Applied Energy 171 (2016) 277–286

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

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

Marc F. Müller [a,*], Sally E. Thompson [a], Maggi N. Kelly [b]

[a] Department of Civil and Environmental Engineering, Davis Hall, University of California, Berkeley, CA, USA
[b] Department of Environmental Sciences, Policy and Management, Mulford Hall, University of California, Berkeley, CA, USA

HIGHLIGHTS

- Information gaps restrict the dissemination of sustainable rural electrification technologies.
- Open source, interactive, webGIS tool addressing these gaps for micro-hydropower.
- Optimizes the placement and size of local designs using remote sensing inputs.
- Collects local economic constraints and generates regional feasibility maps.
- Successfully predicts the location of existing micro-hydropower plants in Nepal.

ARTICLE INFO

Article history:
Received 5 September 2015
Received in revised form 4 March 2016
Accepted 15 March 2016

Keywords:
Micro hydropower
WebGIS
Nepal
DEM

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.

© 2016 Elsevier Ltd. All rights reserved.

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.

Despite their promise, micro hydropower programs have had mixed success globally. In Nepal, despite a huge hydropower

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.

* Corresponding author.
E-mail addresses: marc.muller@berkeley.edu (M.F. Müller), sally.thompson@berkeley.edu (S.E. Thompson), maggi@berkeley.edu (M.N. Kelly).

http://dx.doi.org/10.1016/j.apenergy.2016.03.052
0306-2619/© 2016 Elsevier Ltd. All rights reserved.

Nomenclature

ρ	density of water, kg m^{-3}
g	gravitational acceleration, m 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 (1 kW) 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}
$P\{Q \geqslant Q_d\}$	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, –

potential [4], favorable policies and substantial local hydropower expertise [5], micro hydropower currently supplies about 200,000 households [6] (about 7 million people remain unconnected [1]), and up to 30% of existing micro hydropower plants are not in operation [7]. These poor outcomes point towards major information gaps between key actors in the micro hydropower sector. These gaps arise at the earliest stage of project development and prior to in situ feasibility assessments. Policy makers at the regional level lack appropriate local information to identify promising locations for micro hydropower development, while would-be project enablers at the local level lack awareness and technical expertise for local resource assessment [8,9]. These gaps are particularly evident in Nepal where, paradoxically, the extreme topography of the region is at once responsible for its enormous hydropower potential, and for the low physical accessibility of most communities. It ensues an ineffective transfer of information between urban centers, where funding agencies and technical expertise are concentrated, and rural communities, where micro hydropower facilities are installed, used and maintained.

This study investigates the combination of two promising recent information technologies, remote sensing and open source webGIS, as a means to address information barriers at early project stages. We devise the tools and analysis framework necessary to assess these technologies in the specific case of Nepal, with the expectation that the methods provide a prototype for other regions where similar opportunities and challenges relating to micro hydropower arise. Specifically, the contributions of this paper are twofold. First, we formulate and assess a novel algorithm using remotely sensed digital elevation models (DEM) and state-of-the-art hydrological models to identify optimal micro hydropower locations. Second, we develop an operational web tool to support micro hydropower development in Nepal. Web-based geographic information systems (webGIS) are increasingly used[1] to collect, merge and disseminate heterogeneous data from a wide variety of stakeholders. Yet to our knowledge, this is the first attempt to leverage its interactive, open-source and cloud-based nature to support rural electrification.

The location of micro hydropower infrastructure components on the landscape is a key design decision: it determines capital costs, hydraulic head and mean flow, which are the features determining the scheme's ultimate economic performance. The effects of location on these features should therefore be incorporated into attempts to map hydropower potential. Infrastructure siting is driven by topography, which affects both the potentially harvested power, through the hydraulic head and the area of the contributing catchment; and the cost of the infrastructure, by affecting the lengths of the 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 platforms[2]. An extensive review of recent DEM-based potential assessment techniques can be found in Punys et al. [15]. 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., [16]. The elevation difference obtained within each reach (or arbitrary river segment as in Kusre et al. [17]) is then multiplied by the area of its contributing catchment and a regional runoff parameter. In a more sophisticated approach, Yi et al. [18] 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. [19], 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 Fig. 1. As a result, headrace canals exceeding 500 m are commonly found in Nepal e.g., [20]. 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 Bozorg Haddad et al. [21]. 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 [22]. Consequently, despite being essential to optimize the capacity of micro hydropower plants, streamflow variability has been largely omitted from

[1] For instance, webGIS has been used to predict environmental [10] and health-related [11] risk, manage environmental resources [12] and support ecological modeling [13].

