insignificant, suggesting either the effect might peter out, or the sample size is too small to see a significant effect. If the effect does peter out with time, that would tally with De Faria (2017), who found the socioeconomic effects of dam construction to be short-lived, noting unlike this study they found a positive effect. Extending the time-series would allow me to investigate this possibility by the inclusion of the VIIRS NTL series (Li et al., 2013, 2017; M. Zhao et al., 2017), in a future study.

## 4.4 Satellite imagery as a tool for measuring socio-economic activity

My study contributes to the existing literature on evaluating the impacts of dams using satellite imagery. Critiques of dams tend towards nuanced political analysis (Bromber et al., 2014; Dukpa et al., 2019; Huber et al., 2017; Huber & Joshi, 2015; Rai, 2008), and it is important to acknowledge that satellites alone cannot provide an understanding of the lived experience of these changes, and their geographic limitations prevent a comprehensive assessment of the net benefits and costs of dams. However, satellite imagery analysis has been used to understand hydrology and related social justice issues in Brazil, demonstrating the drastic changes to Xingu River wrought by the Belo Monte Dam and profound impacts on Indigenous peoples (Das et al., 2022). Satellite imagery has also been used to investigate the correlation between the economy and land cover in recently constructed dams in the Global North and South, finding differentiated impacts in those two regions between 2001 and 2015 (Fan et al., 2022). Finally, using satellite imagery, Higginbottom et al. (2021) showed that African irrigation schemes often fall short of projected benefits, raising questions about their potential limitations in promoting socio-economic development.

The aforementioned Higginbottom et al. (2021) study relates to the literature on mega-project failure and the planning fallacy (Ansar et al., 2014; Warner et al., 2019). While it is attractive to relate my findings to this literature, given that my results show large Global South schemes do not deliver socio-economic improvement, the scale of my investigation does not warrant this. With the exception of employment (Mayer et al., 2021), and tourism (Naithani & Saha, 2018) project documents rarely make claims that there will be an improvement to local GDP, instead, the focus is on national and regional development (THDC, 2017; World Bank, 2012). I could make the modest claim that if there are local employment activities and spillover effects from dams, this is not offsetting the decrease in socio-economic activity associated with dam construction. However, I should also note that given the limitations noted in section 3.5, I only make this claim for three years after construction.

Large dams represent "long-term investments that are hard to erase" (Legese et al., 2018), whose negative impacts may be felt 1,000 km away (Soukhaphon et al., 2021). Deep consideration of socio-economic impacts at different scales will enable the better implementation of frameworks to improve governance, for example, around energy justice (Siciliano et al., 2018, 2019). A better understanding of impacts is important as people's perspectives on dams are shaped by how they experience those impacts (Mayer et al., 2021; Voegeli & Finger, 2021). A finding of my study is that negative impacts attenuate with distance. A significant factor in shaping perspectives and public opinion on energy infrastructure is the distance between the public and the infrastructure (Bird et al., 2014).

Economist Thomas Sowell said "There are no solutions. There are only trade-offs.", as others have articulated (X. Zhao et al., 2020) there are trade-offs in the energy transition, and this study suggests the national benefits from large dams trade off with negative socioeconomic impacts in the local area around dams. Whether or not those trade-offs are worthwhile will be determined by your politics and ideology (Clarke et al., 2016; Dye, 2019). Legese et al. (2018) argue that articulating and quantifying the trade-offs is to reveal and discuss the "social cost of decisions" as a component of "risk governance" which enables risks to be "grasped, maybe minimized, and pushed in this or that direction" whatever ethical or political framework is being employed. I hope this paper goes some way towards revealing and discussing the trade-offs around large dams.

### 4.5 Conclusion

In conclusion, the conducted research suggests that local communities may lose out when a large dam is constructed. This aligns with some literature but contrasts with others and draws attention to the trade-offs within the energy transition. Future studies should lean into the complexities and avoid win-win narratives to make trade-offs explicit. This study does not say who loses or benefits, whether women or men, business owners, or those without land tenure. However, it shows that those areas that host dams are fundamentally changed compared to their equivalent neighbourhoods in the Global South.

## 5. Bibliography

Abrahams, A. (2018). GitHub - alexeiabrahams/nighttime-lights: Scripts for deblurring DMSP nighttime lights imagery. GitHub. https://github.com/alexeiabrahams/nighttime-lights

Abrahams, A., Oram, C., & Lozano-Gracia, N. (2018). Deblurring DMSP nighttime lights: A new method using Gaussian filters and frequencies of illumination. Remote Sensing of Environment, 210(December 2016), 242–258. https://doi.org/10.1016/j.rse.2018.03.018

Angrist, J. D., & Pischke, J.-S. (2008). Mostly harmless econometrics: An empiricist's companion. Princeton university press. https://doi.org/10.1017/CBO9781107415324.004

Ansar, A., Flyvbjerg, B., Budzier, A., & Lunn, D. (2014). Should we build more large dams? The actual costs of hydropower megaproject development. Energy Policy, 69(Supplement C), 43–56. https://doi.org/https://doi.org/10.1016/j.enpol.2013.10.069

Archsmith, J. (2017). Dam Spillovers: The Direct and Indirect Costs from Environmental Constraints on Hydroelectric Generation. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3046246

Arsel, M. (2022). The Journal of Peasant Studies ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/fjps20 Climate change and class conflict in the Anthropocene: sink or swim together? https://doi.org/10.1080/03066150.2022.2113390

ASDSO. (2014). Lesson Learned: The first filling of a reservoir should be planned, controlled, and monitored. https://damfailures.org/lessons-learned/the-first-filling-of-a-reservoir-should-be-planned-controlled-and-monitored/

Azevedo, J. P. (2020). WBOPENDATA: Stata module to access world bank databases.

Baghel, R., & Nüsser, M. (2010). Discussing large dams in Asia after the World Commission on Dams: Is a political ecology approach the way forward? Water Alternatives, 3(2), 231–248.

Baker, A., Larcker, D. F., & Wang, C. C. Y. (2021). How Much Should We Trust Staggered Difference-In-Differences Estimates? SSRN Electronic Journal, March. https://doi.org/10.2139/ssrn.3794018

Bargain, O. B., Caldeira, É., & Vincent, R. C. (2023). Shine a (night)light: Decentralisation and Economic Development in Burkina Faso. https://doi.org/10.3929/ethz-b-000604542

Basbay, M. M., Elgin, C., & Torul, O. (2016). Energy consumption and the size of the informal economy. Economics, 10. https://doi.org/10.5018/economics-ejournal.ja.2016-14

Baskaran, T., Min, B., & Uppal, Y. (2015). Election cycles and electricity provision: Evidence from a quasi-experiment with Indian special elections. Journal of Public Economics, 126, 64–73. https://doi.org/10.1016/j.jpubeco.2015.03.011

Beames, P., Lehner, B., & Anand, M. (2019). Global Reservoir and Dam (GRanD) database: Technical documentation v1.3. 3(feb), 12.

Bhandari, L., & Roychowdhury, K. (2011). Night Lights and Economic Activity in India: A study using DMSP-OLS night time images. Proceedings of the Asia-Pacific Advanced Network, 32(0), 218. https://doi.org/10.7125/apan.32.24

Bhatia, R., & Malik, R. P. S. (2007). Direct and indirect economic impacts of the Bhakra multipurpose dam, India. Irrigation and Drainage, 56(2–3), 195–206. https://doi.org/10.1002/ird.315

Biermann, F., Abbott, K., Andresen, S., Bäckstrand, K., Bernstein, S., Betsill, M. M., Bulkeley, H., Cashore, B., Clapp, J., Folke, C., Gupta, A., Gupta, J., Haas, P. M., Jordan, A., Kanie, N., Kluvánková-Oravská, T., Lebel, L., Liverman, D., Meadowcroft, J., … Zondervan, R. (2012). Navigating the anthropocene: Improving earth system governance. In Science. https://doi.org/10.1126/science.1217255

Bird, D. K., Haynes, K., van den Honert, R., McAneney, J., & Poortinga, W. (2014). Nuclear power in Australia: A comparative analysis of public opinion regarding climate change and the Fukushima disaster. Energy Policy, 65, 644–653. https://doi.org/10.1016/j.enpol.2013.09.047

Biswas, A. K. (2004). Dams: Cornucopia or disaster? International Journal of Water Resources Development, 20(1), 3–14. https://doi.org/10.1080/0790062032000170571

Biswas, A. K. (2012). Impacts of Large Dams: Issues, Opportunities and Constraints. In Water Resources Development and Management (pp. 1–18). Springer. https://doi.org/10.1007/978-3-642-23571-9_1

Biswas, A. K., & Tortajada, C. (2012). Impacts of the high Aswan Dam. In Impacts of Large Dams: A Global Assessment (pp. 379–395). Springer.

Braeckman, J. P., & Guthrie, P. (2016). A typology of the effects of pre-construction delay for largehydropower projects.

Bromber, K., Féaux de la Croix, J., & Lange, K. (2014). The temporal politics of big dams in Africa, the Middle East, and Asia: by way of an introduction. Water History, 6(4), 289–296. https://doi.org/10.1007/s12685-014-0111-9

Byers, L., Friedrich, J., Hennig, R., Kressig, A., McCormick, C., & Malaguzzi Valeri, L. (2021). A Global Database of Power Plants. World Resources Institute, x, 1–18. http://globalenergyobservatory.org

Cai, W., Wang, C., Chen, J., & Wang, S. (2011). Green economy and green jobs: Myth or reality? The case of China's power generation sector. Energy, 36(10), 5994–6003. https://doi.org/10.1016/j.energy.2011.08.016

Callaway, B. (2022). Difference-in-Differences for Policy Evaluation.

Callaway, B., & Sant'Anna, P. H. C. (2018). Difference-in-Differences with Multiple Time Periods and an Application on the Minimum Wage and Employment. In DETU Working Paper 18-04. https://doi.org/10.2139/ssrn.3148250

Callaway, B., & Sant'Anna, P. H. C. (2020). Difference-in-Differences with multiple time periods. In Journal of Econometrics. https://doi.org/10.1016/j.jeconom.2020.12.001

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. Journal of Econometrics, 225(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Callaway, B., & Sant'Anna, P. H. C. (2022, December 1). Getting Started with the did Package. GitHub Blog; Elsevier Ltd. https://doi.org/10.1016/j.jeconom.2020.12.001

Cao, X., Hu, Y., Zhu, X., Shi, F., Zhuo, L., & Chen, J. (2019). A simple self-adjusting model for correcting the blooming effects in DMSP-OLS nighttime light images. Remote Sensing of Environment, 224(c), 401–411. https://doi.org/10.1016/j.rse.2019.02.019

Castro-Diaz, L., Garcia, M. A., Villamayor-Tomas, S., & Lopez, M. C. (2022). Impacts on locals' livelihoods of hydropower development in the Global South. Manuscript Submitted for Publication, 169, 106285. https://doi.org/10.1016/j.worlddev.2023.106285

Cernea, M. M. (2004a). Impoverishment Risks, Risk Management, and Reconstruction: A Model of Population Displacement and Resettlement. In UN Symposium on Hydropower and Sustainable Development. https://commdev.org/wp-content/uploads/2015/06/Impoverishment-Risks-Risk-Management-and-Reconstruction.pdf

Cernea, M. M. (2004b). Social impacts and social risks in hydropower programs: preemptive planning and counter-risk measures. Proceedings of United Nations Symposium on Hydropower and Sustainable Development, 1–22. http://www.un.org/esa/sustdev/sdissues/energy/op/hydro_cernea_social impacts_backgroundpaper.pdf

Cestti, R., & Malik, R. (2012). Indirect Economic Impacts of Dams. In Impacts of Large Dams: A Global Assessment (pp. 19–35). Springer. https://doi.org/10.1007/978-3-642-23571-9

Ch, R., Martin, D. A., & Vargas, J. F. (2021). Measuring the size and growth of cities using nighttime light. Journal of Urban Economics, 125. https://doi.org/10.1016/j.jue.2020.103254

Chen, J., Shi, H., Sivakumar, B., & Peart, M. R. (2016). Population, water, food, energy and dams. Renewable and Sustainable Energy Reviews, 56, 18–28. https://doi.org/10.1016/j.rser.2015.11.043

Chen, W., Mrkaic, M., & Nabar, M. (2019). The Global Economic Recovery 10 Years After the 2008 Financial Crisis, WP/19/83, April 2019.

Clarke, C. E., Budgen, D., Hart, P. S., Stedman, R. C., Jacquet, J. B., Evensen, D. T. N., & Boudet, H. S. (2016). How geographic distance and political ideology interact to influence public perception of unconventional oil/natural gas development. Energy Policy, 97, 301–309. https://doi.org/10.1016/j.enpol.2016.07.032

Cowger, T. L., Murray, E. J., Clarke, J., Bassett, M. T., Ojikutu, B. O., Sánchez, S. M., Linos, N., & Hall, K. T. (2022). Lifting Universal Masking in Schools — Covid-19 Incidence among Students and Staff. New England Journal of Medicine, 387(21), 1935–1946. https://doi.org/10.1056/nejmoa2211029

Cunningham, S. (2020). Callaway and Sant'Anna DD estimator - a story of differential timing and heterogeneity.

Dasgupta, N. (2022). Using satellite images of nighttime lights to predict the economic impact of COVID-19 in India. Advances in Space Research, 70(4), 863–879. https://doi.org/10.1016/j.asr.2022.05.039

Dasgupta, P. (2021). The Economics of Biodiversity: The Dasgupta Review.

de Faria, F. (2016). Hydropower Development in the Brazilian Amazon. Carnegie Mellon University.

de Faria, F., Davis, A., Severnini, E., & Jaramillo, P. (2017). The local socio-economic impacts of large hydropower plant development in a developing country. Energy Economics, 67, 533–544. https://doi.org/10.1016/j.eneco.2017.08.025

Del Bene, D., Scheidel, A., & Temper, L. (2018). More dams, more violence? A global analysis on resistances and repression around conflictive dams through co-produced knowledge. Sustainability Science, 1–17. https://doi.org/10.1007/s11625-018-0558-1

Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangecroft, S., Veldkamp, T. I. E., Garcia, M., van Oel, P. R., Breinl, K., & Van Loon, A. F. (2018). Water shortages worsened by reservoir effects. In Nature Sustainability (Vol. 1, Issue 11, pp. 617–622). Nature Publishing Group. https://doi.org/10.1038/s41893-018-0159-0

Diduck, A. P., Pratap, D., Sinclair, A. J., & Deane, S. (2013). Perceptions of impacts, public participation, and learning in the planning, assessment and mitigation of two hydroelectric projects in Uttarakhand, India. Land Use Policy, 33, 170–182. https://doi.org/10.1016/j.landusepol.2013.01.001

Doll, C. H., Muller, J.-P., & Elvidge, C. D. (2000). Night-time Imagery as a Tool for Global Mapping of Socioeconomic Parameters and Greenhouse Gas Emissions. Ambio, 29(3). https://doi.org/10.1579/0044-7447-29.3.157

Dube, A., Girardi, D., Jordà, O., & Taylor, A. M. (2022). A Local Projections Approach to Difference-in-Differences Event Studies.

