Evaluating the Impact of a Hydroelectric Power Investment in the Democratic Republic of the Congo

Authors: Edward Hedley

Acknowledgements

Itad would like to extend our sincere gratitude to Atlas AI and Steward Redqueen for their invaluable contributions to this report. Their expertise and insights have been instrumental in shaping the research. We are also appreciative of the time and information provided by the staff at British International Investment. We would also like to thank Virunga Energies S.A.U. for supplying the essential data that underpins this report; their cooperation and generosity have been greatly appreciated.

Disclaimer

This report has been prepared by Itad for the Foreign, Commonwealth and Development Office (FCDO), for services specified in the Terms of Reference and contract of engagement.

For reports that are formally put into the public domain, any use of the information in this report should include a citation that acknowledges Itad as the author of the report.

This material has been funded by UK aid from the UK government; however, the views expressed in this report are those of the authors. They do not represent those of British International Investment (BII), the FCDO or any of the individuals and organisations referred to in the report.

Suggested citation

Itad (2024) Evaluating the Impact of a Hydroelectric Power Investment in the Democratic Republic of the Congo. Brighton: Itad.

Copyright

Contents

List of figures

List of tables

List of acronyms

AI	artificial intelligence
AWI	Asset Wealth Index
BII	British International Investment
DFI	development finance institution
DHS	Demographic and Health Surveys
DRC	Democratic Republic of the Congo
FCDO	Foreign, Commonwealth & Development Office
GHG	greenhouse gas
HREA	High Resolution Electricity Access
iDMC	Internal Displacement Monitoring Centre
IDP	internally displaced person
IPP	independent power producer
LASSO	Least Absolute Shrinkage and Selection Operator
MW	megawatt
OSM	OpenStreetMap
PCA	principal component analysis
RCT	randomised control trial
RGB	red, green and blue
SCM	synthetic control method
SME	small and medium-sized enterprises
SSA	sub-Saharan Africa
T&D	transmission and distribution
USAID	United States Agency for International Development
VE	Virunga Energies
VIIRS	Visible Infrared Imaging Radiometer Suite

Executive Summary

Overview

In 2019, the Foreign, Commonwealth & Development Office (FCDO) commissioned Itad and Steward Redqueen to independently evaluate British International Investment's (BII's) infrastructure portfolio. The purpose of this evaluation is to better understand the development outcomes and impacts associated with BII's investments in the infrastructure sector. The assignment consists of two phases, namely an evidence and portfolio-level review (Phase 1), published in 2022, and a subsequent series of in-depth case studies (Phase 2).

This in-depth study has two purposes. First, it aims to **develop an evidence-based understanding of the impact** generated as a result of new or improved access to electricity for communities connected to the Virunga Energies (VE) hydroelectric grid. This is to support the aims of the wider evaluation of the infrastructure portfolio, to understand where BII is generating most impact. Second, it aims to **develop and test a cost-effective, replicable and scalable approach to evaluation** using satellite data and machine learning techniques, which BII can use in ongoing or future investments. The study focuses on BII's 2016 investment in VE, which in 2017 began constructing a new hydroelectric minigrid and since then has been expanding access to electricity. The report outlines the study context, evaluation approach, methodology and lessons learned in the application of the geospatial impact evaluation approach. It also presents evidence of impact for two groups of settlements that have been connected to the new VE hydroelectric minigrid.

Study context

This study builds from Itad and Steward Redqueen's 'Phase 1 Evaluation Report',[1] which systematically reviewed evidence against BII's sector impact framework for power, to identify areas in which BII can deepen its understanding of the impact of its investments. This study focuses on one particular area, which was identified as having a limited evidence base globally: understanding the impact of enhanced rural electrification for poorer and harder-to-reach households. Extending the evidence base in this area is particularly relevant to BII, given that data compiled for the 2022 Phase 1 Evaluation Report revealed that power investments make up approximately 70% of BII's investments in infrastructure. Of these investments, the majority (approximately 75%) are in independent power producers (IPPs), but a significant slice is in off-grid and minigrid solutions relevant to this study (approximately 20%–25% of the non-IPP power portfolio).

The investment selected for study

This study focuses on BII's investment in VE[2] to develop mini hydro renewable electricity generation capacity and transmission and distribution infrastructure in Nord-Kivu province in the Democratic Republic of the Congo. The initial investment by BII in March 2016 was for mezzanine finance of up to $9 million to expand the existing grid and to construct two further generation assets.[3]

The Kivu region is one of the most densely populated areas in rural Africa and one of the most challenging operating environments in the world, because of decades of conflict and

1 Final Report: Evaluating the Impact of British International Investment's Infrastructure Portfolio

2 This is a multi-donor project, with additional investment by the European Union, the Howard G. Buffett Foundation, the Schmidt Family Foundation, the United States Agency for International Development (USAID) and the World Bank.

3 Further information is available at: Virunga

political instability. The region's communities are severely afflicted by poverty, and the province of Nord-Kivu suffers from a chronic lack of electricity, with a 3% electrification rate, compared to 17% nationally. Local industry runs on expensive diesel or on charcoal that is made from trees illegally felled inside the park.

VE aims to open access to clean and reliable electricity for an additional 10,000–12,000 households and small and medium-sized enterprises located in and around the Virunga National Park. This is expected to provide benefits for both households and business customers, including skills development and the creation of employment opportunities for at-risk youth, reduced greenhouse gas emissions from charcoal use, and improved health outcomes (as a result of subsidised electricity provision to local health centres).

Alongside its financial investment, BII has supported VE with dedicated technical assistance to strengthen its approach to environmental and social management and to reorient its business model away from grant funding towards a more sustainable, commercially oriented approach.

Study research questions

This study focuses on impacts for households connected to the minigrid as a result of BII's investment. It aims to answer two key questions: (i) how have connections developed over time and what does this mean for access to electricity? (ii) have households experienced improvements to living standards as a result of connections to the minigrid?

Given the study design and available budget, the study does not cover anticipated investment impacts for businesses (including job creation), and is not able to cover additional project benefits, including lowered carbon emissions and improved health outcomes.

Study approach and concepts

The study set out to develop an innovative impact assessment approach which meets the typical challenges of evaluating the impact of infrastructure investments, including non-randomisation, incomplete datasets and high cost. The solution developed in this study to address these challenges combines recent advancements in 'synthetic control' impact evaluation design with the latest developments in artificial intelligence (AI)-derived geospatial datasets. The synthetic control method (SCM) is particularly useful to measure impact where there is difficulty in identifying real-life counterfactuals (or control groups) 'on the ground' that share sufficient similarities with the treatment group (electrified households) but do not engage with the investment over time (i.e. do not become contaminated). It offers a robust mechanism to establish causal impact and to identify *if* and *to what extent* an investment has resulted in positive impacts in these circumstances.

The impact assessment approach has been designed in partnership with Atlas AI and uses Atlas AI's geospatial data sources – in particular its proprietary **Asset Wealth Index (AWI)** – to capture impact. Atlas AI's AWI builds on secondary data sources on asset wealth, drawn primarily from USAID's Demographic and Health Surveys, which have been widely collected through household surveys for 30 years. These surveys collect data on household assets, including appliances, livestock, property and vehicles. Asset wealth is seen as a robust proxy for livelihood changes because it is based on multiple dimensions of wealth and, as a measure of longer-run economic well-being, is considered to be more straightforward to collect and more reliable than alternative measures such as spending.

Historically, a key challenge in using these secondary datasets to measure the impact of particular investments is that they are not updated frequently enough, and there are often gaps in the data record, especially in conflict-affected countries. Atlas AI uses a proprietary AI model which combines secondary data on assets with other inputs (including daytime and nighttime satellite imagery at a resolution of 2km × 2km) to provide annual estimates of asset wealth across the globe. It is this data (available for the years 2012–21) that is used in this study to calculate impact from the VE investment.

This approach, which combines secondary data and satellite imagery with machine learning techniques to evaluate investment projects, is still in its infancy. This study therefore seeks to further 'expand the envelope' of methodological tools and data sources available to investors in this space. It is intended to offer a more detailed and credible understanding of impact than is possible either through self-reported data or through existing modelling techniques of the type typically used by development finance institutions (DFIs). It was designed from the outset to be replicable, scalable and cost-effective and therefore to offer an alternative to traditional impact assessment approaches, which are typically time-consuming and expensive to implement. Although this approach offers clear advantages to DFIs, it is still limited in a number of areas, such as the extent to which impacts can be disaggregated to the intra-household level, e.g. differentiating impacts within the household for men and women.

Implementing the study approach

The study approach was implemented through three key steps.

Step 1: Identification and mapping of geotagged data on new connections and infrastructure

VE provided the study team with data on the locations and timings of new connections and infrastructure, which was cleaned and mapped into Atlas AI's database of human settlements. This enabled the study team to track where and when the investment was rolled out over time. The team were able to identify 25,856 new connections from 2017 in three principal settlement clusters. Thirty-one settlements in the Rutshuru Region were selected for inclusion from this dataset, based on their connection date (these are referred to as the 'treated' settlements). These settlements were the earliest connected in 2017 and, given that AWI was available up to 2021, it was determined that they would meet the minimum threshold of four years' 'lag time' to allow impacts to emerge.

Step 2: Identification and selection of non-treated locations

The study team identified and mapped all 9,423 'non-treated' settlements in Nord-Kivu province. From this broad 'candidate pool' the team identified a shortlist ('donor pool') of 161 settlements which shared significant similarities with the treated settlements across key attributes (AWI, population size and distance to major roads). This was done to speed up the downstream data analysis process. From this shortlist, 'synthetic' control units were created that mirrored closely the behaviour of the treated locations prior to the data of connection.

Step 3: Comparisons of asset wealth accumulation over time

To understand if, and to what extent, connection to the electricity grid has resulted in changes in living standards, the study team compared the asset wealth scores of the treated settlements to those of the synthetic control units for the years post-treatment (2017–21). This enabled the study team to isolate the 'net' effects of the investment.

Key findings and recommended next steps

Findings and recommendations related to the impact of this investment:

The investment has been highly successful in reaching new customers. By accessing geotagged data on new connections and new electricity infrastructure, this study charts the roll-out of the rural electrification project to additional settlement clusters. In total, the minigrid achieved 25,856 new connections from 2017 to 2022 against an initial target (for the first phase of the investment) of 10,000–12,000.

There is strong evidence that the minigrid has improved access to electricity for underserved communities. Analysis of satellite nightlight data reveals that 18 out of 31 settlements in the main settlement cluster being studied (Rutshuru) are very likely to have had access to electricity for the first time as a result of this investment. Analysis of the non-treated settlements reveals that only 16 of 161 non-treated settlements had outperformed the treated ones between 2017 and 2021, suggesting that the results are highly unlikely to have occurred at random.[4]

Newly connected settlements have experienced an improvement in their standard of living as a result of connection to the minigrid. Analysis of asset wealth data reveals a net increase in asset wealth for households that have been connected to the electricity grid, with this impact being strongest among households who have accessed electricity for the first time. The identified rate of growth in the AWI for these latter households has doubled since connection, leading to a jump from the 79th to the 86th percentile for asset wealth (set against the distribution of all households in Nord-Kivu).

It is not possible at this stage to isolate the specific drivers of change that explain increasing AWI among connected households using the methodology developed for this study. However, reference to the way the Asset Wealth Index for the DRC is constructed from secondary data provides strong clues. The Index for the DRC captures a range of indicators which are likely influenced by new or improved electricity connections in the short, medium and longer terms. For instance, in the short term, the index captures the presence of attributes which will be impacted almost immediately as households shift to make use of a connection to the minigrid, including the presence of an electricity connection in the household, household ownership of a range of small appliances which rely on an electricity connection (including telephones, radios, televisions, fridges and sewing machines) and the type of energy used by the household for cooking (either an electric stove or other fuel).

Recommended next steps:

1. **Based on the evidence collected through this study, BII should consider making additional investments in minigrids or similar solutions, especially in underserved rural areas.** This study provides strong evidence that such solutions are effective in improving access to electricity in rural areas and in driving changes in standards of living, especially where these investments open access to electricity for populations which currently have limited or no access to electricity.
2. **Deepen the evidence base for this investment, including in additional treatment locations, as impacts begin to emerge.** This study makes use of data over a relatively short time horizon to explore evidence of impact (2017–21). BII should consider repeating this study in about five years, focusing in particular on the way impact has developed as this investment is rolled out to new locations. This will increase confidence

4 This analysis suggests the results are significant at a 90% confidence interval.

in the results and further strengthen learning on the situations in which this investment (and minigrids more broadly) has the greatest impact.

3. **Identify opportunities to ground-truth findings for this investment and to understand the drivers of change at the household level**. BII should seek opportunities to ground-truth the findings of this study by comparing these results to evidence collected through other methods, including primary data. This includes an ongoing study by the University of Antwerp, which is a larger-scale study using a more traditional difference-in-difference evaluation design to look more broadly at impact generated by the VE investment.

Findings and recommendations related to the evaluation approach:

This study demonstrates the successful development and use of a rapid, cost-effective, flexible and technically rigorous approach to measuring the impact of infrastructure investments. The use of a geospatial impact evaluation approach allied to the SCM offers a robust mechanism to establish causal impact and to identify if, and to what extent, an investment has resulted in positive livelihood impacts. It overcomes the typical challenges of establishing credible control groups, and it can be applied retrospectively in situations where baseline data is not available. The approach places little burden on investment owners, and it offers a new tool that BII can use to make robust estimates of impact without the requirement for time-consuming and typically more expensive on-the-ground surveys.

The approach can be used in situations where it is possible to draw a straight line between investees and end users of a service. The approach relies on the identification of end users (either individually or in groups). The approach is not appropriate in situations where it is not possible to make this identification, such as where investments provide a public good and/or have a systemic impact (for instance where an investment adds additional generation capacity to a national grid). The approach is, therefore, not relevant to all investments in the BII infrastructure portfolio, but it applies to a significant slice (approximately 25%).

Recommended next steps:

1. **Continue to develop the approach presented in this study to be applicable to larger sections of the infrastructure portfolio.** A useful next step is to expand on and test the approach in other subsectors in the infrastructure portfolio and in situations where information on customers is available only at a more aggregate level. The evaluation team is currently adapting and testing the approach in the telecommunications sector in this scenario.
2. **Identify investments that could/should collect geotagged and time series data on connections.** BII should consider identifying relevant investments in the portfolio which could feasibly collect geotagged connection data on end users and infrastructure installations, and should support investment owners to do this and report it through the BII monitoring and evaluation system.
3. **Roll out further studies in the investment portfolio to deepen the evidence base for current and future investments.** BII and FCDO should consider rolling out additional studies in the infrastructure portfolio for a subset of investments where feasible (in particular, where geotagged data on end users is available). Such a rolling programme would build up rigorous evidence of impact across the portfolio.

1 Introduction

In 2019, the Foreign, Commonwealth & Development Office (FCDO) commissioned Itad and Steward Redqueen to independently evaluate British International Investment's (BII's) infrastructure portfolio. The purpose of this evaluation is to better understand the development outcomes and impacts associated with BII's investments in the infrastructure sector. The assignment consists of two phases, namely an evidence and portfolio-level review (Phase 1), published in 2022, and a subsequent series of in-depth case studies (Phase 2).

This study has two purposes. First, it aims to **develop an evidence-based understanding of the impact** generated as a result of new or improved access to electricity through BII's investment in Virunga Energies (VE). Second, it aims to **develop and test a cost-effective, replicable and scalable approach to evaluation**, using satellite data and machine learning techniques, which BII can use in ongoing or future investments. Itad and Steward Redqueen have been working together with Atlas AI to develop this approach. The report is structured as follows.

Section 2: The **study context** provides the background to the study and the link to the previous phase of our evaluation work, in which we systematically identified areas of BII's infrastructure portfolio that could benefit from more in-depth evidence. This section also discusses what the study is trying to achieve, emphasising its strong learning focus, with the aims of helping BII understand where it is generating impact in its infrastructure portfolio as well as demonstrating a new cost-effective, flexible and replicable approach to impact evaluation. It provides an overview of the challenges associated with assessing impacts of infrastructure investments and the study design adopted for addressing these challenges.

Section 3: In the **evaluation approach and concepts,** we discuss how the study defines impact, focusing on household asset wealth and how this measure has been adapted to assess the impact of infrastructure investments on underserved rural communities for the purpose of this study.

Section 4: The **methodology** provides a step-by-step description of how the study was implemented in practice. This includes a discussion of the data accessed, the identification and selection process for settlements to include in the analysis, and how the geospatial impact evaluation approach with the synthetic control method (SCM) has been defined and used to isolate impact.

Section 5: In the **key findings**, we discuss the results of the study, focusing on: the development impact of the investment by applying the geospatial impact evaluation approach; how robustness of the results has been tested; how results compare to each other; and what we have learned about applying the approach in comparison to alternatives.

Part 6: The **conclusions and ways forward** section discusses the key takeaways from the study and proposes a set of recommendations and next steps for BII and FCDO, based on the study findings and learning from applying the new approach.

2 Study context

This section outlines the overall purpose of the study and how it fits with the wider evaluation of the BII infrastructure portfolio. It also includes a discussion of the rationale for the focus on minigrid solutions and its strategic importance to BII. This is followed by an overview of the investment studied – BII's 2016 investment in a hydroelectric minigrid owned by VE in the Democratic Republic of the Congo (DRC) – as well as the research questions the study aims to address.

2.1. Purpose

This study has two primary aims:

- First, it seeks to develop an **evidence-based understanding of the impact generated as a result of BII's investment in VE**. This is linked to the wider goals of Itad and Steward Redqueen's evaluation, which seeks to **deepen BII's evidence base on the impact it is generating through infrastructure investments** (in this case focusing on the impact of minigrid solutions on households).
- Second, it aims to develop a **low-cost, flexible and scalable approach that can be replicated by BII to evaluate the impact of minigrids**, using satellite data and machine learning techniques allied to recent thinking in the use of synthetic control analysis.

