Bridging the information gap: A webGIS tool for rural electrification in data-scarce regions

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Abstract

Rural electrification in developing countries is often hampered by major information gaps between local communities and urban centers, where technical expertise and funding are concentrated. The tool presented in this paper addresses these gaps to support the implementation of off-grid micro hydropower infrastructure. Specifically, we present a method to site, size and evaluate the potential for micro hydropower based on remote sensing data. The method improves on previous approaches by (i) incorporating the effect of hillslope topography on the optimal layout of the infrastructure, and (ii) accounting for the constraints imposed by streamflow variability and local electricity demand on the optimal size of the plants.

An assessment of the method's performance against 148 existing schemes indicates that it correctly identifies the most promising locations for hydropower in Nepal, but does not generally reproduce the specific design features of constructed plants, which are affected by site-specific constraints. We develop a proof-of-concept computer tool to explore the potential of webGIS technology to account for these constraints by collecting site-specific information from local users.

Keywords: Micro hydropower, WebGIS, Nepal, DEM

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Symbol	Description	Unit
ρ	Density of water	$kg \cdot m^{-3}$
g	Gravitational Acceleration	$m \cdot s^{-2}$
η	Plant efficiency	—
k	Linear friction losses	—
Δz	Elevation difference (along penstock)	m
H	Net hydraulic head	m
A	Catchment area	km^2
L	Penstock length	m
α_0	Average cost of a unit (1kW) micro hydropower scheme	Nep. Rupees (NRp)
α_C	Scale elasticity of micro hydropower costs	—
γ_0	Household electricity demand at unit price	kW
γ_p	Price-elasticity of household electricity demand	—
Q_d	Capacity flow	$m^3 s^{-1}$
$P\{Q \geq Q_d\}$	Exceedance probability of Q_d	—
C	Electrical capacity	kW
pop	Community size	Number of households
p	Unit price of electrical capacity	NRp per kW
TSI	Topographic suitability index	—
CVI	Community value index	—

Table 1: Nomenclature

1. Introduction

Access to electricity remains an impediment to development in many parts of the world, particularly in rural areas that will stay out of reach of centralized power grids due to low population densities and prohibitive grid extension costs [1]. In this context, decentralized distributed generation, whereby electricity is generated at the point of consumption, offers a promising and affordable strategy for rural electrification [2]. Community-scale run-of-river hydropower – *micro hydropower* – is a particularly attractive technology in mountainous regions, where appropriate slope and runoff conditions are encountered, and where grid extension is expensive because of the complex topography. Thanks to the low level of technology of its components, micro hydropower often emerges as the most cost effective distributed generation option for mountain communities [3]. Unlike conventional hydropower, micro hydropower has a limited impact on the landscape and on the flow regime of the stream because it does not store nor divert significant volumes of water.

Abbreviations: AEPC, Alternative Energy Promotion Center of the Government of Nepal; CSR, Complete Spatial Randomness; DEM, Digital Elevation Model; GIS, Geographic Information System; NGO, Non Governmental Organization; VDC, Village Development Committee.

38 Despite their promise, micro hydropower programs have had mixed success globally.
39 In Nepal, despite a huge hydropower potential [4], favorable policies and substantial lo-
40 cal hydropower expertise [5], micro hydropower currently supplies about 200,000 house-
41 holds [6] (about 7 million people remain unconnected [1]), and up to 30% of existing
42 micro hydropower plants are not in operation [8]. These poor outcomes point towards
43 major information gaps between key actors in the micro hydropower sector. These gaps
44 arise at the earliest stage of project development and prior to in-situ feasibility assess-
45 ments. Policy makers at the regional level lack appropriate local information to identify
46 promising locations for micro hydropower development, while would-be project enablers
47 at the local level lack awareness and technical expertise for local resource assessment
48 [10, 9]. These gaps are particularly evident in Nepal where, paradoxically, the extreme
49 topography of the region is at once responsible for its enormous hydropower potential,
50 and for the low physical accessibility of most communities. It ensues an ineffective
51 transfer of information between urban centers, where funding agencies and technical
52 expertise are concentrated, and rural communities, where micro hydropower facilities
53 are installed, used and maintained.

54 This study investigates the combination of two promising recent information tech-
55 nologies, remote sensing and open source webGIS, as a means to address information
56 barriers at early project stages. We devise the tools and analysis framework necessary
57 to assess these technologies in the specific case of Nepal, with the expectation that the
58 methods provide a prototype for other regions where similar opportunities and chal-
59 lenges relating to micro hydropower arise. Specifically, the contributions of this paper
60 are two-fold. First, we formulate and assess a novel algorithm using remotely sensed
61 digital elevation models (DEM) and state-of-the-art hydrological models to identify
62 optimal micro hydropower locations. Second, we develop an operational web tool to
63 support micro hydropower development in Nepal. Web-based geographic information
64 systems (webGIS) are increasingly used¹ to collect, merge and disseminate heteroge-
65 neous data from a wide variety of stakeholders. Yet to our knowledge, this is the first
66 attempt to leverage its interactive, open-source and cloud-based nature to support rural
67 electrification.

