The socio-economic impact of electrifying rural areas in Senegal

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Abstract

A reliable and affordable access to electricity has become one of the basic needs for humans and is, as such, at the top of the development agenda. It contributes to socio-economic development by transforming the whole spectrum of people’s lives – food, education, health care; it spurs new economic opportunities and thus improves livelihoods. Using a comprehensive dataset of pseudonymised mobile phone records, provided by the market share leader in Senegal, we analyse the socio-economic impact of rural electrification. We use communication and mobility flows extracted from the call detail records (CDRs) to study how electrification impacts the attractivity of rural areas. We show that electrification has a small, yet positive, impact on centrality measures and on the volume of out-going calls and incoming visitors. This increased influence is however circumscribed to a limited spatial extent, creating a complex competition with nearby areas. We finally show that the level of electrification of the destination and the level of wealth at the origin are good predictors for the volume of visitor flows between any two sites. In view of these results, we discuss the best planning strategy to electrify rural areas in Senegal. We determine that electrifying clusters of rural sites is a better solution than attempting to centralise electricity supplies to maximise the development of specifically targeted sites.

Keywords: Rural electrification; Developing countries; Mobile phone networks

Introduction

Providing reliable and affordable access to modern energy services is specified as one of the top social priorities in the United Nation’s 2015 Sustainable Development Goals [1]. Getting access to energy can potentially transform the whole spectrum of people’s lives: stored energy can be used to improve health-care services, to help pump water for domestic usage or irrigation, to access...
safe fuel for cooking and heating; it positively impacts education by providing better lighting and access to technological support and it facilitates income generating activities by increasing overall productivity. It is therefore recognised as a critical element to enable human beings to thrive and no one should fall short on it. Yet, according to the International Energy Agency (IEA), nearly 12% of humanity lacked any access to electricity supply in 2018, including about half of the sub-Saharan African population [2].

Concurrently, a symbiotic relationship exists between access to energy and the development of information and communication technologies (ICT). Such technologies are, in their own right, already playing an essential role in global development as a communication tool, a facilitator of connections between individuals, information, services and markets [3]. The penetration rate of mobile phones has dramatically increased in the last decades, creating an unprecedented demand for electricity supply to both charge phones and power communication towers. Despite the wide-coverage of mobile phone networks, usage remains low in Sub-Saharan rural areas, constrained, among other factors, by limited access rates to electricity (about 26% in 2018, compared to 74% in urban areas [2]). Yet, powering entertainment appliances such as radios, television sets and mobile-phones, all linked to knowledge and information access and sharing and to the possibility of connecting with their urban counterpart, comes second after lighting in rural households’ electricity usages [4,5]. This holds promise for establishing deep ties between energy access and the underlying network effect.

Much of the debate in the literature about the impact of electrification programs on development outcomes centres around metrics directly related to productivity levels, income and quality of life [6]. A small, but growing, body of studies with a focus on mobile phone usage is emerging. Kirubi et al. [7] have conducted a detailed case study of a community-based electric micro-grid in rural Kenya and have found positive impact on internet access at the community level. Lenz et al. [8] assess the impact of a large-scale rural electrification program in Rwanda, connecting 370,000 new users within less than four years, and find significant increase in mobile phone ownership and usage. Armey et al. [9] assess the impact of access to electricity on digital divide in a panel of 40 low-income countries, finding an increase in within-countries adoption of the Internet. However, despite the overall positive impact on the uptake of the technology, very little has been written on the specificity of related usages, their spatial and temporal patterns, and the associated spillover and network effects.

This paper seeks to investigate the contribution of energy access to the socio-economic development of rural areas in Senegal by proposing an original quantitative framework to measure it, accordingly discuss the best planning strategies and eventually support progress in reaching a global target for universal access to energy services by 2030 [10]. Measuring is central to the implementation of any global target. It is, on its own, a development agenda, especially in data-poor countries, where standard sources of data may not be available.