Duflo, E., & Pande, R. (2007). Dams. The Quarterly Journal of Economics, 122(2), 601–646. http://www.jstor.org/stable/pdf/25098854.pdf

Dukpa, R., Joshi, D., & Boelens, R. (2019). Contesting Hydropower Dams in the Eastern Himalaya: The Cultural Politics of Identity, Territory and Self-Governance Institutions in Sikkim, India. Water, 11(3), 412. https://doi.org/10.3390/w11030412

Dye, B. J. (2019). Dam building by the illiberal modernisers: ideology and changing rationales in Rwanda and Tanzania.

http://hummedia.manchester.ac.uk/institutes/gdi/publications/workingpapers/futuredams/futuredams-working-paper-005-dye.pdf

Earth Observation Group. (2023). DMSP Nighttime Lights. https://eogdata.mines.edu/products/dmsp/

Elvidge, C. D., Baugh, K. E., Anderson, S. J., Sutton, P. C., & Ghosh, T. (2012). The Night Light Development Index (NLDI): A spatially explicit measure of human development from satellite data. Social Geography, 7(1), 23–35. https://doi.org/10.5194/sg-7-23-2012

Elvidge, C., Hsu, F.-C., Baugh, K., & Ghosh, T. (2014). National Trends in Satellite-Observed Lighting: 1992–2012 (pp. 97–120). https://doi.org/10.1201/b17012-9

Elvidge, C., Sutton, P. C., Ghosh, T., Tuttle, B. T., Baugh, K., Bhaduri, B., & Bright, E. (2009). A global poverty map derived from satellite data. Computers and Geosciences, 35(8), 1652–1660. https://doi.org/10.1016/j.cageo.2009.01.009

Fan, P., Cho, M. S., Lin, Z., Ouyang, Z., Qi, J., Chen, J., & Moran, E. F. (2022). Recently constructed hydropower dams were associated with reduced economic production, population, and greenness in nearby areas. Proceedings of the National Academy of Sciences of the United States of America, 119(8). https://doi.org/10.1073/pnas.2108038119

Garrett-Peltier, H. (2017). Green versus brown: Comparing the employment impacts of energy efficiency, renewable energy, and fossil fuels using an input-output model. Economic Modelling, 61(March 2016), 439–447. https://doi.org/10.1016/j.econmod.2016.11.012

Ghimire, L. P., & Kim, Y. (2018). An analysis on barriers to renewable energy development in the context of Nepal using AHP. Renewable Energy, 129, 446–456. https://doi.org/10.1016/j.renene.2018.06.011

Ghosh, T., Anderson, S. J., Elvidge, C. D., & Sutton, P. C. (2013). Using nighttime satellite imagery as a proxy measure of human well-being. Sustainability (Switzerland), 5(12), 4988–5019. https://doi.org/10.3390/su5124988

Gibson, J. (2019). A Test of DMPS and VIIRS Night Lights Data for Estimating GDP and Spatial Inequality for Rural and Urban Areas Jo. 1–18. https://ideas.repec.org/p/wai/econwp/19-11.html

Gibson, J., Boe-Gibson, G., & Stichbury, G. (2015). Urban land expansion in India 1992-2012. Food Policy, 56, 100–113. https://doi.org/10.1016/j.foodpol.2015.08.002

Gibson, J., Datt, G., Murgai, R., & Ravallion, M. (2017). For India's Rural Poor, Growing Towns Matter More Than Growing Cities. World Development, 98. https://doi.org/10.1016/j.worlddev.2017.05.014

Gibson, J., Olivia, S., & Boe-Gibson, G. (2020). Night Lights in Economics: Sources and Uses. Journal of Economic Surveys, 34(5), 955–980. https://doi.org/10.1111/joes.12387

Gibson, J., Olivia, S., Boe-Gibson, G., & Li, C. (2021). Which night lights data should we use in economics, and where? Journal of Development Economics, 149(November 2020), 102602. https://doi.org/10.1016/j.jdeveco.2020.102602

Gilpin, G., Karger, E., & Nencka, P. (2021). The Returns to Public Library Investment. https://doi.org/10.21033/wp-2021-06

Gipper, B., Leuz, C., & Maffett, M. (2015). Public Audit Oversight and Reporting Credibility: Evidence from the PCAOB Inspection Regime. Working Paper. https://doi.org/10.3386/w21530

Goodman-Bacon, A. (2018). Difference-in-Differences With Variation in Treatment Timing. In National Bureau of Economic Research (Vol. 17, Issue 5). https://doi.org/10.1016/j.smr.2019.08.005%0Ahttp://dx.doi.org/10.1016/j.smr.2009.02.001%0Ahttps://scholarship.shu.edu/student_scholarship

Granoff, I., Hogarth, J. R., & Miller, A. (2016). Nested barriers to low-carbon infrastructure investment. In Nature Climate Change (Vol. 6, Issue 12, pp. 1065–1071). Nature Publishing Group. https://doi.org/10.1038/nclimate3142

GRASS Development Team. (2017). Geographic Resources Analysis Support System (GRASS) Software (7.2). http://grass.osgeo.org

Hall, C. J., Jordaan, A., & Frisk, M. G. (2011). The historic influence of dams on diadromous fish habitat with a focus on river herring and hydrologic longitudinal connectivity. Landscape Ecology, 26(1), 95–107. https://doi.org/10.1007/s10980-010-9539-1

Hartmann, J. (2015). Chaglla hydropower project. http://www.hydrosustainability.org/getattachment/d0303e6e-2bce-4b18-a724-5c0c21e51217/IHA-Chaglla-Assessment-Final-Report-2-Oct-2015-small.pdf.aspx?ext=.pdf

Hay, M., Skinner, J., & Norton, A. (2020). Dam-Induced Displacement and Resettlement: A Literature Review. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3538211

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring Economic Growth from Outer Space. American Economic Review, 102(2), 994–1028. https://doi.org/10.1257/aer.102.2.994

Higginbottom, T. P., Adhikari, R., Dimova, R., Redicker, S., & Foster, T. (2021). Performance of large-scale irrigation projects in sub-Saharan Africa. Nature Sustainability. https://doi.org/10.1038/s41893-020-00670-7

Howe, C., Suich, H., Vira, B., & Mace, G. M. (2014). Creating win-wins from trade-offs? Ecosystem services for human well-being: A meta-analysis of ecosystem service trade-offs and synergies in the real world. Global Environmental Change. https://doi.org/10.1016/j.gloenvcha.2014.07.005

Hsu, F. C., Baugh, K. E., Ghosh, T., Zhizhin, M., & Elvidge, C. D. (2015). DMSP-OLS radiance calibrated nighttime lights time series with intercalibration. Remote Sensing, 7(2), 1855–1876. https://doi.org/10.3390/rs70201855

Huang, Q., Yang, X., Gao, B., Yang, Y., & Zhao, Y. (2014). Application of DMSP/OLS nighttime light images: A meta-analysis and a systematic literature review. Remote Sensing, 6(8), 6844–6866. https://doi.org/10.3390/rs6086844

Huber, A., Gorostiza, S., Kotsila, P., Beltrán, M. J., & Armiero, M. (2017). Beyond “Socially Constructed” Disasters: Re-politicizing the Debate on Large Dams through a Political Ecology of Risk. Capitalism, Nature, Socialism, 28(3), 48–68. https://doi.org/10.1080/10455752.2016.1225222

Huber, A., & Joshi, D. (2015). Hydropower, Anti-Politics, and the Opening of New Political Spaces in the Eastern Himalayas. World Development, 76, 13–25. https://doi.org/10.1016/j.worlddev.2015.06.006

Hunter, J. M. (2003). Inherited burden of disease: Agricultural dams and the persistence of bloody urine (Schistosomiasis hematobium) in the Upper East Region of Ghana, 1959-1997. Social Science and Medicine. https://doi.org/10.1016/S0277-9536(02)00021-7

IPCC. (2023). Synthesis Report of the Sixth Assessment Report - IPCC (AR6) Summary for Policymakers.

Iyer, R. R. (2007). Towards water wisdom: Limits, justice, harmony. Sage Publications India.

Jiang, L., Liu, Y., Wu, S., & Yang, C. (2021). Study on urban spatial pattern based on DMSP/OLS and NPP/VIIRS in democratic people’s Republic of Korea. Remote Sensing, 13(23). https://doi.org/10.3390/rs13234879

Jiménez-Inchima, I., Polanco, J. A., & Escobar-Sierra, M. (2021). Good living of communities and sustainability of the hydropower business: mapping an operational framework for benefit sharing. In Energy, Sustainability and Society (Vol. 11, Issue 1). BioMed Central Ltd. https://doi.org/10.1186/s13705-021-00284-7

Jobin, W. (1999). Dams and disease: ecological design and health impacts of large dams, canals and irrigation systems. In Dams and disease: ecological design and health impacts of large dams, canals and irrigation systems.

Kibler, K., Tullos, D., Tilt, B., Wolf, A., Magee, D., Foster-Moore, E., & Gassert, F. (2012). Integrative Dam Assessment Model (IDAM) Documentation: Users Guide to the IDAM Methodology and a Case Study from Southwestern China. http://www.transboundarywaters.orst.edu/research/IDAM/IDAM Manual 12.pdf

Kirchherr, J., Ahrenshop, M.-P., & Charles, K. (2019). Resettlement lies: Suggestive evidence from 29 large dam projects. https://doi.org/10.1016/j.worlddev.2018.10.003

Kirchherr, J., & Charles, K. J. (2016). The social impacts of dams: A new framework for scholarly analysis. Environmental Impact Assessment Review, 60, 99–114. https://doi.org/10.1016/j.eiar.2016.02.005

Kocornik-Mina, A., McDermott, T. K. J., Michaels, G., & Rauch, F. (2020). Flooded cities. American Economic Journal: Applied Economics, 12(2), 35–66. https://doi.org/10.1257/app.20170066

Kummu, M., Taka, M., & Guillaume, J. H. A. (2018). Gridded global datasets for Gross Domestic Product and Human Development Index over 1990-2015. Scientific Data, 5, 1–15. https://doi.org/10.1038/sdata.2018.4

Kuriqi, A., Pinheiro, A. N., Sordo-Ward, A., Bejarano, M. D., & Garrote, L. (2021). Ecological impacts of run-of-river hydropower plants—Current status and future prospects on the brink of energy transition. In Renewable and Sustainable Energy Reviews (Vol. 142). Elsevier Ltd. https://doi.org/10.1016/j.rser.2021.110833

Lavers, T., & Dye, B. (2019). Theorising the political economy of dams: towards a research agenda. www.futuredams.org

Legese, G., Van Assche, K., Stelmacher, T., Tekleworld, H., & Kelboro, G. (2018). Land for food or power? Risk governance of dams and family farms in Southwest Ethiopia. Land Use Policy, 75, 50–59. https://doi.org/10.1016/j.landusepol.2018.03.027

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J. C., Rödel, R., Sindorf, N., & Wisser, D. (2011). Global Reservoir and Dam (GRanD) database Technical documentation Version. http://www.gwsp.org/fileadmin/downloads/GRanD_Technical_Documentation_v1_1.pdf

Li, X., Li, D., Xu, H., & Wu, C. (2017). Intercalibration between DMSP/OLS and VIIRS night-time light images to evaluate city light dynamics of Syria's major human settlement during Syrian Civil War. International Journal of Remote Sensing, 38(21), 5934–5951. https://doi.org/10.1080/01431161.2017.1331476

Li, X., Xu, H., Chen, X., & Li, C. (2013). Potential of NPP-VIIRS nighttime light imagery for modeling the regional economy of China. Remote Sensing, 5(6), 3057–3081. https://doi.org/10.3390/rs5063057

Mayer, A., Castro-Diaz, L., Lopez, M. C., Leturcq, G., & Moran, E. F. (2021). Is hydropower worth it? Exploring Amazonian resettlement, human development and environmental costs with the Belo Monte project in Brazil. Energy Research and Social Science, 78. https://doi.org/10.1016/j.erss.2021.102129

McCully, P. (2001). Silenced rivers: the ecology and politics of large dams. London : Zed Books.

Michalopoulos, S., & Papaioannou, E. (2017). Spatial Patterns of Development: A Meso Approach. http://www.nber.org/papers/w24088.pdf

MoHA. (2011). Census tables | Government of India. Ministry of Home Affairs . https://censusindia.gov.in/census.website/data/census-tables

Moran, E. F., Lopez, M. C., Moore, N., Müller, N., & Hyndman, D. W. (2018). Sustainable hydropower in the 21st century. Proceedings of the National Academy of Sciences of the United States of America, 115(47), 11891–11898. https://doi.org/10.1073/pnas.1809426115

Murray-Li, T. (2007). The Will to Improve: Governmentality, Development, and the Practice of Politics. In The Will to Improve: Governmentality, Development, and the Practice of Politics (Vol. 53). https://doi.org/10.1017/CBO9781107415324.004

Mveyange, A. (2015). Night Lights and Regional Income Inequality in Africa. In WIDER Working Paper. http://www.worldbank.org/content/dam/Worldbank/Feature Story/Africa/afr-anthony-mveyange.pdf

Naithani, S., & Saha, A. K. (2018). Changing landscape and ecotourism development in a large dam site: a case study of Tehri dam, India. Asia Pacific Journal of Tourism Research, 1665. https://doi.org/10.1080/10941665.2018.1557226

National Register of Large Dams. (2018). Dams of national importance (completed and under construction) and statewise distribution of under construction large dams in India. http://www.indiaenvironmentportal.org.in/files/file/NRLD 2018.pdf

Nguyen-Tien, V., Elliott, R. J. R., & Strobl, E. A. (2018). Hydropower generation, flood control and dam cascades: A national assessment for Vietnam. Journal of Hydrology, 560, 109–126. https://doi.org/10.1016/j.jhydrol.2018.02.063

Niu, Y., & Shah, F. A. (2021). Economics of Optimal Reservoir Capacity Determination, Sediment Management, and Dam Decommissioning. Water Resources Research, 57(7). https://doi.org/10.1029/2020WR028198

Nüsser, M. (2003). Political ecology of large dams: a critical review. Petermanns Geographische Mitteilungen, March, 20–27. http://www.sai.uni-heidelberg.de/geo/pdfs/Nuesser_2003_PoliticalEcologyOfLargeDams_PGM_147(1)_20-27.pdf

Oak Ridge National Laboratory. (2018). LandScan (2018)TM High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certa.