68 The location of micro hydropower infrastructure components on the landscape is a
69 key design decision: it determines capital costs, hydraulic head and mean flow, which
70 are the features determining the scheme’s ultimate economic performance. The effects
71 of location on these features should therefore be incorporated into attempts to map
72 hydropower potential. Infrastructure siting is driven by topography, which affects both
73 the potentially harvested power, through the hydraulic head and the area of the con-
74 tributing catchment; and the cost of the infrastructure, by affecting the lengths of the

¹For instance, webGIS has been used to predict environmental [24] and health-related [25] risk, manage environmental resources [26] and support ecological modeling [27].

penstock and headrace canal. This dependence on topography allows layout optimization to be automated – albeit in a simplified fashion – for the purpose of mapping hydropower potential, thanks to the global availability of free, high resolution DEMs from remote sensing platforms². An extensive review of recent DEM-based potential assessment techniques can be found in Punys et al. [14]. In their most basic form, existing algorithms estimate gross hydropower potential by computing watershed boundaries and river reaches from a digital elevation model [e.g., 15]. The elevation difference obtained within each reach (or arbitrary river segment as in Kusre et al. [16]) is then multiplied by the area of its contributing catchment and a regional runoff parameter. In a more sophisticated approach, Yi et al. [17] implemented a cell-by-cell search algorithm along the drainage network. Unlike previous approaches, the method allows for water diversions from lower to higher order streams and identifies potential (straight line) waterways from each stream pixel within a series of predefined search radii. The hydropower potential of each waterway is then evaluated based on its average (straight distance) slope. A similar search algorithm was further developed by Larentis et al. [18], allowing for water storage reservoirs, and accounting for the effect of preexisting schemes on the exploitable potential.

A common aspect of all these methods is their sole reliance on the elevation profile of the stream channel itself to evaluate the hydraulic head. Yet hillslopes are typically steeper than channels in mountainous regions, and the optimal penstock position may be located on a favorable slope at a significant distance from the stream, as illustrated in Figure 1. As a result, headrace canals exceeding 500 meters are commonly found in Nepal [e.g., 19]. Secondly, hydropower potential is constrained by streamflow variability, as described by the flow duration curve of the stream. The effects of flow constraints on the optimal size of hydropower plants are well understood and have been the focus of substantial recent research. An extensive review of recent optimization approaches to size run-of-river hydropower plants is available in Haddad et al. [20]. However, existing methods were typically developed to design grid-connected schemes in developed countries, where electricity prices are exogenously determined (e.g., through feed-in tariffs). They are not applicable off the grid, where micro hydropower revenue is affected by local electricity demand. Further, flow duration curves are notoriously difficult to predict *a priori* in ungauged catchments, particularly in hydrologically complex and poorly gauged mountainous regions like Nepal [21]. Consequently, despite being essential to optimize the capacity of micro hydropower plants, streamflow variability has been largely omitted from previous potential mapping tools that typically only consider average flow availability, if anything. Lastly, existing studies generally suffer from the absence of a robust statistical framework for ground validation.

²For instance, ASTER GDEM v2 used in this paper provides quasi global land surface elevation (i.e. between 83°N and 83°S) with 30m grid postings [13].

112 We address these shortcomings by developing a micro hydropower siting algorithm
 113 that accounts for hillslope topography (Section 2.1), which we couple to an economic ca-
 114 pacity optimization that incorporates state-of-the-art hydrological regionalization mod-
 115 els and accounts for local electricity demand (Section 2.2). We formulate a statistical
 116 framework using point pattern analysis (Section 2.3) to validate these techniques against
 117 existing plant locations (Section 3). Lastly, we describe a proof-of-concept webGIS tool
 118 to assist micro hydropower development in Nepal (Section 4). The tool collects and
 119 merges remotely sensed and locally imparted resource constraints, and disseminates
 120 preliminary design and feasibility information (obtained using the siting algorithm) to
 121 relevant stakeholders, both at local and regional level, thus brighting the information
 122 gap. We discuss the potential and limitations of the tool and the potential of webGIS
 123 technology to support rural electrification, in Nepal and at a global level.

Figure 1: Stylized example showing the relevance of hillslope topography in the optimization of run-of-river hydropower layout. In panel (a), layouts are evaluated solely based on streambed topography. Under these conditions, there is no diversion canal and the location of the penstock is constrained by the location of the stream. Layout B is preferable to layout A because its has a steeper average slope. Panel (b) accounts for local hillslope topography by allowing canals to divert water. Layout A can now take advantage of the steep hillslope conditions East of the stream and becomes preferable to layout B

124 2. Methods

125 2.1. DEM-based micro hydropower siting

126 This section focuses on the development of a novel algorithm using a Digital Eleva-
 127 tion Model to optimize the siting of micro hydropower infrastructure. Unlike previous