We take advantage of a real-world dataset, gathered from mobile phone users in Senegal, complemented by census data and satellite images, to quantify the impact of rural electrification on the accessibility and attractivity of rural areas. We consider accessibility and attractivity as alternative intermediate indicators of impact that are affected in the short run. They measure the opportunity for interaction and access to information and ideas, leading to potential increases in productivity [11].

We use mobility and communication flow-based approaches to study accessibility. Antenna sites with higher centrality in the communication network generally detain more information and
have greater control over arising opportunities \[12,13,14\]. Similarly, a higher diversity of contacts has been directly linked to higher incomes \[15\]. Furthermore, the approximate residence location of mobile phone users can be estimated from the mobile phone data, allowing us to map the network of temporary visitors and international migrants. We can therefore study how electrification impacts the attractiveness of rural areas. In particular, the following question arises: can we predict the volume and profile of visitor flows towards these areas from their electrification rate? We find that electrification has a small, yet positive, impact on centrality measures and on the volume of outgoing calls and incoming visitors, which is distinct from other indicators of wealth. This increased influence is circumscribed to a limited spatial extent. We also find that the level of electrification of the destination and the level of wealth at the origin are good predictors for the volume of flows between any two sites. In view of these results, we discuss the best planning strategy to electrify rural areas in Senegal. We determine that electrifying clusters of rural sites is a better solution than attempting to centralise electricity supplies to maximise the development of specifically targeted sites.

1 Materials and methods

In this section, we provide details on four elements that are central in all subsequent analyses: the content of the mobile phone dataset and the creation of related communication and mobility networks, the measurement of access to electricity from the census and satellite images, the creation of reference wealth indicators from the census, and the definition of ‘rural’ in our context. Any other data preparation or method that is specific to a subsection of the Results and discussion section is presented there.

1.1 Mobile-Phone Data

Mobile phone networks are today one of the major vectors of information flows. A large number of services and activities in our everyday life pass through mobile phones, one of the most pervasive and ubiquitous technologies in the last decades. Mobile phone network operators, on their hand, collect a large amount of data on communications passing through their network infrastructure: date, duration, location, nature of communication (voice calls, SMS, applications, etc.). These data, namely Call Detail Records (CDRs), constitute an extremely rich source of information and, under well-specified ethical and data privacy regulations, can be analysed and exploited to answer very diverse and challenging questions.

Indeed, mobile phone data analysis has become today a mature research field with a wide range of applications \[16\], which has been further fostered by the Orange Data for Development Challenge \[17\]. The past few years have seen the rise of research studies that have shown how to turn these data into actionable information to improve social and operational efficiency. Areas of application include public health to minimise the spread of infectious diseases \[18\], national statistics to help mapping populations \[19\] and associated socio-economic indicators \[15\], the estimation of transportation and electricity demands \[20,21,22\] or the monitoring of population displacement after disasters \[23\].

For the purpose of this research, we use a pseudonymised dataset of mobile phone CDRs collected by Orange-Sonatel, the market leader, between January and December 2013 in Senegal. It
consists of spatio-temporal information about the telecommunication activity: each record contains
details about the caller’s and the callee’s IDs, timestamp, duration and type of communication, as
well as an identifier of the antenna that handled the communication.

From the CDRs, we estimate the cell sites corresponding to the users’ residences (i.e. their
‘home sites’) by following a standard approach that evaluates users’ activity at night time (9 p.m.
to 6 a.m.), the period of the day people are most likely to be at home [24]. We define the ‘home
site’ of a user as the antenna site where they make and receive calls or text messages (SMS) the
most. After removing holiday-periods from the dataset, we count, for each user and each distinct
day of the year, the number of calls and text messages made and received at night by cell site, and
select the site with the highest records associated. The final home site is the one with the highest
number of selected days over the observed period. We then build a communication network and
a mobility network. Nodes in both networks represent Orange-Sonatel cell sites located across
mainland Senegal. Links are weighted respectively by the volume of exchanged calls between
residents and by the number of residents from one node visiting another node. Both networks are
directed (calls and trips have identified origins and destinations).