[2] For instance, ASTER GDEM v2 used in this paper provides quasi global land surface elevation (i.e. between 83°N and 83°S) with 30 m grid postings [14].

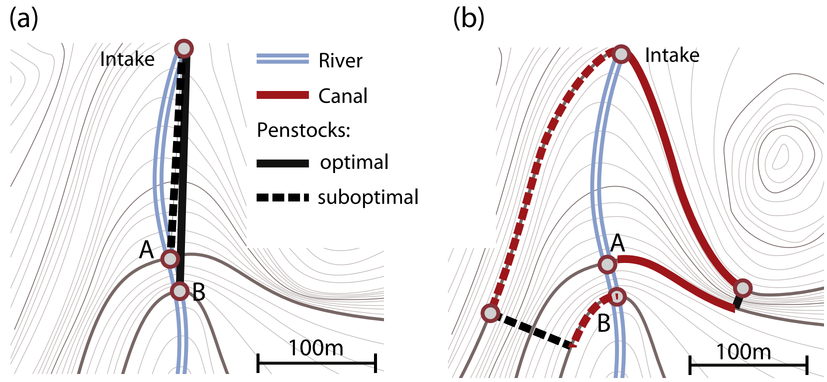

Fig. 1. Stylized example showing the relevance of hillslope topography in the optimization of run-of-river hydropower layout. In panel (a), layouts are evaluated solely based on streambed topography. Under these conditions, there is no diversion canal and the location of the penstock is constrained by 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*.

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.

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

2. Methods

2.1. DEM-based micro hydropower siting

This section focuses on the development of a novel algorithm using a digital elevation model to optimize the siting of micro hydropower infrastructure. Unlike previous methods, we explicitly include hillslope topography in the layout optimization. To minimize energy losses to friction, micro hydropower infrastructure is typically laid out to minimize the slope of the canal diverting water from the stream, while maximizing the slope of the penstock feeding water to the turbines. The algorithm optimizes the position of the intake, forebay and power house of micro hydropower schemes to maximize a topographic suitability index (TSI):

$$\mathrm{TSI} = \rho \cdot g \cdot \Delta z \cdot A, \tag{1}$$

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

Micro hydropower layouts are further restricted to technically feasible options using heuristic constraints. In line with anecdotal evidence from Nepal [20], the lengths of the headrace canal and penstock are capped at 2 km and 200 m respectively, and intakes with contributing catchment areas of less than 10 km^2 are rejected. The average slope of the penstock is also restricted to values between 0.176 and 1. The higher bound is suggested by Junejo et al. [23, p. 52] for reasons of cost, constructability and slope stability. The lower bound is obtained by considering maximum friction losses of 10% of the net hydraulic head, as recommended in Chitrakar [24], and assuming a linear head loss coefficient of 0.016 (see Appendix A).

The ensuing algorithm consists of the following steps, illustrated in Fig. 2:

1. The first step generates a stream network using topographic information from the DEM. Slope, aspect and flow accumulation rasters are computed using the A^T search algorithm implemented in the *r.watershed* function in the GRASS GIS environment [25].
2. The second step identifies and excludes DEM raster cells that cannot contain the penstock. Valid cells are (i) within the administrative boundaries of the community, (ii) within 2 km of a river, (iii) within the altitude range covered by the rivers in the community and (iv) have a slope between 0.176 and 1.
3. The third step optimizes the layout of the penstock. Its position and direction are determined by considering each valid DEM cell in decreasing order of slope and extracting an elevation profile along the local flow direction given by the aspect raster. Penstock length L along the elevation profile is determined by maximizing the net hydraulic head:

$$H(L) = \Delta z(L) - k \cdot L \tag{2}$$

   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 200 m. 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 2 km, or if the catchment area A upstream of the intake is smaller than 10 km^2.