128 methods, we explicitly include hillslope topography in the layout optimization. To min-
 129 imize energy losses to friction, micro hydropower infrastructure is typically laid out to
 130 minimize the slope of the canal diverting water from the stream, while maximizing the
 131 slope of the penstock feeding water to the turbines. The algorithm optimizes the posi-
 132 tion of the intake, forebay and power house of micro hydropower schemes to maximize
 133 a topographic suitability index (*TSI*):

$$TSI = \rho \cdot g \cdot \Delta z \cdot A, \quad (1)$$

134 with g the gravitational acceleration, ρ the density of water, Δz the elevation dif-
 135 ference across the penstock and A the area of the catchment above the intake. The
 136 last two variables are determined by the position of the infrastructure to be optimized.
 137 The TSI indicates the theoretical (maximal) electrical capacity (in Watts) that can be
 138 extracted from the infrastructure per unit of annual rainfall (in mm/y) in the con-
 139 tributing watershed. It only considers the effect of topography on the gross extractable
 140 energy and neglects the effects of energy losses, streamflow variability and economic
 141 constraints on the design and performance of the plant.

142 Micro hydropower layouts are further restricted to technically feasible options using
 143 heuristic constraints. In line with anecdotal evidence from Nepal [19], the lengths of
 144 the headrace canal and penstock are capped at $2km$ and $200m$ respectively, and intakes
 145 with contributing catchment areas of less than $10km^2$ are rejected. The average slope
 146 of the penstock is also restricted to values between 0.176 and 1. The higher bound is
 147 suggested by Junejo et al. [29, p. 52] for reasons of cost, constructability and slope
 148 stability. The lower bound is obtained by considering maximum friction losses of 10%
 149 of the net hydraulic head, as recommended in Chitrakar [12], and assuming a linear
 150 head loss coefficient of 0.016 (see Appendix A).

151 The ensuing algorithm consists of the following steps, illustrated in Figure 2:

- 152 1. The first step generates a stream network using topographic information from
 153 the DEM. Slope, aspect and flow accumulation rasters are computed using the
 154 A^T search algorithm implemented in the *r.watershed* function in the GRASS GIS
 155 environment[30].
- 156 2. The second step identifies and excludes DEM raster cells that cannot contain
 157 the penstock. Valid cells are (i) within the administrative boundaries of the
 158 community, (ii) within 2km of a river, (iii) within the altitude range covered by
 159 the rivers in the community and (iv) have a slope between 0.176 and 1.
- 160 3. The third step optimizes the layout of the penstock. Its position and direction are
 161 determined by considering each valid DEM cell in decreasing order of slope and
 162 extracting an elevation profile along the local flow direction given by the aspect
 163 raster. Penstock length L along the elevation profile is determined by maximizing
 164 the net hydraulic head:

$$H(L) = \Delta z(L) - k \cdot L \quad (2)$$

where $\Delta z(L)$ is the elevation difference along the penstock and $k = 0.016$ are the assumed linear friction losses. Penstock length L is capped at $200m$. The forebay and power house are located at the higher and lower end of the penstock respectively.

4. The headrace canal is determined as the DEM contour line running through the forebay, and the intake is positioned at the intersection of the contour line with the nearest stream. The layout is discarded if the length of the canal is larger than $2km$, or if the catchment area A upstream of the intake is smaller than $10km^2$.

Steps 3 and 4 are iterated until the desired number of infrastructure layouts are found and returned in order of decreasing topographic suitability. By default, the method generates five valid layouts per community.

Figure 2: Topographic layout optimization algorithm: DEM analysis to determine the location of streams and generate slope and aspect rasters (a); Pixel selection based on elevation (b) and slope (c) criteria; Determination of optimal penstock location (black line on subfigure c); Optimization of penstock length based on the elevation profile (d); Determination of the head race canal using DEM contours (e).

2.2. Economic optimization of plant capacity

While topography determines the gross extractable energy, the hydropower potential that is economically exploitable is ultimately constrained by local factors, including

streamflow variability and economic considerations. We account for these constraints by coupling the topographic siting algorithm with an economic optimization to determine the size of the infrastructure.

The economic optimization of off-grid micro hydropower has received little attention in the literature, despite being overwhelmingly prevalent in developing countries. The economic performance of off-grid systems is driven by the demand of local users, which energy consumption is often unmetered. Following their demand curves, Nepalese households pay an agreed-upon fee for a chosen electrical capacity. Consequently, households do not purchase energy units, but rather options on peak energy consumption. Further, in contrast to grid-connected schemes, power utilities managing off-grid infrastructure are in a position of natural monopoly, and price regulation mechanisms are required to ensure equitable access to electricity [31]. In Nepal, many off-grid micro hydropower schemes are indeed subject to some level of participative pricing [8, p. 36] and do not operate solely on a profit maximizing basis. Although numerous types of public pricing policies exist [31], we assume average cost pricing as recommended by Junejo [11, p. 61]. This implies that the price of the produced electricity is regulated so as to allow the full recovery of infrastructure costs, but no profit.

Cost recovery occurs when average costs are exactly compensated by average revenues, which are only accrued when streamflow is sufficient to deliver the agreed upon electrical capacity. Accordingly, the optimal capacity flow Q_d of off-grid micro hydropower schemes can be obtained by solving:

$$\alpha_0 \cdot C^{\alpha_C - 1} = p \cdot P\{Q \geq Q_d\} \quad (3)$$

$$\frac{C}{pop} = \gamma_0 \cdot p^{\gamma_p} \quad (4)$$

where $C = gH\rho\eta Q_d$ is the electrical capacity generated by a capacity flow Q_d , H is the hydraulic head of the scheme, ρ the density of water, g the gravitational acceleration, and η the efficiency of the plant at full capacity. The relation between the level of utilization of the plant and its efficiency can be ignored under the assumption that the plant only generates revenue when running at full capacity.