The study focuses on **three areas of BII's impact framework for the power sector:** customers reached, improved access to electricity, and (ultimately) an improved standard of living. Phase 1 of the evaluation reviewed global evidence against the sector impact framework for power. In Figure 1, the evidence base presented in the Phase 1 Evaluation Report[5] is illustrated against the BII impact framework for the power sector. Phase 1 found strong evidence linking minigrids to customers reached, which suggests that they contribute to increased access. However, there is currently limited evidence linking minigrids to improved standards of living; currently the main evidence related to this area links minigrids to improved incomes.[6]

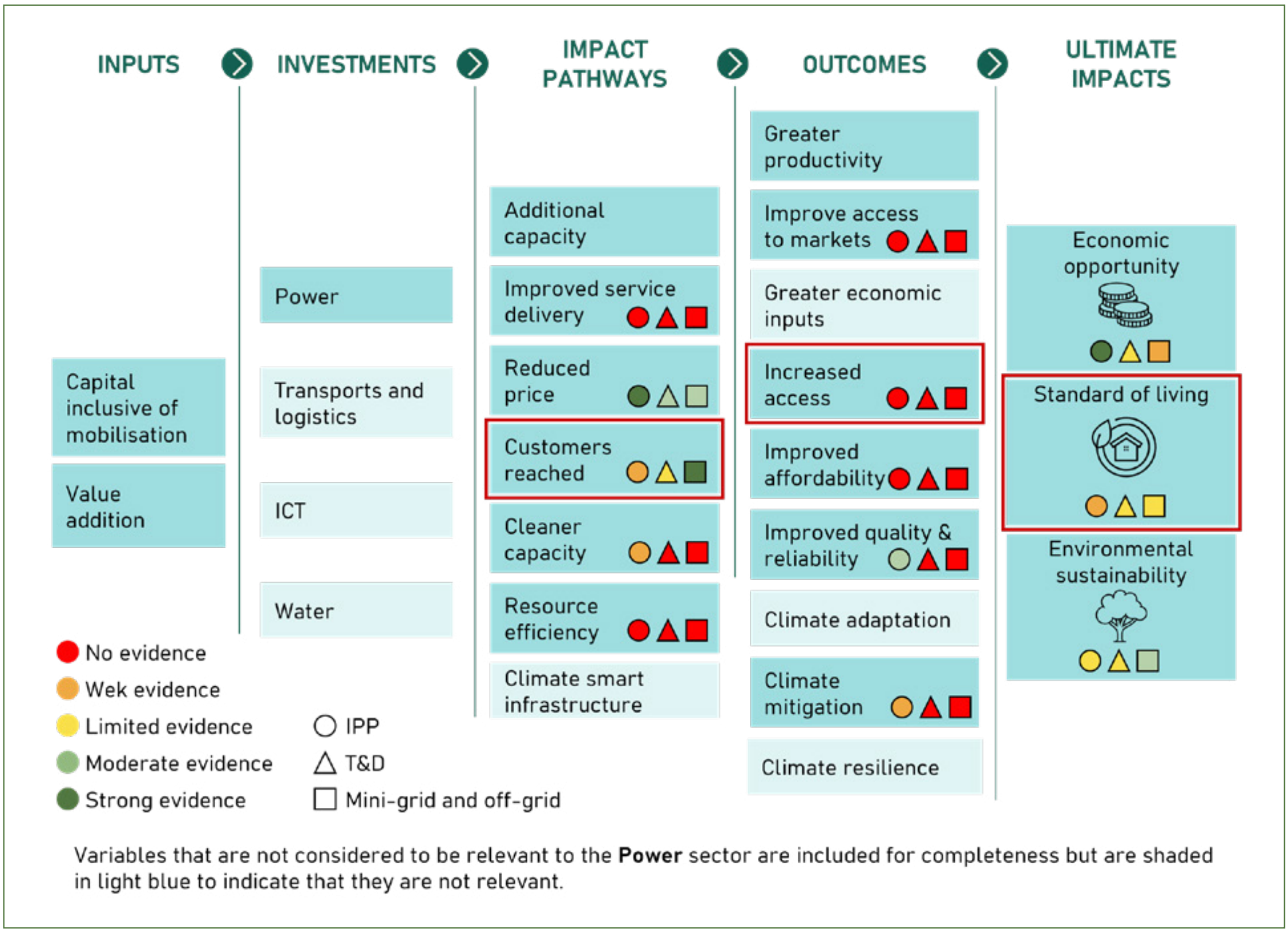
This study therefore aims to deepen the evidence base around the three links highlighted in red in Figure 1, in particular **building further evidence on the impact of minigrids on standards of living**. As explained in Section 3, asset wealth is used as a proxy for improved living standards, as captured in the Asset Wealth Index (AWI) developed by Atlas AI. It also offers an opportunity to 'extend the toolkit' of impact assessment options available to BII, given that a lot of current evidence of impact across the portfolio is reliant on modelling techniques (using methodologies such as the Joint Impact Model)[7] and on self-reporting by investees. This study goes further by assessing observational data of impact, but aims to do so in a way that is appropriate and feasible for BII to replicate.

5 Final Report Evaluating the Impact of British International Investment's Infrastructure Portfolio

6 Cited by five previous studies, based on reduced energy/time costs: Calderón, C. and Servén, L., 2004; Dinkelman, T., 2011; Groth, A., 2019; Gustavsson, M. and Ellegård, A., 2004; and Pueyo, A., Carreras, M., and Ngoo, G., 2020. Please refer to Annex 1: References.

7 Comparability, accountability, transparency

Figure 1. BII impact framework for the power sector, highlighting strength of evidence from Phase 1



Because of time, budget and data limitations, this study is not able to cover other aspects of the sector framework. Additional impact pathways and outcomes are being covered by other studies in Phase 2 of this evaluation. For instance, the impact that additional power capacity has for businesses in terms of improved productivity, affordability and reliability across various countries in Africa is being assessed as part of a separate study. It should also be noted that the VE project aims to have additional impacts, which are beyond the scope of this study, including climate mitigation (by reducing greenhouse gas (GHG) emissions from charcoal use), improved health outcomes (as a result of subsidised electricity provision to local health centres), and improved access to electricity for local businesses.

2.2. Strategic importance and relevance to BII

This study is being undertaken as part of Itad's wider evaluation of the BII infrastructure portfolio and follows the Phase 1 evaluation, conducted by Itad and Steward Redqueen, which reviewed BII's infrastructure portfolio. The Phase 1 evaluation identified a longlist of 13 '*evidence opportunities*' where the existing evidence of impact in the infrastructure sector was weakest and where it was feasible that BII could deepen its evidence base. One of the opportunities identified is in the area of minigrids, which forms the basis of this study.

Extending the evidence base on the impact of minigrid solutions is of strategic importance, given the urgent need for new investments to increase access to electricity. Although nearly 600 million people in sub-Saharan Africa (SSA) lack access to modern electricity,[8] the amount invested annually is only a fraction of that required to ensure continent-wide access in the next 20 years.[9] At the same time, as the Phase 1 Portfolio Review and a comparison with global literature revealed, the evidence base on the impact of access to electricity in SSA is mixed. Studies note a general lack of consistent evidence, especially around increased access and improved standards of living for households.

Extending the evidence base on impact for minigrids is relevant to BII, given that data compiled for the 2022 Portfolio Review revealed that power investments make up by far the largest slice (approximately 70%) of BII's investments in infrastructure.[10] Of these, the significant majority are in independent power producer (IPP)-type investments. However, investments in home solar, off-grid and minigrid solutions (which all share similarities) contribute prominently to the remainder of the power portfolio **and are particularly important in extending impacts to underserved rural communities**. This study is being implemented alongside others that target other prominent aspects of the power and non-power infrastructure portfolio.

2.3. Background on Virunga Energies

The investment selected for study is BII's investment in VE to develop mini hydro renewable electricity generation capacity and transmission and distribution (T&D) infrastructure in the Nord-Kivu province in the DRC. The initial investment by BII in March 2016 was for mezzanine finance of up to $9 million to expand the existing grid and to construct two further generation assets, resulting in almost 30 megawatts (MW) of new generation capacity.[11] Through this funding, the project aimed to offer reliable and affordable power to an additional 10,000–12,000 households and small and medium-sized enterprises (SMEs) as well as poorer rural households who have an average consumption below $1.90/person/day.[12] [13] Instalment of electricity infrastructure began in 2017; this study focuses on the period 2017–21 as settlements were becoming connected to the new minigrid.

The investment was approved and implemented before the development of the BII 2022–26 technical strategy. However, it has relevance for all three strategic objectives in the current strategy to support productive, sustainable and inclusive development: (i) by improving access to affordable and reliable power, it is expected to boost investment and productivity for the region's businesses; (ii) by reducing reliance on fossil fuels for heat, light and electricity generation, it aims to reduce GHG emissions; and (iii) by focusing on energy access in a poorer rural region of the DRC, it aims to enhance inclusive development by positively impacting a low-income population.[14] Given its design and data availability, this study is primarily relevant to the third of these impact dimensions.

The VE project operates in Nord-Kivu province in the East of DRC. The province is large (covering an area of around 60,000 km^2) and is home to 6.6 million people. It is very poor (3.2 million of its residents live in extreme poverty)[15] and is largely rural, with an urbanisation rate of 36% (this figure is skewed by the presence of Goma, the region's largest city, which has a population of approximately 1.5 million). By the standards of the DRC, the province's

8 IEA. World Energy Outlook, 2019.

9 IEA. World Energy Outlook, 2019.

10 Final Report: Evaluating the Impact of British International Investment's Infrastructure Portfolio

11 This is a multi-donor project, with additional investment by the European Union, the Howard G. Buffett Foundation, the Schmidt Family Foundation, the United States Agency for International Development (USAID) and the World Bank.

12 Further information is available at Virunga

13 BII provided additional mezzanine financing of $10 million to VE in 2021 to expand its network into the city of Goma, connecting over 19,000 customers.

14 The project is aligned to BII's commitments under the Paris Agreement and qualifies as 100% climate (mitigation) finance.

15 World Bank, 2021, North Kivu InfraSAP Report

population has low asset ownership, with 21.7% of households in the province having a television (ranking 9th out of 11 regions in the DRC), 3.69% households having a refrigerator (ranking 8/11), and 10.3% having a motorbike (ranking 8/11).[16]

The province has poor provision of basic infrastructure, which constrains growth. The Kivu region has a very low electrification rate (only 3% electrification rate vs 15% in the DRC overall), and in many of the rural areas in which VE operates there was effectively a zero electrification rate before the project started. Industry and households in the region, if they have access to an energy source, typically rely on diesel generators or on charcoal made from trees illegally felled inside the park (providing a major source of income for armed groups). Nevertheless, despite these layered constraints and challenges, North Kivu shows signs of a dynamic private sector and considerable growth potential, with the province rich in agricultural and mineral resources such as tin, gold and coltan.

The installation of the new minigrid by VE is a significant development in the province and holds the potential to open access to clean and reliable energy to many for the first time and to provide significant social and environmental benefits. VE specifically aims to increase rates of rural electrification in harder-to-reach locations; in line with this ambition, VE initially focused on supplying rural locations in the province closer to the Virunga National Park and resisted pressure to expand the minigrid to the nearby large conurbation of Goma. Over time, VE has reached agreements to supply electricity to a discrete set of businesses and expand the minigrid to the city. This has the benefit of enhancing the commercial viability of the project. In spite of these changes to its approach, VE continues to focus on supplying electricity to poorer, rural locations and providing subsidised access to electricity for public lighting and to public health centres.

The investment in VE is feasible to study due to the availability of geotagged data. VE collects anonymised data on electricity infrastructure and clients, enabling the **geolocation of end users of new infrastructure investments and tracking of their socioeconomic outcomes over time**. This is typically the case with off-grid, minigrid and home solar power solutions, where investees can identify customers and collect geotagged data on them. In contrast, 'systemic' investments in additional national grid generation capacity do not allow investees to identify individual customers.

BII has played a pivotal role in supporting VE to establish itself as a financially sustainable company which aims to improve access to electricity and to contribute to socioeconomic development through a commercial model of electricity generation (rather than relying on grant funding). BII structured the 2016 investment with this aim in mind and to be appropriate to VE's situation. Recognising challenges in offering equity to VE as an early-stage investee, BII structured the deal as senior corporate debt with equity-like characteristics (including a seat on the Board and an upside sharing mechanism). VE had tried, but failed, to attract institutional investors or commercial debt financing in the past; the only other funders working with VE at the time were development actors providing grant finance and Congolese banks offering (expensive) overdraft financing. BII also recognised that there would be challenges with regard to how quickly VE could absorb the new capital; BII therefore decided to increase funding incrementally over time, linked to VE proving the business model and making changes to business processes.

Alongside its investment, BII provided VE with non-financial forms of support. In terms of its business model, BII provided advice in prioritising particular customer types, with a view to supporting VE to become financially sustainable as quickly as possible. BII also provided

16 Global Data Lab 2018: GDL Area Profile Report

support to VE to improve business integrity, including risk management, and worked with VE to audit its risk management capacity and develop an Action Plan to close identified gaps.

BII has since provided a further round of funding, and additional investment has been provided by the European Union, the Howard G. Buffett Foundation, the Schmidt Family Foundation, the United States Agency for International Development (USAID) and the World Bank.

This study aims to answer the following research questions, related to new connections and changes in standards of living as a result of this investment:

- Understanding how power infrastructure and connections have developed over time:
- How have minigrid power generation and T&D infrastructure developed geographically over time following investment by VE and BII?
- How, to what extent, and where have VE and BII's investments in minigrid power generation and T&D increased connections and customers reached?
- What is the socioeconomic profile of the communities that have been reached by new connections? (This profile will include data points such as AWI, population density and gender profile.)

Understanding the impact of these investments:

- How have communities connected to the minigrid developed over time?
- Is there evidence – which can be attributed to the investment – that connected communities have demonstrated increased growth rates (of community average household wealth) relative to non-connected communities?
- How have these growth rates developed over time?

Other potential outcomes and impacts of this investment, such as changes in electricity pricing, improvements in reliability or reductions in GHG emissions, cannot be assessed using the selected approach and are beyond the scope of this study.

3 Evaluation approach and concepts

This section highlights the research challenges typically associated with evaluating infrastructure projects (time, cost and methodology) and describes the research solution, which takes recent advances in **synthetic control impact evaluation design** and combines these with **artificial intelligence (AI)-derived geospatial data** to develop a **low-cost and scalable geospatial impact assessment approach** which BII can use in future studies. This section also discusses how the study defines impact, focusing on household asset wealth and how and why this measure has been adopted for the purposes of this study, as well as the approach to utilising Atlas AI's AWI as a proxy for livelihood improvements. Finally, this section outlines some of the limitations of the study.

3.1. The research challenges

Evaluating infrastructure impacts is difficult and typically expensive and time-consuming. This study has been designed to offer a lower-cost, more flexible approach to meet these challenges. Challenges in evaluating infrastructure projects include: non-randomisation; controlling for differences between control and treatment groups; incomplete datasets; and the high costs associated with evaluating infrastructure impacts. First, new infrastructure is not randomised in delivery, which requires the identification of an adequate counterfactual, which can be resource-intensive and can be difficult to achieve when dealing with large and diverse treatment areas. Second, recipients of infrastructure may have differences from surrounding untargeted populations (such as higher underlying rates of economic growth), which complicates the use of more traditional evaluation designs (such as difference-in-difference). Third, national surveys of living standards typically do not revisit the same households or locations across survey waves, or they are repeated infrequently, making it difficult to construct repeated local-level measurements using secondary datasets. This is true of the available datasets for Eastern DRC. Lastly, traditional impact evaluation designs that seek to close gaps in existing datasets through 'on-the-ground' surveys are typically time-consuming and expensive to administer. This is particularly true for Eastern DRC, where challenges in access further complicate and increase the cost of large-scale survey work.

3.2. The study approach

The approach developed through this study to address the challenge of evaluating power investments is to combine recent advancement in synthetic control impact evaluation design with the latest developments in AI-derived geospatial datasets. The SCM is a particularly useful approach to measure impact where it is difficult to identify real-life, on-the-ground counterfactuals (or real-life control groups) that share sufficient similarities with the treatment group and which are not impacted by the project over time (i.e. become 'contaminated'). Both challenges are present in the case of electrification projects. The SCM differs from 'traditional' (difference-in-difference) impact evaluation approaches in that it does not attempt to identify 'real-life' control units on the ground and track their progress over time; rather, it is based on a series of simulated control units that are developed to best mimic the behaviour of the treated units in the years pre-treatment.[17]

The synthetic controls act as the (unobservable) counterfactual of what would have happened without the intervention. They have typically been used to date in the evaluation of large policy decisions that affect large treatment units (such as the impact of the introduction of the California Tobacco Control Program).[18] They have not yet been used as frequently in

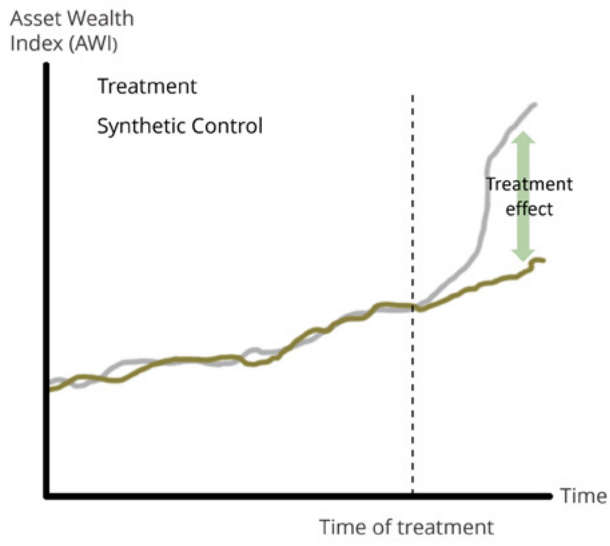
17 These are developed as the weighted average of non-treated units across a series of predetermined metrics.

18 Abadie, A., Diamond, A. and Hainmueller, J. (2010) 'Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program'. Journal of the American Statistical Association 105(490): 493–505.

other areas, such as the evaluation of infrastructure projects. In this case, the approach has been tailored to be more relevant to the identification of impact in multiple treatment units in a more localised investment. Because they are simulated, a further advantage of the method is that they can be 'tailored' to the purposes of the study.[19]

In this study, **synthetic control analysis is used to isolate the net impact** (as captured by settlements' changing asset wealth) of connection to the newly constructed hydroelectric minigrid. The process to implement the synthetic control analysis approach is described in detail in Section 4. As illustrated in Figure 2, synthetic control units are developed to closely **match the behaviour of settlements** that have been connected to the minigrid over time (our 'treatment' settlements) in the period before they were connected (the time of treatment). We then use statistical analysis to identify differences in the behaviour of the treated units and synthetic control units in the period after the time of treatment. This is the 'treatment effect' of the intervention.