Palmer-Jones, R. (2021). Dams and Development in India: Revisiting the Evidence. In FutureDAMS & Institute of Economic Growth Workshop 27th Apil 2021.

Papaioannou, E., & Michalopoulos, S. (2013). Pre-Colonial Ethnic Institutions and Contemporary African Development. Econometrica, 81(1), 113–152. https://doi.org/10.3982/ECTA9613

Petsch, D. K. (2016). Causes and consequences of biotic homogenization in freshwater ecosystems. In International Review of Hydrobiology (Vol. 101, Issues 3–4, pp. 113–122). Wiley-VCH Verlag. https://doi.org/10.1002/iroh.201601850

Poff, L., & Hart, D. (2002). How Dams Vary and Why It Matters for the Emerging Science of Dam Removal. BioScience.

Poff, N. L., & Hart, D. D. (2002). How dams vary and why it matters for the emerging science of dam removal. BioScience, 52(8), 659–668. https://doi.org/10.1641/0006-3568(2002)052[0659:HDVAWI]2.0.CO;2

Poff, N. L., Olden, J. D., Merritt, D. M., & Pepin, D. M. (2007). Homogenization of regional river dynamics by dams and global biodiversity implications. www.pnas.orgcgidoi10.1073pnas.0609812104

Proville, J., Zavala-Araiza, D., & Wagner, G. (2017). Night-time lights: A global, long term look at links to socio-economic trends. PLOS ONE, 12(3), e0174610. https://doi.org/10.1371/journal.pone.0174610

Rai, K. (2008). The Dynamics of Social Inequality in the Kali Gandaki 'A' Dam Project in Nepal: The Politics of Patronage Introduction: Dams, development and social inequalities. Hydro Nepal: Journal of Water, Energy and Environment, 1, 22–28. https://doi.org/10.3126/hn.v1i0.881

Reddy, A. (2016). Rehabilitation and Resettlement in Tehri Hydro Power Project (Issue December 2016).

Richter, W., Vereide, K., Pikl, F. G., & Pummer, E. (2020). Economic and Sustainable Energy Transition Enabled by Pumped-Storage Hydropower Plants. 1–10.

Robbins, P., & Moore, S. A. (2013). Ecological anxiety disorder: Diagnosing the politics of the Anthropocene. In Cultural Geographies. https://doi.org/10.1177/1474474012469887

Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2022). What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature. http://arxiv.org/abs/2201.01194

Ryan, A. M., Burgess, J. F., & Dimick, J. B. (2015). Why we should not be indifferent to specification choices for difference-in-differences. Health Services Research, 50(4), 1211–1235. https://doi.org/10.1111/1475-6773.12270

Safford, T. G., Ulrich, J. D., & Hamilton, L. C. (2012). Public perceptions of the response to the Deepwater Horizon oil spill: Personal experiences, information sources, and social context. Journal of Environmental Management, 113, 31–39. https://doi.org/10.1016/j.jenvman.2012.08.022

Schulz, C., & Adams, W. M. (2019). Debating dams: The World Commission on Dams 20 years on. Wiley Interdisciplinary Reviews: Water, 6(5), 1–36. https://doi.org/10.1002/wat2.1369

Scudder, T. (2012). Resettlement Outcomes of Large Dams. In Impacts of Large Dams: A Global Assessment. https://doi.org/10.1007/978-3-642-23571-9

Scudder, T. T. (2010). Lost in development's shadow: The downstream human consequences of dams. Water Alternatives, 3(2), 14–42. https://doi.org/10.1007/s11195-009-9131-2

Shi, H., Chen, J., Liu, S., & Sivakumar, B. (2019). The Role of Large Dams in Promoting Economic Development under the Pressure of Population Growth. Sustainability. https://doi.org/10.3390/su11102965

Siciliano, G., Del Bene, D., Scheidel, A., Liu, J., & Urban, F. (2019). Environmental justice and Chinese dam-building in the global South. Current Opinion in Environmental Sustainability, 37, 20–27. https://doi.org/10.1016/j.cosust.2019.04.003

Siciliano, G., Urban, F., Tan-Mullins, M., & Mohan, G. (2018). Large dams, energy justice and the divergence between international, national and local developmental needs and priorities in the global South. Energy Research and Social Science. https://doi.org/10.1016/j.erss.2018.03.029

Sigman, H., & Olmstead, S. M. (2015). Droughts, dams, and economic activity.

Singhal, A., Sahu, S., Chattopadhyay, S., Mukherjee, A., & Bhanja, S. N. (2020). Using night time lights to find regional inequality in India and its relationship with economic development. PLoS ONE, 15(11 November). https://doi.org/10.1371/journal.pone.0241907

Smith, B., & Wills, S. (2018). Left in the dark? Oil and rural poverty. Journal of the Association of Environmental and Resource Economists, 5(4), 865–904. https://doi.org/10.1086/698512

Soukhaphon, A., Baird, I. G., & Hogan, Z. S. (2021). The Impacts of Hydropower Dams in the Mekong River Basin: A Review. https://doi.org/10.3390/w13030265

Sovacool, B., & Walter, G. (2018). Major hydropower states, sustainable development, and energy security: Insights from a preliminary cross-comparative assessment. Energy, 142, 1074–1082. https://doi.org/10.1016/j.energy.2017.09.085

Strezhnev, A. (2017). Generalized Difference-in-Differences Estimands and Synthetic Controls. https://static1.squarespace.com/static/5931baca440243906ef65ca3/t/5966ed55b8a79b4498bfa8a3/1499917654432/generalized_diff_in_diff.pdf

Sun, L., & Abraham, S. (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics, 1–25. https://doi.org/10.1016/j.jeconom.2020.09.006

Tahseen, S., & Karney, B. W. (2016). Reviewing and critiquing published approaches to the sustainability assessment of hydropower. Renewable and Sustainable Energy Reviews, 67, 225–234. https://doi.org/10.1016/j.rser.2016.09.031

Tanaka, K., & Keola, S. (2017). Shedding Light on the Shadow Economy: A Nighttime Light Approach. Journal of Development Studies, 53(1), 32–48. https://doi.org/10.1080/00220388.2016.1171845

THDC. (2017). Sustainability report 2017-18.

Tortajada, C. (2015). Dams: An essential component of development. Journal of Hydrologic Engineering, 20(1). https://doi.org/10.1061/(ASCE)HE.1943-5584.0000919

Voegeli, G., & Finger, D. C. (2021). Disputed dams: Mapping the divergent stakeholder perspectives, expectations, and concerns over hydropower development in Iceland and Switzerland. Energy Research and Social Science, 72. https://doi.org/10.1016/j.erss.2020.101872

Warner, J., Jomantas, S., Jones, E., Ansari, Md., & de Vries, L. (2019). The Fantasy of the Grand Inga Hydroelectric Project on the River Congo. Water, 11(3), 407. https://doi.org/10.3390/w11030407

Wheeler, K. G., Basheer, M., Mekonnen, Z. T., Eltoum, S. O., Mersha, A., Abdo, G. M., Zagona, E. A., Hall, J. W., & Dadson, S. J. (2016). Cooperative filling approaches for the Grand Ethiopian Renaissance Dam. Water International, 41(4), 611–634. https://doi.org/10.1080/02508060.2016.1177698

Wiejaczka, Ł., Piróg, D., Tamang, L., & Prokop, P. (2018). Local residents' perceptions of a dam and reservoir project in the Teesta Basin, Darjeeling Himalayas, India. Mountain Research and Development, 38(3), 203–210. https://doi.org/10.1659/MRD-JOURNAL-D-16-00124.1

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing Difference in Difference Studies: Best Practices for Public Health Policy Research. Annual Review of Public Health Annu. Rev. Public Health, 39, 453–469. https://doi.org/10.1146/annurev-publhealth

Wooldridge, J. M. (2016). Introductory econometrics: A modern approach. Nelson Education.

Wooldridge, J. M. (2023). Simple Approaches to Nonlinear Difference-in-Differences with PanelData. Econometrics Journal.

World Bank. (2012). Project Appraisal Document on a Proposed Credit in the Amount of SDR 85.2 Million (US$132 Million Equivalent) to the Republic of Cameroon for a Lom Pangar Hydropower Project. (Vol. 11, Issue 4). https://doi.org/10.1080/13563460600991028

World Bank. (2017). Atlas of Sustainable Development Goals 2017: From World Development Indicators. The World Bank.

World Commission on Dams. (2000). Dams and Development: A new framework for decision-making. In The Report of the World Commission on Dams (Vol. 23, Issue November). https://doi.org/10.1097/GCO.0b013e3283432017

Wu, J., He, S., Peng, J., Li, W., Zhong, & X., & Zhong, X. (2013). International Journal of Remote Sensing Intercalibration of DMSP-OLS night-time light data by the invariant region method Intercalibration of DMSP-OLS night-time light data by the invariant region method. International Journal of Remote Sensing, 34(20), 7356–7368. https://doi.org/10.1080/01431161.2013.820365org/10.1080/01431161.2013.820365doi.org/10.1080/01431161.2013.820365

Zhao, M., Cheng, W., Zhou, C., Li, M., Wang, N., & Liu, Q. (2017). GDP spatialization and economic differences in South China based on NPP-VIIRS nighttime light imagery. Remote Sensing, 9(7). https://doi.org/10.3390/rs9070673

Zhao, X., Wu, L., & Qi, Y. (2020). The Energy injustice of hydropower: Development, resettlement, and social exclusion at the Hongjiang and Wanmipo hydropower stations in China. Energy Research and Social Science, 62. https://doi.org/10.1016/j.erss.2019.101366

Zheng, Q., Weng, Q., & Wang, K. (2020). Correcting the Pixel Blooming Effect (PiBE) of DMSP-OLS nighttime light imagery. Remote Sensing of Environment, 240(February), 111707. https://doi.org/10.1016/j.rse.2020.111707

Zhu, Y., Xu, D., Ali, S. H., Ma, R., & Cheng, J. (2019). Can nighttime light data be used to estimate electric power consumption? New evidence from causal-effect inference. Energies, 12(16). https://doi.org/10.3390/en1216

# 6. Supplementary Appendices

## 6.1. Summary statistics

**Table 8. Treated and untreated site characteristics**

| Treated status | Treated | Untreated |
|---|---|---|
| Reservoir size km2 (SD) | 41 (104) | 49 (70) |
| Dam height in metres (SD) | 98 (59) | 119 (78) |
| Number of 30-arc seconds pixels per dam site | 697 | 697 |
| Number of dam sites | 102 | 43 |

**Table 9. Primary use of dams, note all are multi-purpose.**

| Main use | Treated | Untreated | Total |
|---|---|---|---|
| Flood control | 10 | 0 | 10 |
| Hydroelectricity | 70 | 32 | 102 |
| Irrigation | 18 | 9 | 27 |
| Water supply | 4 | 2 | 6 |
| **Total** | **102** | **43** | **145** |

**Table 10. Countries of treated and never-treated dam sites.**

| Country | Treated | Never-treated | Totals |
|---|---|---|---|
| **China** | 49 | 13 | 62 |
| **Vietnam** | 11 | 5 | 16 |
| **Brazil** | 9 | 2 | 11 |
| **Iran** | 7 | 8 | 15 |
| **Turkey** | 6 | 5 | 11 |
| **India** | 5 | 0 | 5 |
| **Saudi Arabia** | 3 | 0 | 3 |
| **Mexico** | 2 | 0 | 2 |
| **Argentina** | 1 | 0 | 1 |
| **Azerbaijan** | 1 | 0 | 1 |
| **Belize** | 1 | 0 | 1 |
| **Chile** | 1 | 0 | 1 |
| **Myanmar** | 1 | 1 | 2 |
| **North Korea** | 1 | 0 | 1 |
| **Oman** | 1 | 0 | 1 |
| **Pakistan** | 1 | 2 | 3 |
| **South Korea** | 1 | 0 | 1 |

| Country | Treated | Never-treated | Totals |
|---|---|---|---|
| **Tajikistan** | 1 | 0 | 1 |
| **Bolivia** | 0 | 1 | 1 |
| **Cambodia** | 0 | 1 | 1 |
| **Colombia** | 0 | 2 | 2 |
| **Indonesia** | 0 | 1 | 1 |
| **Malaysia** | 0 | 1 | 1 |
| **Venezuela** | 0 | 1 | 1 |
| **Total** | **102** | **43** | **145** |

**Table 11. Dam sites with detected lit pixels in any year, where lit pixels are considered to be above a threshold of digital number 5.**

| Country | Never-treated | Treated | Total |
|---|---|---|---|
| China | 1 | 1 | 2 |
| Turkey | 1 | 0 | 1 |
| Vietnam | 1 | 2 | 3 |
| **Total** | **3** | **3** | **6** |

**Table 12. Reservoir size in absolute terms in $km^2$ by year of construction, and treatment cohort.**

| Year of Construction | Average reservoir Size ($km^2$) | SD reservoir size |
|---|---|---|
| Post 2013 (untreated) | 49.6 | 70.5 |
| 2005 | 91.2 | 221.0 |
| 2006 | 70.9 | 126.0 |
| 2007 | 20.1 | 16.8 |
| 2008 | 16.3 | 18.2 |
| 2009 | 28.4 | 54.2 |
| Overall | 43.8 | 95.6 |

**Table 13. Panel statistics of dam sites, through the years of analysis, by treatment status. Mean number of lit pixels (where anything over digital number 5 is lit) in 15 pixels around the central dam site pixel – available pixels to be lit is 697.**

| Year of lights | Never-treated | | | | Post-treated | | | | Pre-treatment | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean (SD) | min | max | n | mean (SD) | min | max | n | mean (SD) | min | max | n |
| 2004 | 21.40 (40.32) | 0 | 189 | 43 | | | | | 20.82 (33.39) | 0 | 230 | 102 |
| 2005 | 19.67 (37.57) | 0 | 186 | 43 | 27.83 (55.54) | 2 | 201 | 12 | 17.00 (26.59) | 0 | 134 | 90 |
| 2006 | 23.81 (46.68) | 0 | 239 | 43 | 23.11 (38.91) | 0 | 192 | 35 | 15.60 (23.33) | 0 | 121 | 67 |
| 2007 | 24.67 (43.98) | 0 | 230 | 43 | 19.91 (36.24) | 0 | 221 | 55 | 20.51 (28.56) | 0 | 114 | 47 |
| 2008 | 23.88 (38.06) | 0 | 188 | 43 | 17.93 (33.74) | 0 | 212 | 75 | 31.37 (36.61) | 0 | 132 | 27 |
| 2009 | 26.72 (35.97) | 0 | 182 | 43 | 22.74 (38.71) | 0 | 229 | 102 | | | | |

**Table 14. Panel statistics of years of analysis by treatment status. The response variable is the natural log of the number of lit pixels within 15 pixels of the central dam site pixel[12].**

| Year | Never-treated | | | | Post-treated | | | | Pre-treatment | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean (SD) | min | max | n | mean (SD) | min | max | n | mean (SD) | min | max | n |
| 2004 | 1.93 (1.61) | 0 | 5.25 | 43 | | | | | 2.34 (1.26) | 0 | 5.44 | 102 |
| 2005 | 1.89 (1.55) | 0 | 5.23 | 43 | 2.52 (1.17) | 1.1 | 5.31 | 12 | 2.17 (1.20) | 0 | 4.91 | 90 |
| 2006 | 1.93 (1.69) | 0 | 5.48 | 43 | 2.48 (1.14) | 0 | 5.26 | 35 | 2.13 (1.19) | 0 | 4.80 | 67 |
| 2007 | 2.18 (1.58) | 0 | 5.44 | 43 | 2.21 (1.31) | 0 | 5.40 | 55 | 2.31 (1.29) | 0 | 4.74 | 47 |
| 2008 | 2.32 (1.47) | 0 | 5.24 | 43 | 2.05 (1.34) | 0 | 5.36 | 75 | 2.84 (1.22) | 0 | 4.89 | 27 |
| 2009 | 2.55 (1.42) | 0 | 5.21 | 43 | 2.16 (1.49) | 0 | 5.44 | 102 | | | | |

**Table 15. Treatment and control means of response variable – the natural log of the sum of lit cells in the area 15km around the cell.**

| Treated status | Mean | Standard error |
|---|---|---|
| Treated | 2.25 | 0.05 |
| Control | 2.13 | 0.10 |

Figure 3 shows some of the dam sites had 0, or no measured light, in the area around the dam – 26 out of 145 in 2009. Table 11 shows which countries had sites that had no lit cells within 15km of the dam, for treated and never-treated groups in all years. It is unlikely that these sites truly had no light within them between 2004 and 2009. Therefore, it suggests the sensitivity of the satellite night lights is low, but not, I argue, unuseful to investigate my topic given light was detected in 139 dam sites.