The left hand side of Equation 3 represents the average unit cost (per kW) of the plant, which we approximate as a power law of its electrical capacity. In line with Basso and Botter [32], we neglect other costs factors (for instance related to hydraulic head, the geometry and materials of the penstock, civil work, site accessibility [see, e.g., 33]) for tractability reasons. This simplification is reasonable for pre-feasibility cost estimations in the context of Nepal, where a significant fraction (around 70% [19]) of infrastructure costs consists of turbine and electrical equipment costs, which approximatively follow a power law relation with plant capacity [34]. In Equation 3, α_0 is the average cost of a 1-kW micro hydropower scheme and α_C the scale elasticity of

214 infrastructure costs, that is the relative decrease in average (unit) cost when doubling
 215 infrastructure size. Economies of scale are possible if $\alpha_C < 1$. The right hand side of
 216 Equation 3 represents the average revenue (per kW) obtained from by selling electrical
 217 capacity to local households at a price p . $P\{Q \geq Q_d\}$ represents the fraction of time
 218 when the plant generates revenue, that is the probability that the available streamflow
 219 equals or exceeds the flow capacity of the turbine. This probability is given by the
 220 flow duration curve of the stream, which we estimate at the location of the plant using
 221 the probabilistic process-based hydrological model described in Müller et al. [36]. We
 222 showed in a recent cross-validation analysis [40] that the method performs remarkably
 223 well in ungauged Nepalese basins and substantially outperforms the regionalization
 224 method currently prescribed in official micro hydropower design manuals in Nepal [e.g.,
 225 12, 41]. The method incorporates key flow generation processes, making it well adapted
 226 for its extension beyond Nepal, particularly where flow gauges are extremely scarce, and
 227 where climate-change is expected to have a strong effect on flow regimes [40]. Lastly,
 228 Equation 4 represents the demand curve of households for electrical capacity, which
 229 we assume to evolve as a power law of price Filippini and Pachauri [35]. Under these
 230 conditions, γ_0 corresponds to the electrical capacity consumed by a household at a unit
 231 price of 1, and γ_p is the price elasticity of electricity demand, which typically takes a
 232 value between -1 and 0.

233 By construction, the resulting micro hydropower designs do not generate profits. It
 234 follows that standard financial performance metrics (e.g., Net Present Value, Internal
 235 Rate of Return) are inappropriate to evaluate the feasibility of infrastructure managed
 236 by local (non-profit) public utilities. Instead, we construct a community value index
 237 (CVI) as the product of the unit cost of the infrastructure and the average electrical
 238 capacity consumed by a household:

$$CVI = p \cdot \frac{C}{pop} \quad (5)$$

239 The CVI is constrained by local community demand and represents the value as-
 240 signed by the households to the generated electricity. This is perhaps the most ap-
 241 propriate metric to be maximized when evaluating community-owned, off-grid power
 242 infrastructure at the pre-feasibility stage.

243 *2.3. Data and Validation Framework*

244 The topographic siting and economic optimization algorithms were implemented
 245 in Nepal, where predicted layouts were validated against the location and capacity of
 246 existing micro hydropower schemes. The siting algorithm was used to predict five micro
 247 hydropower layouts per community based on the ASTER GDEM v2 digital elevation
 248 model [13]. The location and characteristics of the median layout in each community,
 249 in terms of topographic suitability, was then considered for economic optimization. The
 250 process-based hydrologic model described in Section 2.2 was applied to determine local

streamflow distribution based on remotely sensed rainfall (TRMM 3B42 v7 [42]) and using daily streamflow observations from 50 Nepalese gauges [43, 44] for calibration. The optimal capacity of each plant was determined using demographic data from the 2011 Nepalese census and the economic characteristics displayed on Table 2.

$\frac{C}{pop}$	Average electrical capacity per household	0.1 kW	[45]
p	Average price per kW of (off-grid) installed capacity	102,000 Nep. Rupee (NRp)	[45]
γ_p	Price elasticity of (off-grid) electricity demand	-0.12	[46]
α_0	Average cost of a 1-kW micro hydropower scheme	$207 \cdot 10^3$ NRp	[45]
α_C	Scale elasticity of micro hydropower costs	0.93	[19]
η	Plant efficiency at full capacity	0.51	[47]

Table 2: Costs and demand parameters used in the economic optimization of micro hydropower capacity in Nepal.

Model outputs were validated against existing infrastructure indexed in the Renewable Energy Data Book [45] published by the Alternative Energy Promotion Center (AEPC) of the Government of Nepal. The dataset is a publicly available infrastructure survey that provides the capacity and cost of 148 micro hydropower schemes that were subsidized by the AEPC and commissioned between 2007 and 2011. Most infrastructure is community-owned and all schemes supply villages that do not have access to the centralized grid. The dataset provides the location of the schemes at the ward level³, as shown in Figure 3 (a), but the exact position of the infrastructure elements is not available.