Figure 2. Illustration of treatment effect (not based on actual data)



The data used in the geospatial impact evaluation design is fed through a machine learning model developed by Atlas AI to make predictions on asset wealth across the Earth's surface. Atlas AI's large-scale proprietary datasets make use of daytime and nighttime satellite imagery, in combination with publicly available data and machine learning techniques, to develop comprehensive datasets covering key livelihood indicators. This technique closes gaps in the time series records of publicly available datasets and offers opportunities to customise indicators to better capture the impact of particular investments. This approach is, in part, inspired by recent work undertaken by Ratledge *et al.* (2022)[20] at the University of Stanford, which used similar datasets to estimate the impact of electricity grid access improvements on the rate of growth in village-level assets. This study builds on learning from this work, which demonstrated how recent advancements in machine learning and satellite imagery can help ameliorate data gaps from traditional wealth indices, such as those from the Demographic and Health Surveys (DHS) Program. The process followed by Atlas AI to build its AWI dataset from available secondary data is outlined in Section 3.3 and Annex 4, including the steps taken to test and evaluate the accuracy of the model.

The use of geospatial data in the evaluation of investment projects is still in its infancy. This study, therefore, seeks to further 'expand the envelope' in terms of the methodological tools and data sources available to investors in this space. The approach holds a series of advantages for BII and other investors, including that: (i) it relies primarily on remote sensing rather than on-the-ground data collection and is therefore highly cost-effective and scalable; (ii) it does not place a significant burden on investees (either in terms of data or time to engage) – the primary data requested of investees is geotagged data on their customers and minigrid infrastructure, ideally with further anonymised information

19 For example, 'confounding variables', which might influence the results of the study, can be stripped out during their construction.

20 Ratledge, N. et al. (2022) 'Using Machine Learning to Assess the Livelihood Impact of Electricity Access'. Nature 611.

on customer profile and service use;[21] and (iii) it does not require the collection of baseline data, instead making use of established geospatial records to enable researchers to 'go back in time' before the investment was made, which makes the approach much more flexible than traditional evaluation alternatives. However, the method currently has limitations, for example with regard to the extent to which impacts identified in secondary datasets can be disaggregated to the household level or by gender, although here we can look to other studies to understand further how impact is generated.

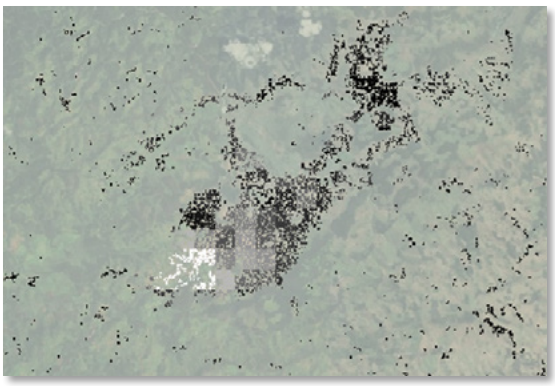
The solution developed in this study is designed to be replicable, scalable and cost-effective and therefore to offer an alternative to traditional impact assessment approaches, which are time-consuming and expensive to implement. The solution is intended to be particularly applicable to data-sparse and fragile contexts, where traditional approaches may not be feasible. This study will produce learning for BII on how and in what circumstances BII can replicate this study and apply similar methods to measure impact across its portfolio.

3.3. Our definition of impact – asset wealth

This study uses Atlas AI's AWI to capture changes in standards of living as a result of being connected to the electricity minigrid. Asset wealth is selected as a robust proxy for living standards in this study because it is based on multiple dimensions of wealth and is considered to be a more reliable measure of households' longer-run economic well-being than alternative monetary measures, such as spending. Atlas AI's AWI is based on data sourced from the many georeferenced, nationally representative surveys conducted in SSA, which collect data on asset wealth. A principal data source is USAID's DHS, which have been collected through representative household surveys for 30 years. Through these surveys, USAID calculates a household Wealth Index. A key advantage of this index is that it is less susceptible to errors in data collection than alternatives, given that many of the enumerated assets are directly observable to surveyors. The methodology Atlas AI uses to construct the AWI is aligned to that used by USAID to construct the Wealth Index. It is calculated based on a household's ownership of selected assets, including televisions and bicycles, materials used for housing construction, and types of water access and sanitation facilities. Annex 4 provides additional detail on the assets included in the construction of the AWI.

In developing the AWI, Atlas AI uses an AI model trained on satellite imagery to make predictions on asset wealth. Historically, a key challenge in using secondary datasets to measure the impact of particular investments is that they are updated infrequently and there are often gaps in the data record, especially in conflict-affected countries. The process developed by Atlas AI combines available secondary data on asset wealth with publicly available daytime and nighttime satellite imagery[22] to predict asset wealth scores, even where the secondary data record is incomplete. The process is illustrated in Figure 4: an AI model (based on a convolutional neural network)

Figure 3. Visualisation of AWI for cluster of settlements (2km × 2km). Lighter colour indicates a higher asset wealth value

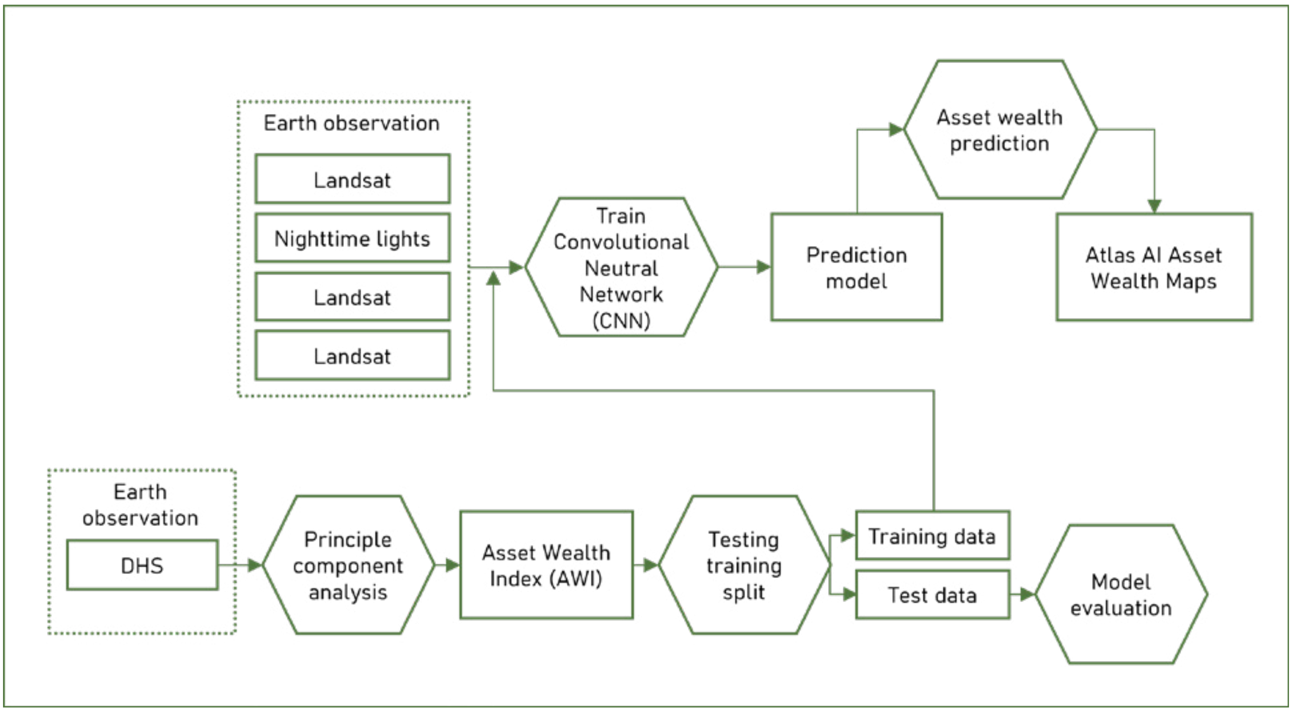


21 It is recommended that this data is anonymised for ethical reasons.

22 Earth Observation' datasets drawn from publicly available satellite image sources with coverage over the last 25 years including multispectral Landsat bands over multiple generations and satellite imagery of nighttime lights.

is trained to make predictions on asset wealth,[23] drawing associations between satellite imagery and underlying secondary data on asset wealth. The model's accuracy is tested against multiple datasets. In doing so, Atlas AI is able to use publicly available satellite data to close data gaps in secondary data on asset wealth. The version of Atlas AI's AWI dataset[24] being used in this study provides annual estimates of asset wealth for the period 2012–21 at a resolution of 2km × 2km polygons, meaning that each polygon and associated value represents a 4km^2 area on the ground.

Figure 4. Illustration of the process and components in developing the AWI



Variables linked to electrification were removed from the AWI to reduce the risk of these potentially confounding variables undermining the results of the analysis. The AI model uses access to electricity (derived from satellite imagery of nightlights), and there was a risk that the independent variable would be confounded by the dependent variable. This component was therefore removed by adjusting both input imagery and correlated field survey indicators as follows:

1. A modified AWI was developed which did not include variables linked to electrification, such as appliances powered by electricity.[25] Verification checks were conducted, which concluded that this modified AWI has an extremely high correlation with the original[26] and therefore remains a robust measure of household wealth.
2. In the training of the AI model, nightlight data was removed to avoid issues of embedding a confounding variable in the data bands used. Verification tests were performed which identified a modest reduction in the predictive performance of the model, but this was judged to be of secondary importance when compared to the greater risk of experimental integrity.

23 The approach to training the AI model using publicly available satellite imagery is discussed by Yeh, C. et al. (2020) 'Using Publicly Available Satellite Imagery and Deep Learning to Understand Economic Well-being in Africa'. Nature Communications 11: 2583.

24 AWI is currently available for SSA and Southeast Asia.

25 This was done using principal component analysis (PCA) on a new set of variables.

26 r2 = 0.99.

3.4 Limitations

Although the approach used in the study has a number of notable benefits,[27] it does have some limitations. It is not possible at present, for example, to disaggregate impacts for different socioeconomic groups (including for men and women), given that the resolution of the AWI dataset is to a maximum of 2km × 2km polygons. Nor is it possible at present to 'look under the hood' to isolate the precise drivers of increased asset wealth as a result of access to electricity. In relation to the findings, we are able to discuss how access to electricity is driving improved asset wealth and improved livelihoods by examining how AWI is created from component data points and with reference to the wider literature.

27 Including the completeness of the AI-derived AWI dataset, the ability to examine impacts retrospectively and the fact that it does not require the collection of primary data, as discussed elsewhere in this report.

4 Evaluation methodology

This section provides a step-by-step explanation of how the approach was defined in practice and implemented. The methodology is broken down into three key steps:

- **Step 1**: Identification of geotagged data on new connections and new infrastructure to map where and when the project was rolled out over time. This enabled the treated location to be identified, selected and included in the study.
- **Step 2**: Identification of non-treated locations in the same province that shared sufficient similarities with the treated locations to form the basis of synthetic controls.
- **Step 3**: Comparisons of asset wealth accumulation over time between the treated and synthetic control units are then used to identify the net effects of the intervention.

Each step is discussed in turn, explaining the design choices made and the substeps and actions in each part of the process.

4.1 Step 1: Identifying and selecting treated locations

4.1.1. Data identification, entry and cleaning

Two principal datasets were identified and used to identify treatment settlements:

1. time series satellite imagery and Atlas AI proprietary datasets; and
2. geotagged data on electricity infrastructure and clients provided by VE.

The Atlas AI proprietary datasets[28] used to identify settlements in this study include (i) the Atlas AI human settlement layer (to identify treated and non-treated settlements) and (ii) satellite data on nighttime light intensity (used as a proxy for prior electrification). The analysis period is 2012–21,[29] and the outcome of interest (asset wealth) varies annually. Further information on how these datasets were used is outlined below. Atlas AI's databases provide a high degree of customisability. The ability to adjust and fine-tune the data points used during the study offers a degree of flexibility which is typically not available in a traditional impact evaluation design once on-the-ground data collection has commenced. With regard to the latter dataset, geotagged data on electricity infrastructure and clients provided by the project owner, VE, was used. This geotagged data on infrastructure and clients enables tracking of the roll-out of the electrification project over time and the identification of when, where and for how long different clients have been connected to the new minigrid. This data was reviewed, cleaned, and entered into Atlas AI's visualisation tool and was matched to the Atlas AI human settlement layer so that connected settlements could be identified in the Atlas AI dataset. (For further explanation of this process, see Sections 4.1.2 and 4.1.3. For a full list of data accessed, see Annex 2.)

28 Available in 2km × 2km polygons globally.

29 2021 was the most recent year for which AWI was available in treatment locations at the time of the study.

4.1.2. Working with Atlas AI's human settlement layer to enter and match geotagged connection data

Atlas AI's human settlement layer represents the footprints of human activity around the world. Atlas AI uses proprietary AI models to fuse a range of input data sources at varying spatial resolutions to detect human settlements. This layer (formed of 2km × 2km polygons) forms the foundation of the analysis. It has been used to identify settlement areas that have been connected to the new hydroelectric scheme over time by VE, as well as non-treated settlements that form the basis of our synthetic controls (in Step 2). Other datasets were overlaid onto this settlement layer, such as population size, distance from roads and AWI. In this way, a series of uniform 2km x 2km polygons was identified for both treated and non-treated locations (the key unit of analysis) and was fused with other datasets to allow changes in the dependent variable (AWI) to be tracked and analysed over time. Non-treated polygons formed the basis of the development of the synthetic controls (see Step 2). Figure 5 shows all settlement areas in Nord-Kivu, with a zoomed-in example of one settlement area with overlaid key attributes of asset wealth and population.

Geotagged data on electricity network assets, such as poles, wires and **time-stamped data on connections**, was provided by VE and **entered into Atlas AI's visualisation tool**. This data was cross-checked against Atlas AI's human settlement layer to identify all settlements and 2km × 2km polygons in Atlas AI's database that overlap with the identified network assets. The dates of connections were used to assess the start of electrification in the treated settlements. Figure 6 highlights the locations of network assets and how they correspond to the locations of treated (in green in Figure 6) and untreated (in purple) settlements. In total, 48 treated settlements were identified across several regions, including Goma, Rutshuru and Lubero. Data validation checks revealed that this process had successfully identified the vast majority of connected settlements.

Figure 5. Nord-Kivu human settlement layer

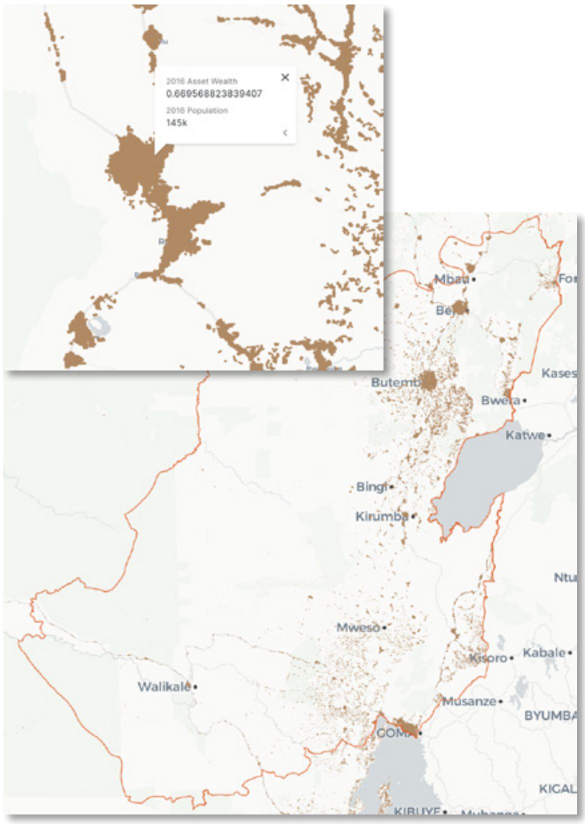
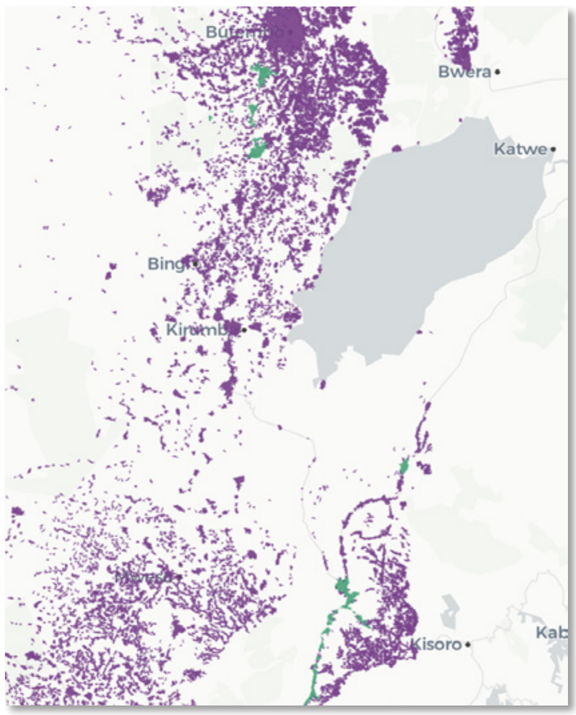


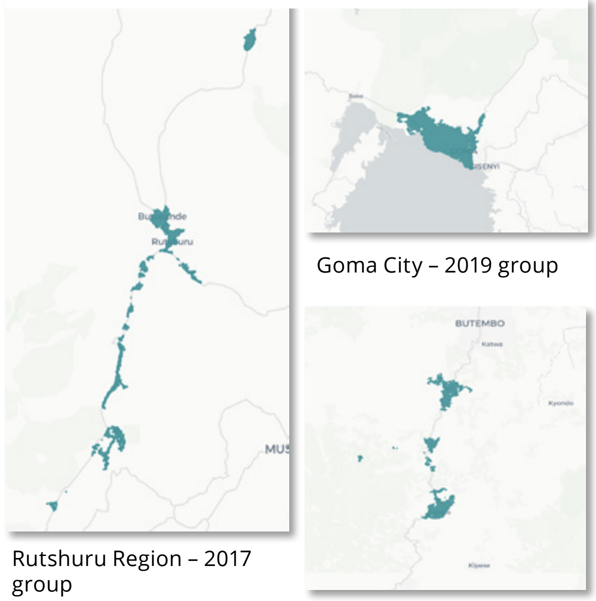
Figure 6. (i) Location of electricity network assets (poles and wires); (ii) treatment sites (green); and all other settlements (purple)



4.1.3. Identifying treated settlement clusters and selecting treated

Geotagged data on new connections and the installation of new electricity infrastructure was provided by VE.[30] This data reveals that the investment has been highly successful in reaching new customers: in total, the minigrid achieved 25,856 new connections from 2017 to 2022 (against an initial target for the first phase of the investment of 10,000–12,000). By entering and mapping time-stamped data on connections into the Atlas AI visualisation tool, we were able to chart the roll-out of the project and identify three principal settlement clusters which were connected at different points in time: Rutshuru Region, electrified in 2017 (in which we can identify 31 settlements in Atlas AI's human settlement layer); Goma City, electrified in late 2019 (in which we can identify one settlement in Atlas AI's human settlement layer); and Lubero Region (in which we can identify 16 settlements in Atlas AI's human settlement layer). Table 1 presents connection data by settlement over time.

