



**HAL**  
open science

## A decision support tool to place drinking water sources in rural communities

Sébastien Ferreira, Simon Meunier, Matthias Heinrich, Judith A. Cherni,  
Arouna Darga, Loïc Quéval

### ► To cite this version:

Sébastien Ferreira, Simon Meunier, Matthias Heinrich, Judith A. Cherni, Arouna Darga, et al. A decision support tool to place drinking water sources in rural communities. *Science of the Total Environment*, 2022, 833, pp.155069. 10.1016/j.scitotenv.2022.155069 . hal-04425270

**HAL Id: hal-04425270**

**<https://hal.science/hal-04425270>**

Submitted on 22 Jul 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

# A decision support tool to place drinking water sources in rural communities

Sébastien Ferreira<sup>a,b,c\*</sup>, Simon Meunier<sup>a,b</sup>, Matthias Heinrich<sup>d</sup>, Judith A. Cherni<sup>e</sup>, Arouna Darga<sup>a,b</sup>, Loïc Quéval<sup>a,b</sup>

<sup>a</sup>Université Paris-Saclay, CentraleSupélec, CNRS, GeePs, 91192 Gif-sur-Yvette, France

<sup>b</sup>Sorbonne Université, CNRS, GeePs, 75252 Paris, France

<sup>c</sup>DargaTech SARL, Ouagadougou, Burkina Faso

<sup>d</sup>COSYS-GRETTIA, Université Gustave Eiffel, Marne-la-Vallée, France

<sup>e</sup>Centre for Environmental Policy, Imperial College London, London SW7 2AZ, UK

\*Corresponding author: Sébastien Ferreira (sebastien.ferreira@centralesupelec.fr)

Declaration of interest: none.

**Keywords: GPS data; Decision support tool; Water source choice; Drinking water; Rural; Developing countries.**

## Highlights:

- The proposed method helps to place drinking water sources in developing countries.
- It is based on GPS data, survey data, and a water source choice model.
- The developed decision support tool is applied to a rural village of Burkina Faso.
- 8 times more people get drinking water with the tool than with random positioning.
- Collecting data to apply the tool costs 2-10% of the cost of a pumping system.

## Abstract:

Installing more drinking water sources is a promising way to achieve the 6<sup>th</sup> sustainable development goal “Clean water and sanitation” in rural communities. A key parameter for the installation of new water pumps is geographical position, because the number of people who could gain access to drinking water depends on the location of the pump. To improve the choice of the most appropriate location, we propose a decision support tool to place a new drinking water source in a rural community. This tool relies on four complementary maps, which are obtained from GPS data, survey data, and a water source choice model. The first map shows the spatial distribution of the households and of the existing water sources in the village. The three remaining maps present the following quantities as a function of the position of a new drinking water source in the village: the number of users of the new drinking water source, the improvement of drinking water access, and the daily water demand per capita at the new drinking water source. The decision support tool is applied to a village in Burkina Faso. Results indicate that using the

28 proposed method could allow eight times more people to gain access to drinking water in comparison to a random positioning of  
29 the new drinking water source. The original contribution of this work is, first, the consideration of existing water sources in the  
30 village, as well as seasonality. Second, we base our analysis on a water source choice model, which accounts for water quality in  
31 addition to the distance to the water source. Third, we consider the variability of the water volume collected by the households  
32 throughout the village. The developed tool is generic, transferable to other villages and useful for various decision-making entities  
33 (e.g. local authorities and non-governmental organizations).

## 34 1 Introduction

35 With the 6<sup>th</sup> sustainable development goal “Clean water and sanitation”, the United Nations aims at a universal and equitable  
36 access to safe and affordable drinking water for all (UN, 2015). However, in 2017, 800 million of people still did not have access  
37 to basic drinking water services (WHO, 2019), mostly in rural areas (Anthonj et al., 2020). The installation of drinking water  
38 sources where water is extracted from aquifers through a hand pump or a motorized pump can contribute to tackling this challenge  
39 (Carrard et al., 2019; WHO, 2008). But the number of people who gain access to drinking water depends on the location of these  
40 new water sources in the village (Logan, 1987). Applying geographic information systems (GIS) is often used to place facilities  
41 (Bruno and Giannikos, 2015; Church, 2002) and favours discussions with local decision-makers (de Palencia and Foguet, 2010;  
42 Garriga et al., 2013). GIS is also considered useful to place new drinking water sources in underserved areas (de Palencia and  
43 Foguet, 2008), scan the functionality of the current water points (de Palencia and Foguet, 2011a), and assess drinking water  
44 coverage (de Palencia and Foguet, 2011b).