1.2 Access to electricity

We compute the electrification rate within each commune of Senegal from the information contained
in the census conducted in 2013 by the Senegalese National Institute of Statistics (ANSD). The
commune level is the smallest sub-division available for which a GIS shapefile is available. We
have access to an extract with the answers of a sample of about 10% of each municipality’s
households, totalling around 1.25 M individuals. Among the questions asked, one relative to the
source of lighting informs us whether individuals have access to a stable source of electricity (main
power grid or solar systems), to an unreliable source (diesel engines), or no access at all. The
electrification rate is taken as the ratio between the number of individuals with a stable access and
the total population count. We then compute the electrification rate around each antenna site by
intersecting its Voronoi neighbourhood with the communes. The intersection is weighted by the
population count, assuming a homogeneous distribution of the population inside each commune.
This assumption, also made for the Grid Population of the World (GDW), albeit at a broader
administrative scale (45 departments in contrast to 552 communes for Senegal), is reasonable,
since the boundaries of all big and medium towns are known and identified as separate communes.
As a control, we have computed the average nighttime lights intensity inside each Voronoi cells
from NOAA’s open access 2013 satellite images [25]. The results were found in good agreements,
and only those with the electrification rates based on the census data are shown.

1.3 Wealth indicators

To evaluate the wealth of the population around each antenna site, we build four indicators based on
the information available in the 2013 census. Each indicator is computed at commune level first, then
at site level by weighted intersection with the mobile phone Voronoi cells, in the same manner used
for electrification rates. A ‘quality of accommodation’ indicator is provided by the first component
of a multiple correspondence analysis applied to the questions relative to the characteristics of
the accommodation (type of house, tenure, main construction material, roofing, flooring, type of
toilets, access to water, cooking appliances, waste disposal and waste water disposal). To make this
indicator more independent from electricity, we do not use any of the questions involving ownership of electrical appliances and equipment. A second ‘level of education’ indicator is defined as a direct count of the average number of years spent studying either at school or in higher education. A third ‘employment status’ indicator is created by applying a principal correspondence analysis to the number of individuals in each employment category (inactive, unemployed, student, intern, fixed-term employed, permanently employed, self-employed, employer). A fourth ‘combined wealth’ indicator results from a principal component analysis on the first three indicators.

1.4 Rural classification

In lack of a generally agreed definition of “rural”, we adopt the traditional approach consisting of defining “urban” first, then defining rural sites as those that are not urban. This approach is used, for example, by the Food and Agriculture Organization (FAO) of the United Nations and by the United Nation Statistics Division (UNSD) [26]. It is admittedly not a perfect solution, since there is no consensual definition of “urban” either. We choose a custom double criteria for this definition. Specifically, we classify any antenna site as “urban” either if it falls within one of the communes tagged by the ANSD as a commune d’arrondissement (division into districts of the five biggest cities) or as a commune urbaine (urban communes) in their official December 2013 redefinition of administrative boundaries; or if the antenna site’s Voronoi neighbourhood contains more than 1000 inhabitant per km$^2$. Although arbitrary, this threshold is commonly used, for example, by the FAO and by the Global Rural Urban Mapping Project (GRUMP) [26]. To evaluate the population density within each Voronoi cell, we rely on the official census. We do not use the land use corrected Landscan mapping to avoid introducing a bias with the electrification variable, since this method uses nighttime lights to make the estimations. According to our classification, we count 708 ‘purely rural’ sites and 879 ‘urban’ sites out of the original 1587 sites.

1.5 Data availability

The 2013 Senegalese census data (10% sample of the full census) and the administrative boundary definitions can be accessed through the official website of the ANSD. The nighttime lights data can be accessed through NOAA’s open database. The mobile phone data is proprietary and confidential. Request for access should be made directly to Sonatel.