The resulting uncertainty on the layout of existing schemes precludes a rigorous validation of the ability of the method to site and size infrastructure with respect to local topography and demand. In fact, both design processes result from ill-defined and eminently local optimizations that are challenging to emulate in a large scale remote assessment tool. Here we used regression techniques and point pattern analysis to test the following three hypotheses:

- H1 The method identifies the most appropriate communities (VDCs) for micro hydropower development, as evidenced by the number of existing schemes in each community.
- H2 The method can successfully identify the most promising wards for micro hydropower within these communities.

³The ward is the smallest administrative subdivision in Nepal. There are 9 wards in a village development committee (VDC).

Figure 3: Validation data. (a) Approximate location of the 148 microhydro schemes of the Renewable Energy Data Book [45]; (b) Layout of the existing micro hydropower scheme on the Lohore Kohla (solid) and infrastructure positions predicted by the method (dashed).

275 H3 The method predicts the position and capacity of existing micro hydropower
276 schemes.

277 Statistical inference based on generalized linear models can be used to test hypoth-
278 esis 1. The 108 communities possessing at least one existing scheme and their 488
279 immediate neighbors were sampled. This sampling strategy minimizes the potential
280 effect of unobserved variables on the presence of a micro hydropower scheme. In partic-
281 ular, neighboring communities are assumed to have access to comparable information,
282 technical expertise and loan conditions as those where micro hydropower facilities are
283 located. A Poisson regression was used to evaluate the method's ability to predict the
284 number of micro hydropower schemes in the considered communities. By assuming
285 a Poisson-distributed response variable, this form of regression analysis is adapted to
286 model count data, here the number of existing micro hydropower schemes per com-
287 munity. The number of schemes was regressed against the topographic suitability and
288 community value indices (TSI and CVI) predicted by the method. Student's t-tests on
289 the regression coefficients were used to evaluate the significance of the relation between
290 these predicted metrics and the presence and number of micro hydropower schemes in
291 the sampled communities.

292 Hypothesis 2 was tested by assessing whether the method improved on the pre-
293 diction of the location of existing micro hydropower schemes within the communities,
294 compared to an alternate method, where predictions were generated randomly. The set
295 of predicted and observed micro hydropower locations was modeled as a marked ran-
296 dom point process. An extension of Ripley's K [48] was used to evaluate the statistical
297 significance of clusters between predicted and observed locations. The K-function was

modified to allow for multiple supports because the method optimizes the location of micro hydropower sites independently for each community: predicted sites can only be compared to actual sites within a community. Individual K-functions must therefore be estimated independently for each community and aggregated across supports. The construction of the aggregated estimator and its use in a Monte Carlo test for statistical inference are detailed in Appendix B.

A linear regression was finally used to test the third hypothesis which addresses the method’s ability to predict the location and capacity of existing micro hydropower plants. In contrast to hypothesis 1, the 148 existing schemes (and not the communities containing them) were sampled, and their capacity regresses against the corresponding predicted capacities. Unfortunately, the absence of exact locational data on existing infrastructure precludes a formal test of the method’s ability to predict their position. Nonetheless, optimal capacity is driven by inherently local topographic effects, as illustrated in Figure 1, so the method’s ability to predict the *capacity* of existing schemes is likely a good indicator of its ability to predict their *position*. We assess both effects using a Student’s t-test to evaluate the significance of the relation between predicted and observed micro hydropower capacities.

3. Results

Evidence suggests that combining the topographic siting and economic optimization algorithms allows promising locations for micro hydropower development to be effectively identified. A significantly positive association was found between the community value index (CVI) and the number of existing schemes, indicating that the method identified those communities where micro hydropower is particularly promising. Results of the Poisson regression (Table 3, column 1) show that the number of schemes per VDC is expected to increase by 1.2% for each marginal unit of CVI estimated by the method. The estimated coefficients also indicate that the topographic suitability index (TSI) is not significantly correlated to the number of schemes. This, along with the positive correlation found for the CVI, illustrates the role of local constraints as a limiting factor for micro hydropower feasibility. Demand side constraints, especially the size of the local community, are particularly crucial for off-grid infrastructure.

The point pattern analysis in Figure 4 (a) further suggests that the method reliably predicts suitable zones for micro hydropower development *within* communities. The position of the empirical curve above the confidence interval shows significant clustering between actual and predicted micro hydropower sites for distances ranging from approximately the median ward radius (0.9km) and approximately the median VDC radius (3km). This indicates that predicted locations are clustered around actual micro hydropower schemes in a statistically significant manner within the VDCs. The clustering effect disappears at distances below 1km, which is consistent with the expected uncertainty on the position of existing schemes, whose locations are approximated at

337 the centroid of the wards.