Figure 7. Principal treated settlement cluster



Rutshuru Region – 2017 group

Goma City – 2019 group

Lubero Region – 2021 group

Table 1. Connection data by settlement over time

Cluster	Connection date	No. of settlements in Atlas AI human settlement layer	Cumulative connections	
			2017	2022
Rutshuru	2017	31	1,880	7,399
Goma	Late 2019	1	0	17,643
Lubero	Late 2021	16	0	230

Two criteria were applied for the selection of treated settlements to include in later impact analyses: (i) the availability of time series data over a sufficiently long time horizon, to account for any time lag between treatment and impact; and (ii) the likelihood of finding credible counterfactuals. A similar study[31] on the impact of electrification on indicators of household well-being highlighted a lag of approximately four to five years between connection and livelihood impact. Given that AWI data (the dependent variable) is available for the period 2012–21, the study focused on the earliest connected settlements in order to maximise the chances of isolating evidence of causal impact. With regard to the likelihood of finding credible counterfactuals, although the approach is based on the construction of synthetic controls, the methodology used still requires the identification of a 'donor pool' of broadly similar real-world non-treated settlements from which these synthetic controls could be developed. For this reason, a decision was taken to exclude significant outlier settlements in the dataset. This resulted in the decision to exclude Goma City, on the basis that it has unique characteristics in Nord-Kivu, with a larger and wealthier population than other settlements.

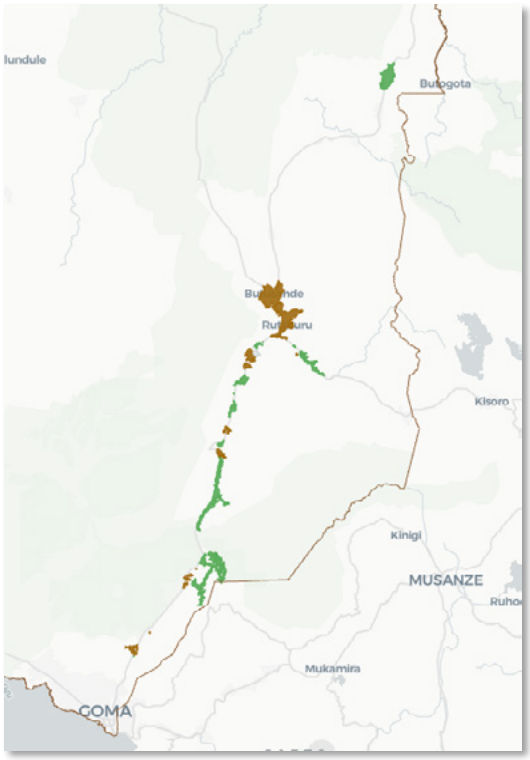
30 This data was available for the period 2017–22.

31 Ratledge, N. et al. (2022) 'Using Machine Learning to Assess the Livelihood Impact of Electricity Access'. Nature 611

After applying both criteria, 31 settlements in Rutshuru Region were selected to be included as part of the later steps of the impact analysis approach.

After selecting treated settlements in Rutshuru Region to focus on as part of the analysis, a check based on time series satellite data of nighttime light intensity was conducted to understand if, and to what extent, the Rutshuru communities had prior access to electricity (before connection to the new grid in 2017).[32] This resulted in Rutshuru settlements being divided into two groups: 'previously electrified' (13 settlements) and 'previously unelectrified' (18 settlements). This separation of treated settlements was used in the analysis to understand if, and to what extent, there is a difference in outcomes between both groups, with the working assumption that improvements in livelihood status will be greatest for settlements which have had no prior access to electricity.

Figure 8. Previously unelectrified group (green) and previously electrified group (brown)

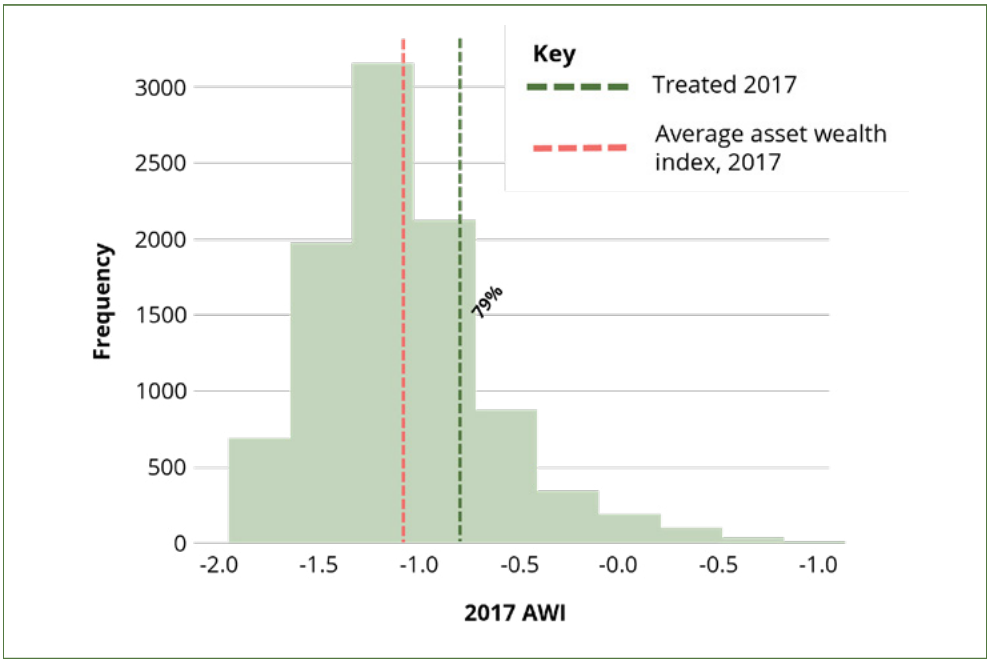


Comparing the average characteristics of the selected treated settlements to the averages for Nord-Kivu province in the year treatment started (2017), we found the following:

1. They have a slightly higher asset wealth than the average for the province. The AWI for this group as a whole places them in the 79th percentile of the AWI distribution for all settlements in the province.
2. They tend to have a slightly larger population than the average for the province. This is explained by the large number of small settlements found in the human settlement layer in Nord-Kivu, in particular in the western half of the province.
3. They tend to be closer to a main road than the average for the province. This is explained by the placement of transmission infrastructure along existing road infrastructur.

32 This analysis used a cut-off of 70% nighttime light intensity to separate 'previously electrified' from 'previously unelectrified'. A light intensity of above 70% is typically aligned to electricity access as opposed to other nighttime light sources such as charcoal or other fuelwood.

Figure 9. Distribution of 2017 asset wealth (baseline) for all settlements in Nord-Kivu, highlighting treated settlements



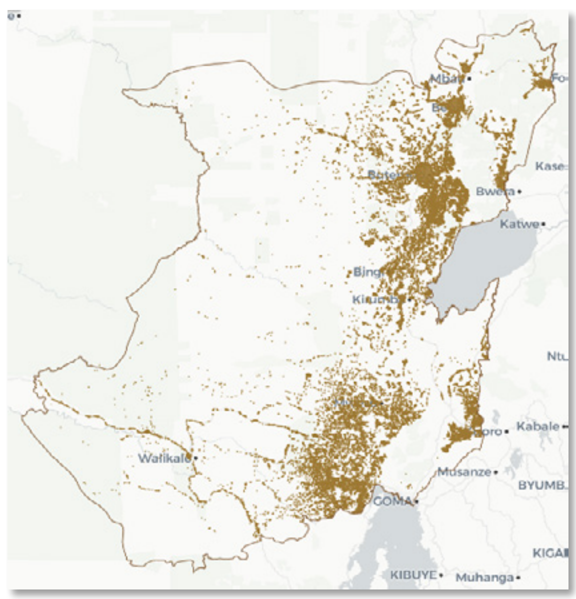
4.2. Step 2: Identifying and selecting non-treated locations

Following identification of treatment locations, the evaluation identified and mapped non-treated settlements in Nord-Kivu province as the starting point from which to develop synthetic control units. This involved a two-stage process: first, identifying and mapping all non-treated settlements in Nord-Kivu; second, identifying a shortlist (a 'donor pool') of sufficiently similar settlements from which we could develop the synthetic control units.

4.2.1. Identifying and mapping non-treated locations in the human settlement layer

The first step in selecting non-treated locations to include in the analysis was to **identify and map all non-treated settlements in Nord-Kivu in the Atlas AI human settlement layer**. The identification of non-treated settlements was constrained to Nord-Kivu province (rather than mapping settlements in adjacent provinces or in the DRC more broadly) for two reasons. First, through the identification nearly every settlement in Nord-Kivu was mapped, which provided a deep 'candidate pool' from which synthetic control groups could be developed (the study identified a total of 9,423 settlements in Nord-Kivu). Second, the study assumed that treated and non-treated settlements in the same province are likely to share a high degree of similarity – higher than treated and untreated settlements in more distant provinces.

Figure 10. Non-treated settlements in Nord-Kivu



4.2.2 Selecting a ‘donor pool’ of non-treated settlements

Rather than developing synthetic control units from all non-treated settlements in Nord-Kivu province, identified non-treated settlements were narrowed down to a shortlist (a ‘donor pool’) of settlements which would form the basis of the synthetic controls. The selection was narrowed down in this way for two reasons. First, it allowed the exclusion of settlements that demonstrated significant differences across key metrics prior to electrification (especially with regard to trends in asset wealth)[33] and hence the achievement of a closer initial match between donor pool and treated settlements. This strategy was adopted in recognition of the fact that VE had not targeted settlements at random; instead, the first settlements to be connected to the minigrid were those located close to newly installed electricity distribution infrastructure, which had in turn been sited along significant roads for ease of construction. It was likely, therefore, that treated settlements would not be typical of the wider region, because they were located closer to significant roads and were therefore likely larger in size and wealthier. The selection strategy therefore took account of these differences and helped ‘match’ treated settlements to a donor pool of broadly similar settlements. Second, constraining the selection of non-treated settlements to a smaller donor pool significantly reduced the complexity of the downstream analysis required to produce synthetic control units.

Cosine similarity analysis was used to sift through the full candidate pool of non-treated settlements in Nord-Kivu province and identify the top 10 most similar sites from the candidate pool for each non-treated settlement, based on similar patterns and trends across four key attributes of interest in the Atlas AI dataset (see Table 2). This was done for both the previously unelectrified and the previously electrified treatment subgroups; duplicate sites[34] that appeared in the analysis were removed. The purpose of the cosine similarity testing process was not to identify a donor pool of settlements that were identical to the treated settlements; rather, it was to develop a donor pool of broadly similar settlements from which the synthetic control units could efficiently be developed, with the synthetic control analysis itself taking care of the remaining differences to produce a much closer ‘fit’.

Table 2. Atlas AI datasets used for cosine similarity testing

Attributes used in cosine similarity testing
2012 Asset Wealth Index
2016 Asset Wealth Index
2016 population size (disaggregated by gender)
Distance to major roads

Asset wealth was identified as a key indicator of similarity between the treatment group and the candidate pool. Cosine similarity testing was conducted between treated settlements and the full candidate pool at two points in time (2012 and 2016) to identify settlements that were trending similarly prior to treatment.

Population size and distance to major roads (as a proxy for accessibility to markets) were adopted as additional key attributes to enhance the matching between the treatment

33 We did not include asset wealth in the post-treatment analysis, because this risks introducing bias into the final results.

34 That is, where the same site in the full candidate pool had been selected more than once as being similar to a treatment site.

group and the donor pool and to select between candidate pool settlements that otherwise had similar characteristics. As with AWI and the human settlement layer dataset, the completeness of the additional datasets used in the cosine similarity testing was reviewed. The study found these to have a high degree of reliability. For instance, although there may potentially be gaps in the data record for the road layer, owing to its reliance on user-provided information, the study found that the data records for primary, secondary and tertiary roads (the categories we utilised to identify major roadways) were comprehensive.

This approach resulted in very few instances of missing data. Settlements were identified using the WorldPop geospatial population dataset, which is limited by the boundaries of settlement areas. Consequently, there were isolated instances where the model failed to recognise a settlement but where Atlas AI's human settlement layer succeeded. However, it is worth noting that such occurrences were extremely infrequent and impacted only a minute fraction of settlements identified by the human settlement layer. As a result, these cases were omitted from the analysis. The number of settlements affected by this removal was not statistically significant and was observed primarily in areas containing approximately 10 houses or fewer.

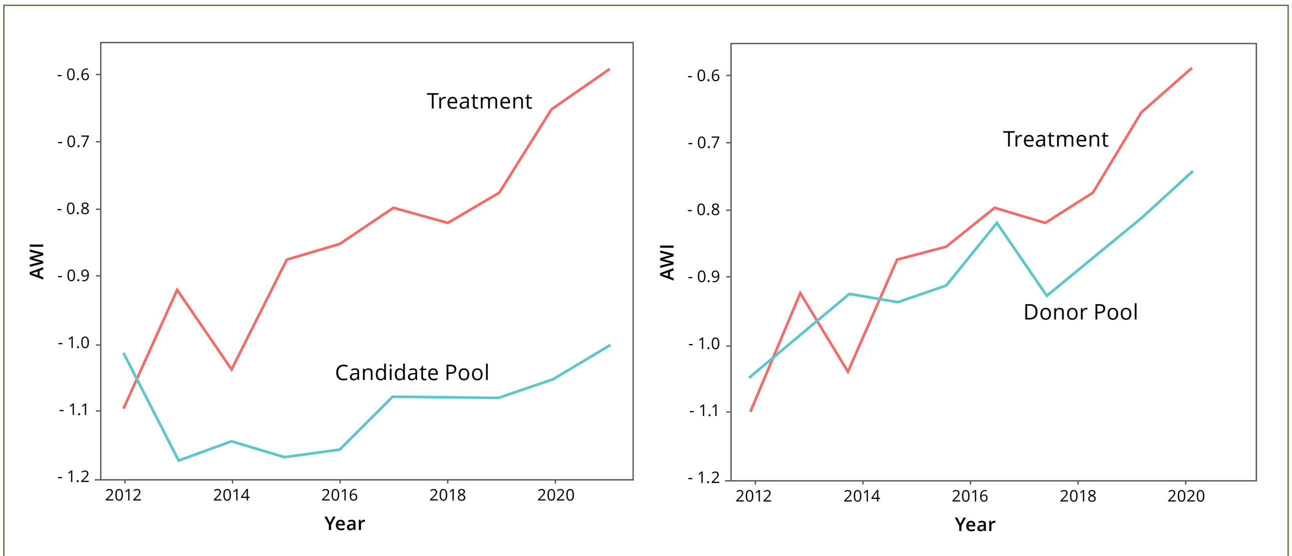
4.2.3. Results of cosine similarity testing to identify a 'donor pool'

The aim of the cosine similarity testing was to identify a donor pool of non-treated settlements that had a higher degree of similarity with the treated settlements than did the wider candidate pool of non-treated settlements as a whole. We carried out cosine similarity testing to identify a donor pool for both the previously unelectrified treatment group and the previously electrified treatment group in Rutshuru.

Previously unelectrified group cosine results

Cosine similarity testing yielded a **donor pool of 161 non-treated settlements**[35] for the unelectrified settlement subgroup. As illustrated in Figure 11, this donor pool identified through the cosine similarity analysis has a much closer fit with the treated settlements than between the treatment group and the candidate pool overall.

Figure 11. Comparison of 'fit' in AWI between previously unelectrified treated settlements and settlements in the full candidate pool (left) and donor pool (right)



35 Once duplicate sites had been removed.

Previously electrified group cosine results

Cosine similarity analysis for the previously electrified group yielded a **donor pool of 96 settlements**. Again, the analysis indicates a much closer fit between these donor pool settlements and the treatment group than between the candidate pool and treated settlements overall.