[12] A constant of 1 is added prior to logarithm calculation as ln(0) is an undefined number.

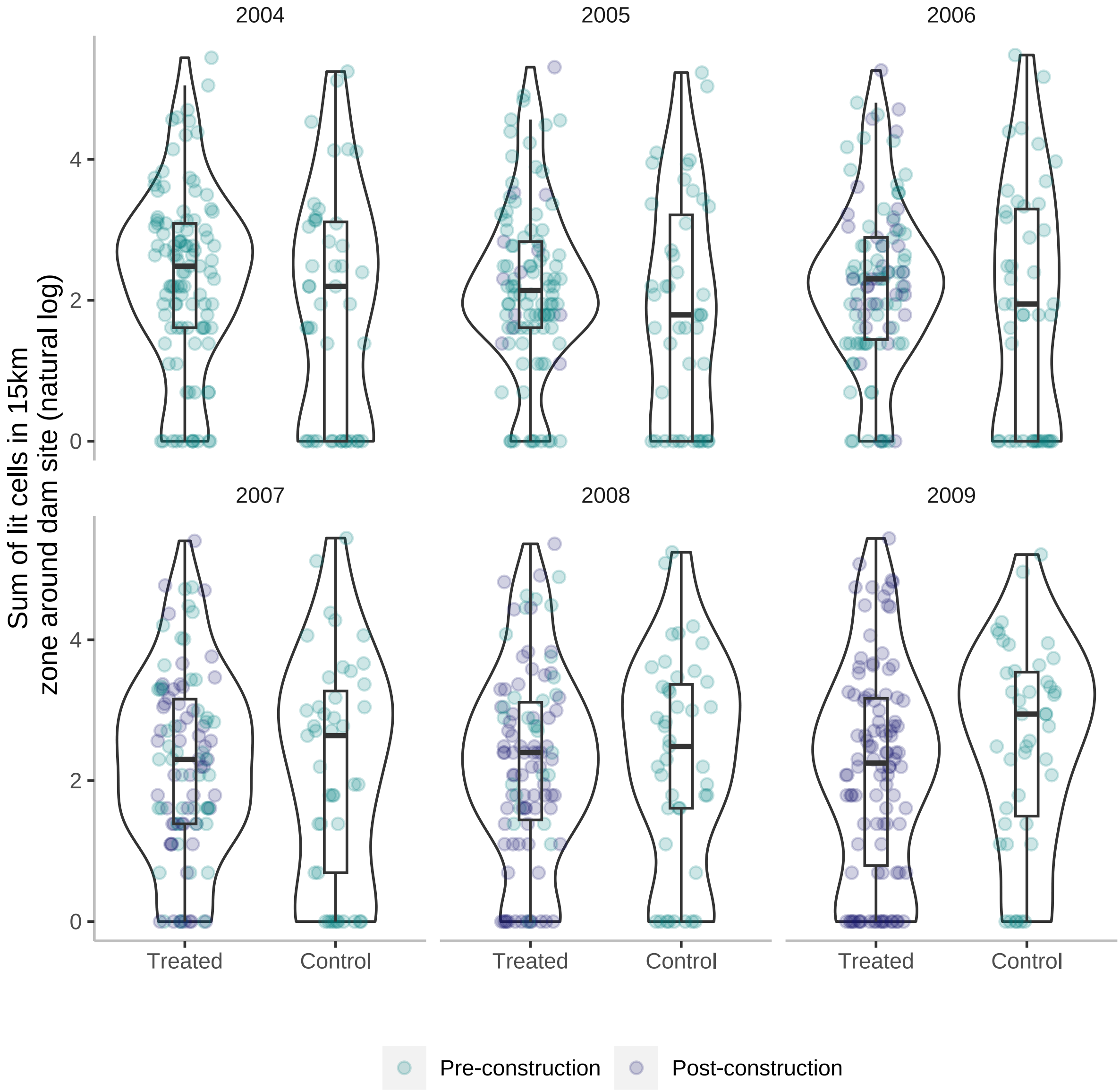



**Figure 3. Violin plot comparison of treated and control sites using the natural log of the number of lit cells within 15km of a dam - the response variable used in the main model. Data points within treated sites are differentiated based on whether or not the dam has been or is yet to be constructed, which is part of the identification strategy of the main model. Outer lines represent the kernel density – the density of the data at that point on the y axis, internal straight lines represent the median and interquartile range.**

## 6.2. Night Time Light Satellite overlaps

There were six satellites within the Defence Meteorological Satellite Program - F10, F12, F14, F15, F16, F18.  Some satellites orbited concurrently, therefore a researcher using this data to investigate night lights must choose between discarding or combining overlapping data.

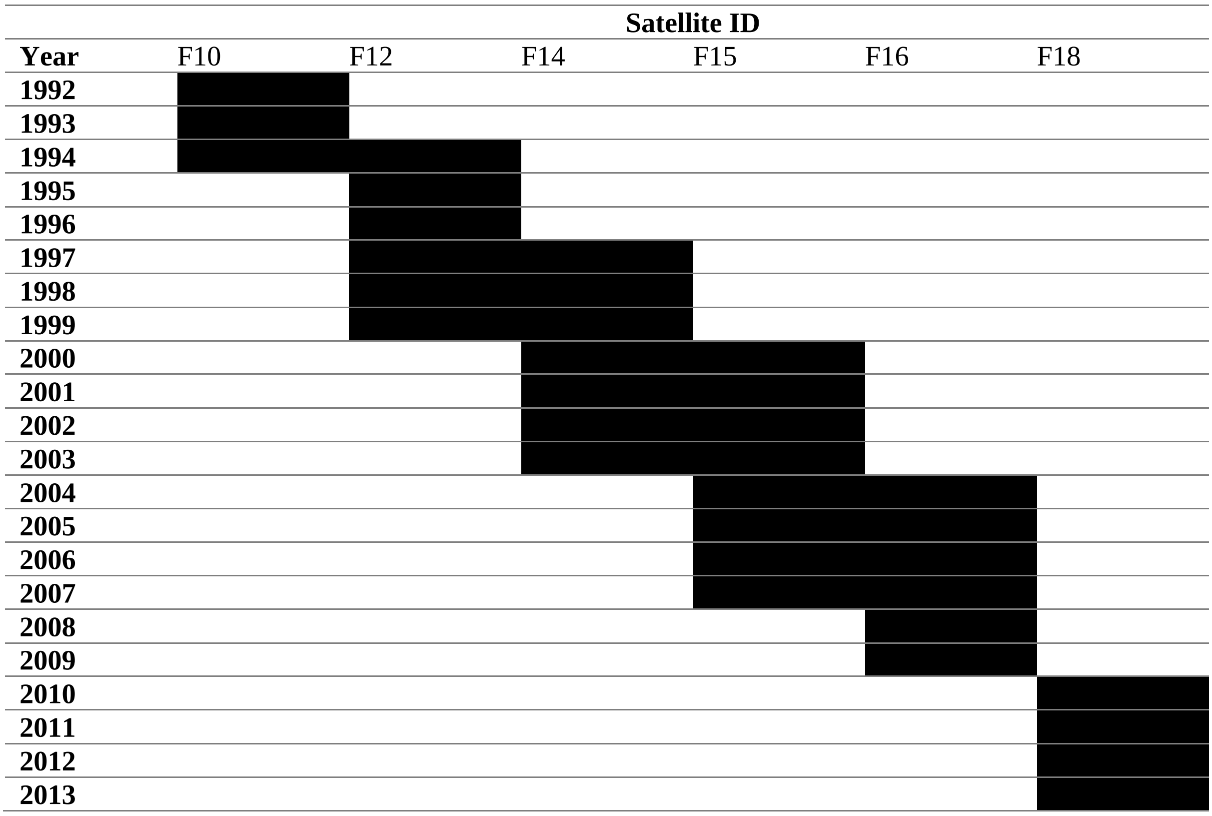



**Figure 4. Years captured by different Defense Meteorological Satellite Program satellites.**

Gibson et al. (2021) stress that despite being used widely in econometric studies, the raw DMSP data is blurred. Three approaches exist in the literature to address the blurring: Abrahams (2018), Zheng (2020) and Cao (2019). I follow the Abrahams paper which was released with a script on GitHub (Abrahams, 2018). As the datasets used in this analysis cover a large geographic region, it was necessary to employ a High-Performance Computing suite which significantly increased processing speed. Only an area of 200 km around the dam sites was deblurred, as a computational economy. Three geographies were deblurred separately as a further economy and then combined, the impact of deblurring is shown in Table 16.

The deblurring process applies two filters. A lens viewing a point source of light expands it into a broader area, and a similar effect occurs when the satellite detects light sources on Earth through the atmosphere. The first filter removes this effect which is a symmetric Gaussian light point-spread phenomenon. The second filter adjusts the Gaussian point-spread size. The light point-spread phenomenon is inconsistent across geographies, satellites and years, and the second filter calibrates and corrects the symmetric Gaussian point-spread for that particular region. For further details, see Abrahams (2018) and the source code on Github (Abrahams, 2018).

**Table 16. The sum of lights, means and distributions from the three geographic regions of satellite F16 that were deblurred for this study. In Appendix** Error! Reference source not found.**, I compare the specific maps before and after deblurring.**

| | **Africa/Europe deblurred** | | **Asia/Australasia deblurred** | | **South America deblurred** | | **Combined deblurred** | | **Blurred** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | Sum of Lights | Mean (SD) | Sum of Lights | Mean (SD) | Sum of Lights | Mean (SD) | Sum of Lights | Mean (SD) | Sum of Lights | Mean (SD) |
| **2004** | 12,401,088 | 1.6 (11.8) | 23,622,482 | 1.7 (11.8) | 11,419,664 | 1.6 (12.3) | 47,443,234 | 1.7 (11.9) | 52,875,175 | 1.9 (6.2) |
| **2005** | 11,171,652 | 1.5 (11.1) | 19,835,048 | 1.5 (10.5) | 10,110,952 | 1.5 (11.3) | 41,117,652 | 1.5 (10.9) | 45,901,986 | 1.6 (5.7) |
| **2006** | 13,249,118 | 1.8 (12.7) | 23,138,441 | 1.7 (11.9) | 11,743,208 | 1.7 (12.8) | 48,130,767 | 1.7 (12.4) | 52,813,284 | 1.9 (6.4) |
| **2007** | 14,473,572 | 1.9 (13.1) | 26,096,621 | 1.9 (12.5) | 12,546,494 | 1.8 (13.4) | 53,116,687 | 1.9 (12.9) | 61,348,983 | 2.2 (6.8) |
| **2008** | 14,698,471 | 1.9 (13.2) | 26,639,602 | 2 (12.6) | 12,508,152 | 1.8 (13.5) | 53,846,225 | 1.9 (13.0) | 59,124,925 | 2.1 (6.8) |
| **2009** | 14,253,846 | 1.9 (13.2) | 26,489,244 | 2 (13.0) | 12,859,904 | 1.9 (13.7) | 53,602,994 | 1.9 (13.3) | 54,362,682 | 1.9 (6.7) |

Deblurring the NTLs transforms it by restacking pixels which blend into adjacent pixels. To avoid further artefacts from this transformation, I use “lit” or “unlit” pixels as my response variable, based on a threshold of digital number 5. This means that I am less beholden to the aberrations in specific pixels, which skew the data, with high sum values above 63 generated by the deblurring script.

Some authors apply inter-calibration formula after deblurring (Ch et al., 2021), however, as noted by those authors, the satellite inter-calibration methods available from the literature are based on equations for the blurred values. Therefore, I believe the deblurred values are unsuitable for satellite annual inter-calibration methods in the literature (Hsu et al., 2015; Wu et al., 2013). Notably, the inter-calibration issue for satellite F15 is particularly acute for the years 2000-2002, light intensity for those years is noticeably higher than from 2003 to

2007 (C. Elvidge et al., 2014, p. 104). While F15 would have been a preferable dataset to work with over satellite F16 regarding its more extended time series, it was not in terms of the potential bias introduced by this calibration issue.