Figure 4: (a) Modified Ripley's K: Ripley's cross-K function is adapted to accommodate multiple support areas, as described in Appendix B, and normalized as $L^*(r) = \sqrt{K(r)/\pi} - r$ to represent deviations from complete spatial randomness (CSR) represented by the horizontal line $L^*(r) = 0$. The 90% confidence interval around the CSR was generated through Monte Carlo ($N=1000$). (b) Predicted vs. observed capacity per scheme: The capacity of the observed micro hydropower schemes is plotted against the median capacity predicted by the method in the corresponding community, assuming off-grid electrification.

338 In contrast, the method does not successfully predict the capacity of existing schemes,
 339 as evidenced by the poor fit ($R^2 < 0.01$) and negative coefficient of the linear regression
 340 (Table 3, column 2).

341 However, it is important to note that the intended purpose of the algorithms was not
 342 to emulate *existing* schemes, as tested by hypothesis 3, but rather to assist communities
 343 in the identification of sites for *new* installations. Thus, the poor fit of the linear
 344 regression is not indicative of the method's ability to fulfill its purpose, but may instead
 345 suggest that the capacity of existing schemes is constrained by local factors that are not
 346 accounted for in the method, as evidenced by its strong tendency to overestimate micro
 347 hydropower capacity (Figure 4 (b))⁴. Such local factors include access to credit, which
 348 remains challenging in rural Nepal [7] and restricts the capacity of financially feasible
 349 schemes. Large capital costs can force communities to develop their local hydropower

⁴These over-estimations cannot be explained by the uncertainty of the hydrological model. A recent cross-validation analysis across Nepal [40] has shown that, although relative prediction errors as large as 50% of the real streamflow quantile values can occur, streamflow predictions are not systematically upwardly biased.

potential gradually by building several smaller schemes: 25% of the communities in our sample have two or more (up to eight) micro hydropower plants.

	<i>Poisson</i>	<i>Ordinary</i>
	<i>Regression</i>	<i>Least Squares</i>
	<i>Dependent variable:</i>	
	$N_{MHP_{REDB}}$	C_{REDB}
TSI	-0.028 (0.029)	
CVI	0.009* (0.004)	
C		-0.047* (0.026)
Constant	-3.880*** (1.235)	21.843*** (2.835)
Observations	597	149
Adjusted R^2		0.009
<i>Note:</i>		
*p<0.1; **p<0.05; ***p<0.01		

Table 3: Linear regression coefficients. The first column presents the estimated coefficient of a Poisson regression of the number of micro hydropower scheme by VDC against the indices predicted by the method. The second column shows the results of an ordinary least squares regression of the capacity of existing plants against capacities predicted by the method.

Local constraints can also arise from the integration of the new power plant with existing local infrastructure. Consider the case of the Lohore Kohla power plant, a 23 kW micro hydropower scheme supplying 312 households in and around the rural market town of Namaule in Western Nepal. The existing scheme, whose GPS coordinates were recorded by the authors in 2012, does not correspond to any of the layouts predicted by the method, as seen on Figure 3 (b). Although topographically more advantageous, all predicted sites are located on the left bank of the Lohore Kohla River: their construction would require a new bridge to transport materials from the road, which would significantly increase costs. In addition to road accessibility, plant proximity to a demand center plays a significant role in the placement of micro hydropower schemes. A significant fraction of the retrieved energy may be used as mechanical power during the day for grain milling. This situation arises frequently in Nepal, where 80% of the plants installed by 1996 were used for grinding grain [8]. In Lohore Kohla the infrastructure itself is owned by the community, but the attached mill belongs to the operator of the scheme. This arrangement provides incentives for the operator to properly maintain the system, but requires the mill to be easily accessible from the market town to generate profits. Infrastructure siting then becomes a multi-objective problem with the mill and power plant facility locations to be optimized jointly.

4. Discussion

Past experiences⁵ underline the importance of reaching out to local communities to (i) put the technical information (viz. the output of the DEM analysis) in the hands of local stakeholders and (ii) obtain and leverage local knowledge. To address these challenges, we developed Micro Hydro [em]Power, a proof-of-concept interactive webGIS tool that integrates the topographic and economic optimization algorithms and hydrological model discussed in this paper to support micro hydropower development in Nepal. All software components (detailed in supplementary materials) are open source, with licenses providing users with the freedom to run, modify and freely redistribute the original or modified program without further limitation or royalty payments [49]. Open source software is widely recognized for its ability to close the digital divide between rich and poor countries by increasing access and encouraging local developments [e.g., 50]. Micro Hydro [em]Power is hosted on a cloud-based server, which makes it accessible online (<https://mfmul.shinyapps.io/mhpower/>) and leverages the increasing availability of web-enabled mobile devices in developing countries⁶. The graphical user interface features an interactive digital map that enables an intuitive interaction with users, who can both access and provide local information.