Steps 3 and 4 are iterated until the desired number of infrastructure layouts are found and returned in order of decreasing

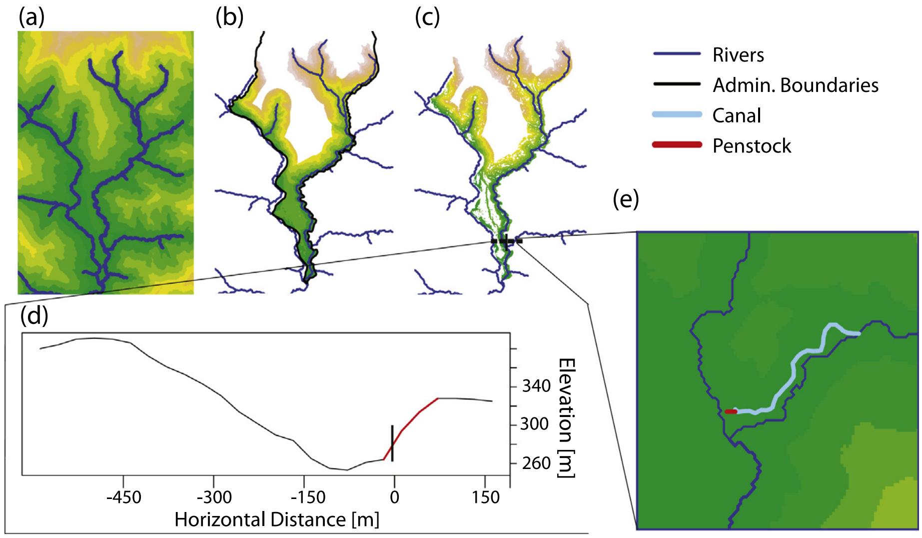

Fig. 2. Topographic layout optimization algorithm: DEM analysis to determine the location of streams and generate slope and aspect rasters (a); pixel selection based on elevation (b) and slope (c) criteria; determination of optimal penstock location (black line on subfigure c); optimization of penstock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

topographic suitability. By default, the method generates five valid layouts per community.

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 [26]. In Nepal, many off-grid micro hydropower schemes are indeed subject to some level of participative pricing [7, p. 36] and do not operate solely on a profit maximizing basis. Although numerous types of public pricing policies exist [26], we assume average cost pricing as recommended by Junejo [27, 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:

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

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

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 Eq. (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 [28], 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., [29]) for tractability reasons. This simplification is reasonable for pre-feasibility cost estimations in the context of Nepal, where a significant fraction (around 70% [20]) of infrastructure costs consists of turbine and electrical equipment costs, which approximatively follow a power law relation with plant capacity [30]. In Eq. (3), α_0 is the average cost of a 1-kW micro hydropower scheme and α_C the scale elasticity of infrastructure costs, that is the relative decrease in average (unit) cost when doubling infrastructure size. Economies of scale are possible if $\alpha_C < 1$. The right hand side of Eq. (3) represents the average revenue (per kW) obtained from by selling electrical capacity to local households at a price p. $P\{Q \geqslant Q_d\}$ represents the fraction of time when the plant generates revenue, that is the probability that the available streamflow equals or exceeds the flow capacity of the turbine. This probability is given by the flow duration curve of the stream, which we estimate at the location of the plant using the probabilistic process-based hydrological model described in Müller et al. [31]. We showed in a recent cross-validation analysis [32] that the method performs remarkably well in ungauged Nepalese basins and substantially outperforms the regionalization method currently prescribed in official micro hydropower design manuals in Nepal e.g., [24,33]. The method incorporates key flow generation processes, making it well adapted for it extension beyond Nepal, particularly where flow gauges are extremely scarce, and where climate-change is expected to have a strong effect on flow regimes [32]. Lastly, Eq. (4) represents the demand curve of households for electrical capacity, which we assume to evolve as a power low of price Filippini and Pachauri [34]. Under these conditions, γ_0 corresponds to the electrical capacity consumed by a households at a unit price of 1, and γ_p is the price elasticity of electricity demand, which typically takes a value between -1 and 0.

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

$$\mathrm{CVI} = p \cdot \frac{C}{pop} \tag{5}$$

The CVI is constrained by local community demand and represents the value assigned by the households to the generated electricity. This is perhaps the most appropriate metric to be maximized when evaluating community-owned, off-grid power infrastructure at the pre-feasibility stage.