2 Results and discussion

We first analyse the impact of electrification on the importance of antenna sites, in particular rural sites, within the communication network. A site that is more central in the network, or that has more diverse contacts, usually detains more information and has greater control over arising opportunities [12, 13, 14]. It may also be perceived as more socially valuable by its neighbours and attract more assets favourable to its development [27]. Such assets could be wealthier or more skilled visitors. To explore this aspect, we measure the size and profile of the flows of visitors in the second subsection. In particular, we show that it is possible to predict satisfactorily the volume of flows between antenna sites from wealth and electrification indicators alone.
### 2.1 Electrification and importance within the communication network

A network based on all the calls made in 2013 is built for the entire country. Each node in the network represents an antenna site. Each edge has two attributes: the average number of calls per day and the physical straight-line distance between the two antenna sites it is linking. For each node, we compute its unweighted and undirected betweenness centrality \[28\] (i.e. the number of shortest paths that pass through the node, independently of the direction travelled by the call) and its leverage centrality (i.e. the degree of the node compared to the degree of its neighbours). Since the betweenness centrality is used to measure how much information a node controls, only significant edges with a number of average calls greater than one per day were kept for this calculation. In addition, we compute the social diversity index and an ad hoc adaptation of the spatial diversity index \[14\]. The social diversity index measures how diverse the contacts of a node are by calculating the Shannon’s entropy corresponding to the distribution of its calls among its contacts. Eagle et al. \[14\] have shown that it is well correlated with income for a CDR dataset collected in the UK. Our spatial diversity index is defined similarly to the social diversity index, with the only addition of distance multiplied to the volume of calls between the node and each of its neighbours. Finally, we compute the average distance between each node and its neighbours, weighted by the volume of calls, and the ratio of in-calls to out-calls.

The Spearman correlations between each of these six indices and the average electrification rate around each tower are shown in Table 1. The first two columns use the entire network, the next two columns use the values for rural sites only, while the last two columns use a recomputation of the seven indices over the sub-network containing only rural nodes. Since the electrification rate variable is highly correlated to our combined wealth indicator (0.92 nationwide and 0.88 for rural areas), we additionally show in the table the partial correlations between the network measures and the electrification rates, controlled by the combined wealth variable (i.e. the correlations between the residuals of each variable predicted from the control variable). This allows to distinguish the specific contribution due to electrification and show that the gain in centrality is not a coincidental consequence of a general perception of wealth, concomitant with electrification, triggering more calls with wealthier areas. The full p-values corresponding to all these correlations are provided in Table S1 of the supplementary information.

| Correlation       | All sites | Rural sites | Rural sub-network |
|-------------------|-----------|-------------|-------------------|
|                   | Direct    | Partial     | Direct            | Partial     | Direct      | Partial      |
| Betweenness       | .50*      | .31*        | .47*              | .21*        | .47*        | .21*         |
| Leverage          | .62*      | .34*        | .58*              | .15*        | .55*        | .17*         |
| Social div.       | .54*      | -.05        | .09*              | -.04        | .05         | .02          |
| Spatial div.      | .46*      | .38*        | .56*              | .06         | .54*        | .15*         |
| Distance          | -.78*     | -.21*       | -.34*             | .04         | -.23*       | .04          |
| In/Out            | -.45*     | -.25*       | -.26*             | -.29*       | -.16*       | -.25*        |

* p-value < 0.05.

We can observe that all six indices are significant when the entire network and direct correlations are considered. We find that electrified areas are indeed more central within the network for both
measures (betweenness and leverage). Their contacts are also more diverse and their inhabitants tend to have a higher out/in ratio than average. The highly negative correlation with the average distance between callers and callees, less pronounced for rural areas, can be explained by the high density of antennas within urban areas. Although slightly lower in value, all indices, with the notable exception of social diversity, are also significant for rural sites. When considering the partial correlations, even though the correlations for the centrality measures are lower, the same conclusions remain. There is therefore a (small) impact of electrification that is distinct from other indicators of wealth. The ratio of in-calls to out-calls remains steadily negative in all cases, which shows that electrification does result in people initiating more calls with their contacts. In contrast, the social diversity, and in some cases the spatial diversity, as well as the average distance for rural areas, are all close to zero, which indicates that they are not a priori correlated specifically to electricity. Interestingly, this could mean that, independently of electrification, the richer the people are, the more local their communication becomes.