45 The literature indicates that a few authors have previously used maps to illustrate issues related to water source choice. Martinez-  
46 Santos (2017) mapped distance and travel time from households to drinking water sources in a village in Mali. Chaudhuri and Roy  
47 (2017) mapped drinking water access inequality in India by comparing the percentage of households with a drinking water access  
48 in rural areas from the one in urban areas. However, Martinez-Santos (2017) and Chaudhuri and Roy (2017) did not consider the  
49 population density. This represents a limitation because they do not show the areas where the number of people without drinking  
50 water access is the highest. In addition, they did not propose to use the obtained maps to help place new drinking water sources,  
51 which could be helpful to improve water access.

52 Although geographic information systems are applied at a large scale for water, sanitation and hygiene improvement (Ferrer et al.,  
53 2009), it has been used, to our best knowledge, in only one study to help local authorities place new water points at the village  
54 scale. Logan (1987) placed water sources to meet the water demand of two villages in Sierra Leone by minimizing the distance  
55 between these sources and the households. Yet, the study contains several limitations. First, it does not account for the potentially  
56 already existing sources in the village, which is often the case (Caplain, 2018; Gross and Elshiewy, 2019). A new source could  
57 then be placed in an area where people already have access to drinking water, thus limiting its impact on socio-economic  
58 development (Garriga et al., 2015). Second, it does not consider seasonality, although it can influence the choice of the water

59 source position as certain sources may dry out during some months of the year (Kelly et al., 2018). Third, it places the new  
60 drinking water sources considering that the households fetch water from their nearest water source. But the water source choice of  
61 the households in low-income countries also depends on other attributes, such as water quality for example (Caplain, 2018;  
62 Nauges and Whittington, 2010). Finally, it assimilates the water demand to the population density, although the volume of water  
63 consumed may significantly vary from one household to another (Keshavarzi et al., 2006; Meunier, 2019).

64 In this article, we present a decision support tool to place new drinking water sources in rural communities. This tool addresses the  
65 identified shortcomings in the literature. It considers the existing water sources in the village and seasonality. Additionally, it is  
66 based on a water source choice model that can include other attributes, such as the water quality, in addition to the distance to the  
67 source. Finally, it accounts for the fact that the volume of water consumed may vary from one household to another.

68 In Section 2, we present the scope of our study, how to build the four maps that are at the center of the decision support tool and  
69 the procedure to use this tool. In Section 3, for illustration purposes, we apply the method to the rural village of Gogma, in  
70 Burkina Faso, and we describe how local stakeholders could use the decision support tool to improve drinking water access in the  
71 village.

## 72 2 Methodology

73 In this Section, we present the geographical setup of the targeted rural communities, we detail how to obtain the four maps of the  
74 decision support tool and the procedure to use this tool for any case study.

### 75 2.1 Geographical setup

76 In this article, we focus on villages without access to piped water. We consider that there are two types of water sources in the  
77 village: non-potable sources, such as open wells (Figure 1a), and drinking water sources, such as hand pumps (Figure 1b). This is  
78 a common situation in rural communities of developing countries (Aberilla et al., 2020; Carlevaro and Gonzalez, 2015). In  
79 addition, we assume that the households fetch water from these water sources for the following uses: drinking, cooking, personal  
80 hygiene and laundering (Meunier, 2019).



(a)



(b)

81 *Figure 1 – (a) Open well; (b) Hand pump.*

## 2.2 Mapping

First, we collect GPS coordinates and socio-economic data. The GPS coordinates list all the households and all the water sources in the village. The socio-economic data are gathered through household surveys that are performed in the village before the installation of the new drinking water source. It includes:

- the number of inhabitants per household;
- the daily water consumption per household for drinking, cooking, personal hygiene and laundering;
- the water source used by each household for each season;
- attributes which influence the water source choice (e.g. perceived water quality at existing sources, see below for more detail).