Figure 12. Comparison of 'fit' in AWI between previously electrified treated settlements and settlements in the full candidate pool (left) and donor pool (right)

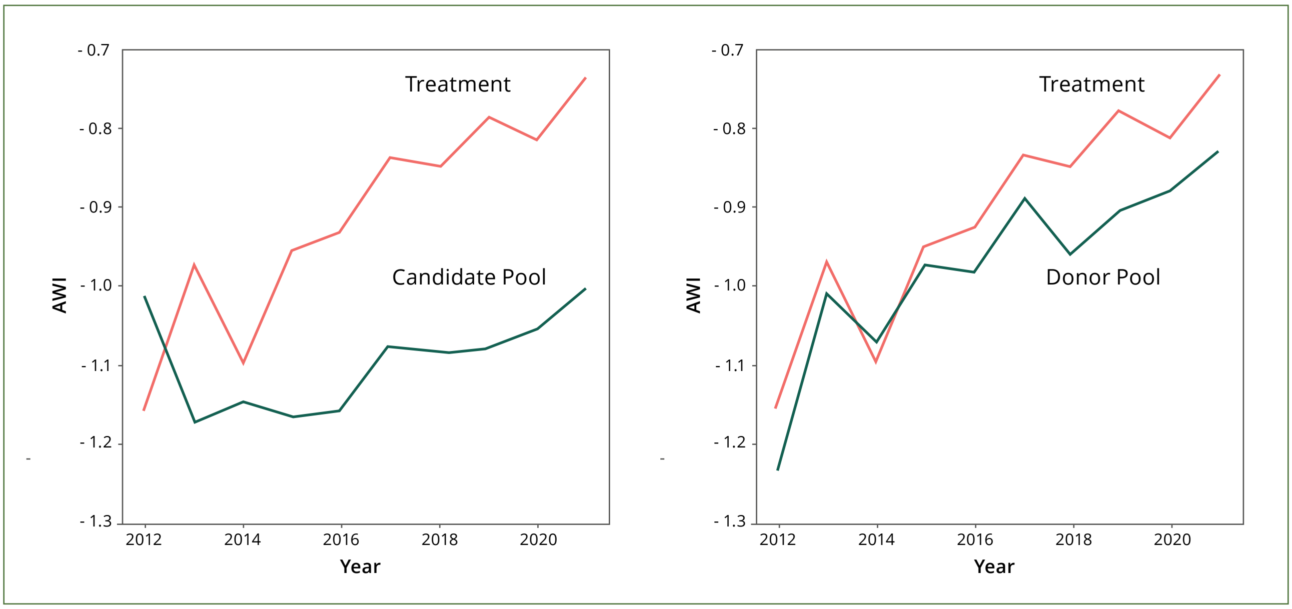
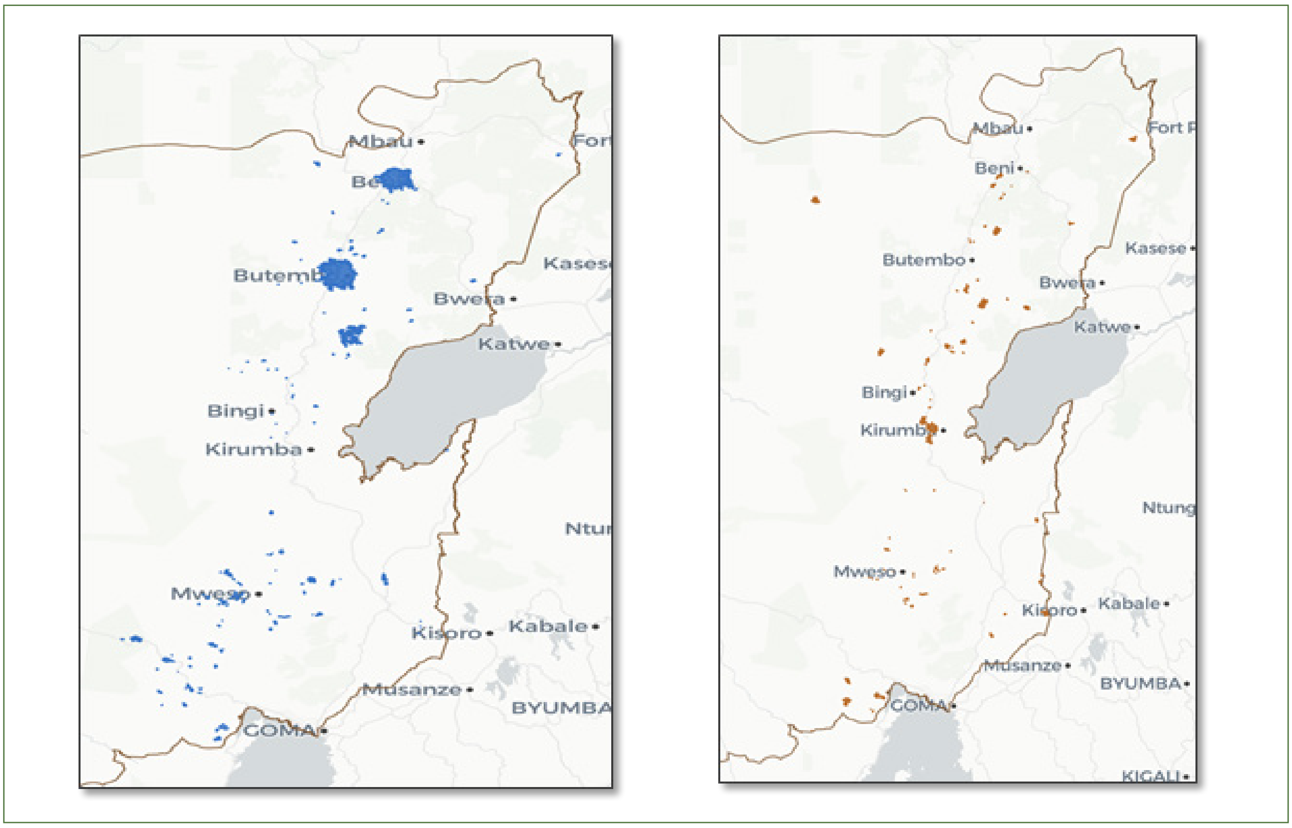


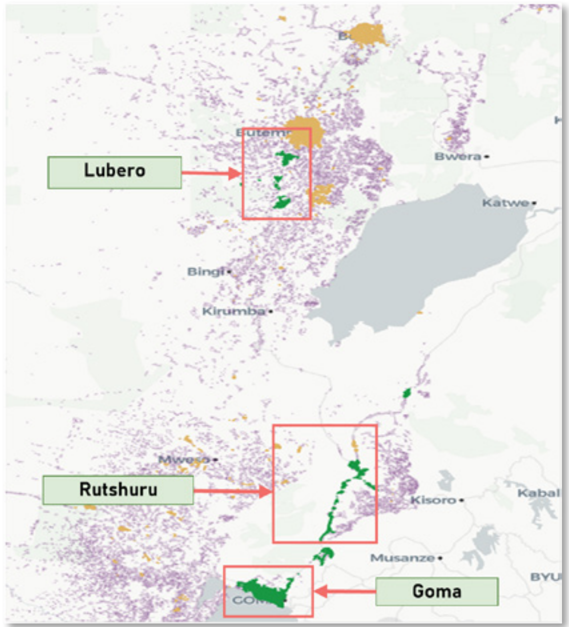
Figure 13 provides an overview of the location of donor pool settlements for both the previously unelectrified and previously electrified subgroups in Rutshuru.



4.2.4. Summary of settlement locations

The study deals with the following categories of settlements in Nord-Kivu: (i) all identified treated settlements (in green in Figure 14), from which the Rutshuru group was purposively selected based on connection date; (ii) all identified non-treated settlements (the candidate pool) (in purple); and (iii) an identified 'donor pool' of non-treated settlements (selected through cosine similarity analysis with treated settlements) (in yellow). The study focused on settlements in Rutshuru selected on the basis of length of connection, dating from 2017. The settlements are divided into previously unelectrified and previously electrified groups. Goma and Lubero clusters were not selected, based on the date of connection and challenges with regard to identifying a suitable comparator (in the case of Goma).

Figure 14. Overview of selected locations



4.3. Step 3: Conducting synthetic control analysis

4.3.1. Synthetic control method with elastic net

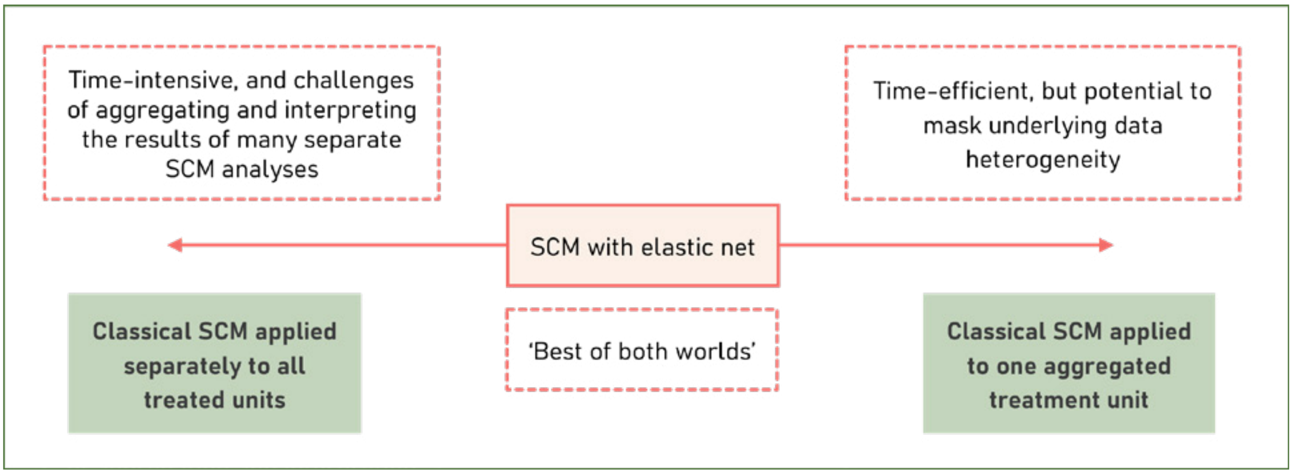
The original classical SCM approach was designed primarily to estimate the effects of large aggregate interventions focused on a small number of large treatment units (typically one), where data is available (for both dependent and independent variables) over a longer time horizon. This study applied this approach in a slightly different context in which there are multiple treated and non-treated units and where data is available over a relatively short time horizon (both pre- and post-treatment). In this context, the data could have been aggregated before the analysis stage, and the classical SCM approach could have been applied across all the treated and non-treated pool units as one, but this would have risked masking underlying data heterogeneity. Alternatively, classical SCM analyses could have been conducted for all individual treated and non-treated units separately, but this would have been highly resource-intensive and would have risked overcomplicating the analysis stage.

A modified version of the classic SCM approach, 'SCM with elastic net', was adopted in this study as being the most appropriate to the given situation. SCM with elastic net offers a more relaxed definition, with a regularisation function that helps the model to make generalisations when predicting the counterfactual for post-treatment years but avoiding overfitting. This is helpful in situations (such as this one) where the data record is not extensive and there are residual differences between treatment units and the donor pool.[36] It is a variation which has been used frequently in the literature.[37] As illustrated in Figure 15, in this context SCM with elastic net offers the 'best of both worlds' in terms of striking a pragmatic balance between applying the classical SCM approach across all treated units separately and running a single classical SCM across all treated units as one.

36 Based on the use of an elastic net drawing on a combination of least absolute shrinkage and selection operator (LASSO) and ridge penalties.

37 Ratledge, N. et al. (2021) Using Satellite Imagery and Machine Learning to Estimate the Livelihood Impact of Electricity Access.

Figure 15. Visualisation of the selection of SCM



Annex 3 provides a more detailed comparison between the classical SCM approach and SCM with elastic net, and provides more detail on the specific technical definition of 'SCM with elastic net' used in this study, including some of the implications of relaxing the constraints of the classical SCM used.

In practice, the version of the SCM with elastic net used in the analysis was defined as follows:

1. Weights of donor units are not restricted to sum to 1.
2. Weights of donor units cannot be negative.
3. No intercepts are allowed (an intercept allows for a level shift where the trend remains the same).

This is a variation on the standard SCM with elastic net. Typically, the 'non-classical' SCM with elastic net also relaxes the SCM approach to allow weights to be negative (which is a further advantage when dealing with data over shorter time horizons). In this case, this further relaxation of the model was deemed not to be necessary, given that an in-depth cosine similarity analysis of untreated settlements had been done to identify a donor pool which is broadly similar to treated settlements pre-treatment.[38] [39]

Synthetic control units were developed to closely approximate the behaviour of the connected settlements before treatment. As discussed in Section 4.1.3, settlements in Rutshuru were divided into two groups: (i) the 18 'previously unelectrified' settlements; and (ii) the 13 'previously electrified' settlements. Synthetic control units were developed to closely match the behaviour (in AWI) of connected settlements in both groups in the period pre-treatment (2012–16). Synthetic control units were composed of the weighted averages of settlements in their respective donor pools (see Annex A3.2 and A3.3 for more information on how these synthetic control units were structured). The model predicts the counterfactual by weighting each post-period control variable. These weights are determined through panel-like regression within the pre-treatment period, in which a single treated unit is regressed on the full panel of control units.

As highlighted in Figure 16 and Figure 17 (Section 5), the created synthetic control units closely matched the behaviour of the connected settlements in the years prior to treatment and therefore formed the basis of a credible counterfactual to identify net treatment effects. The study team tested different versions of the SCM approach; the modified version of the SCM with elastic net produced the closest fit without excessive overfitting.

38 It was determined not to allow weights to be negative, to produce a more 'real' and less overly 'synthesised' effect.

39 In terms of technical specification, the model used did not include covariates and incorporated an alpha of 0.5 (elastic net), which is a mix of LASSO and ridge penalties.

5. Key findings

This section discusses the findings of the impact evaluation. The section looks first at whether the SCM was successful in mimicking the behaviour of connected settlements in the study years prior to treatment (2017–21). It then presents evidence of impact for two groups of settlements which have been connected to the new VE hydroelectric minigrid: (i) settlements which received access to electricity for the first time; and (ii) settlements which are more likely to have had some form of access to electricity before the investment was made. The size of the treatment effect (in terms of a change in AWI score) is highlighted for both groups, and a robustness check is performed on the results. The section then puts the findings into broader context, firstly to understand how they compare to the results of similar studies and secondly to discuss how connection to the electricity minigrid is likely driving changes in asset wealth at the household level.

5.1. Change in asset wealth for connected settlements

Analysis indicates that connection to the minigrid produced an identifiable increase in asset wealth for settlements in the Rutshuru group, over and above the synthetic control. In the period post-treatment (2017-21), changes in asset wealth in connected settlements were compared to changes in asset wealth in the synthetic control units, to identify a net treatment effect. In both the previously unelectrified and previously electrified groups, the behaviour of the connected settlements diverged from their synthetic control units after connections to the minigrid in Rutshuru began (in 2017), with the AWI scores for both groups increasing more rapidly than those of their respective synthetic control units. This indicates that connection to the minigrid resulted in a net increase in asset wealth.

The identified net treatment effect is strongest and most consistent in the 'previously unelectrified' group, which were more likely to have no prior access to electricity. The divergence in behaviour between connected settlements and their synthetic control units is greater and more consistent in the previously unelectrified group (Figure 16), indicating a stronger treatment effect in these settlements. This is a plausible finding given that these settlements are more likely to have experienced the full benefit of a new connection to the electricity grid, in contrast to the previously electrified settlements, which are more likely to have shifted from an alternative source of electricity (such as a more expensive and less reliable diesel generator).

Figure 16. Change in Asset Wealth Index scores for the previously unelectrified settlements vs synthetic control (treatment time indicated by dotted line)

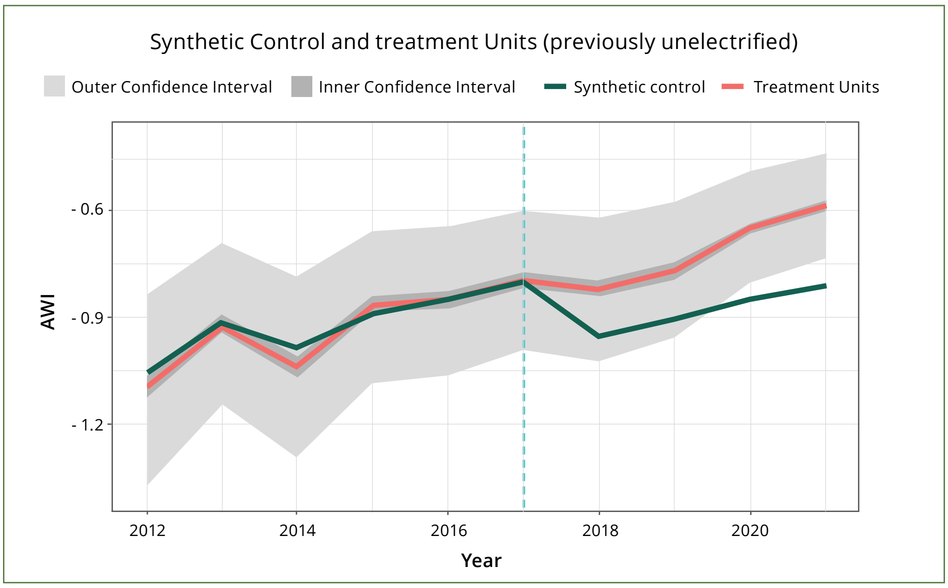
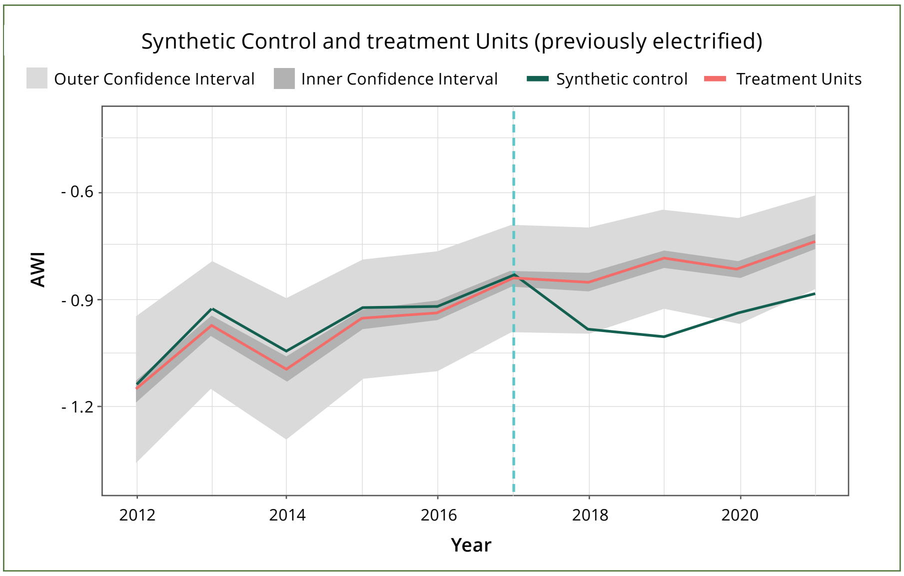


Figure 17. Change in Asset Wealth Index scores for the previously electrified settlements vs synthetic control (treatment time indicated by dotted line)



Further detail on the size of the treatment effect for the previously unelectrified and previously electrified groups is provided in Table 3 and Table 4. The AWI score for the previously unelectrified treatment group increased by 0.223 above that of the synthetic control group over the treatment period.[40] Although AWI cannot be expressed as a dollar value, by calculating standard deviations it is possible to get a sense of the relative size of this change. The standard deviation is 0.46, suggesting that this is a significant change relative to AWI scores for the whole of Nord-Kivu (see also Section 4.3). The net increase in AWI for the previously electrified group was smaller: 0.146 (Table 4).

In the previously unelectrified group, AWI grew strongly in the period post-treatment. As illustrated in Table 3, it grew by 28% in the period 2018–21 vs 15% for the synthetic control group, providing further evidence of the impact of connection to the minigrid on livelihood. Early evidence suggests that this rate of growth is increasing over time; this is in line with other studies which suggest that the impact of electrification takes some time to emerge.