Note that the high density of antennas within urban areas “dilutes” their activity: although cities are expected to be highly central when considered as single entities, the importance of any particular node within the city is diminished by the competition from similar nodes near them. To compensate for this effect, we merge all antennas within a set number of kilometres of each other into one “super-antenna”. For example, with a distance set to 5 km, this process allows to aggregate all the major cities into single entities (see fig. 1(a)), and with a distance set to 10 km, we can isolate major continuous regions in terms of antenna density (see fig. 1(b)). According to our definition of ‘rural’, the full network contains 708 rural antenna sites out of 1587 sites, the 5 km aggregated network contains 515 purely rural clusters out of 768 clusters, and the 10 km aggregated network contains 235 purely rural clusters out of 364 clusters. With these aggregations, we can compare the structure of long range calls with the structure of short-range calls.

![Figure 1: Clusters identifying all sites within a given distance of each other.](image)

The evolution of the Spearman correlations for all cases reported in table 1 is shown in fig. 2 for aggregation distances comprised between 0 km and 15 km. For direct correlations, we observe that the aggregation process induces a steady decrease of the correlations with the centrality measures, which is much sharper for rural areas. The fact that the correlations with the social and spatial
diversities rapidly become negative, except for the rural sub-network, indicates that the initial high
diversity of calls is primarily due to intra-urban and urban to close-by rural calls, showing a clear
divide of usage between urban and rural areas (see [29], reporting similar results). For partial
correlations, the lines appear more constant, although they seem to become unstable from around
6-8 km. All these observations indicate that the gain in importance linked to electrification is mainly
local. To discard a possible smoothing of the electrification rate distributions within clusters with
higher aggregation levels as a possible explanation for the convergence to zero of the correlations,
we indicate with a black line the evolution of the ratio between the standard deviation and the mean
of the distribution of electrification rates within the considered areas (all or only rural), and find
that these lines are indeed almost constant. For reference, the full histograms of electrification rates
within rural and urban areas are shown in fig. [S1] in the supplementary information.

In summary, we have evidenced that electrification has a rather small impact, yet positive and
distinct from the impact of wealth alone, on the centrality of both urban and rural inhabitants. This
impact is quite local, especially in rural areas. In addition, there seems to be a noticeable divide
between rural and urban areas. The higher social diversity for electrified rural areas close to urban
areas indicates, however, that more interactions between rural and urban areas can become possible.
In particular, the fact that electrification allows a higher outgoing to incoming calls is a positive
sign that it can help initiate more interactions.

2.2 Visitor flows to electrified areas

Despite calls being immaterial, we have seen that the composition of the physical neighbourhood
surrounding a node has a large influence on its characteristics within the network. We will now see
that this is also true for the volume and socio-economic profile of visitors to rural antenna sites.
We first study both the size and the wealth profile of the incoming visitor flows as a function of
electrification. We then try to predict the volume of these flows using gravitation models from the
factors that we found predominant: wealth at origin and electrification at destination.

2.2.1 Socio-economic profile of the visitors

A visitor is defined as an individual who made a call through an antenna site that is not their
assigned home site. They inherit the average wealth profile of their home antenna site. In fig. [3],
the average quality of accommodation, level of education and employment status wealth indicators
of each node’s visitors is plotted against the node’s level of electrification. We observe a clear
correlation between electrification rate and average wealth of visitors. To avoid any bias, we
apply the same method as in section [2.1] and compute the partial correlations between average
quality of accommodation, level of education and status of employment of visitors on one side,
and electrification rate of the visited location on the other side, controlled by combined level of
wealth of the visited location. We find correlations of 0.27, -0.25 and -0.26 respectively, with
p-values ranging from $e^{-28}$ to $e^{-25}$, for all areas, and correlations of 0.18, -0.27 and -0.24, with p-
values ranging from $e^{-14}$ to $e^{-7}$ for rural areas. Interestingly, this means that electrification attracts
materially wealthier visitors, but not visitors with higher levels of skills. This might be due to a
dynamic where individuals from deprived areas and with higher education are more likely to have
studied and worked away from their birth home, creating a bias in their visits towards less electrified
areas. Meanwhile, the positive correlation between electrification and quality of accommodation
Figure 2: Spearman correlations through successive levels of aggregation. (a) All antenna sites; direct correlation. (b) All antenna sites; partial correlation. (c) Rural antenna sites; direct correlation. (d) Rural antenna sites; partial correlations. (e) Rural sub-network; direct correlation. (f) Rural sub-network; partial correlation. The x-axis indicates the merging threshold.

of visitors could simply be due to the fact that the area around an antenna site is more likely to get electrified if it is already part of a larger wealthier area, or close to an already electrified city. Since frequent visitors are more likely to come from nearby areas, the apparent extra wealth of visitors could only be due to wealthier residents already living nearby before electrification.