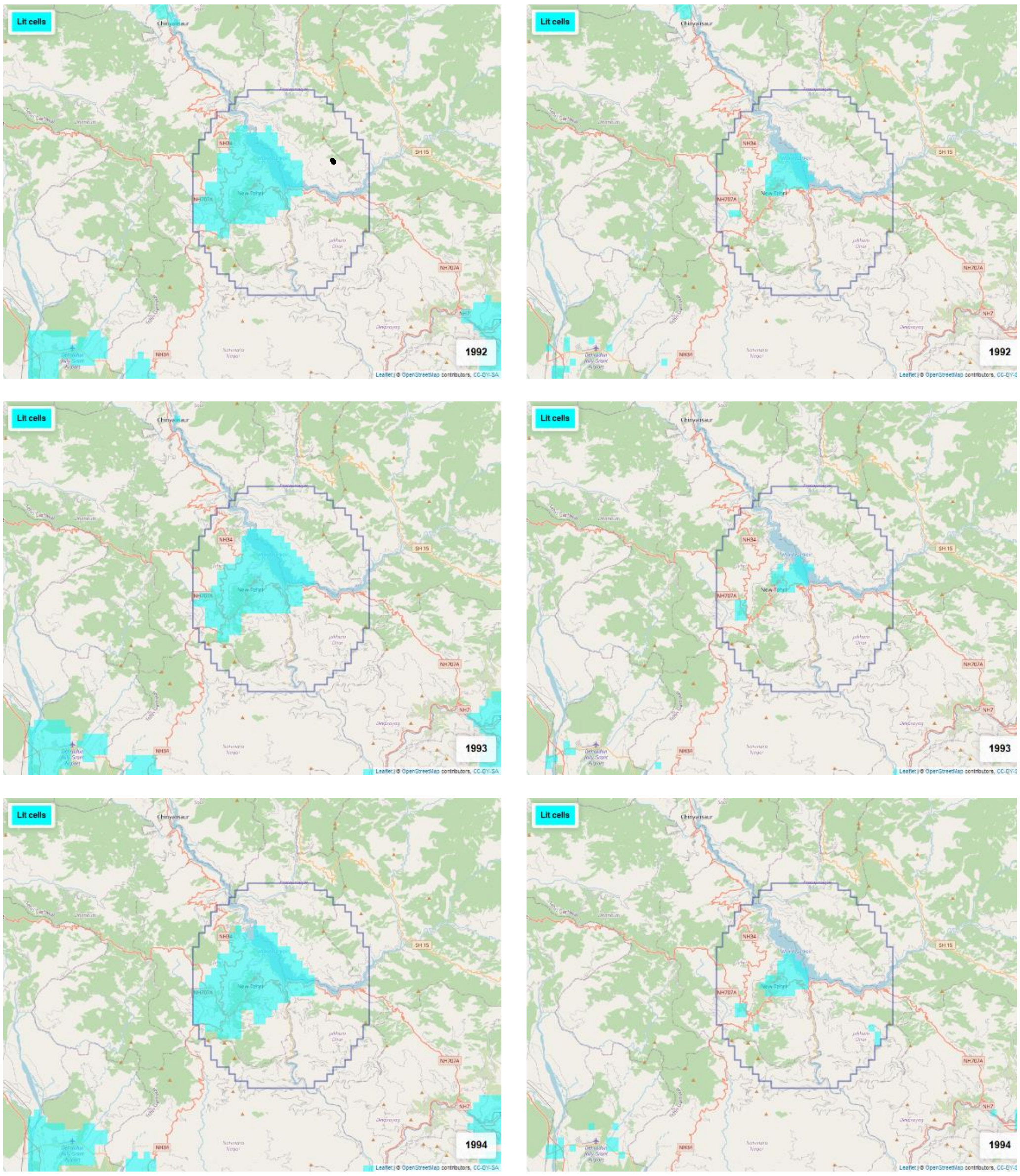
**Figure 5. The impact of deblurring on the area immediately around the Tehri reservoir for each year, using the approach described in Abrahams (2018). Pixels are blue and "lit" if they exceed or equal to 5 digital numbers.**

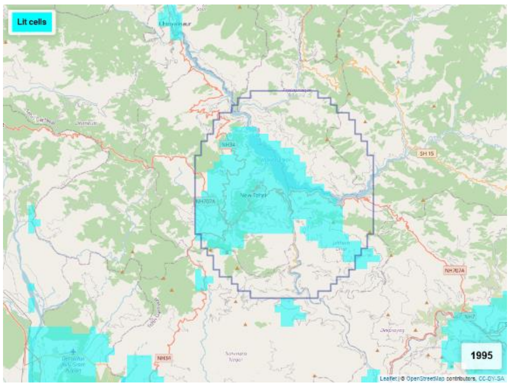
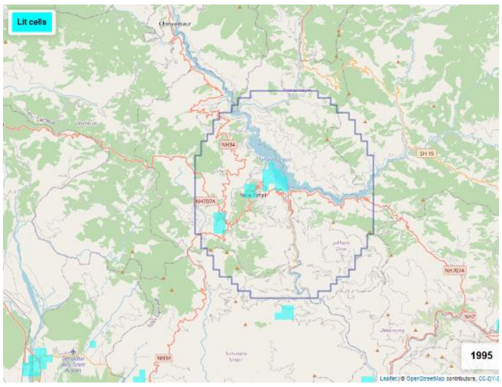
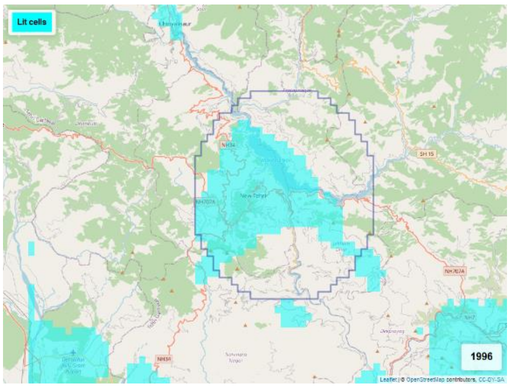
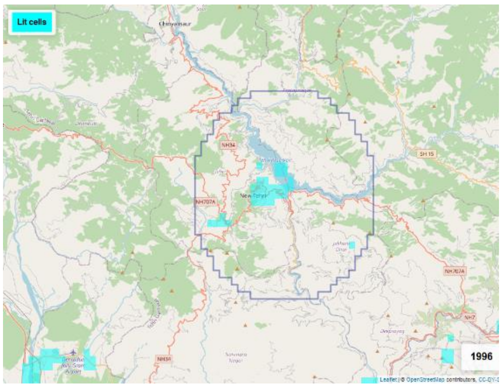
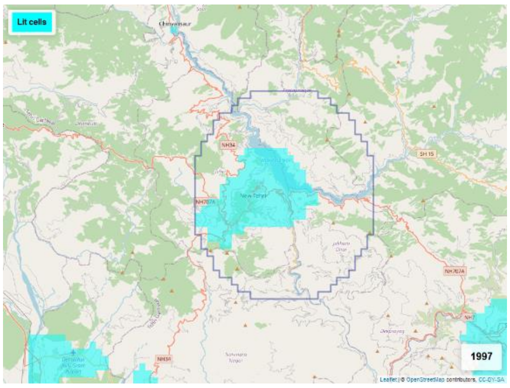
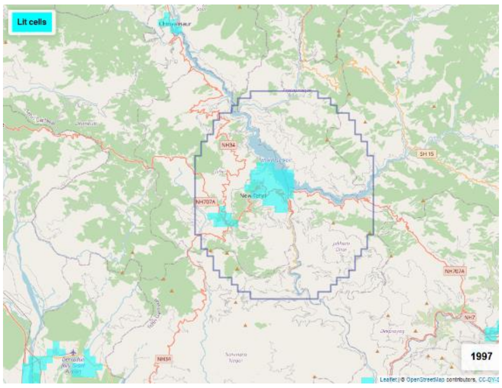
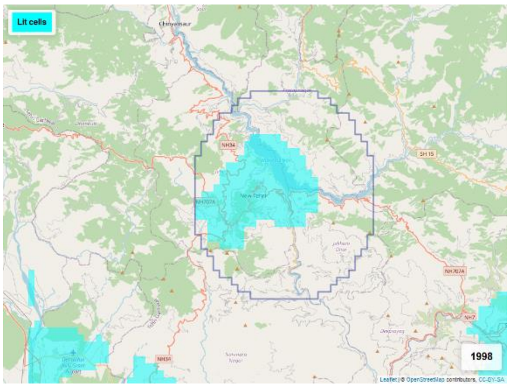
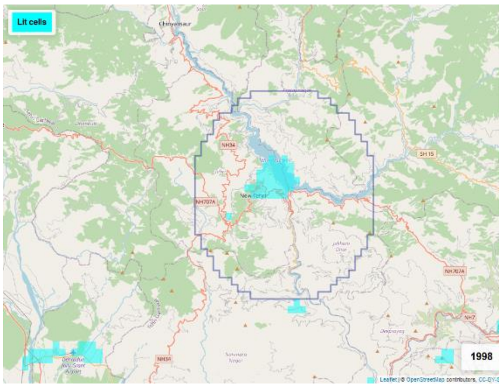
**Blurred images** **Deblurred images**

1992

1993

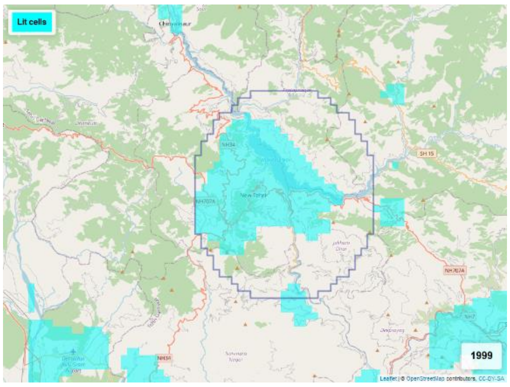
1994

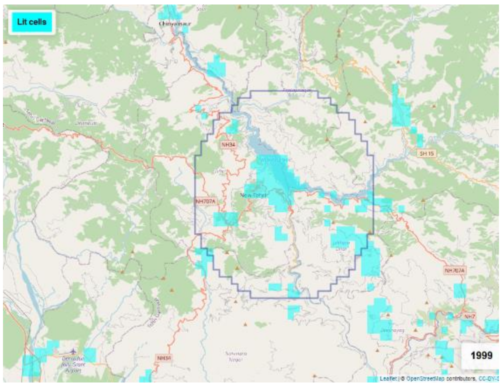


| | **Blurred images** | **Deblurred images** |
|---|---|---|
| 1995 |   |   |
| 1996 |   |   |
| 1997 |   |   |
| 1998 |   |   |

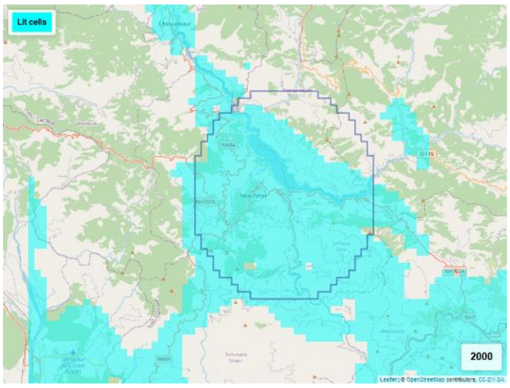
**Blurred images** | **Deblurred images**

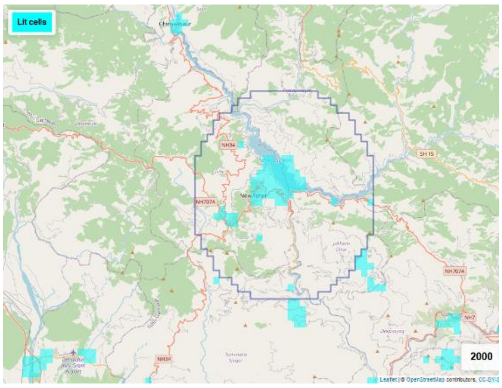
1999



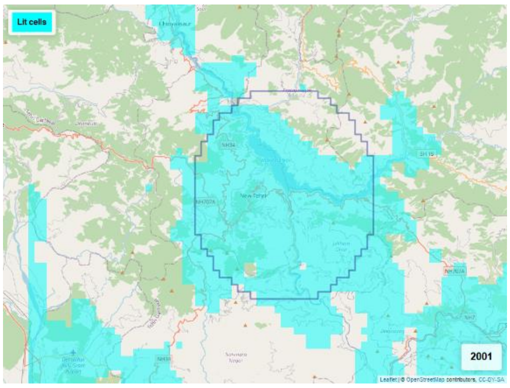



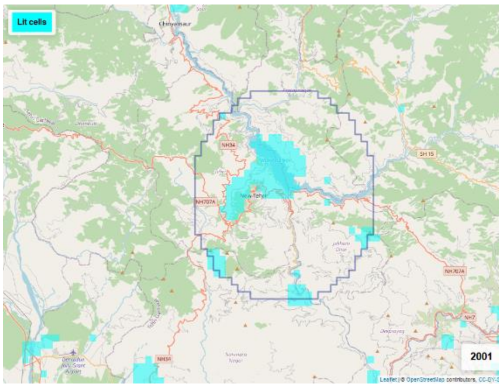

2000



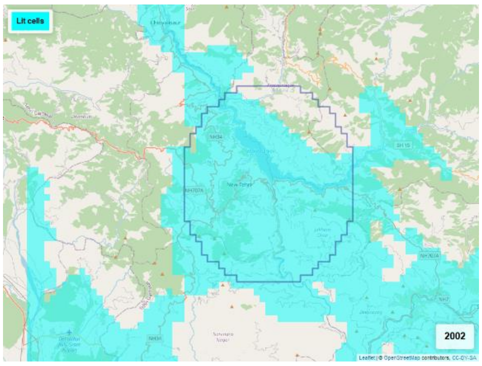



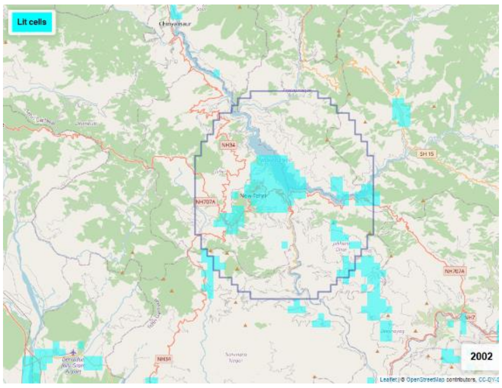

2001



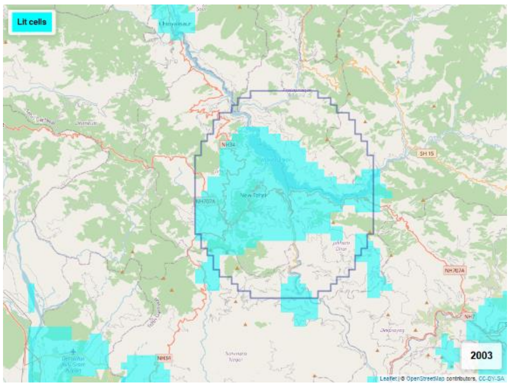

2002

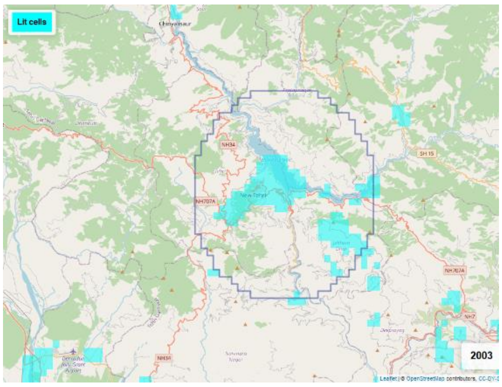


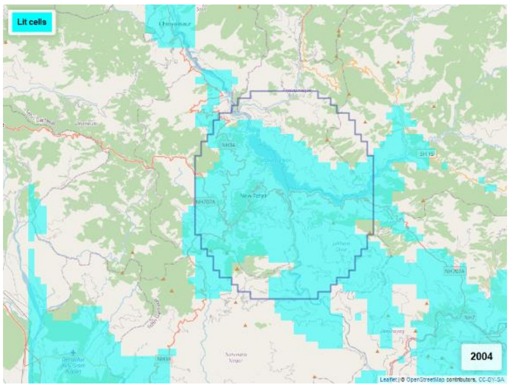
**Blurred images** | **Deblurred images**