2.3. Data and validation framework

The topographic siting and economic optimization algorithms were implemented in Nepal, where predicted layouts were validated against the location and capacity of existing micro hydropower schemes. The siting algorithm was used to predict five micro hydropower layouts per community based on the ASTER GDEM v2 digital elevation model [14]. The location and characteristics of the median layout in each community, in terms of topographic suitability, was then considered for economic optimization. The process-based hydrologic model described in Section 2.2 was applied to determine local streamflow distribution based on remotely sensed and bias-corrected [35] daily rainfall (TRMM 3B42 v7 [36]). The hydrologic model was calibrated using daily streamflow observations from 50 Nepalese gauges [37,38]. Topological restricted maximum likelihood (TopREML [39]) was used to regionalize calibrated parameters to ungauged basins. The optimal capacity of each plant was determined using demographic data from the 2011 Nepalese census and the economic characteristics displayed on Table 1.

Model outputs were validated against existing infrastructure indexed in the Renewable Energy Data Book [40] 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 level,[3] as shown in Fig. 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.
- H3 The method predicts the position and capacity of existing micro hydropower schemes.

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

Hypothesis 2 was tested by assessing whether the method improved on the prediction of the location of existing micro hydropower schemes within the communities, compared to an alternate method, where predictions were generated randomly. The set of predicted and observed micro hydropower locations was modeled as a marked random point process. An extension of Ripley's K [43] was used to evaluate the statistical 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 Fig. 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.

Table 1
Costs and demand parameters used in the economic optimization of micro hydropower capacity in Nepal.

$\frac{C}{pop}$	Average electrical capacity per household	0.1 kW	[40]
p	Average price per kW of (off-grid) installed capacity	102,000 Nep. Rupee (NRp)	[40]
γ_p	Price elasticity of (off-grid) electricity demand	−0.12	[41]
α_0	Average cost of a 1-kW micro hydropower scheme	$207 \cdot 10^3$ NRp	[40]
α_C	Scale elasticity of micro hydropower costs	0.93	[20]
η	Plant efficiency at full capacity	0.51	[42]

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

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

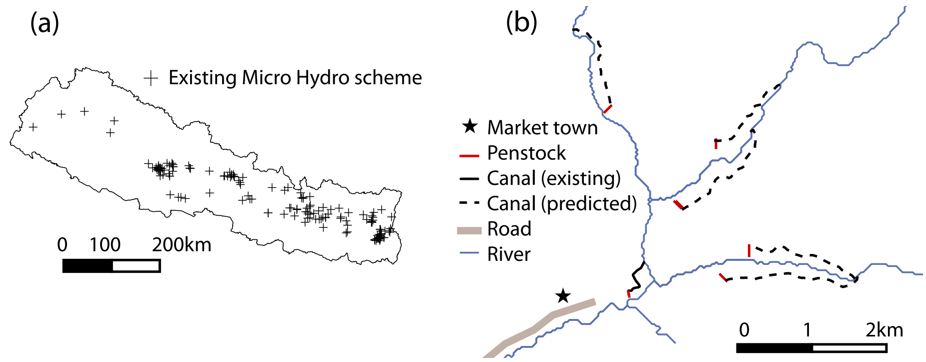

Fig. 3. Validation data. (a) Approximate location of the 148 microhydro schemes of the Renewable Energy Data Book [40]; (b) layout of the existing micro hydropower scheme on the Lohore Kohla (solid) and infrastructure positions predicted by the method (dashed).

Table 2
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.

	Poisson regression	Ordinary lease squares
	Dependent variable:	
	$N_{MHP_{REDB}}$	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

* $p < 0.1$.
*** $p < 0.01$.

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 2, 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 Fig. 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 (0.9 km) and approximately the median VDC radius (3 km). 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 1 km, which is consistent with the expected uncertainty on the position of existing schemes, whose locations are approximated at the centroid of the wards.

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

However, it is important to note that the intended purpose of the algorithms was not to emulate *existing* schemes, as tested by hypothesis 3, but rather to assist communities in the identification of sites for *new* installations. Thus, the poor fit of the linear regression is not indicative of the method's ability to fulfill its purpose, but may instead suggest that the capacity of existing schemes is constrained by local factors that are not accounted for in the method, as evidenced by its strong tendency to overestimate micro hydropower capacity (Fig. 4(b)).[4] Such local factors include access to credit, which remains challenging in rural Nepal [44] and restricts the capacity of financially feasible schemes. Large capital costs can force communities to develop their local hydropower potential gradually by building several smaller schemes: 25% of the communities in our sample have two or more (up to eight) micro hydropower plants.