Table 3. Treatment effect size and AWI growth rate in treatment and synthetic control groups for previously unelectrified settlements by year

Year	2017	2018	2019	2020	2021
Mean AWI for treatment group	-0.7986	-0.8220	-0.7685	-0.6504	-0.5898
Mean AWI for synthetic control group	-0.7998	-0.9534	-0.9115	-0.8512	-0.8130
5th percentile AWI for treatment group	-1.2287	-1.3120	-1.2596	-1.1991	-1.1071
95th percentile AWI for treatment group	-0.4154	-0.3816	-0.2773	-0.1991	-0.0559
Treatment effect	0.001	0.131	0.142	0.200	0.223
Treatment group growth rate	-2.9%	6.5%	15.4%	9.3%	
Synthetic control growth rate	-19.2%	4.4%	6.6%	4.5%	

40 The version of AWI being used in this study has the following min/max values: -1.0113611 (min), 2.0468638 (max).

Table 4. Net treatment effect size for previously electrified settlements by year

Year	2017	2018	2019	2020	2021
Mean AWI for treatment group	-0.8393	-0.8503	-0.7844	-0.8152	-0.7373
Mean AWI for synthetic control group	-0.8271	-0.9928	-1.0001	-0.9362	-0.8837
5th percentile AWI for treatment group	-1.1627	-1.1610	-1.1592	-1.2524	-1.1970
95th percentile AWI for treatment group	-0.3469	-0.3171	-0.2338	-0.1822	-0.1282
Treatment effect	-0.012	0.142	0.216	0.121	0.146
Treatment group annual growth rate	-1.3%	7.8%	-3.9%	9.6%	
Synthetic control annual growth rate	-20.0%	-0.7%	6.4%	5.6%	

A drop in AWI was detected in the synthetic control units in the years immediately post-treatment, and it is not clear what has caused this change. This drop is consistent for the synthetic control units for both previously unelectrified and previously electrified groups, and it is consistent in different versions of the synthetic controls that were tested. It should be noted that it is not uncommon in this type of impact assessment for impact to result from a fall in the dependent variable(s) in the control units; this is likely driven by broader dynamics in the region, as discussed below. The challenge here is the relatively short time horizon in data post-treatment (2017–21); repeating this study over a longer time horizon would likely help even out these effects.

Given that AWI is a relative index which is normalised across the region, it is likely that it is influenced by changes in AWI scores and other socioeconomic indicators both in Nord-Kivu and in adjacent regions. A review of AWI trends in other untreated settlements in the wider candidate pool consistently identified this fall in AWI. A review of trends in socioeconomic indicators in the DRC more broadly can also provide clues as to why these variations in AWI may be occurring. Although detailed data is not available for Nord-Kivu province specifically, data taken from available sources suggests that the DRC experienced a high degree of volatility in headline development indicators during the treatment period, and especially in the period immediately following the treatment in 2017. This volatility might help to explain this fall in AWI. For instance, data taken from the World Bank's World Development Indicators (Figure 18) reveals that GDP per capita generally increased in the period post-treatment but experienced a notable fall in the period immediately prior to treatment (2015–16). Likewise, data from the Internal Displacement Monitoring Centre (iDMC) reveals that there was a significant spike in internally displaced people in the DRC in 2016 and 2017 (Figure 19), which would also be expected to negatively affect livelihood indicators, including AWI. Although this data cannot be disaggregated by region, reporting from Human Rights Watch indicates that Nord-Kivu province was significantly affected by violence during this period, with more than 3,000 violent incidents reported in the province from 2017 to 2019.[41]

41 DR Congo: 1,900 Civilians Killed in Kivus Over 2 Years

Figure 18. GDP per capita for the DRC 2012–22 (source: World Bank World Development Indicators)

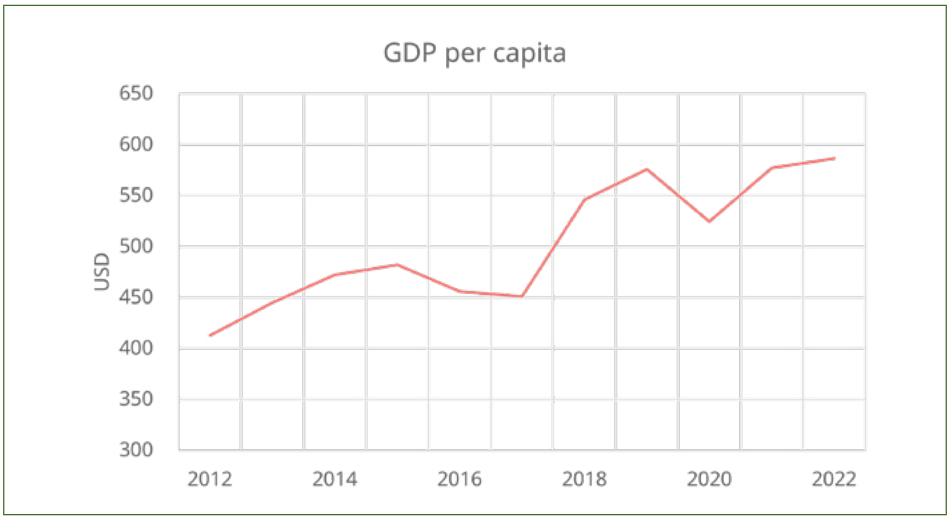
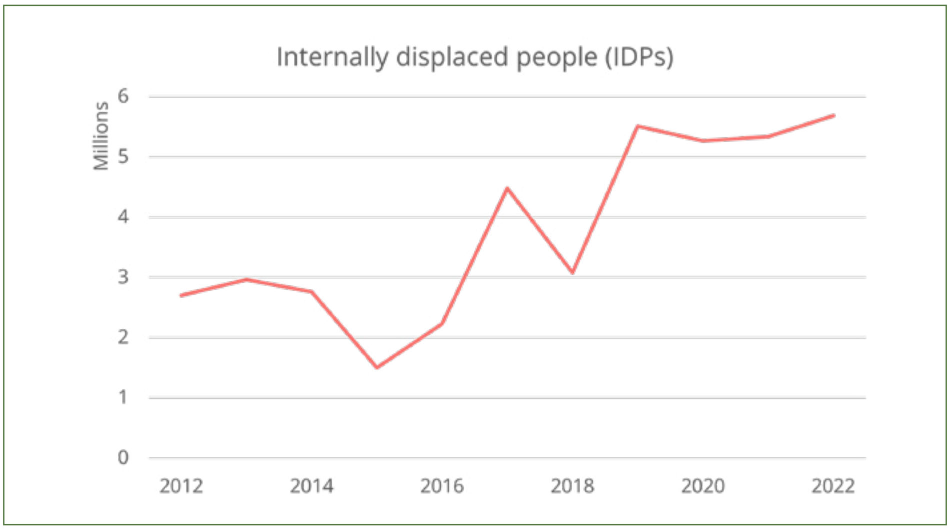


Figure 19. Internally displaced people in the DRC 2012–22 (source: iDMC)



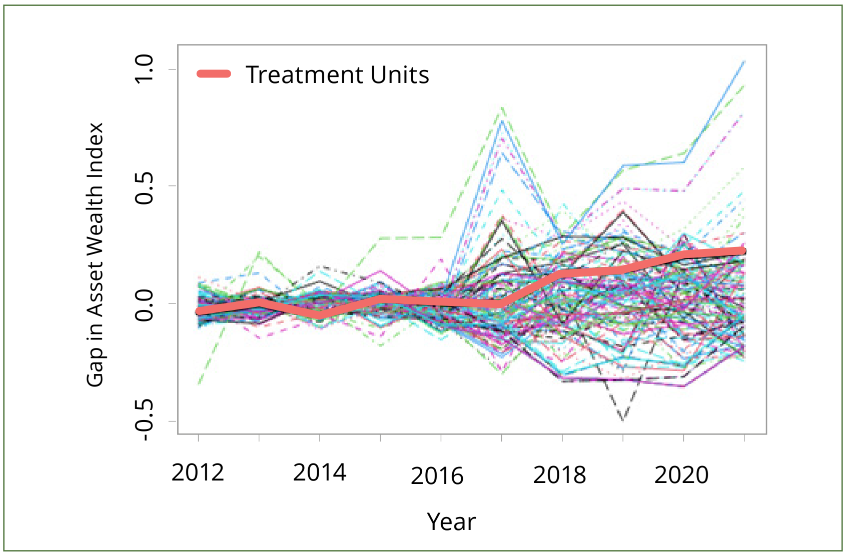
5.2. Robustness check

To understand the significance of the results, a robustness check was performed. This indicates that the results are significant at a 90% confidence level. To check the significance of the results, the average AWI score for the previously unelectrified settlements was plotted against the AWI scores for all units in the donor pool of untreated settlements (161 settlements). The purpose of this analysis is to put the change observed in the treated settlements into a broader perspective and to help determine the extent to which the trends seen in the Rutshuru group of treated settlements are also happening in the wider donor pool of unconnected (but similar) settlements.[42] This is to give enhanced confidence that it is connection to the minigrid that is driving the change in AWI rather than other factors outside of the project (for example, 'could the change be happening by chance?'). In their influential study of the effect of the California Tobacco Control Program, Abadie, Diamond and Hainmueller (2010) perform this type of robustness check by overlaying the performance of their treatment unit (California) with those of their placebo units (their donor pool of non-treated US states).[43]

42 Which in other key respects are very similar to the treated settlements, as discussed in Section 3.

43 Abadie, A., Diamond, A. and Hainmueller, J. (2010) 'Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program'. Journal of the American Statistical Association 105(490): 493–505.

Figure 20. AWI score for previously unelectrified settlements plotted against AWI scores for all units in the donor pool of untreated settlements



When a similar approach is adopted as part of this study, as illustrated in Figure 20, over the course of the treatment period from 2017 to 2021, the treated settlements in the 'previously unelectrified' group (represented by the dark line) are found to outperform all but 16 of the untreated settlements in the donor pool. This equates to only 16 out of 161 untreated settlements (or one in 10) in the donor pool outperforming connected settlements. This can be further interpreted as indicating that the results are significant at a 90% confidence level.[44] In statistical terms, a 'gold standard' confidence level is typically 95%. Nevertheless, this result is still considered significant, and it strongly suggests that the result did not happen by chance and that connection to the grid was a significant factor in driving the increase in asset wealth in connected settlements. These observations are based on relatively short time horizons, however; repeating the analysis over a longer time horizon as this investment continues to mature, including analysing AWI for additional treatment clusters, will further increase confidence in the results.

5.3. Putting results into context: placing connected settlements' AWI onto Nord-Kivu province's AWI distribution

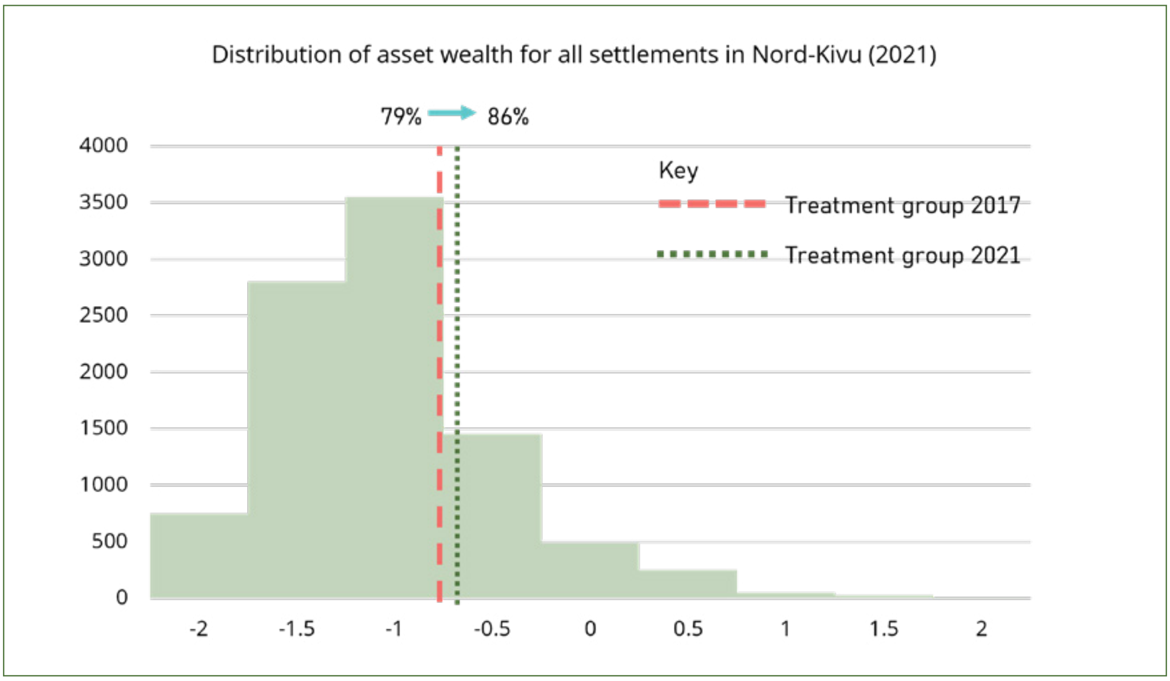
Because it is not possible to express AWI as a benchmarked income figure, the change in AWI for newly connected settlements was analysed against the distribution of AWI for the whole of Nord-Kivu province. To understand the significance of the change in AWI for the 'previously unelectrified' group of settlements, their 2021 AWI scores were plotted on the distribution of AWI scores for all settlements in Nord-Kivu province. Ideally, the change in AWI would be converted to a benchmarked income figure (such as $/month) in order to understand the impact of grid connection on settlements' poverty levels. However, this is not currently possible, and therefore this approach provides a second-best alternative. Plotting the change in AWI against the asset wealth scores for the province as a whole helps to put the change into context and to understand how much connection to the minigrid helped 'move the needle' on asset wealth relative to the performance of all other settlements in the province.

44 We calculate the confidence interval based on the probability that the results were not caused by treatment: 16/161 gives a probability of 0.1 that the effects found were not due to treatment, and therefore a 90% confidence interval.

It is helpful to think of the change in asset wealth in these relative terms, given that the AWI is a relative measure (calculated on a normalised index with both positive and negative values, ranging from –2 to 2). This analysis follows on from that presented in Section 3, which plotted the 'previously unelectrified' group's AWI scores against those of the whole province in 2017, before treatment began.

Analysis of AWI scores for the whole province reveals that the newly connected settlements' asset wealth has increased significantly relative to the provincial average. Plotting the 'previously unelectrified' group's AWI against the distribution of AWI for the whole of Nord-Kivu province in 2017 and 2021 reveals that the connected settlements' growth in asset wealth has improved significantly vis-à-vis all settlements in the province. In the period post-treatment (2017–21), the growth in asset wealth propelled them from the 79th to the 86th percentile (see Figure 21). At the same time, the synthetic control group fell in the distribution from the 79th percentile in 2017 to the 75th percentile in 2021. The treatment effect size equates to an increase of around 0.46 standard deviations.

Figure 21. The changing position of the treatment group in terms of asset wealth when set against the distribution of asset wealth for all settlements in Nord-Kivu



5.4. Comparing the results to other studies

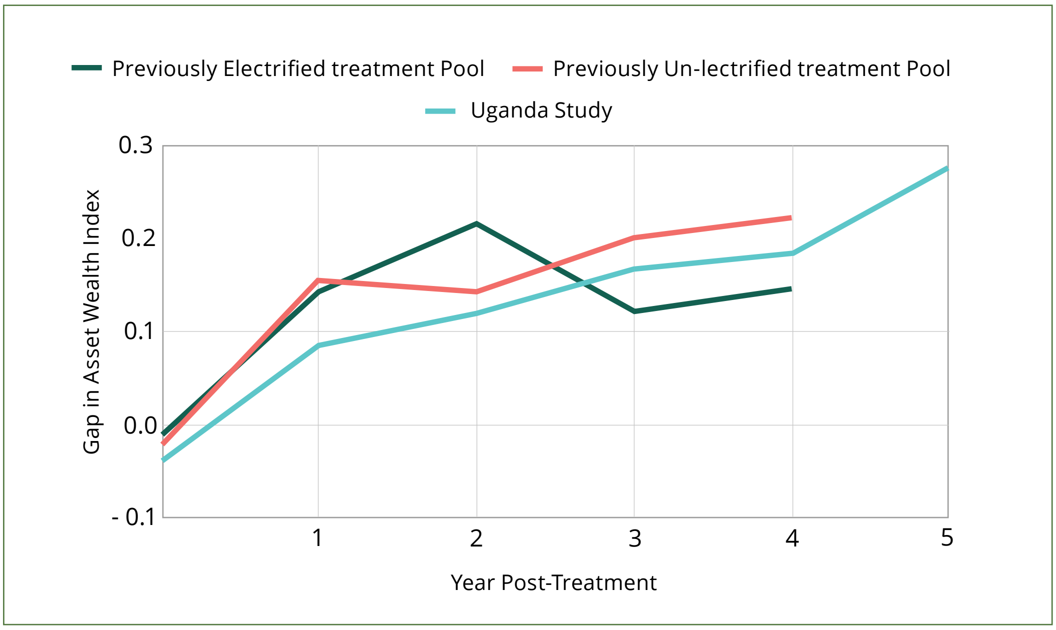
Although there are few comparable studies to draw on, the results of this study are broadly comparable to those of a similar study undertaken in Uganda. To date, the use of AWI to assess the impact of connections to electricity grids is still in its infancy and has been used in relatively few published studies. However, a prominent study published in *Nature* in 2022[45] made use of AWI derived through satellite imagery and machine learning techniques in a broadly similar manner to assess the impact of electricity access in Uganda, albeit without the use of synthetic control units to establish the counterfactual. This study also used AWI as a reliable and cost-effective proxy to estimate the livelihood impact of electricity access in a data-sparse location.

The Uganda study found evidence that connection to the electricity grid has a net positive impact on AWI scores, with the treatment effect increasing over time. Figure 22 highlights the

45 Ratledge, N. et al. (2022) 'Using Machine Learning to Assess the Livelihood Impact of Electricity Access'. Nature 611.

net treatment effect observed for the treated groups in this study and in the Uganda study (calculated as the change in AWI scores for treated settlements minus the change in AWI scores for the synthetic control units). The estimated size of the treatment effect is generally in the same band, with the behaviour of this study's 'previously unelectrified' group and the Uganda study's treatment group being broadly comparable. In the case of the Uganda study, connection to the grid was found to increase village-level asset wealth by up to 0.15 standard deviations and doubled the growth rate in AWI for treated villages during the post-treatment period relative to untreated areas.

Figure 22. Comparison of the net treatment effect observed for this study's 'previously unelectrified' and 'previously electrified' groups and the treatment group in the Uganda study



The wider literature provides clues as to how electricity connections drive improvements in asset wealth for households. Through our study approach we are not able to 'look under the hood' to isolate the precise drivers of increased asset wealth at the household level as a result of improved access to electricity. However, we can identify some of these drivers, and explore how access to electricity affects men and women differently, with reference to the wider literature (although this is still sparse). One study[46] which reviewed the impact of home solar connections asked respondents to identify the most significant improvements in their household as a result of first-time access to electricity. The improvements most frequently cited by respondents included: studying/reading at night (58%); entertainment (47%); extension of business and working hours (16%); and cooking at night (16%). A further study[47] finds evidence that access to electricity:

- significantly impacts female employment (around 9.5 % within five years), partly by 'freeing up' women's time for the job market;
- facilitates new activities for men and women in the home, allowing them to produce goods to sell in local markets; and
- results in large increases in the use of electric lighting and cooking, and reductions in wood-fuelled cooking, over a five-year period.