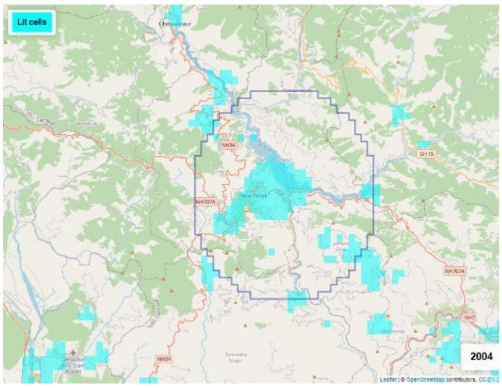
2003



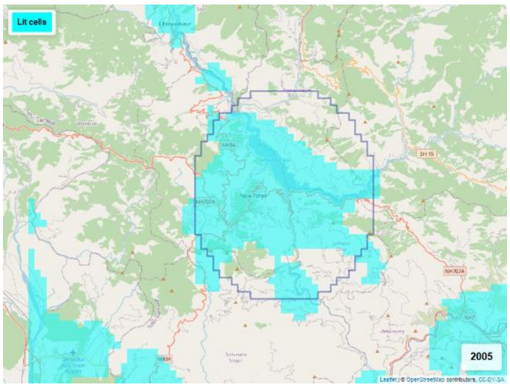



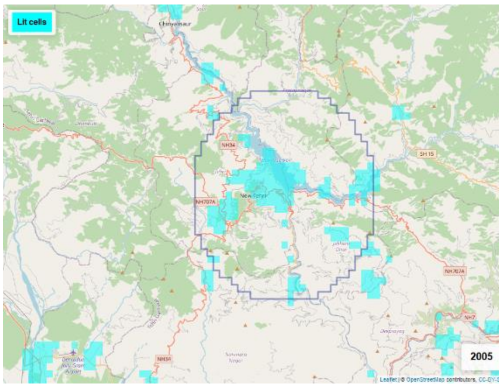

2004



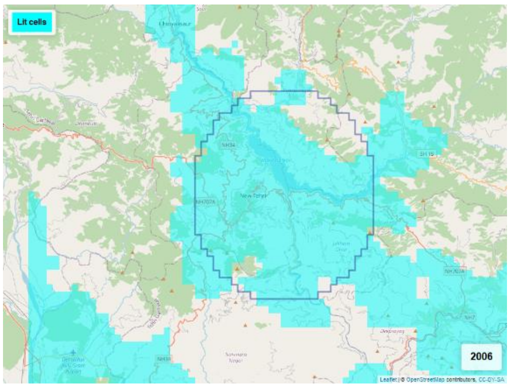



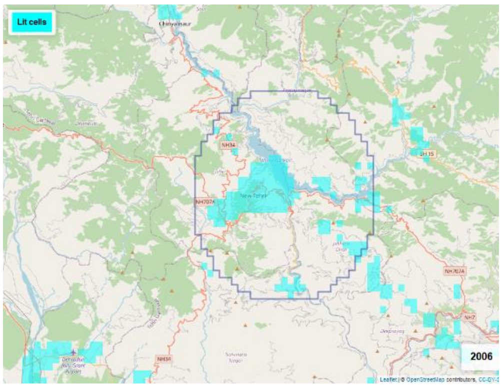

2005




2006



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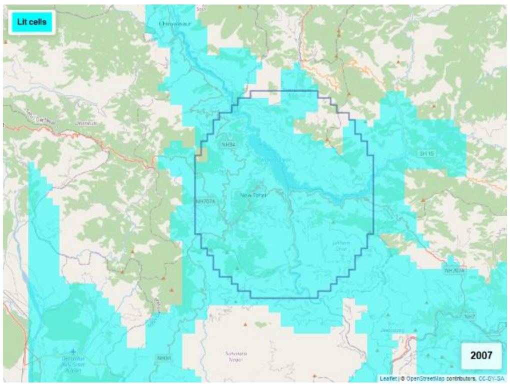
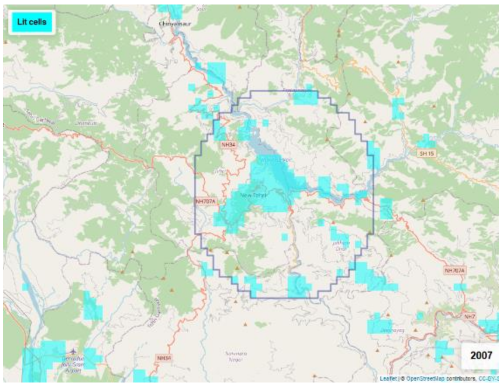
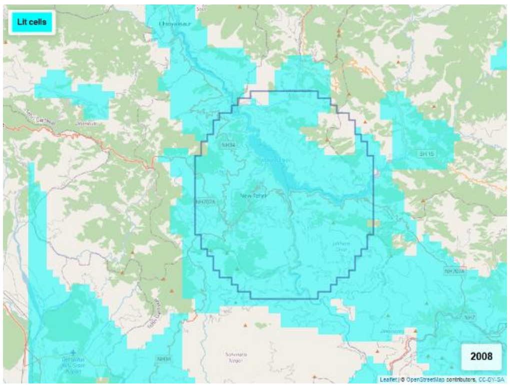
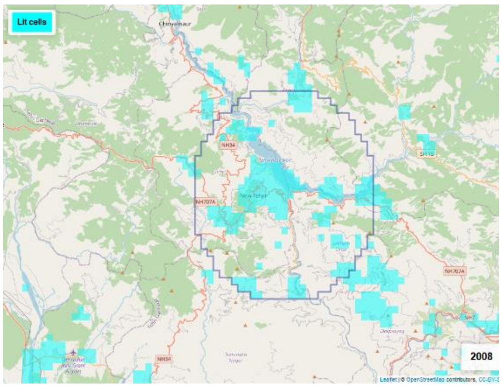
2007



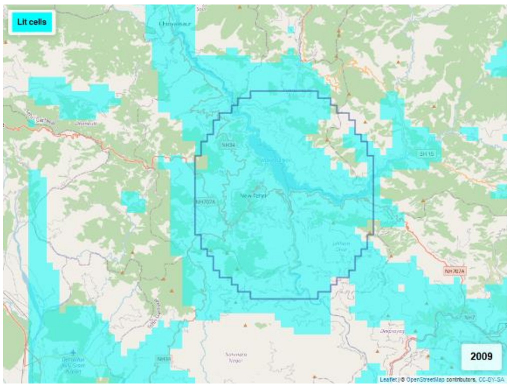



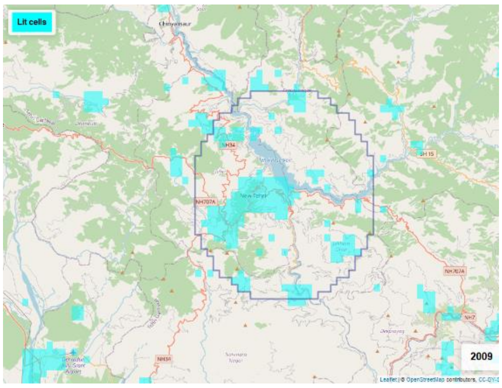

2008



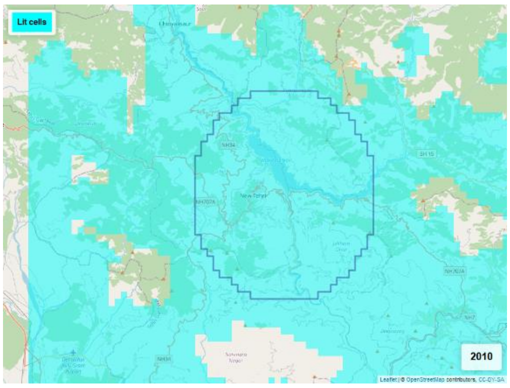



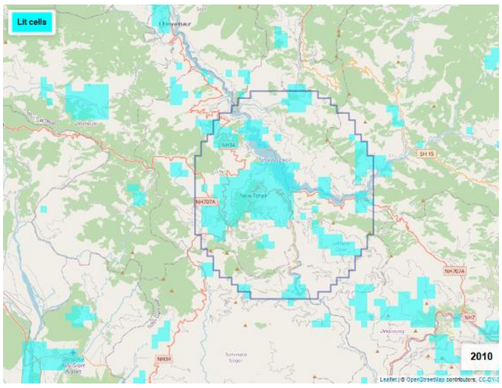

2009




2010



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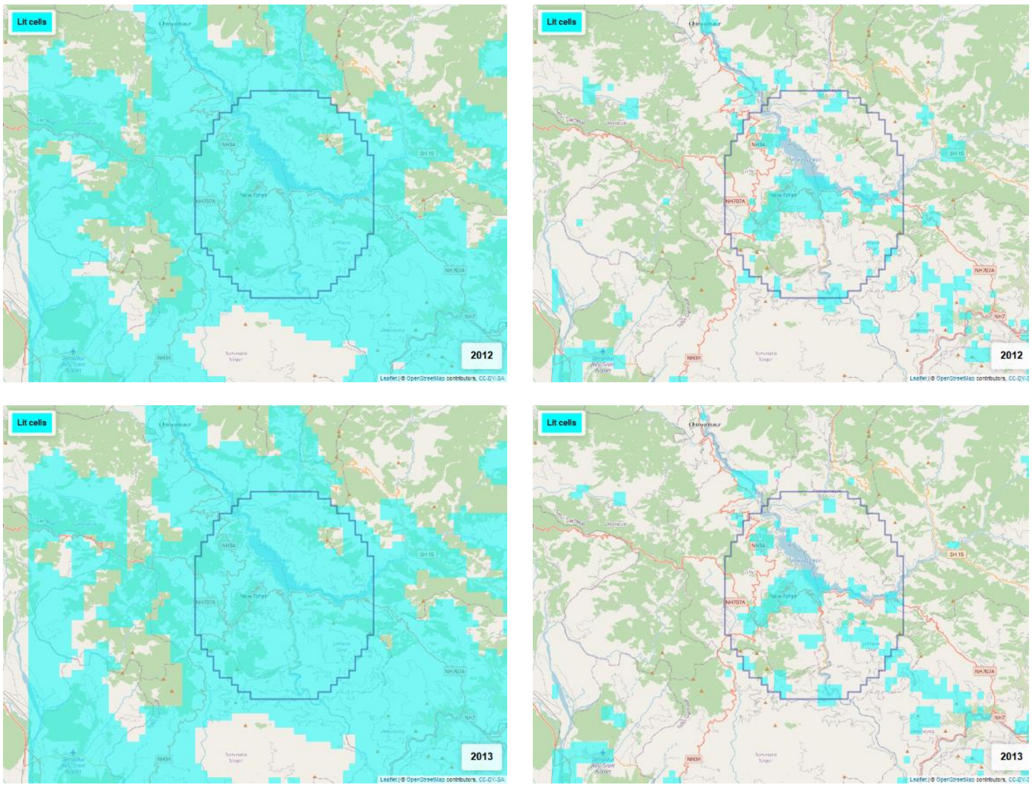
2012 *

2013




***Note that due to the percentage cloud cover data being missing for 2011, it was not possible to deblur the year 2011. As a result, it is missing from this figure (Earth Observation Group, 2023).**

## 6.3. Creating zones of investigation around dam locations

Previous studies have used administrative boundaries as the limit of their zone of influence around a dam (de Faria, 2016; Duflo and Pande, 2007; Sovacool and Walter, 2018). A weakness of this approach is that there may be intra-provincial and certainly intra-national variations in dam impact. Further, rivers may make up administrative borders, complicating analysis when dams are between two counties or districts used as units of aggregation for socio-economic data.

The 1992-2013 NTL are available as GeoTIFFs with a resolution of 30-arc seconds, although Gibson et al. (2020, p. 20) suggest that the accurate and appropriate resolution of DMSP night lights data would be 25 $km^2$ given geolocation errors and how the data is smoothed and processed onboard the satellite. Unlike studies which use administrative boundaries by necessity, those employing NTL need to define the area of investigation. There is no internationally recognised zone of influence around a dam in the Global South, although there are national definitions, such as the "command area" in India (Kumar and Shivasharanappa, 2014). The zone of influence is likely related to the dam's functions, i.e., irrigation or hydropower. Based on interviews, I chose a 15 cell buffer around each dam site (Figure 7), equating to approximately 706 $km^2$ circles of investigation.

Dam sites overlapped in the sample given their locations once 15 cells were considered on all sides of the dam site point. Therefore, I had to exclude some dams from the sample. This meant the final sample was smaller than total number of dam sites eligible. The dams excluded due to overlap were chosen randomly by a script run in GRASS GIS (GRASS Development Team, 2017) – see Figure 7.

As a robustness check, I also consider pixel radii of 5, 10, 30 and 50 (Figure 7), allowing an investigation of how the impact of distance on dam impacts.