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 Fig. 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 [7]. 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 experiences[5] underline the importance of reaching out to local communities to (i) put the technical information (viz. the out-

[4] These over-estimations cannot be explained by the uncertainty of the hydrological model. A recent cross-validation analysis across Nepal [32] 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.

[5] E.g., [9] in Thailand, [8] in sub-Saharan Africa and [44] in Nepal.

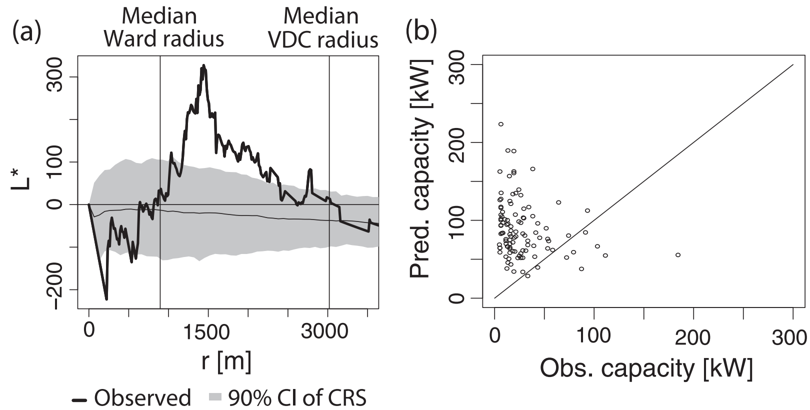

Fig. 4. (a) Modified Ripley's K: Ripley's cross-K function is adapted to accommodate multiple support areas, as described in Appendix B, and normalized as $L^*(r) = \sqrt{K(r)/\pi} - r$ to represent deviations from complete spatial randomness (CSR) represented by the horizontal line $L^*(r) = 0$. The 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.

put 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 [45]. 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., [46]. 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 countries.[6] 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. [44]) 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 [7]. 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 affecting micro hydropower development in Nepal through four key developments:

1. Improved terrain based optimization algorithms that account for hillslope topography and electricity demand at the local level. There is a crucial data shortage regarding the number and capacity of built and operational micro hydropower plants in Nepal (primarily because most facilities are too small to require licenses, and are thus unrecorded). Improved GIS-based algorithms are thus one of the few immediate options to improve the evidence base for policy making.
2. Improved flow-duration curve prediction, based on recent developments in hydrological modeling which improve prediction accuracy compared to alternate available approaches. The method is process based, easily transferable to other climates and is robust to shifts in precipitation regimes (e.g. due to climate change).
3. Capacity to incorporate local knowledge regarding costs, electricity demand and loan conditions, which are essential to understanding the economic feasibility of micro hydropower infrastructure. Off-grid power schemes are strongly sensitive to such local conditions, which are challenging to predict from existing demand curves (mostly available for grid-electricity) or from publicly available data. An interface by which local data can be recorded and incorporated into planning circumvents these data issues.
4. Lastly, anecdotal evidence suggests that access to technical knowledge remains a major challenge impeding the expansion of microhydropower, even when local intermediaries would advocate for its use [44]. Although several decision support systems have been developed to help off-grid communities evaluate the technical and financial viability of potential clean energy projects e.g., [48], these tools typically require advanced technical and computational tools, meaning that they are still challenging for rural communities to adopt. Thanks to its web-based nature, Micro Hydro [em]Power can be accessed by local enablers in rural communities, provided they have web access. Its interactive map and graphic user interface allows users to manipulate the tool with little to no technical background and a rudimentary of the english language.

[6] Recent 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 [47].

Despite its promises, an important current limitation of Micro Hydro [em]Power lies in its inability to account for local qualitative constraints, as evidenced by the Lohore Kohla case study discussed in Section 3. Site accessibility and institutional arrangements are two key local factors constraining the design of micro hydropower infrastructure worldwide. These factors are challenging to assess *a priori*. They are often ill-defined and represent an inherent source of uncertainty in large scale assessment tools. The interactive nature of Micro Hydro [em]Power allows local demand, which appears to be a key constraining factor (see Table 2(1)), to be assessed. Recent developments in participatory GIS platforms e.g., [49] 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 [50]. 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.