46 Gustavsson, M. and Ellegård, A. (2004) 'The Impact of Solar Home Systems on Rural Livelihoods. Experiences from the Nyimba Energy Service Company in Zambia'. Renewable Energy 29(7): 1059–72.

47 Dinkelman, T. (2011) 'The Effects of Rural Electrification on Employment: new evidence from South Africa'. American Economic Review 101(7): 3078–3108.

The way the AWI used is constructed helps us to understand how changes in asset wealth at the household level are driven by access to electricity. The AWI for the DRC captures a range of factors which are influenced by new or improved electricity connections in the short, medium and longer terms. For instance, the index captures the presence of attributes which will be impacted almost immediately by a connection to the minigrid, including a household electricity connection, ownership of a range of small appliances which rely on an electricity connection (including telephones, radios, televisions, fridges and sewing machines) and the type of energy used for cooking (either an electric stove or other fuel).

In the medium term, such changes are likely to lead to new or improved livelihood opportunities for connected households, for example enabling households to start or expand business activities in the home (such as establishing small shops). In turn, these benefits will allow connected households to purchase larger assets which feature in the AWI, some of which will strengthen this livelihood effect further (such as improved access to markets through the purchase of a motorcycle). In the longer term, these benefits will enable connected households to make additional and more significant asset purchases captured by their asset wealth scores, including improvements to sanitation or the fabric of their homes. The *Nature* (2022) study suggests a time horizon of between four and five years for the first significant livelihood impacts to emerge as a result of improved access to electricity, although initial impacts are expected to emerge more quickly than this.[48] Annex 4 provides further detail on the individual assets captured by the AWI for the DRC.

48 Ratledge, N. et al. (2022) 'Using Machine Learning to Assess the Livelihood Impact of Electricity Access'. Nature 611.

6. Conclusions and recommended next steps

This section outlines key conclusions and recommends next steps for BII and FCDO. The key conclusions are framed according to the original two key study purposes, focusing on: (i) the extent to which the study has been able to identify evidence of impact from BII's investment in VE and, in doing so, fill a strategic evidence gap for BII in the infrastructure portfolio; and (ii) whether this study has been able to demonstrate 'proof of concept' for an innovative, low-cost and rigorous approach to assessing impact in infrastructure projects, including identifying some of the key issues that BII and FCDO should take into account in applying this approach in future.

6.1. Evidence of impact from BII's investment in Virunga Energies

The investment has been highly successful in reaching new customers. By accessing geotagged data on new connections and the installation of new electricity infrastructure, this study charted the roll-out of the rural electrification project to three settlement clusters. In total, the minigrid achieved 25,856 new connections from 2017 to 2022 against an initial target (for the first phase of the investment) of 10,000–12,000.

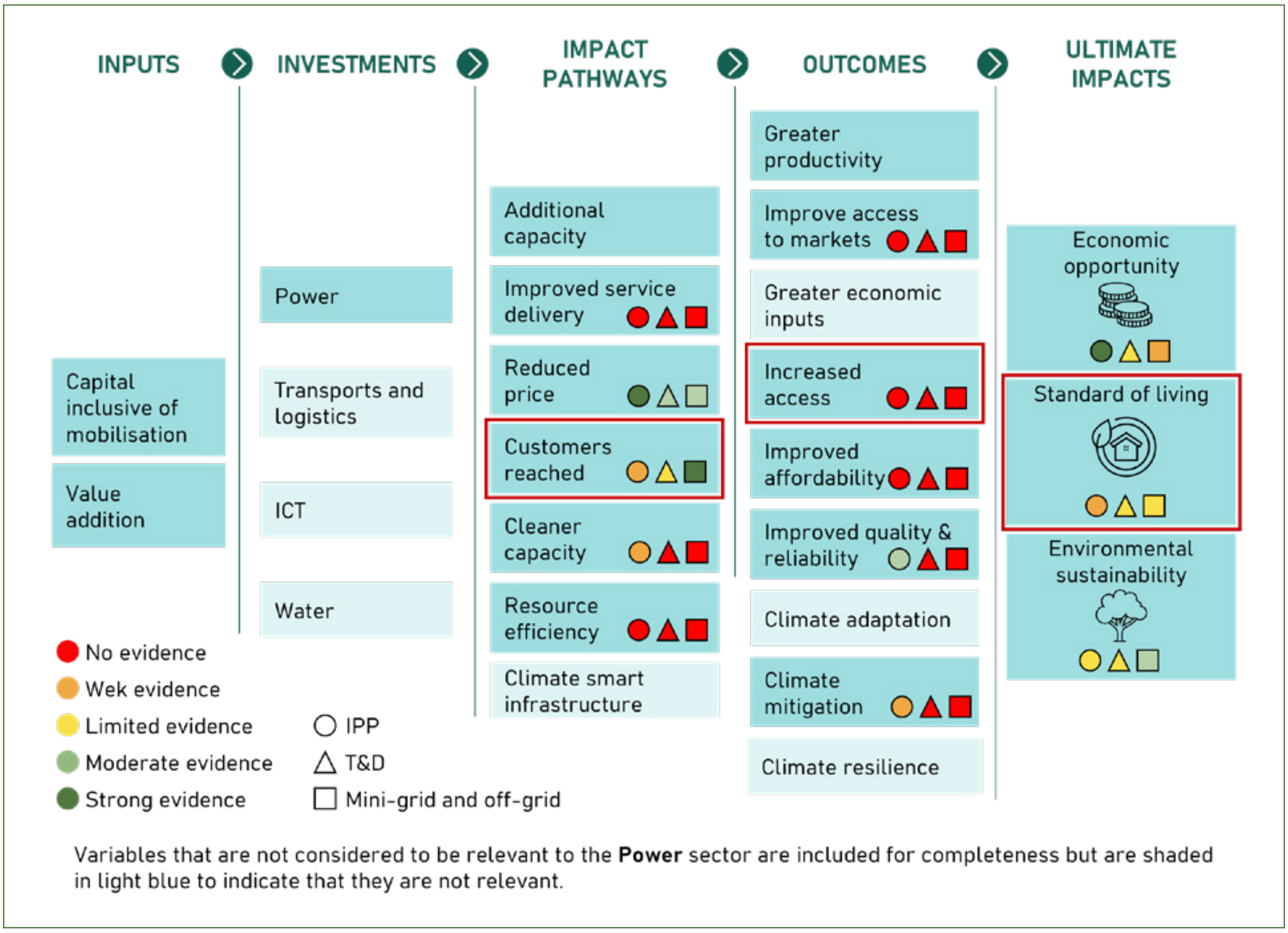
The study has found strong evidence that the minigrid has improved access to electricity for poorer and underserved communities. The study focused attention on one main settlement cluster, Rutshuru, as this was the earliest to be connected (in 2017) and therefore had the longest time horizon for impact to emerge. By analysing satellite nightlight data, this study is able to make a firm conclusion that 18 out of 31 settlements in this cluster are very likely to have had access to electricity for the first time as a result of this investment.

Newly connected settlements have experienced an improvement in their standard of living as a result of connection to the minigrid. The study uses asset wealth as a robust and widely accepted proxy for living standards. By applying the new approach, this study identifies a net increase in asset wealth for households that have been connected to the electricity grid, with this impact being strongest among households who have accessed electricity for the first time. The identified rate of growth in the AWI for households which have accessed electricity for the first time doubled since connection, leading to a jump from the 79th to the 86th percentile for asset wealth (set against the distribution of all households in Nord-Kivu).

The results of this study are relevant to three currently 'under-evidenced' areas in BII's sector impact framework for power infrastructure. These three areas, highlighted in red in Figure 23, focused on: (i) reaching new customers; (ii) expanding access to electricity for previously underserved communities; and (iii) improving standards of living. Alongside minigrids, the results of this study are particularly relevant to investments which have similar business models and objectives, in particular home and off-grid solar.[49]

49 A minigrid is a set of small-scale electricity generators interconnected to a distribution network that supplies electricity to a small, localised group of customers and operates independently from the national transmission grid. Home solar systems typically consist of solar panels (either with or without battery storage) which are built on the roof of a home or business. Off-grid solar solutions are typically built off site (of a household or businesses), involve battery storage, and are completely autonomous from the grid.

Figure 23. Study results linked to BII impact framework for power investments



Recommended next steps:

1. **Based on the evidence collected through this study, BII should consider making additional investments in minigrid or similar solutions, especially in underserved rural areas.** This study provides strong evidence that such solutions are effective in improving access to electricity in rural areas and in driving changes in standards of living, including in poorer and previously underserved locations. To maximise impact, BII should consider making additional investments in this space, especially where these investments open access to electricity for populations which currently have limited or no access to electricity. Additional evidence is needed to understand impacts in other contexts (such as urban and peri-urban locations) and to understand the comparative benefits of related investment types, such as home solar and off-grid solutions.
2. **Deepen the evidence base for this investment, including in additional treatment locations, as impacts begin to emerge.** This study makes use of data over a relatively short time horizon to explore evidence of impact (2017–21). Given the likelihood that impact will deepen over time, BII should consider repeating this study in about five years, focusing in particular on the way impact has developed as this investment is rolled out to new locations. This will increase confidence in the results and further strengthen learning on the situations in which this investment (and minigrids more broadly) has the greatest impact.
3. **Identify opportunities to ground-truth findings for this investment and to understand the drivers of change at the household level.** BII can seek opportunities

to ground-truth the findings of this study by comparing the results to evidence collected through other methods, including primary data. For example, the University of Antwerp is currently undertaking a study which is looking more broadly at impact accruing to the VE investment, using an impact assessment methodology based on difference-in-difference analysis. This study involves on-the-ground primary data collection at household and settlement levels and provides a good opportunity to ground-truth the findings of this study and to understand more about how and why connections to the minigrid drive improvements in living standards. It should be noted that this is a much larger study with a different purpose and that it involves data collection over several years.

6.2. Demonstrating ‘proof of concept’

This study demonstrates the successful development and use of a rapid, cost-effective, flexible and technically rigorous approach to measuring the impact of infrastructure investments, based on new thinking in impact evaluation design. The use of a geospatial impact evaluation approach allied to the SCM in this study offers a robust mechanism to establish causal impact and to identify if, and to what extent, an investment has resulted in positive livelihood impacts and has overcome the typical challenges of establishing credible control groups. To this extent, it provides a more detailed and credible understanding of impact than is possible either through self-reported data or through existing modelling techniques.

The approach overcomes some of the typical evaluation challenges associated with infrastructure evaluations and offers a series of benefits in comparison to traditional evaluation alternatives (see Annex 6). By making use of recent advances in geospatial data and remote sensing, the approach outlined in this study is **relatively low-cost and quick to implement**, with fewer cost drivers than are associated with more traditional approaches (such as on-the-ground surveys). As the methodology continues to mature, the marginal time and cost to implement additional studies will continue to fall.

The approach is also **flexible, scalable and replicable**. In contrast to more traditional alternatives, it can readily be adapted and scaled to cover changing patterns of implementation. By making use of recorded satellite imagery and machine learning techniques to close data gaps in secondary datasets, the approach enables researchers to ‘go back in time’ and track changes in treatment and control groups before the start of implementation; this offers the key benefit that baseline data collection (a lack of which often undermines impact evaluations) is not required before the start of implementation.

The approach places little burden on investment owners and is **not data-intensive to implement**. Limited time and information are required on the part of investees beyond geotagged client data. Traditional alternatives require more engagement on the part of investment owners and investees, such as facilitating access to field sites to collect primary data.

The new approach is limited with regard to the extent to which the findings can explore the drivers of change at the household level and can be disaggregated to particular beneficiary groups. The approach is not able to answer all questions of interest on its own, such as exploring how and why connection to the grid drives livelihood changes at the household level. As noted in this report, some of these drivers of change can be inferred from other published complementary studies. The approach is also not able (as yet) to isolate impact for particular groups (such as different socioeconomic groups and women).

The approach is most applicable in situations where there is a clear line of sight to end users, and it is more appropriate for localised investments; it is not applicable to all investments. In this study, a clear line of sight to end users was established through access to geotagged data on individual connections and time series data on electricity infrastructure installations. As currently designed, it is more challenging to implement the approach where specific end users are not known. As such, the approach is typically more appropriate to localised investments in sectors such as water and sanitation, power and manufacturing, etc., where investees are able to identify and collect geotagged data on service users/beneficiaries (ideally over a minimum period of five years post-investment). It is not appropriate for investments that have an impact at a systemic level and/or provide a public good. As such, it is not appropriate for all investments in the BII infrastructure portfolio, but it applies to a significant slice of investments (approximately 25%), where it is possible to identify end users.

Recommended next steps:

1. **Continue to develop the approach presented in this study to be applicable to larger sections of the infrastructure portfolio.** A useful next step is to expand on and test the approach in other subsectors in the infrastructure portfolio and in situations where information on end users is available only at a more aggregate level. This will enhance the applicability of the approach to a broader cross-section of the portfolio. For example, the evaluation team of Itad, Steward Redqueen and Atlas AI is currently adapting and testing the approach in the telecommunications subsector in a situation in which geotagged customer data is not available but where it is possible to identify treated locations more broadly with a high degree of confidence.
2. **Identify investments that could/should collect geotagged and time series data on connections.** BII should consider identifying relevant investments in the portfolio which could feasibly collect geotagged connection data on end users and infrastructure installations, and should support investment owners to do this and report it through the BII monitoring and evaluation system. This will increase the number and range of investments which can be evaluated effectively through this approach.
3. **Roll out further studies in the investment portfolio to deepen the evidence base for current and future investments.** BII and FCDO should consider rolling out additional studies in the infrastructure portfolio for a subset of investments where feasible (in particular, where geotagged data on end users is available and accounts for 'time lags' between treatment and the emergence of impact).[50] Such a rolling programme would build up rigorous evidence of impact across the portfolio, as well as lessons on what works best and in which contexts.

50 In the case of electrification, the wider literature suggests a minimum time horizon of approximately four to five years, as noted earlier in this report.

7. Annexes

Annex 1: References

Abadie, A., Diamond, A. and Hainmueller, J., 2010. 'Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program'. *Journal of the American Statistical Association* 105(490): 493–505.

Calderón, C. and Servén, L., 2004. The Effects of Infrastructure Development on Growth and Income Distribution. Policy Research Working Papers. The World Bank.

Dalberg, 2019. IDF Evidence Mapping Report. FMO 2019.

Dinkelman, T., 2011. 'The Effects of Rural Electrification on Employment: new evidence from South Africa'. *American Economic Review* 101(7): 3078–3108.

Groth, A., 2019. Socio-economic impacts of rural electrification in Tanzania. *Int. J. Sustain. Energy Plan. Manag., 21* (2019).

Gustavsson, M. and Ellegård, A., 2004. 'The Impact of Solar Home Systems on Rural Livelihoods. Experiences from the Nyimba Energy Service Company in Zambia'. *Renewable Energy* 29(7): 1059–72.

Human Rights Watch, 2019. DR Congo: 1900 Civilians Killed in Kivus Over 2 Years.

International Energy Agency (IEA), 2019. World Energy Outlook.

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., and Ermon, S., 2016. Combining satellite imagery and machine learning to predict poverty. *Science (New York, N.Y.),* 353(6301), 790–794.

Joint Impact Model (n.d.) Home page.

Kim, R., Sutherland, Z., Verhoeven, S., Binet, S., Düring, N., Barnett, C., Lemma, A., and Beckmann, L., 2022. Final Report: Evaluating the Impact of British International Investment's Infrastructure Portfolio. e-Pact consortium: Itad, Steward Redqueen, Overseas Development Institute.

Pueyo, A., Carreras, M., and Ngoo, G., 2020. Exploring the Linkages Between Energy, Gender, and Enterprise: Evidence from Tanzania. *World Dev. 128*, 104840.

Ratledge, N., Cadamuro, G., de la Cuesta, B., Stigler, M., and Burke, M., 2022. Using Machine Learning to Assess the Livelihood Impact of Electricity Access. *Nature*, 611(7936), 491–495.

Steward Redqueen, 2016. What is the Link Between Power and Jobs in Uganda? Final Report. CDC. November 2016.

Yeh, C., Perez, A., Driscoll, A., Azzari, G., Tang, Z., Lobell, D., Ermon, S., and Burke, M., 2020. Using Publicly Available Satellite Imagery and Deep Learning to Understand Economic Well-being in Africa. *Nature Communications,* 11(1), 2583.

Annex 2: Data accessed

Source	Year(s)	Variable	Definition	Format	Use
Virunga Energies	Current	Poles, cables, zones	Location of poles, cables and zones in Nord-Kivu	Vector shapefile	Used to identify treatment communities.
Atlas AI datasets	2012–21	Per capita spending	Estimate of poverty ($/person/day)	High-resolution rasters at 1km × 1km scale	Used to understand general characteristics of settlements in the treatment and donor pools, but not used in cosine similarity analysis or in developing synthetic controls (AWI is preferred as a superior measure).
		Asset wealth	Relative wealth of community (index)	High-resolution rasters at 2km × 2km scale	The dependent variable in the causal inference analysis and used in the cosine similarity analysis.
		Population	Population count (number)	High-resolution rasters at 1km × 1km scale	Used as a comparison to the WorldPop population dataset.
		Electrification	Status of electrification (yes/no)		Used as a comparison to the High Resolution Electricity Access (HREA) electrification dataset.
		Atlas of Human Settlements	All built-up areas (yes/no)	Vector shapefile	Used to delineate settlements and represent each unit in the treatment or donor pool.
Demographic and Health Surveys (DHS)	2013/14	Occupation	Percentage of population employed in various industries	Country-wide survey data	Used to understand general characteristics of settlements but not used in cosine similarity analysis or in developing synthetic controls (not deemed to add additional value beyond selected variables).
WorldPop	2012–20	Population density	Population density (people/km^2)	High-resolution rasters at 100m × 100m scale	Used to understand general characteristics of settlements but not used in cosine similarity analysis or in developing synthetic controls (not deemed to add additional value beyond selected variables).
		Population	Population count (number)	High-resolution rasters at 10m × 10m scale	Used in the cosine similarity analysis.
University of Michigan HREA	2012–19	Electrification	Probability of electrification (0–100)	High-resolution rasters at 10m × 10m scale	Used to subset the treatment group into previously electrified and not previously electrified.
OpenStreetMap (OSM)	Current	Health facilities	Location of health facilities	Vector shapefile	Used to understand general characteristics of settlements but not used in cosine similarity analysis or in developing synthetic controls (not deemed to add additional value beyond selected variables).
		School facilities	Location of school facilities	Vector shapefile	Used to understand general characteristics of settlements but not used in cosine similarity analysis or in developing synthetic controls (not deemed to add additional value beyond selected variables).
		Roads	Location of roads	Vector shapefile	Used in the cosine similarity analysis.