A random sample of households in the village is selected to be surveyed. In this article, we assume that the households which are not surveyed fetch water from the same source and have the same characteristics (number of inhabitants, water consumption and attributes which influence the water source choice), as the closest surveyed household (Meunier, 2019).

Second, we build a water source choice model, which predicts the water source choice of each household. This is done by computing  $\rho_{h,s}$  for each couple (household  $h$ , source  $s$ ):

$$\rho_{h,s} = f(\mathbf{X}_{hs}) \quad (1)$$

where  $\mathbf{X}_{hs}$  are the predictors which influence the water source choice. These predictors can be related solely to the household (e.g. the number of inhabitants in the household  $h$ ) or to the household and the source (e.g. the distance between the household  $h$  and the source  $s$ ) (Meunier et al., 2019).  $f$  is a regression (e.g. linear, logistic) (Nauges and Whittington, 2010) trained with the previously collected data. Depending on the selected regression, we assume that the household  $h$  goes to the water source  $s$  which maximizes the utility or the probability  $\rho_{h,s}$ . A practical implementation of the model is given in Section 3.1. In this article, ‘water source choice’ refers to the water point that households choose to use, therefore ‘water demand’ refers to the demanded water volume by the households.

Third, we build four maps:

- *Map 1, spatial distribution of the households and the water sources.* In this map, we show all the households and existing water sources in the village. The positions of the households and of the water points are obtained from the collected GPS data. A grid is superimposed on the map, where each cell represents one possible location of the new drinking water source. The cell size fits in with the area explored by a single geophysical test. The same grid is kept for the three other maps.
- *Map 2, number of users of the new drinking water source.* In this map, we show the number of people who would go to the new drinking water source for each possible location. We use the water source choice model to predict which household would go to the new drinking water source. Then, we sum the number of people living in each of these households obtained from the household surveys.

- *Map 3, improvement of drinking water access.* In this map, we show the number of people who would gain access to drinking water for each possible location. This map is obtained by subtracting to the map 2 the number of people who already use a drinking water source, according to the households surveys, and who would thus not gain drinking water access by going to the new drinking water source.
- *Map 4, daily water demand per capita.* In this map, we show the daily water demand per capita for each possible location. We assume that each household that would go to the new drinking water source collects the same daily water quantity as it used to at its previous source (Caplain, 2018; Meunier, 2019). For each possible location of the new drinking water source, we use the water source choice model to predict which household would go there. Then, we sum the daily water volume consumed by each of these households, obtained from the household surveys, to compute the water demand. Then, we divide it by the number of people who would go there given by the map 2 to obtain the water demand per capita.

### 2.3 Decision support tool

The proposed decision support tool consists of the 9 steps shown in Figure 2, and relies on the four maps described above. A practical implementation of the procedure is given in Section 3.2. Following these steps allows to suitably place a new drinking water source by considering:

- the purpose of the decision-maker (e.g. drinking water access, profitability), where the four maps provide a visual help to select a position (a cell in the grid) for the new drinking water source.
- the water resource, through a reconnaissance step to gather existing information about groundwater resources (e.g. groundwater maps and data on existing boreholes), through geophysical tests to check the presence of water at the selected position, and through pumping tests to evaluate the maximum flow rate (MacDonald et al., 2005; Meunier, 2019).
- the factual water quality, by performing, before the installation, physico-chemical tests and, after the installation, bacteriological tests to check if the international recommendations are satisfied (MIT, 2008; Senedak, 2008).
- the size of the installation, based on the water demand to cover all the water uses and on the results of the pumping tests (Meunier et al., 2020; Vezin et al., 2020).

It could be interesting, in future works, to study, through a cost-benefit analysis, if it would be relevant to perform further data collection before choosing the position.