Acknowledgements

We would like to thank Helvetas Swiss Intercooperation (Nepal), particularly Agnes Montagero, Mohan Bhatta, Bikram Rana and Moritz Guettinger, for their logistical support in the field. Hydrological data have been graciously provided by the Department of Hydrology and Meteorology of Nepal and the HKH-FRIEND project. The Swiss National Science Foundation and the Blum Center for Developing Economies at UC Berkeley are gratefully acknowledged for funding (M.F.M).

Appendix A. Linear head loss coefficient

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

Diameter:	$d = 25$ cm	Median value in [20]
Roughness:	$\epsilon = 25$ mm	Lightly rusted mild steel [51]
Flow Velocity:	$u = 2$ m/s	Median value in [20]

Using Moody's chart [51] with a relative roughness of $\epsilon/d = 0.001$ and a Reynolds number of $Re = \frac{uL}{\nu} = 500{,}000$, the resulting friction factor $f = 0.02$ can be inserted in the Darcy–Weisbach equation to compute a linear head loss coefficient:

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

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

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

$$K(t)_{ij} = \frac{1}{\lambda_j}\mathsf{E}\left[\mathsf{E}\left[N_j \in B(i,t)|i\right]\right] \tag{B.1}$$

where type i and type j events indicate observed and predicted micro hydropower sites. $B(i,t)$ indicates a ball of center i and radius t and λ_j is the intensity of type j events, that is the number of events per area. It can be shown e.g., [43] that for a homogeneous Poisson process, here referred to as *complete spatial randomness* (CSR), the cross K function can be expressed as

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

The observed cross-K function is expected to be smaller than πt^2 for a regular pattern and larger if events of type i are clustered to events of type j. A widely used estimator for $K_{ij}(t)$ [52] is:

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

with $\hat{\lambda}_j = \frac{N_j}{A}$, where A is the area of the support, $d_{i,j}$ the distance between the kth event of type i and the lth 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 [43]. $\widehat{K}_{ij}(t)$ 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 $\widehat{K}_{ij}(t)$ 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

$$K_{ijs}(t) = \frac{1}{\lambda_j}\mathsf{E}\left[\mathsf{E}\left[\mathsf{E}\left[N_j \in B(i,t)|i,s\right]|s\right]\right] \tag{B.4}$$

The associated estimator can be obtained by averaging Eq. (B.2) over the considered supports

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

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

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

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 $\widehat{K}_{i}js(t)=\pi t^2$ for a homogeneous Poisson process, as visible in Fig. 4, where a Monte Carlo procedure was used to generate a confidence interval for a CSR process.

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.03.052.

References

[1] International Energy Agency. World energy outlook. Paris: OECD Publishing; 2012.

[2] Narula K, Nagai Yu, Pachauri Sh. The role of decentralized distributed generation in achieving universal rural electrification in South Asia by 2030. Energy Policy 2012;47:345–57. http://dx.doi.org/10.1016/j.enpol.2012.04.075.

[3] Paish O. Micro-hydropower: status and prospects. Proc Inst Mech Eng, Part A: J Power Energy 2002;216(1):31–40. http://dx.doi.org/10.1243/095765002760024827.

[4] The World Bank, Washington DC. <http://www.worldbank.org/en/country/nepal/overview> [last checked May 2015].

[5] Joshi RD, Amatya VB. Mini and micro hydropower development in the Hindu Kush – Himalayan Region – the Nepal perspective. ICIMOD, Kathmandu; 1996.

[6] Nepal Micro Hydropower Development Association, Kathmandu. <http://www.microhydro.org.np> [last checked May 2015].

[7] Khennas S, Barnett A, et al. Best practices for sustainable development of micro hydropower in developing countries ESMAP technical paper, 6. World Bank, Washington, DC; 2000.

[8] Karekezi S. Disseminating renewable energy technologies in sub-saharan africa. Ann Rev Energy Environ 1994;19(1):387–421. http://dx.doi.org/10.1146/annurev.eg.19.110194.002131.