In particular, the tool is intended to be used by visionary local enablers to assess the feasibility of micro hydropower infrastructure. Local enablers typically consist of influential community members, local investors (as in Ghale et al. [7]) or Non Governmental Organizations (NGO) that have a deep knowledge of the community, a strong motivation to implement the infrastructure and the basic quantitative skills and ability to communicate with funding agency and technical expert. The active involvement of such local project champions in all phases of micro hydropower development is widely recognized as a key prerequisite to success [8]. Micro Hydro [em]Power allows users to locate their community on the interactive map and to input basic local information on current costs and energy consumption. The tool then maps, sizes and evaluates the most topographically suitable infrastructure layouts and provides the quantitative information necessary to initiate further in situ feasibility studies. At the other side of the information chain, Micro Hydro [em]Power can also be accessed by regional or global decision makers (e.g., funding agencies, donors and policy makers). Thanks to its ability to collect local information and merge it with global remote sensing data, the tool provides them with critical information on the spatial distribution of micro hydropower potential and allows promising regions to be identified.

Although observation data are still missing to formally evaluate its operational performance, Micro Hydro [em]Power is a promising tool to address information barriers

⁵E.g., [9] in Thailand, [10] in sub-Saharan Africa and [7] in Nepal.

⁶Recent estimates indicate 39 active (web-enabled) mobile broadband subscriptions per 100 inhabitants in developing countries and 82 mobile phone subscription per 100 inhabitants in Nepal [22]

406 affecting micro hydropower development in Nepal through four key developments:

- 407 1. Improved terrain based optimization algorithms that account for hillslope topog-
408 raphy and electricity demand at the local level. There is a crucial data shortage
409 regarding the number and capacity of built and operational micro hydropower
410 plants in Nepal (primarily because most facilities are too small to require licenses,
411 and are thus unrecorded). Improved GIS-based algorithms are thus one of the
412 few immediate options to improve the evidence base for policy making.
- 413 2. Improved flow-duration curve prediction, based on recent developments in hy-
414 drological modeling which improve prediction accuracy compared to alternate
415 available approaches. The method is process based, easily transferable to other
416 climates and is robust to shifts in precipitation regimes (e.g. due to climate
417 change).
- 418 3. Capacity to incorporate local knowledge regarding costs, electricity demand and
419 loan conditions, which are essential to understanding the economic feasibility of
420 micro hydropower infrastructure. Off-grid power schemes are strongly sensitive
421 to such local conditions, which are challenging to predict from existing demand
422 curves (mostly available for grid-electricity) or from publically available data. An
423 interface by which local data can be recorded and incorporated into planning
424 circumvents these data issues.
- 425 4. Lastly, anecdotal evidence suggests that access to technical knowledge remains
426 a major challenge impeding the expansion of microhydropower, even when local
427 intermediaries would advocate for its use [7]. Although several decision support
428 systems have been developed to help off-grid communities evaluate the technical
429 and financial viability of potential clean energy projects [e.g., 51], these tools typ-
430 ically require advanced technical and computational tools, meaning that they are
431 still challenging for rural communities to adopt. Thanks to its web-based nature,
432 Micro Hydro [em]Power can be accessed by local enablers in rural communities,
433 provided they have web access. Its interactive map and graphic user interface
434 allows users to manipulate the tool with little to no technical background and a
435 rudimentary of the english language.

436 Despite its promises, an important current limitation of Micro Hydro [em]Power
437 lies in its inability to account for local qualitative constraints, as evidenced by the
438 Lohore Kohla case study discussed in Section 3. Site accessibility and institutional
439 arrangements are two key local factors constraining the design of micro hydropower
440 infrastructure worldwide. These factors are challenging to assess *a priori*. They are
441 often ill-defined and represent an inherent source of uncertainty in large scale assess-
442 ment tools. The interactive nature of Micro Hydro [em]Power allows local demand, which

appears to be a key constraining factor (see Table 3 (1)), to be assessed. Recent developments in participatory GIS platforms [e.g., 52] offer considerable scope for future improvement and incorporation of more complex sets of local constraints. Participatory GIS uses interactive web maps to create, assemble and disseminate geographic information provided voluntarily by individuals [53]. These capabilities can be used in future implementations of the tool to better incorporate local qualitative constraints, for example by allowing users to constrain the topographic optimization algorithm to specific zones within their community.

5. Conclusion

This paper presents Micro Hydro [em]Power, an open-source application to design and assess the feasibility of micro hydropower for rural electrification. The predictive performances of the underlying siting and sizing algorithms were evaluated against 148 existing schemes, showing their ability to identify promising communities and spot regions within these communities that are most favorable for micro hydropower development. The tool is easy to access and operate, and we are confident in its potential to be used by local project developers in rural communities. Its web-based nature allows it to scale easily and be operated by multiple distributed users. Once fully deployed and promoted, the interactive nature of the tool will allow cost and demand information to be assessed at the local level, in order to map the potential for micro hydropower more accurately at a regional scale.

The analysis also illustrates that assessing qualitative constraints pertaining to existing local infrastructure and institutions remains a significant outstanding challenge. These local characteristics are often ill-defined and challenging to incorporate in a transferable design tool. Ultimately, Micro Hydro [em]Power will not replace proper participative planning and field-informed, site-specific engineering design. Its purpose is rather to initiate the process by bridging the information gap between local knowledge and technical expertise in data-scarce regions.