To study the importance of the composition of the surrounding area, we invert the problem:
how more likely is it that a given visitor originating from a specific antenna site would choose a more electrified destination among the antenna sites in their neighbourhood? The mean distance travelled by a visitor between two antenna sites is about 37 km nationwide, 41 km between two rural sites and about 75 km if one end of the trip is a rural site and the other end is an urban site. Long trips are rare and usually involve travelling to and from the capital city, Dakar, or to and from the big mosque of Touba; they are difficult to complete within rural areas, due to the use of either donkey carts or buses as main mean of transportation. To ensure that we encompass most types of travels, we define neighbourhoods of increasing size by 10 km increments, from 10 km to 100 km. For each neighbourhood size, we compute the average electrification rate of visited areas (weighted by frequency of visits) divided by the average electrification rate of the neighbourhood (taking into account the population count around each antenna site). We also compute the direct Pearson correlation between the frequency of visits and the electrification rate of the destination. These results are reported in fig. 4(a). It is not possible to compute reliably the partial correlation controlled by combined wealth in this case, as the samples inside each neighbourhood are too small to smooth the added variance. We observe that more electrified areas have a small edge, in the sense that they are more likely to be visited, over less electrified areas nationwide, although it is less pronounced for rural areas. However, when we only consider trips in between rural areas, electrification appears to be a slight disadvantage. This can be explained by the competition that results from the urban areas that are often found near well electrified villages: fellow rural visitors are more likely to bypass the other villages and go directly to the urban areas.

Furthermore, wealthier visitors do not seem to be influenced by the electrification rate of the destination they choose. This can be seen in fig. 4(b), where the average level of education of a visitor is plotted against the ratio of electrification rates between the visited locations and all sites within a 20 km radius (some very similar plots for employment status and quality of accommodation can be found in fig. S2 of the supplementary information). The wealth of the visitors does have an impact, however, on their probability of starting a journey (we find a Pearson correlation of 0.63 – 0.47 for rural areas – between the combined wealth indicator at origin and the size of outgoing
flows). Similarly, the electrification rate of the destination is very well correlated to the size of the overall incoming flows (Pearson coefficient of 0.68 – 0.43 for rural areas). In conclusion, if a site is electrified, it has a higher chance to be picked as a destination, but it will be chosen as a destination by residents of the surrounding area indifferently of their own level of wealth (although wealthier residents do travel more). This confirms that the correlations identified in fig. 3 are more due to the pre-existing composition of the neighbourhood, than they are a consequence of electrification triggering visits from individuals with a higher profile on average. In other words, electrification gives a competitive advantage in terms of volume of visits, but not in terms of visitor profiles.

2.2.2 Prediction of the volume of visits

Since we have observed that the volume of visits between any two sites depends heavily on the wealth at origin and the electrification at destination, we can try to predict the flows directly from these variables using gravitation models [30]. The general form of the gravitation model is

$$T = k \frac{O_i^{\alpha_1} \cdots O_p^{\alpha_p} D_1^{\beta_1} \cdots D_q^{\beta_q}}{d^\gamma}, \quad (1)$$

where $T$ is the size of the flows between an origin and a destination, $\{O_i\}_{1 \leq i \leq p}$ and $\{D_j\}_{1 \leq j \leq q}$ are a set of variables depending respectively on the origin and the destination, $d$ is the distance between the origin and the destination, and $k$, $\{\alpha_i\}_{1 \leq i \leq p}$, $\{\beta_j\}_{1 \leq j \leq q}$ and $\gamma$ are parameters to be
determined. Often, the variables at origin and at destination are reduced to a single variable, the size of the population, but we can consider any variable that may have predictive power, such as electrification rate and level of wealth. In particular, we can put directly in competition several variables to identify which are the most important factors in driving the volume of the flows.