[9] Greacen CE. The marginalization of small is beautiful: micro-hydroelectricity, common property, and the politics of rural electricity provision in Thailand. PhD Dissertation, University of California, Berkeley; 2004.

[10] Demir I, Krajewski WF. Towards an integrated flood information system: centralized data access, analysis, and visualization. Environ Model Software 2013;50:77–84.

[11] Moreno-Sanchez R, Anderson G, Cruz J, Hayden M. The potential for the use of open source software and open specifications in creating web-based cross-border health spatial information systems. Int J Geogr Inf Sci 2007;21(10):1135–63.

[12] Rao M, Fan G, Thomas J, Cherian G, Chudiwale V, Awawdeh M. A web-based GIS decision support system for managing and planning USDA's Conservation Reserve Program (CRP). Environ Model Software 2007;22(9):1270–80.

[13] Feng M, Liu S, Euliss NH, Young C, Mushet DM. Prototyping an online wetland ecosystem services model using open model sharing standards. Environ Model Software 2011;26(4):458–68.

[14] United States National Aeronautics and Space Administration (NASA) and Ministry of Economy, Trade, and Industry (METI) of Japan. ASTER Global Digital Elevation Model v2. <http://asterweb.jpl.nasa.gov/gdem.asp> [last checked May 2015].

[15] Punys P, Dumbrauskas A, Kvaraciejus A, Vyciene G. Tools for small hydropower plant resource planning and development: a review of technology and applications. Energies 2011;4(9):1258–77.

[16] Lee R, Brizzee J, Cherry S, Hall DG. Virtual hydropower prospecting: a foundation for water energy resource planning and development. J Map Geography Libr 2008;4(2):336–47. ISSN 1542-0353.

[17] Kusre BC, Baruah DC, Bordoloi PK, Patra SC. Assessment of hydropower potential using GIS and hydrological modeling technique in Kopili River basin in Assam (India). Appl Energy 2010;87(1):298–309.

[18] Yi CS, Lee JH, Shim MP. Site location analysis for small hydropower using geo-spatial information system. Renew Energy 2010;35(4):852–61.

[19] Larentis DG, Collischonn W, Olivera F, Tucci CEM. GIS-based procedures for hydropower potential spotting. Energy 2010. http://dx.doi.org/10.1016/j.energy.2010.07.014.

[20] Renewable Energy for Rural Livelihood Programme. Detailed project reports. Technical report, Alternative Energy Promotion Centre (AEPC), Government of Nepal, Kathmandu. <http://www.rerl.org.np/publication/cat.php?c=10> [last checked May 2015].

[21] Bozorg Haddad O, Moradi-Jalal M, Mariño MA. Design–operation optimisation of run-of-river power plants. Proc ICE – Water Manage 2011;164(9):463–75.

[22] Blöschl G, Sivapalan M, Wagener T, Viglione A, Savenije H. Runoff prediction in ungauged basins: synthesis across processes, places and scales. Cambridge: Cambridge University Press; 2013.

[23] A.A. Junejo, A. Karki, R.K.L Karna, Manual for private micro-hydropower-survey and layout design. ICIMOD, Kathmandu; 1999.

[24] Chitrakar P. Micro-hydropower design aids manual. SHPP/GTZ-MGSP/AEPC, Kathmandu; 2004.

[25] Ehlschlaeger C. Using the A^T search algorithm to develop hydrologic models from digital elevation data. In: International Geographic Information Systems (IGIS) symposium, vol. 89. Baltimore, MD; 1989. p. 275–81.

[26] Apgar W, Brown HJ. Microeconomics and public policy. Glenview (IL): Scott Foresman and Company; 1987. Chapter 16 "Public pricing".

[27] Junejo AA. Manual for private and community-based mini-micro hydropower development in the Hindukush Himalayas. ICIMOD, Kathmandu; 1997.

[28] Basso S, Botter G. Streamflow variability and optimal capacity of run-of-river hydropower plants. Water Resour Res 2012;48. http://dx.doi.org/10.1029/2012WR012017.

[29] Caralis G, Zervos A. Analysis of the combined use of wind and pumped storage systems in autonomous greek islands. IET Renew Power Gener 2007;1(1):49–60. http://dx.doi.org/10.1049/iet-rpg:20060010.

[30] Aggidis GA, Luchinskaya E, Rothschild R, Howard DC. The costs of small-scale hydro power production: impact on the development of existing potential. Renew Energy 2010;35(12):2632–8.