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477 Appendix A. Linear Head Loss Coefficient

478 The assumed linear head loss coefficient is obtained by considering a penstock with
479 the following characteristics:

Diameter:	$d = 25cm$	Median value in [19]
Roughness:	$\epsilon = 25mm$	Lightly rusted mild steel [54]
Flow Velocity:	$u = 2m/s$	Median value in [19]

480 Using Moody's chart [54] with a relative roughness of $\epsilon/d = 0.001$ and a Reynolds
481 number of $Re = \frac{uL}{\nu} = 500,000$, the resulting friction factor $f = 0.02$ can be inserted in
482 the Darcy-Weisbach equation to compute a linear head loss coefficient:

$$k = f \frac{u^2}{2gd} = 0.016 \quad (A.1)$$

483 Appendix B. Bivariate Ripley's K on multiple supports

484 Ripley's K can be used for statistical inferences on patterns of completely mapped
485 spatial point processes, whereby the locations of all events related to these processes
486 can be included in a predefined study area, here referred to as the support. In the
487 case of a bivariate spatial process, where events are marked with a binary attribute
488 (here *predicted* and *observed* micro hydropower locations), the cross-function $K_{ij}(t)$ is
489 proportional to the expected number N_j of predictions falling within a distance t of a
490 randomly chosen observation:

$$K(t)_{ij} = \frac{1}{\lambda_j} \mathbb{E} [\mathbb{E} [N_j \in B(i, t) \mid i]] \quad (B.1)$$

491 where type i and type j events indicate observed and predicted micro hydropower
492 sites. $B(i, t)$ indicates a ball of center i and radius t and λ_j is the intensity of type
493 j events, that is the number of events per area. It can be shown [e.g., 48] that for a
494 homogeneous Poisson process, here referred to as *complete spatial randomness* (CSR),
495 the cross K function can be expressed as

$$K_{ij}(t) = \pi t^2. \quad (B.2)$$

496 The observed cross-K function is expected to be smaller than πt^2 for a regular
497 pattern and larger if events of type i are clustered to events of type j . A widely used
498 estimator for $K_{ij}(t)$ [55] is:

$$\hat{K}(t) = \frac{1}{\hat{\lambda}_j} \sum_{i=k} \sum_{j=l} \frac{1}{w(i, d_{i_k, j_l})} \frac{\delta(d_{i_k, j_l} < t)}{N_i} \quad (B.3)$$

with $\hat{\lambda}_j = \frac{N_j}{A}$, where A is the area of the support, $d_{i,j}$ the distance between the k th event of type i and the l th event of type j , and $\delta(\cdot)$ a Dirac delta. Edge effects are corrected by multiplying by $\frac{1}{w(i, d_{i_k, j_l})}$, the proportion of the circumference of a ball centered on i_k and of radius d_{i_k, j_l} falling inside the support area. Indeed, in order to account for points falling outside the support (and therefore not observed), the estimator is weighted inversely by the probability that such a point would be observed [48]. $\hat{K}_{ij}(t)$ can be used for statistical inference by using a Monte Carlo analysis to generate a confidence interval around $K_{ij}(t) = \pi t^2$, that is the null hypothesis that the observed pattern is a CSR process. Patterns in the point distribution are statistically significant if $\hat{K}_{ij}(t)$ falls outside the confidence interval.

The cross-K function cannot be implemented as such in the considered application because the model optimizes the location of micro hydropower sites *independently* for each community: predictions in a given community cannot be associated with observations in another community. Such cross-community associations are here prevented by considering each community as an independent support. The global cross-K function is then defined across multiple supports s as the expectation of the cross-K functions on the individual supports

$$K_{ijs}(t) = \frac{1}{\lambda_j} \mathbf{E} [\mathbf{E} [\mathbf{E} [N_j \in B(i, t) \mid i, s] \mid s]] \quad (\text{B.4})$$

The associated estimator can be obtained by averaging Equation B.2 over the considered supports

$$\begin{aligned} \hat{K}_{ijs}(t) &= \frac{1}{N_s \hat{\lambda}_j} \sum_{s=m} \sum_{i=k} \sum_{j=l} \left(\frac{1}{w(k, d_{k,l})} \frac{\delta(d_{k,l} < t)}{N_i} + v_m(t) \right) \\ &= \frac{1}{N_s \hat{\lambda}_j} \sum_{s=m} \left(\hat{\lambda}_{jm} \hat{K}_{ijm}(t) + v_m(t) \right) \end{aligned} \quad (\text{B.5})$$

where $\hat{\lambda}_{jm} = \frac{N_{jm}}{A_m}$ is the intensity of type j events on support m , and $\hat{K}_{ijm}(t)$ the cross-K function estimated on support m . Non-uniform support sizes are accounted for by using the correction term:

$$v_m(t) = \begin{cases} \pi \lambda_{jm} (t - d_{kl}^{\max_m})^2 & \text{if } t - d_{kl}^{\max_m} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (\text{B.6})$$

The correction term acknowledges the fact that no pattern can occur at a scale larger than the maximum distance $d_{kl}^{\max_m}$ between observed events in the support. This estimator is approximately unbiased and admits $\hat{K}_{ijs}(t) = \pi t^2$ for a homogeneous Poisson process, as visible in Figure 4, where a Monte Carlo procedure was used to

525 generate a confidence interval for a CSR process.

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