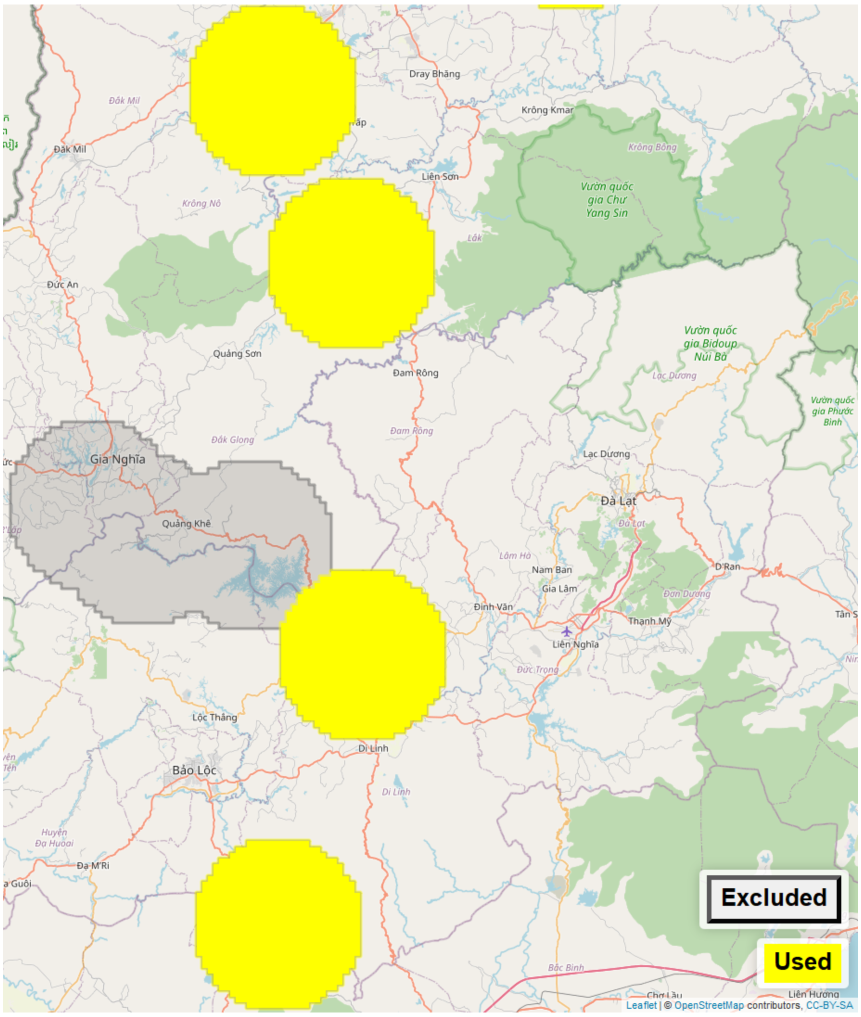



**Figure 6. If dam sites were within 30 pixels of each other, then only one per group would be included in the analysis. This figure shows a region in Viet Nam, and dam sites considered for inclusion are highlighted in yellow, those sites within 30 km of each other outlined in black were excluded.**

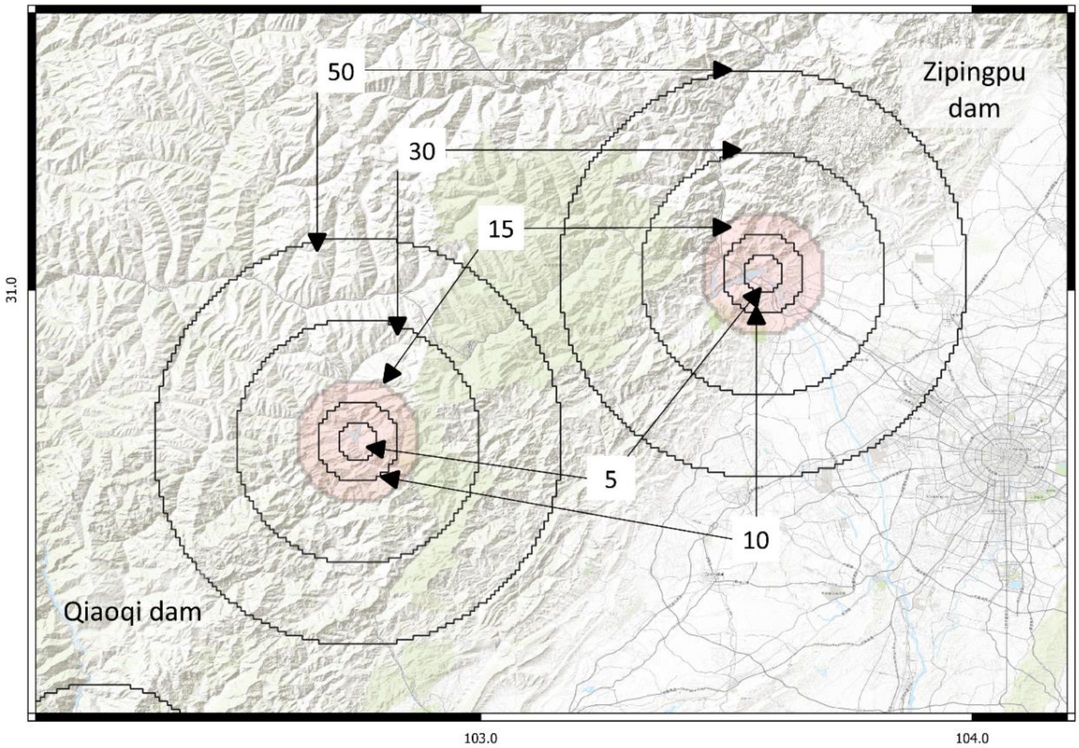



**Figure 7. Illustration of the different pixel numbers around two dam sites in China (Zipingpu and Qiaoqi). The pink area is 15 pixels around the dam site, forming the main model. Chengdu city is visible in the Eastern corner.**

## 6.4. Log transformation of Night-Time Light data

Researchers can derive multiple potential socio-economic indicators from the NTL dataset, for example, sum of NTL intensity, inequality by combining the NTL data with population datasets (Gibson et al., 2020) or a comparison of unlit/lit pixels. In their paper on pre-colonial Institutions and post-colonial development Papaioannou and Michalopoulos (2013) did not find coefficients with opposite signs when employing NTL intensity or lit/unlit pixels as response variables in their investigation of development and pre-colonial institutions. However, the effect size was different between the two response variables.

Prior to deblurring, NTL intensity ranges from 0-63 digital numbers, but deblurring increases the range from 0-239, as NTL from overglow is reassigned (stacked) from adjacent pixels to the pixels from which the light came see Abrahams et al. (2018) for a discussion. Using nighttime light intensity would skew my interpretation, as the range of digital numbers is not constant between years after deblurring. Therefore, following Smith and Wills (2018) and Gibson (2019; 2015) I identify the number of "lit" pixels in my area of interest. I consider the pixel 'lit' if it has an NTL intensity of 5 digital numbers or more.

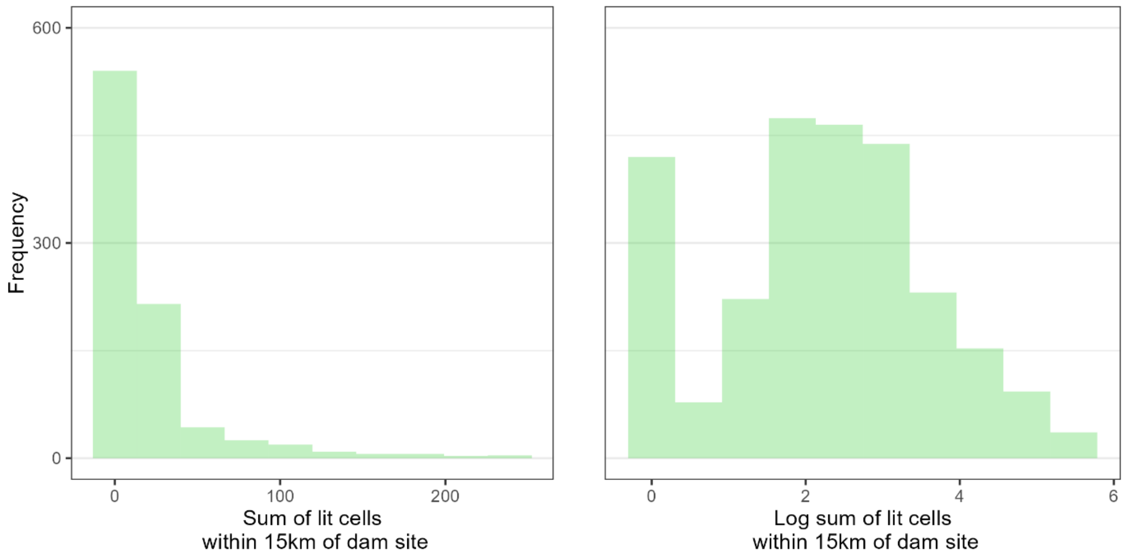



**Figure 8. Comparison of untransformed data – sum of lit cells in 15 km - and transformed natural log sum lit cells across all treated and untreated sites. To avoid log(0), a constant of 1 is added to all site values before the logarithm is derived.**

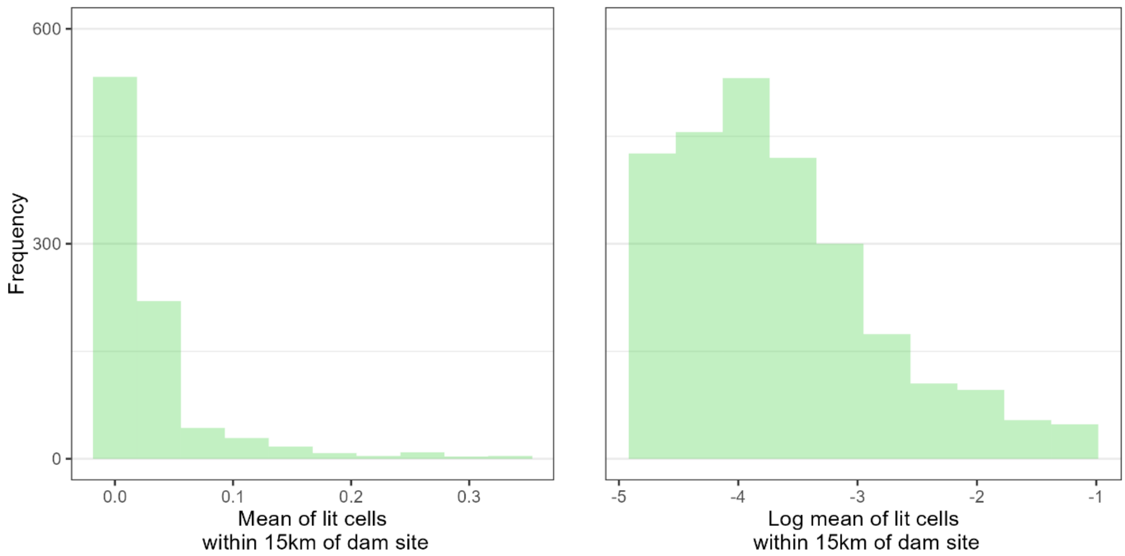



**Figure 9. Comparison of untransformed data – mean of lit cells in 15 km - and transformed natural log mean lit cells across all treated and untreated sites. To avoid log(0), a constant of 0.01 is added to all site values before the logarithm is derived.**

However, lit pixels in my sample are not normally distributed, therefore, I transform the response variable with a natural log prior to use (see Figure 8). There are dam sites with no recorded lit cells, which have a value of 0. As the logarithm of 0 is undefined, I add 1 to all dataset values, following Baskaran (2015).

For the model set up where the reservoirs were masked and excluded from the analysis, I changed the response variable from a sum of lit cells to the mean of lit cells, as the number of cells considered in the sum within 15 km would be different once the reservoirs were excluded. I took the natural log of the mean and added a constant of 0.01 to address 0 as an undefined number. The transformed mean data (Figure 9) is not as close to a normal distribution as the transformed sum (Figure 8) and is a less desirable response variable.

## 6.5. Potential treatment endogeneity

My identification strategy selects similar treated and never-treated sites in this natural experiment. However, there are potential sources of endogeneity within the treatment group linked to the temporal nature of that identification strategy. Dam sites constructed earlier may be different to those constructed later.

For example, dam sites with low population density may be developed first, as they receive fewer objections on a social basis. Policies to improve the negative impacts of large dams may also be developed in response to past poor experiences around large dam construction and have far-reaching consequences (Archsmith, 2017). In 2000, the World Commission on Dams released its report with the ambition of improving social and environmental issues around large dams; this may have caused a gradual policy shift, although scholars note that it was not widely adopted (Schulz & Adams, 2019).

To investigate whether population density was different between treated and untreated sites, I compared the mean population density in 2004 in Table 17 using the LandScan dataset (Oak Ridge National Laboratory, 2018). Unlike many satellite-derived population datasets, LandScan does not use NTL as an input (C. Elvidge et al., 2009). Mean population density is similar in treated and untreated sites. While some sources of potential endogeneity can be investigated, such as population size, others, such as policy shift, will not, meaning any casual claims should be made with caution.

**Table 17. Mean population density in year 2004 of the treated and never treated dam sites, derived from the LandScan dataset (Oak Ridge National Laboratory, 2018).**

| Treatment Status | Mean population density (standard error) | Number of dam sites |
|---|---|---|
| Never treated | 68.8 (24.4) | 43 |
| Treated | 64.0 (6.8) | 102 |

## 6.6. Equations for aggregating effects

The Callaway and Sant'Anna (CS) estimation for difference in differences (DiD) is both intuitive and complex. DiD should compare the difference in pathways between treated groups and control groups (which are untreated). Under DiD assumptions, it is possible to estimate the difference in pathways and therefore the treatment effect, if there are only two time periods with the canonical DiD Two-Way Fixed Effects regression, but when there are multiple time periods this method considers already treated groups as controls, which is intuitively wrong, and has been shown to diminish or reverse estimands of the treatment effect (Caetano & Callaway, 2023; Callaway, 2022; Callaway & Sant'Anna, 2021; Cunningham, 2020; Zeldow et al., 2023).

CS corrects for this and other criticisms but the underlying equations for the assumptions, control groups and aggregations involve complex notation, those pertinent to the study I give here, a full explanation and relevant notation is in Section 3 of Callaway and Sant'Anna (2021).

My identification assumption assumes that treated and control sites will have similar pathways in the absence of treatment.

Equation 1

$$ATT = (\ Yt = 1, D = 1\ -\ Yt = 0, D = 1) - (Yt = 1, D = 0\ -\ Yt = 0, D = 1)$$

Equation 1 expresses this expectation. $ATT$ is the average treatment effect for the treated, and $Y$ the response variable. $t$ is the time period and $D$ is the treatment status, 0 is untreated and 1 is treated. This expectation would be violated if dam sites constructed earlier differed from those constructed later, as this is the basis of my identification strategy for control and treatment groups.

For example, one might expect dams' socio-economic impact to be greater in earlier years while rural areas have less electricity (World Bank, 2017). This would suggest that dams constructed in 2005 might have a larger treatment effect when compared to those constructed in 2007. In addition, dam sites with low population density may be developed first, as they receive fewer objections even as they impact the most marginalised. Finally, policies to improve the negative impacts of large dams may also be developed in response to past poor experiences around large dam construction and have far-reaching consequences (Archsmith, 2017). These potential sources of treatment endogeneity are discussed and explored in Appendix 6.6.