Annex 3: SCM approach

A3.1 Different versions of the synthetic control approach

There are many versions of the SCM, which can be tailored to different implementation scenarios.

Version	Description	Useful in situations where…	Implications for this study
Classical SCM	Designed primarily to estimate the effects of large aggregate interventions focused on a small number of large treatment units (typically one). Can, in theory, be applied to a larger number of treatment units through separate classical SCM for all treated units, but this has implications.	…there is one treatment unit of interest, with many potential donor units, and where data (for both dependent and independent variables) is available over a longer time horizon, for example an assessment of policy changes at a national level.	High degree of rigidity: donor unit weights must be non-negative; donor unit weights must sum to 1; values of the predictors for the treated unit should be near or inside the convex hull of the values for the donor pool. Risk of masking underlying data heterogeneity if data is aggregated before analysis, or risk of overcomplicating analysis if individual classical SCM is performed for all treatment units. Resource-intensive if separate SCM applied to all treated units.
SCM with elastic net	Similar to classical SCM, but with a more relaxed definition with a regularisation function to reduce overfitting,[51] which has been used frequently in the literature.[52] Allows for aggregation at analysis stage rather than of the underlying data.	…there are multiple treatment units, and a balance is sought between applying a single classical SCM or running many individual classical SCMs in parallel for all treated units. Typical applications include assessments at regional or settlement level. More relevant in situations where data is available over shorter time horizons as a result of relaxations.[53]	More flexibility/less rigidity allows for more treatment units than years of treatment; donor weights can be negative; donor unit weights do not have to sum to 1. Less susceptible to overfitting in situations where the data record is not extensive. Offers a 'middle ground' between either applying a single classical SCM to all treatment units together, as the approach was initially intended (this leads to challenges in aggregating underlying data pre-analysis) or attempting to run separate classical SCMs for each treatment unit (this leads to challenges associated with the complexity of later analysis).

51 Based on the use of an elastic net drawing on a combination of LASSO and ridge penalties.

52 Ratledge, N. et al. (2021) 'Using Satellite Imagery and Machine Learning to Estimate the Livelihood Impact of Electricity Access'.

53 Nevertheless, a minimum of five years pre- and post-treatment is recommended.

A3.2 The donor units and weights used to create synthetic controls for the previously unelectrified group

The synthetic control is composed of a weighted average of some settlements in the donor pool. Atlas AI first mask (i.e. only populated areas are considered as having any AWI), and then any calculations (such as average AWI) are weighted by the relevant population. As such, small settlements with big changes in values do not have a disproportionate impact.

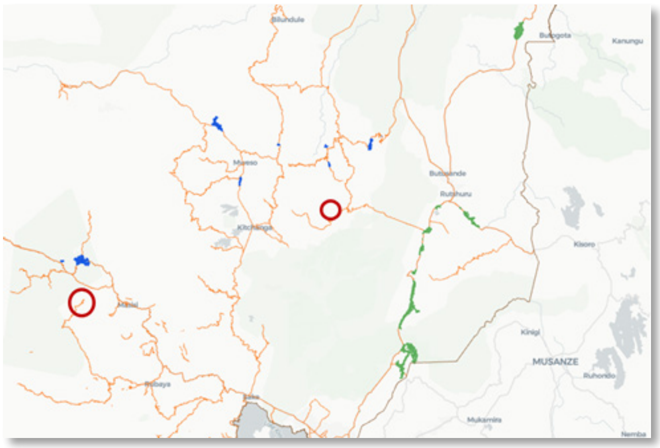
In this approach, 10 settlements contributed to the synthetic control, with all units having a positive weight; however, the constraint ‘weights needed to sum to 1’ was relaxed. Although most of the units in the synthetic control have very low weights, two units contributed the most, and these are circled in red below. These units were selected by SCM because they most closely match the pre-treatment trend in the treatment pool.

Donor unit IDs and their weight

Donor unit ID	Weight
467798	0.105948094
467804	0.005762979
468175	0.055643912
468611	0.023339608
505541	0.152024077
505564	0.047028516
505573	0.104956808
508008	0.033705409
508036	0.025975718
508188	0.096140378
Total Weight	**0.650525499**

Donor units in synthetic control (blue settlements) and previously unelectrified treatment pool (green settlements)

Note: The settlements with the highest weights are circled in red. Major roads are shown in orange to highlight similar connectivity.



A3.3 Implications of relaxing the constraints of the synthetic control method

The SCM constructs a synthetic control unit by combining weighted observed units in order to estimate the counterfactual outcome for a treated unit. One of the assumptions of the classical SCM is that the weights assigned to the observed units should sum to 1. We decided to relax this constraint in our analysis. We are aware of a few potential implications of doing this:

- **Bias in estimated treatment effect**. The constraint that weights sum to 1 ensures that the synthetic control is a convex combination of the observed units. This convexity property is important for maintaining a balanced and unbiased estimate of the treatment effect. If the constraint is relaxed, it is possible that the synthetic control will become skewed towards certain units, leading to biased treatment effect estimates.
- **Model overfitting**. Relaxing the weights sum constraint can lead to overfitting, where the synthetic control becomes too tailored to the pre-treatment outcomes of the treated unit.

- **Loss of interpretability**. The weights sum constraint enhances the interpretability of the synthetic control. When weights are required to sum to 1, each weight represents the proportion of the corresponding observed unit's characteristics in the synthetic control. Without this constraint, it is possible that the resulting weights will not have clear interpretive value.

Although recognising these potential implications, we opted to relax the classical SCM requirement that weights should sum to 1. This is a recognised tactic when using our chosen analytical approach (SCM with elastic net). It offers more flexibility/less rigidity and is especially appropriate in cases where there is a relatively large number of treatment units but relatively few treatment years. We combined this approach with a regularisation function to reduce susceptibility to overfitting.

Annex 4: Key definitions and derived metrics

Asset Wealth Index

Atlas AI's asset wealth layer estimates household asset wealth based on asset ownership. This draws directly on household asset wealth data collected by USAID's Demographic and Health Surveys (DHS) Program. The most recent DHS data for the DRC is available for 2013/2014 and includes attributes such as: i) electricity connection; ii) small-scale appliances (radio, televisions, sewing machines etc.); iii) cooking source (electricity or fuel etc.); iv) type of owned transport (bicycles, cars, animals etc.); v) source of water (including piped or well etc); vi) type of sanitation; vii) type of household flooring (dirt, vinyl etc.); and viii) roofing and house construction materials.

Given that Atlas AI's AWI inherently relies on the presence of electricity in its calculation (such as through the incorporation of satellite nightlight data and underlying USAID data on electricity connections) we developed a modified version by making adjustments to both input imagery and correlated field survey indicators, which strips out these potentially confounding aspects. This resulted in a slight reduction in the performance of the AI predictive model, but the impact was not significant. The finalised asset wealth layer was then attributed to settlement areas across Nod-Kivu for the years 2012–21.

Population and population density

Population and *population density* are measures of population count and population per km^2. This variable will be used to assess how population and population density have been changing over time. The layer has been attributed to the settlement areas with data for the years 2012–21.

Road access, length and density

Road access is a derived indicator using road locations from OSM and Atlas AI settlement areas. This metric measures the Euclidean distance between each catchment area and the nearest major road, defined as primary, secondary or tertiary. The distance to the nearest roads provides a way to determine the accessibility of each settlement. *Road length* and *density* are similar metrics and provide a way to further describe settlements that contain roads. *Road length* is the total length of major roads within a settlement area; *density* is the total length of major roads divided by the settlement area. Of the 148,157 catchment areas, only 31,328 contained a major road. If a settlement area contains a higher density of major roads compared to another settlement area, this could indicate that the settlement is more connected.

A4.1 Asset Wealth Index interpretation

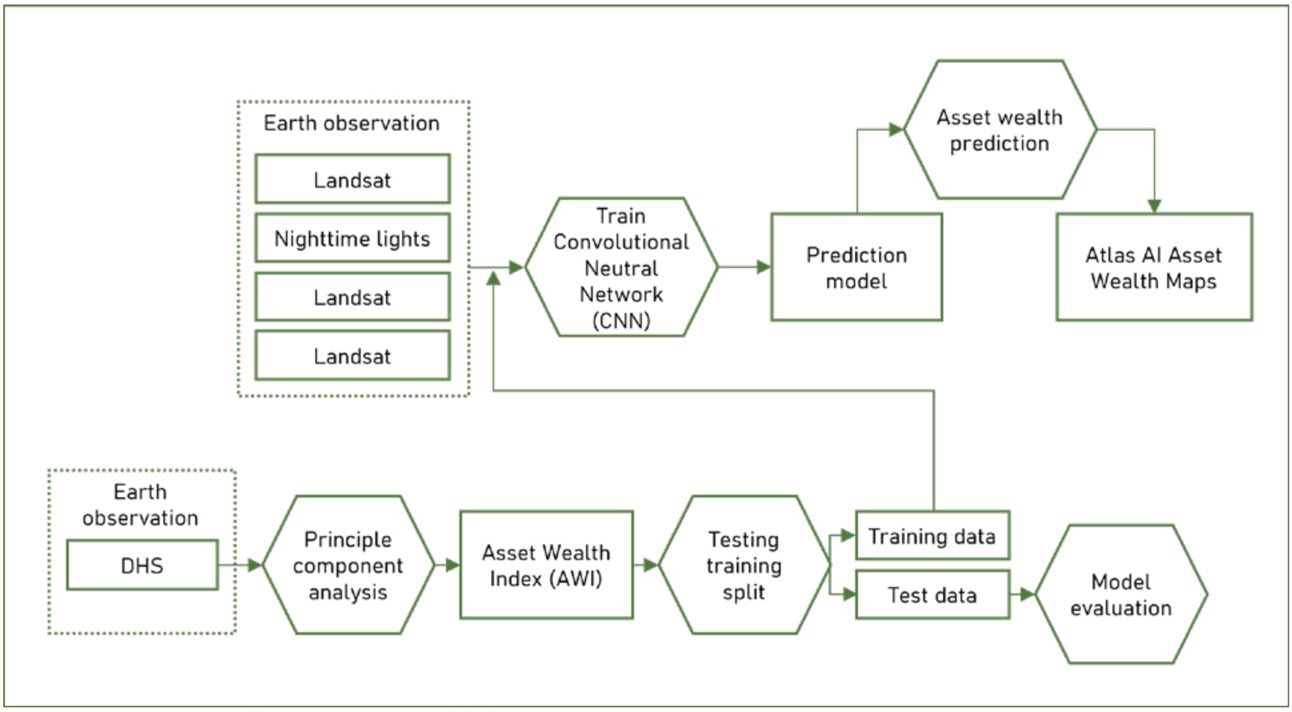
The AWI is an economic construct that estimates the accumulated wealth and well-being of a household, derived from an inventory of the valuable items purchased and collected over time, for example appliances, livestock, property and vehicles. The AWI is a valuable metric when income statistics, tax records or other evidence of monetary wealth are not available.

Although the AWI can be calculated household by household, a more robust statistical estimate is obtained by cluster households within a community or across small proximate communities. The interpretation of AWI is therefore the average indexed wealth per household in a community of interest. Furthermore, by comparing the non-dimensional index across space and time (spatial time series), we can draw insights about the changes in well-being within and across communities on average at the household level.

The AWI has a 2km × 2km resolution. This resolution refers to the level of detail and granularity present in each pixel (or polygon) of the raster image. Resolution is typically measured in terms of the size of the smallest discernible unit on the ground, often represented in metres, feet or other units of distance. Therefore, a 2km × 2km pixel (or polygon) has one value for that entire area. We combined this raster with our settlement areas and calculated the average household AWI for each settlement area. Because we have an average of household-level AWI for each settlement, it would not be possible to pull out an individual household AWI. Using this dataset, it is only possible to perform a community-level impact assessment.

A4.2 Asset Wealth Index production

The asset wealth layer is produced from a deep learning model that predicts survey-based estimates from satellite imagery. To facilitate comparison within and across countries, we transformed asset wealth into a normalised index. To generate this data, we collate locally representative survey data on household asset ownership to create an AWI, which is the first principal component of a principal component analysis (PCA) computed on those assets over those households. We then train a random forest model to predict village-aggregated values with satellite imagery, validating on data the model was not trained on.



A4.3 Asset Wealth Index modification (excluding nightlights)

The creation of the AWI layer, excluding nighttime lights, is based on the methodology first defined by Jean *et al.* (2016), with two key modifications. In the original work, the goal was to predict an indicator of asset wealth over entire countries, using remote sensing data as the input features and labels based on known settlements appearing in the DHS. The two modifications we made for this were in particular to isolate the independent variable of electrification, and they are described in more detail by Ratledge *et al.* (2021). In their work, they were also seeking to assess the impact of electrification on household wealth.

The first change relates to how we define the dependent variable of asset wealth. In the original work this was defined by performing a PCA on a subset of questions asked in the DHS surveys. However, those questions related to whether a household had access to electricity, and there was a concern that including this would embed our independent variable of interest in our dependent variable. Instead, we computed a new AWI, using PCA on a new set of variables not including electrification. It was noted that this new AWI had an extremely high correlation with the original AWI (r2 = 0.99), and so we are not meaningfully changing the notion of what household wealth is with this variation.

The second change was in the data bands used in the training of the Convolutional Neural Network. The original work by Jean *et al.* (2016) used both Landsat and the Visible Infrared Imaging Radiometer Suite (VIIRS). Landsat is a freely available satellite with six bands: the standard three red, green and blue (RGB) visual bands, one near-infrared band and two shortwave infrared bands. The bands have a native resolution of 30m per pixel. Conversely, VIIRS is a nighttime illumination dataset which records how bright 450m × 450m pixels are during a given night. The original work used an annual median of these as an extra input band into the model. In order to avoid issues with embedding the independent variable with a dependent variable, we decided not to introduce this into our model as the seventh band. Although this leads to a modest reduction in the predictive performance of the model, this is judged to be of secondary importance when compared to the greater risk of experimental integrity.

Annex 5: Detailed comparison between donor pool and treatment settlements

For each settlement group, we calculated the mean and median population by gender across all settlements in each group. We also calculated the mean and median distance to a major road across all settlements in each group. A road distance of 0m would mean that a major road intersects the settlement and implies that settlement is easily accessible.

Median values by settlement area

	Previously unelectrified treatment pool (Rutshuru)	Previously electrified treatment pool (Rutshuru)	Previously unelectrified donor pool	Previously electrified donor pool	Candidate pool
Female population (count)	663	1,464	73	79	44
Male population (count)	577	1,276	63	68	39
Total population (count)	1,240	2,740	136	147	83
Distance to major roads (metres)	0	0	421	0	1,563
2012 AWI	-1.181	-1.310	-1.136	-1.255	-1.077
2016 AWI	-1.007	-1.084	-1.062	-1.037	-1.228

Mean values by settlement area

	Previously unelectrified treatment pool (Rutshuru)	Previously electrified treatment pool (Rutshuru)	Previously unelectrified donor pool	Previously electrified donor pool	Candidate pool
Female population (count)	4,668	6,298	7,019	1,469	299
Male population (count)	4,068	5,489	6,117	1,280	261
Total population (count)	8,736	11,787	13,136	2,749	560
Distance to major roads (metres)	4	65	623	1,664	3,505
2012 AWI	-1.097	-1.155	-1.047	-1.230	-1.015
2016 AWI	-0.851	-0.929	-0.908	-0.983	-1.157

The two tables show key metrics, such as female and male populations and distance to major roads, for each group of settlements: (i) previously unelectrified treatment pool; (ii) previously electrified treatment pool; (iii) donor pools; (iv) overall candidate pool.

The cosine similarity analysis was used to select untreated settlements which share significant similarities with the treatment pool. Compared to the candidate pool, the donor pool is more similar to the treatment pool across all metrics. However, there are still some residual differences, and we also see that the donor pool has a high variance across all metrics, as shown by the large differences in median vs mean values. Nevertheless, despite the variance and level differences, we are still seeing more similarity between the donor pool and treatment pool compared to that between the candidate pool and treatment pool.

It should be noted that the SCM accounts for these differences between the treatment pool and donor pool to produce a closer fit when calculating the synthetic control units.

Annex 6: Summary of comparisons to other approaches

Note we include randomised control trials (RCTs) here for reference purposes as the 'gold standard'. In reality, RCTs are rarely feasible to apply to investment projects, given the requirement to randomise treatment.

Approach	Cost	Time required	Data requirements	Engagement by investment owners	Flexibility	Evidence standard
Randomised control trial (RCT)	High	High	High	High	Low	Gold standard (but rarely feasible)
	Costs will vary by scope.	Requires before and after data collection on the ground, with sufficient time intervals for impact to emerge.	Primary data typically required at household level, before and after.	Requires adaptation of implementation models to enable randomised treatment.	Typically, not possible to adapt or scale up after baseline data collected.	Requires randomised assignment of treatment and control units.
Quasi experimental designs (e.g. difference-in-difference)	Medium (different from RCTs?)	High	High	Medium	Medium	Very strong (but limited flexibility).
	Costs will vary by scope.	Requires before and after data collection on the ground with sufficient time intervals for impact to emerge.	Primary data typically required at household level, before and after.	Requires support to identify and access treated and untreated locations on the ground.	Allows for some flexibility in application post-baseline.	Flexibility is limited once baseline data is collected; there is risk of contamination of control units over time. Difficult to apply to investments with rapidly expanding customer base. Can be difficult to identify plausible counterfactual on the ground.
Geospatial analysis with synthetic controls	Low	Low	Low	Low	High	Strong (and flexible).
	Marginal cost will fall in subsequent applications and as approach matures.	Can be done quickly and retrospectively.	Requires access to secondary geospatial datasets and geotagged data on clients, but no other primary data.	Limited engagement needed beyond providing geotagged data on clients.	Can be scaled and repeated quickly; does not require a baseline.	Flexible – can offer a robust counterfactual even where difficult to identify physical control groups.

We provide expert monitoring, evaluation, learning and strategy services to help build a more equitable and sustainable world for all.

itad.com

@ItadLtd

Itad

mail@itad.com

Itad Ltd
International House
Queens Road
Brighton, BN1 3XE
United Kingdom
Tel: +44 (0)1273 765250

Itad Inc
c/o Open Gov Hub
1100 13th St NW, Suite 800
Washington, DC, 20005
United States