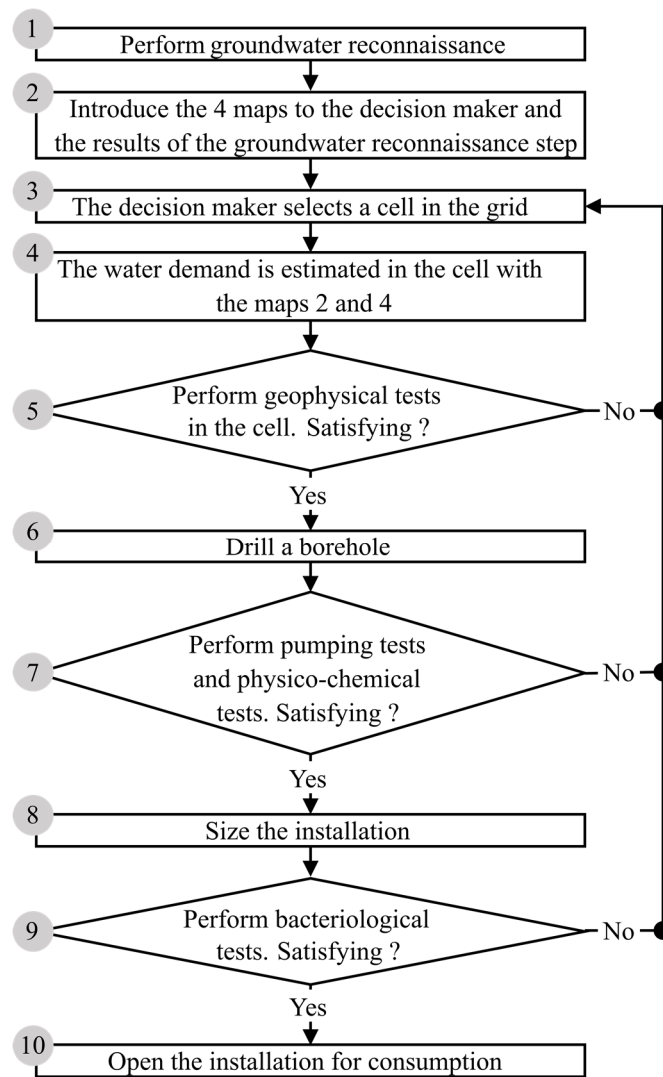


Figure 2 – Decision support tool to place a new drinking water source in a village.

### 3 Case study

In this Section, we apply the proposed method to the case of the rural village of Gogma in Burkina Faso for illustrative purposes.

#### 3.1 Inputs

The village of Gogma (*Lat*: 11.73 ; *Lon*: -0.58) is in the “Center-East” region of Burkina Faso. The village counts 1100 inhabitants who live in 126 households (Figure 3). Most of them live with less than \$1/capita/day. We gathered the GPS coordinates and performed 90 household surveys in the village in 2019. People fetched water from 16 open wells and 5 hand pumps.





Figure 3 – The village of Gogma.

According to equation (1), different regression functions and multiple sets of predictors can be used. For this case study, we consider that household's  $h$  utility from choosing source  $s$ ,  $\rho_{h,s}$ , is written as (Caplain, 2018; Meunier, 2019):

$$\rho_{h,s} = \beta_0 + \beta_d \cdot X_d(h, s) + \beta_{pwq} \cdot X_{pwq}(h, s) \quad (2)$$

where  $X_d$  is the Euclidean distance (in m) between the household  $h$  and the water source  $s$  (Nesbitt et al., 2014).  $X_{pwq}$  is the perceived water quality (0 = high quality, 1 = low quality) at the water source  $s$  by the household  $h$ .  $\beta_0$ ,  $\beta_d$  and  $\beta_{pwq}$  are the regression coefficients. It is considered that each household will choose the source which provides the highest utility. Equation (2) means that we consider only two attributes for the source choice of a household: its distance to the water sources and how it perceives quality at the sources. In this case, the water cost was not included as a model variable as it has been demonstrated to strongly correlate with the perceived water quality (Meunier, 2019); nonetheless, its inclusion could be relevant for other case studies. Other attributes could be included if deemed necessary (Caplain, 2018; Kulinkina et al., 2016).