For the CS approach, I employ standard potential outcome notation to describe my set-up (Baker et al., 2021; Gilpin et al., 2021) with multiple treatment timings $G$ and multiple treatment periods $T$. As the CS approach investigates the group treatment effect, a group in my study is defined as the time-period in which dam sites were constructed, for example, all dam sites constructed in 2005 would be considered in group $g$ 2005, all dams sites treated in 2006 group $g$ 2006 and so on. For each group $g$, in each time period $t$, we can recover the group time ATT denoted as $ATT(g, t)$ when $C$ is the never-treated group (Callaway & Sant'Anna, 2020; Gilpin et al., 2021):

Equation 4

$$ATT(g, t) = [\mathrm{Y(g)t} - \mathrm{Y(C)t}] - [\mathrm{Y(g)(g-1)} - \mathrm{Y(C)(g-1)}]$$

Note this is similar to how one would calculate the difference in pathways for a DiD with two time periods, only it is limited to one treatment year $g$, and never treated units $C$.

There are three steps to estimating $ATT(g, t)$: first, the optional calculation of the propensity scores for matching control and treatment groups using time-invariant covariates; second, the calculation of an individual ATT for each pairwise combination of time-period and treatment period using the fitted values from the first step (Equation 2); and, finally, aggregation of these pairwise combinations, for which there are multiple possible aggregations for different purposes – group ATT (Equation 5), overall ATT (Equation 6) and event-study style coefficients (**Error! Reference source not found.**). Calculation of standard errors is done by the recommended (Gilpin et al., 2021, p. 13) multiplier-type bootstrap, clustered on individual dam sites – the modalities of this are discussed in Callaway (2021, pp. 214–215). All these steps are automated in the DiD R package (Callaway & Sant'Anna, 2021).

Equation 4 produces an average treatment effect for each group in each year. This can make interpretation convoluted when the research question of interest is more generic, i.e. how do dams impact economic activity in the area around the dam. In order to aggregate the effect I use the following for each group cohort, i.e. dams constructed in 2005, 2006, 2007, 2008 and 2009:

Equation 5

$$\theta_S(g) = \frac{1}{T - g + 1}\sum_{t=2}^{T} 1\{g \leq t\} ATT(g, t)$$

where $\theta_S(g)$ is the parameter of interest, the treatment effect of each group $g$. The term $\frac{1}{T-g+1}$ weights each average treatment effect for a group and time-period given by $ATT(g, t)$, which are summed when the group is less than or equal to time $t$, given by the term $1\{g \leq t\}$. Consider the dam group constructed in 2009. The weight assigned to this group in the year 2009 is 1 – and 0 in all other time-periods. Meanwhile, the group of dams constructed in 2005 will comprise θ of five weighted $ATT(g = 2006, t)$.

This allows the investigation of whether or not there is a different trend depending on the year the dam was constructed. A priori, I do not expect to see a difference between groups of dams constructed in different years. Therefore, estimating each group individually is a helpful robustness check.

$\theta_S(g)$ forms the basis of a single aggregator used to look at the overall impact of dam construction.

Equation 6

$$\theta_S^{O} = \sum_{t=2}^{T} \theta_S(g) P(G = g)$$

$\theta_S^{O}$ aggregates the ATT of each group, based on the probability $P$ that the dam site belongs to the treatment group. The number of dam sites by year of construction is given in Table 19. This parameter gives an overall estimate of the impact of dam construction on economic activity in response to the research question.

Event-study style presentations of DiD help infer whether the ATT is constant or dynamic over time. De Faria (2017) found that the impact of dams on socio-economic activity changed over time, and therefore I can assume that this warrants investigation. Callaway (2021) provides an estimator for this (Equation 1), which overcomes the anomalies identified by Goodman-Bacon (2020) and Baker (2021), while also estimating whether the treatment effect attenuates or strengthens over time.

## 6.7. Parallel trends

The difference-in-difference identification strategy assumes that if a dam site had not been treated in time $g$ , or a dam had not been constructed, then the outcome would be the same as the trends seen in the control dam sites, where no dam was constructed but a dam is planned and is yet to be constructed.

Roth et al. (2022) discuss the limitations of relying simply on observations of parallel trends, as it is not possible to compare that parallel trends would have occurred had the sites not been treated. Further, Sun (2020) discusses that the typical event-study approach may suffer when treatment timing is selected in medical studies, when those who have the most to benefit from a treatment might apply first. This kind of systematic bias in treatment timings may occur in dam construction, where depopulated areas are less likely to experience delays to construction due to an absence of protest and likely to experience the greatest uptick in economic activity if they were previously depopulated.

**Table 18. Wald statistic p-values to reject parallel trends test of all models.**

| Model | p-value | Size of treated group | Size of untreated group |
|---|---|---|---|
| With conditioning on co-variates (main model) | 0.31 | 102 | 43 |
| With two years of anticipation of treatment effect | 0.56 | 102 | 43 |
| Without the year 2004 | 0.68 | 90 | 43 |
| | | | |
| Dams with bottom 50th centile reservoirs | 0.33 | 58 | 14 |
| Dams with top 50th centile reservoirs | 0.00 | 44 | 29 |
| Reservoir areas masked | 0.37 | 102 | 43 |

The evidence I have to support the parallel trends assumption is the Walds statistic from estimating the group-time average treatment effects in the Callaway package (Callaway & Sant'Anna, 2021) and inspection of the pre-treatment trends in the groups in Figure 1. As summarised in Table 18, all variations of the main model show that we fail to reject the parallel trends hypothesis except for the investigation of large reservoirs.

## 6.8. Disaggregated results from group-specific average treatment effect on the treated

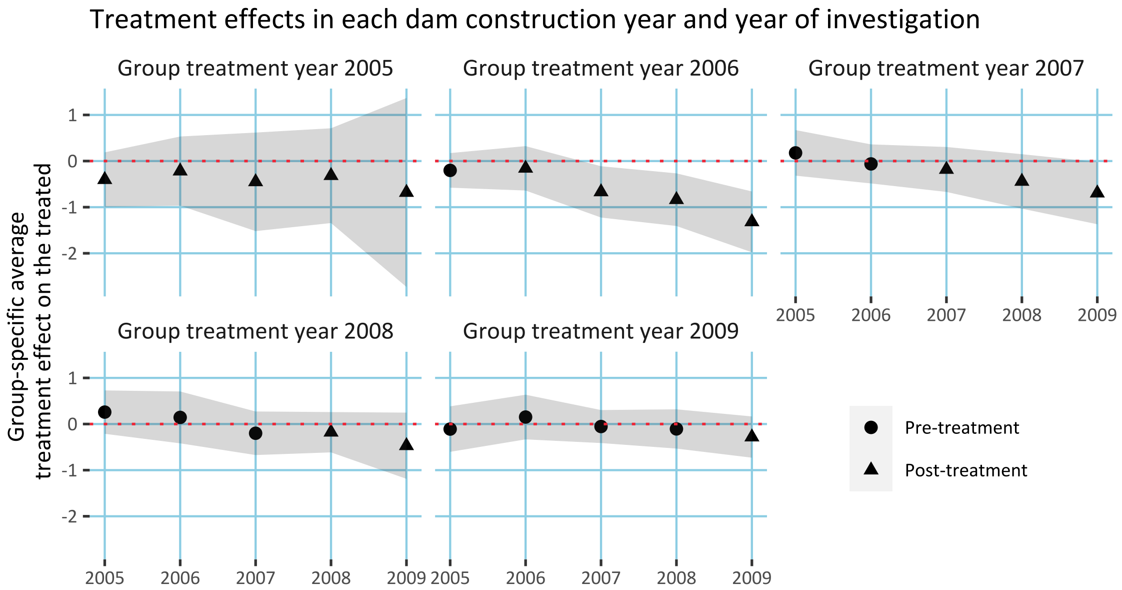



**Figure 10. Treatment effects for each construction year cohort for each calendar year investigated. Each panel represents one treatment group or cohort, those dam sites treated in 2005, 2006, 2007, 2008 and 2009, x axis is the calendar year of investigation. The natural logarithm of lit cells is given as the response variable – a proxy for socioeconomic activity. Confidence bands are at 95% - if these cross 0 (red dotted line) – then effect is not significant (*p*<0.05) – standard errors are calculated by bootstrap and clustered at the dam site level.**

Figure 10 shows the group trends in night lights between 2004 and 2009, where groups are the year in which a dam was constructed. Although, in isolation, these do not indicate the impact of large dams on socio-economic activity, given the decomposed nature of reporting the interaction between the construction year and the year that the night lights were recorded, there are two things to observe.

First, this figure provides evidence that the parallel trends assumption is met, for the pre-treatment groups (the red lines) the confidence bands cross zero. There are no significant changes until treatment takes place.

Second, the post-treatment confidence bands cross zero, except for the latter years treated in 2006 and 2007. If the confidence bands cross zero, the group-time average treatment effects are not significant. This corresponds to Figure 11, which gives the group treatment effects for each cohort, which shows that dams constructed in 2006 and 2007 have significantly lower socio-economic activity when compared to the never treated sites.

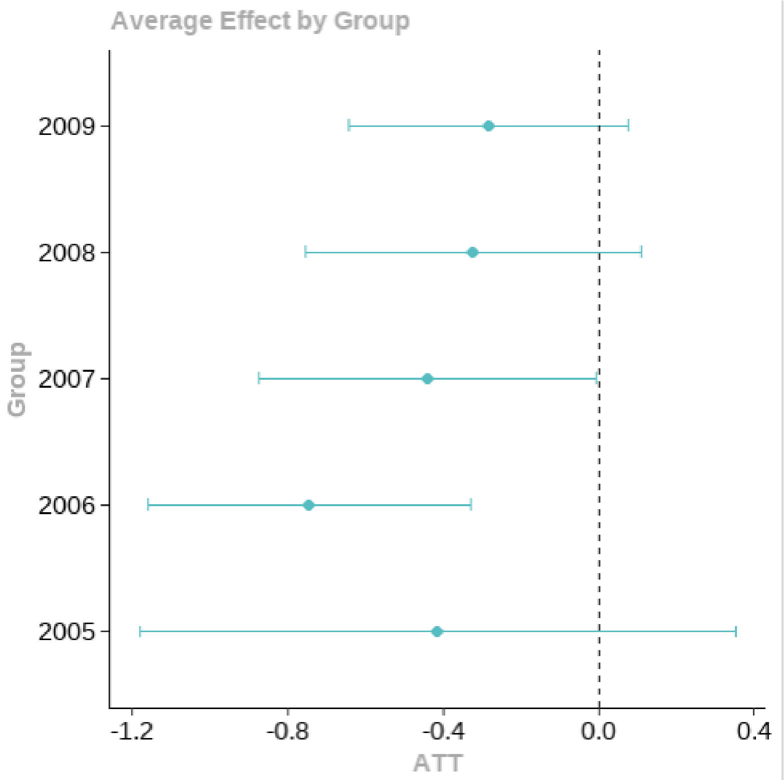



**Figure 11. ATT is Average Treatment effect on the Treated, confidence bands are at 95%, and significant years do not overlap with 0. This shows that the number of lit cells decreased within 15 km after dam construction in 2006 and 2007.**

The power of the analysis is low for any given pairwise comparison of never treated sites to treated sites in a particular year. Therefore, it is not surprising that every group is not significant. For example, the group constructed in 2005 had only 12 dams (see Table 19).

The third thing to note is that socio-economic activity decreases after treatment compared to the pre-treatment periods. This is reflected in the aggregated results for each year group in Figure 11. It is also observed when I aggregate the group treatment effects, following Callaway et al. (2020) as described in section 2.1.5.

**Table 19. The number of dams constructed in each year in the sample.**

| Year of construction | Number of dams in sample |
|---|---|
| Yet to be constructed (0) | 43 |
| 2005 | 12 |
| 2006 | 23 |
| 2007 | 20 |
| 2008 | 20 |
| 2009 | 27 |
| **Total** | 145 |

## 6.9. Calibration of satellites

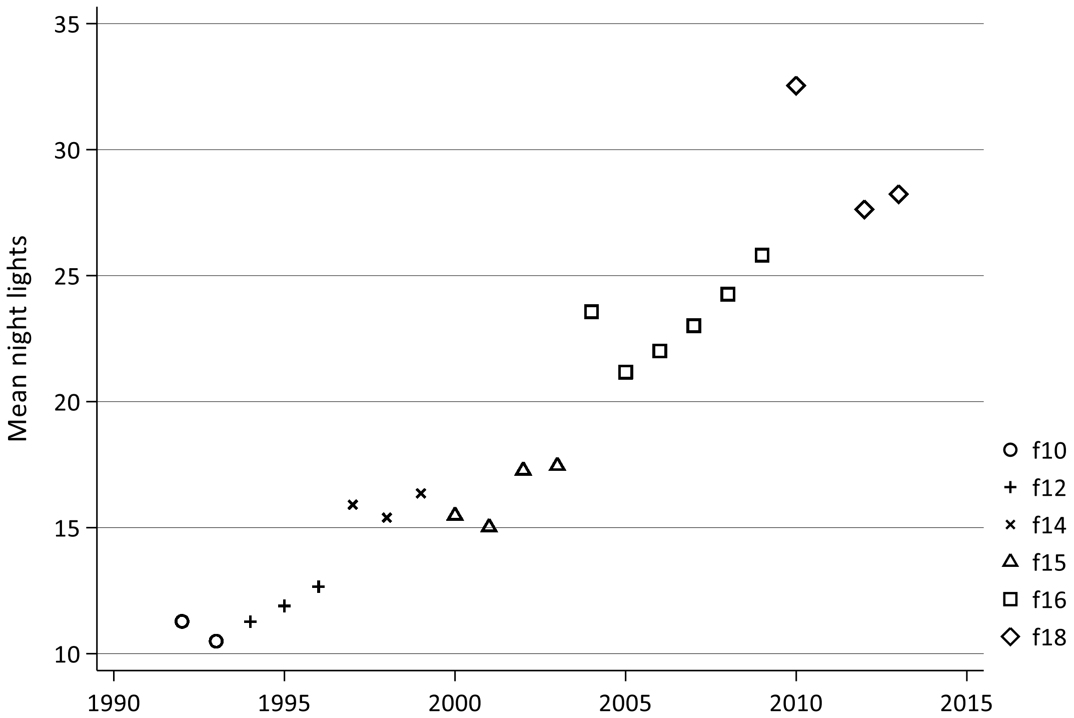



**Figure 12. Each satellite has a distinct signature and trend. F16, used as the main model, has one year out of trend, but is otherwise the smoothest and longest period.**

# 7. Acknowledgements

Shaun Larcom and Bhaskar Vira both provided invaluable feedback on drafts. Many thanks to Paul Lohmann for his patient coding assistance, Clara Galeazzi for being a sound sounding board and Martin "Magic" Baur for his help with the High-Performance Computing Suite.