[31] Müller MF, Dralle DN, Thompson SE. Analytical model for flow duration curves in seasonally dry climates. Water Resour Res 2014;50(7):5510–31. http://dx.doi.org/10.1002/2014WR015301.

[32] Müller MF, Thompson SE. Comparing statistical and process-based flow duration curve models in ungauged basins and changing rain regimes. Hydrol Earth Syst Sci 2016;20:669–83. http://dx.doi.org/10.5194/hess-20-669-2016.

[33] Alternative Energy Promotion Centre (AEPC). Construction and installation manual for micro hydropower project installers (in Nepalese). Government of Nepal, Kathmandu, Nepal; 2014.

[34] Filippini M, Pachauri S. Elasticities of electricity demand in urban Indian households. Energy Policy 2004;32(3):429–36.

[35] Müller MF, Thompson SE. Bias adjustment of satellite rainfall data through stochastic modeling: methods development and application to Nepal. Adv Water Resour 2013;60:121–34.

[36] Huffman GJ, Bolvin DT, Nelkin EJ, Wolff DB, Adler RF, Gu G, et al. The TRMM multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. J Hydrometeorol 2007;8(1):38–55. http://dx.doi.org/10.1175/JHM560.1.

[37] HKH-FRIEND. Hindu Kush Himalayan – Flow Regimes from International Experimental and Network Data. UNESCO International Hydrological Programme; 2004.

[38] Department of Hydrology and Meteorology. Daily streamflow and precipitation data. Kathmandu; 2011.

[39] Müller MF, Thompson SE. TopREML: a topological restricted maximum likelihood approach to regionalize trended runoff signatures in stream networks. Hydrol Earth Syst Sci 2015;19(6):2925–42. http://dx.doi.org/10.5194/hess-19-2925-2015.

[40] Alternative Energy Promotion Centre (AEPC). Renewable energy data book. Technical report, Government of Nepal; 2011.

[41] Müller MF. Chapter 5: How (in)elastic is off-grid electricity demand? In: Bridging the information gap: remote sensing and micro hydropower feasibility in data-scarce regions. PhD Dissertation, University of California, Berkeley; 2015.

[42] Meier V, Baumer JM, et al. Harnessing water power on a small scale; local experience with micro-hydro technology. In: Harnessing water power on a small scale; local experience with micro-hydro technology. Skat, Sankt Gallen; 1982.

[43] Ripley BD. Spatial statistics. Hoboken (NJ): John Wiley & Sons; 2005. http://dx.doi.org/10.1002/0471725218.

[44] Ghale BB, Shrestha GR, DeLucia RJ. Private micro-hydro power and associated investments in Nepal: the Barpak village case and broader issues. Natural resources forum, vol. 24. Wiley Online Library; 2000. p. 273–84. http://dx.doi.org/10.1111/j.1477-8947.2000.tb00952.x.

[45] GNU General Public License. Version 3. Free Software Foundation; 2007. <http://www.gnu.org/copyleft/gpl.html> [last checked May, 13: 2015].

[46] Naronha F. Developing countries gain from free/open source software. Linux J 2003. <http://www.linuxjournal.com/article/6884> [last checked May 2015].
[47] International Telecommunication Union. ICT indicators database, ITU World Telecommunication, Geneva, Switzerland; 2015.
[48] Blanco CJC, Secretan Y, Amarante Mesquita AL. Decision support system for micro-hydro power plants in the Amazon region under a sustainable development perspective. Energy Sust Dev 2008;12(3):25–33.
[49] Brent Hall G, Chipeniuk R, Feick RD, Leahy MG, Deparday V. Community-based production of geographic information using open source software and web 2.0. Int J Geogr Inf Sci 2010;24(5):761–81.
[50] Goodchild MF. Citizens as sensors: the world of volunteered geography. GeoJournal 2007;69(4):211–21.
[51] Moody LF. Friction factors for pipe flow. Trans ASME 1944;66(8):671–84.
[52] Dixon PM. Ripley's *K* function. In: Piegorsch W, El-Shaarawi AH, editors. Encyclopedia of environmetrics. Chichester: John Wiley & Sons; 2002. http://dx.doi.org/10.1002/9780470057339.