This kind of modelling is sensitive to the modifiable areal unit problem [31]. In our case, we are trying to model simultaneously intra-urban short-range flows and long-range flows between far apart antenna sites. A single value of the distance parameter $\gamma$ may not be enough to characterise these very different situations. Rather than merging according to the arbitrary administrative boundaries, we tackle this issue by applying a hierarchical clustering algorithm to the matrix containing the distances between all our antenna sites. We then merge all the branches of the resulting dendrogram whose distance is less than 5 km. This results in the 817 clusters visible in fig. 5. Out of these, 523 clusters are considered purely rural under our definition of rural. Although in appearance similar to the merging method used in section 2.1, this method produces a different output. In the dendrogram, the branches are considered situated at the barycentre of the leaves they contain. As a result, the clusters contain only a few antenna sites that are closer to each other than to the rest of the sites, rather than a continuous stretch of nearby sites. In addition, we use nighttime lights intensity instead of electrification rates for this particular modelling, since the nighttime lights intensity is smoother and therefore more stable under an exponent.

![Figure 5: Flows of visitors between antenna sites.](image)

In each case, the quality of the prediction is shown in the first column as a Pearson $r^2$, and the parameter exponents assigned to each predictive variable are shown next. We observe that both nighttime lights intensity and wealth at destination are better predictors than population size when all trips are considered. Similarly, wealth at origin is a better predictor than population at origin. We can achieve significantly better results when population, wealth at origin and nighttime lights intensity

$$
\{\alpha_i\}_{1 \leq i \leq p}, \{\beta_j\}_{1 \leq j \leq q} \text{ and } \gamma
$$

obtained by multilinear regression of the logs for different choices of variables at origin and destination are shown in table 2. In each case, the quality of the prediction is shown in the first column as a Pearson $r^2$, and the parameter exponents assigned to each predictive variable are shown next. We observe that both nighttime lights intensity and wealth at destination are better predictors than population size when all trips are considered. Similarly, wealth at origin is a better predictor than population at origin. We can achieve significantly better results when population, wealth at origin and nighttime lights intensity
at destination are considered together. When origin constraints are added, i.e. when we force the total outgoing volume of visitors from each cluster to be equal to its known value (see [30]), we can achieve a \( r^2 \) of 0.91 for the trips between all clusters. The same method applied within the rural sub-network achieves a \( r^2 \) of 0.65 with coefficients \( \beta_1 = 0.18 \) for population, \( \beta_2 = 0.10 \) and \( \gamma = 2.28 \) for distance.

Table 2: **Gravitation models: quality of predictions and fitted parameters.** Pop stands for population, Ele for nighttime lights intensity, Acc for quality of accommodation, Edu for level of education, Emp for employment status and Com for combined wealth index. The last model in the bottom row is an origin constrained variant of the one immediately above. The p-values for all exponents are \(< 2.2e^{-16}\).

| O / D       | \( r^2 \) | \( \alpha \) | \( \beta \) | \( \gamma \) |
|-------------|-----------|--------------|-------------|-------------|
| Pop / Pop   | .59       | .96          | .79         | 1.26        |
| Pop / Ele   | .84       | .88          | .59         | 1.14        |
| Pop / Acc   | .79       | .89          | 2.56        | 1.21        |
| Pop / Edu   | .72       | .96          | 6.34        | 1.31        |
| Pop / Emp   | .74       | .96          | 2.28        | 1.32        |
| Pop / Com   | .78       | .91          | 2.33        | 1.24        |
| Pop / Acc+Ele| .84      | .87          | .48+.49     | 1.14        |
| Acc / Pop   | .68       | 2.67         | .75         | 1.26        |
| Edu / Pop   | .54       | 6.23         | .85         | 1.37        |
| Emp / Pop   | .61       | 2.35         | .83         | 1.37        |
| Com / Pop   | .63       | 2.39         | .78         | 1.30        |
| Pop+Acc / Pop+Ele + constraints | .87 | .70+.81 | .26+.45 | 1.07 |
|             | .91       | N.A.         | .29+.46     | 1.11        |

The results confirm those obtained in the previous section. Wealth at origin and electrification at destination are good predictors for the volume of flows. In addition, we can observe that electrification has an impact that is independent of wealth, since adding nighttime lights intensity at destination to quality of accommodation at destination slightly increases the predictive power compared to quality of accommodation at destination alone. Note also that the exponent for distance is almost twice higher in rural areas compared to all sites. This is a strong indication that the cost of transport has a much higher impact in rural areas.

**Conclusions**

Throughout the previous section, we have shown that electrification does bring some positive outcomes, which are distinct from other indicators of wealth. However, these outcomes are usually small and, more importantly, hinge on the pre-existing composition of the larger surrounding area. Most of the trips between antenna sites cover less than 50 km. This creates an important regional effect. In section 2.1, we have identified that electrification marginally increases the centrality of antenna sites, even in the rural sub-network. However, this increase disappears rapidly when sites are merged using a buffer of increasing size. In section 2.2, we have shown that electrification generally increases the volume of visitors. Nonetheless, the socio-economic profile of these visitors
is determined by the socio-economic profile of the individuals already living nearby. Electrification does attract a larger number of wealthy visitors if these profiles already exist in the larger surrounding area, but does not draw wealthier visitors from further away. We have also enlighten that people living in electrified areas are slightly more likely to initiate contact effectively with other antenna sites. This positive trend exists at all scales. In contrast, the higher the socio-economic profile of an individual is, the more local their communication gets. In particular, urban dwellers rarely engage contact with rural dwellers. Furthermore, it appears that the proximity of urban areas near electrified rural areas can be detrimental to these, as they are more likely to be bypassed by visitors from other rural areas.

How positive is it to electrify rural areas then? If such an area lies close to an urban area or lies inside a relatively wealthy region, it will benefit from a slight competitive edge compared to the non-electrified rural sites in the same area, and will potentially attract a larger number of wealthy visitors. In contrast, if such an area is more isolated, it is unlikely that it will draw wealthy visitors from afar, although it will still benefit from a slightly higher centrality among its local rural cluster, increasing its perceived importance in the region. Considering that isolated rural areas are generally quite poor and given the slowness of changes following electrification, a strategy based on the development of selected isolated rural areas by favouring the centralisation of nearby opportunities does not appear efficient. On the contrary, since electrification is well correlated to all indicators of wealth at the nation scale and since the development of an area seems largely determined by the wealth of its surroundings, our results support strategies that favour global solutions to electrify an entire cluster of sites, rather than a diversity of limited specific solutions.

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Supplementary information

![Graphs showing electrification rate distributions of antenna sites.](image)

**Figure S1:** Electrification rate distributions of antenna sites.

![Graphs showing impact of wealth at origin on the choice of a destination.](image)

**Figure S2:** Impact of wealth at origin on the choice of a destination. (a) Ratio between the electrification rate of visited places and the electrification of a neighbourhood around the origin of travel against the quality of accommodation of the traveller. (b) Same with employment status of the traveller.
| Correlation     | All sites | Rural sites | Rural sub-network |
|-----------------|-----------|-------------|-------------------|
|                 | Direct    | Partial     | Direct            | Partial | Direct    | Partial |
| Betweenness     | e-102     | e-36        | e-41              | e-08    | e-41      | e-03    |
| Leverage        | e-167     | e-45        | e-65              | e-05    | e-58      | e-05    |
| Social div.     | e-122     | 0.055       | 0.013             | 0.274   | 0.159     | 0.611   |
| Spatial div.    | e-85      | e-56        | e-60              | 0.103   | e-54      | 0.049   |
| Distance        | e-320     | e-17        | e-20              | 0.246   | e-10      | 0.016   |
| In/Out          | e-78      | e-23        | e-12              | e-15    | e-05      | 0.983   |