There are two seasons in Gogma. The dry season lasts for 7 months. The wet season lasts for 5 months. During the dry season, 5 open wells dry up; as a result, several households switch water source. Thus, we compute the regression coefficients of equation (2) for both seasons. We summarize in Table 1 the regression coefficients, their corresponding p-values and the  $R^2$  for both seasons obtained with the Matlab 'fitlm' function (MATLAB, 2021a). Results indicate that both predictors have a high statistical significance. In addition, the encountered low  $R^2$  is not uncommon for water source choice studies (Mu et al., 1990). To obtain a yearly map, we add the results for the dry and the wet seasons respectively weighted by  $\frac{7}{12}$  and  $\frac{5}{12}$ .

Table 1 – Values of the regression coefficients.

Season	$\beta_0$	$\beta_d$ (m <sup>-1</sup> )	$\beta_{pwq}$	$R^2$
Dry	0.28*** (0.018)	-0.00015*** (0.000013)	-0.13*** (0.015)	0.16
Wet	0.24*** (0.016)	-0.00013*** (0.000011)	-0.09*** (0.014)	0.13

\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1, no star p ≥ 0.1.

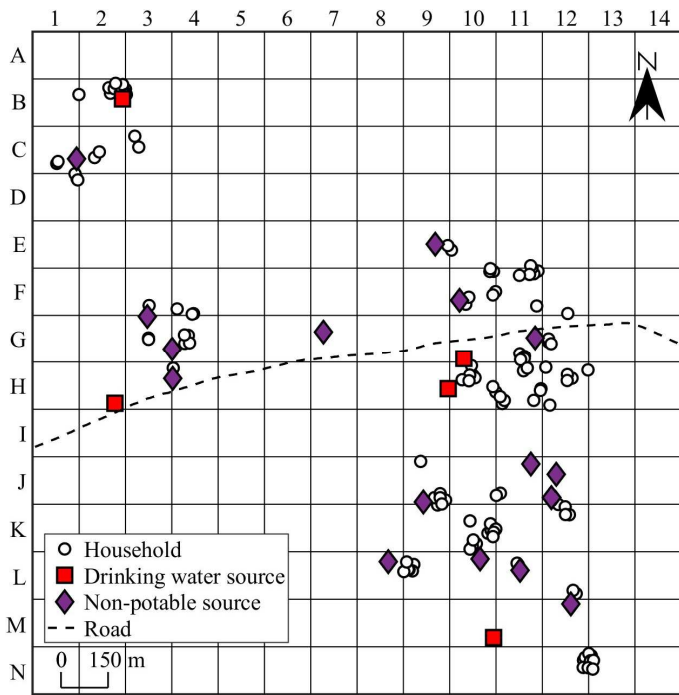
Regression coefficients not in parentheses. Standard error in parentheses.



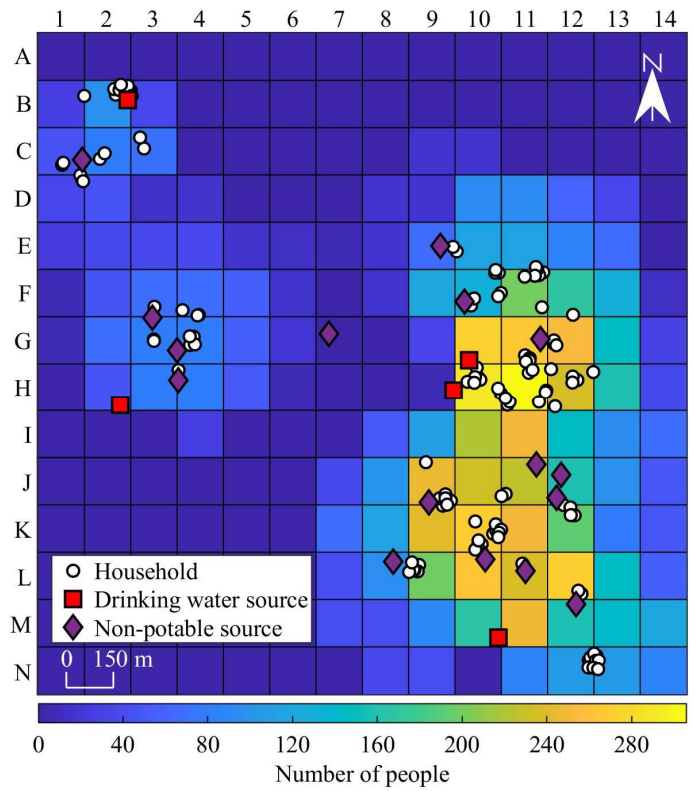
## 3.2 Results

With the data collected in Gogma and equation (2), we use the geographic information system software Matlab Mapping Toolbox (MATLAB, 2021b) to plot the four maps described in Section 2.2. They are shown in Figure 4:

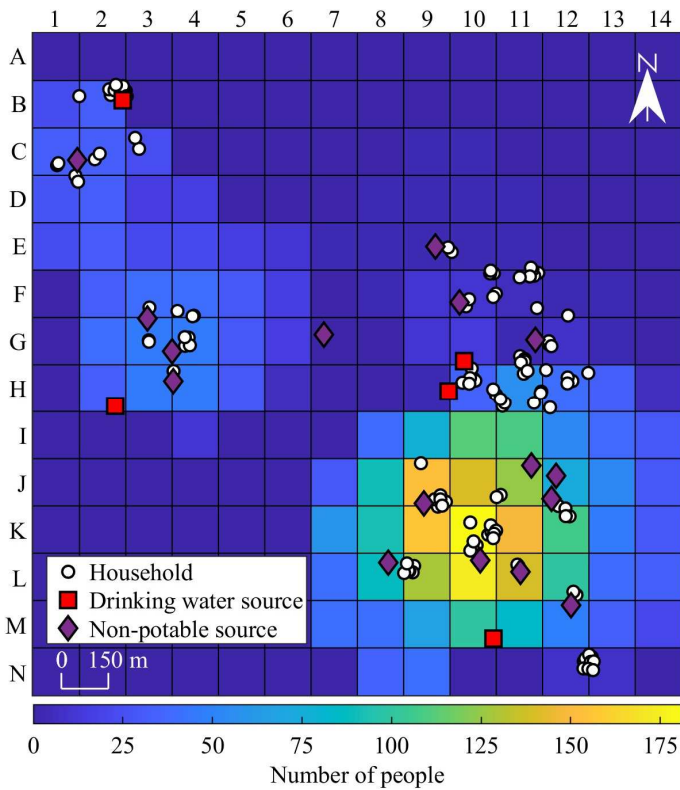
- *Map 1, spatial distribution of the households and the water sources (Figure 4a):* One road passes through the village. In the east, there are two large groups of households. The first one is near two drinking water sources. The second one is far from drinking water sources. In the northwest, there are two small groups of households which are close to drinking water sources. For Gogma, we chose a grid resolution of 150 m×150 m as it corresponds to the area explored by a single geophysical tests (Meunier, 2019). This resolution can of course be adapted to the needs of the considered case study.
- *Map 2, number of users of the new drinking water source (Figure 4b):* The brighter the colour, the more people would go to the new drinking water source if it were installed in that cell. We distinguish two zones on the map. The cells in the eastern zone are brighter than the ones in the northwest, which reflects the higher population density.
- *Map 3, improvement of drinking water access (Figure 4c):* The brighter the colour, the more people would gain access to drinking water if the new source were installed in that cell. We distinguish three zones on the map. The first one is located in the northeast of the village where the cells are dark. There, the population density is high, but many people already fetch water from a drinking water source. Consequently, the installation of a new water source in that area would not much improve the water access. The second zone is located in the southeast of the village, where the cells are the brightest. There, the population density is high and the only neighbouring sources are non-potables, explaining why the potential drinking water improvement is high. In the third zone, located in the northwest of the village, the cells are darker than in the second zone because the population density is lower and people fetch water from both drinking and non-potable water sources.
- *Map 4, daily water demand per capita (Figure 4d):* The brighter the colour, the higher the per capita water quantity demanded at the new water source if it were installed in that cell. We observe some slight variations of this quantity across populated areas of the village. The mean and the standard deviation of the non-zero cell values are respectively ~46 L/cap/day and ~9 L/cap/day. For comparison, the mean water quantity demanded is more than twice the quantity required for basic water access (20 L/cap/day), according to international recommendations (Howard and Bartram, 2003).



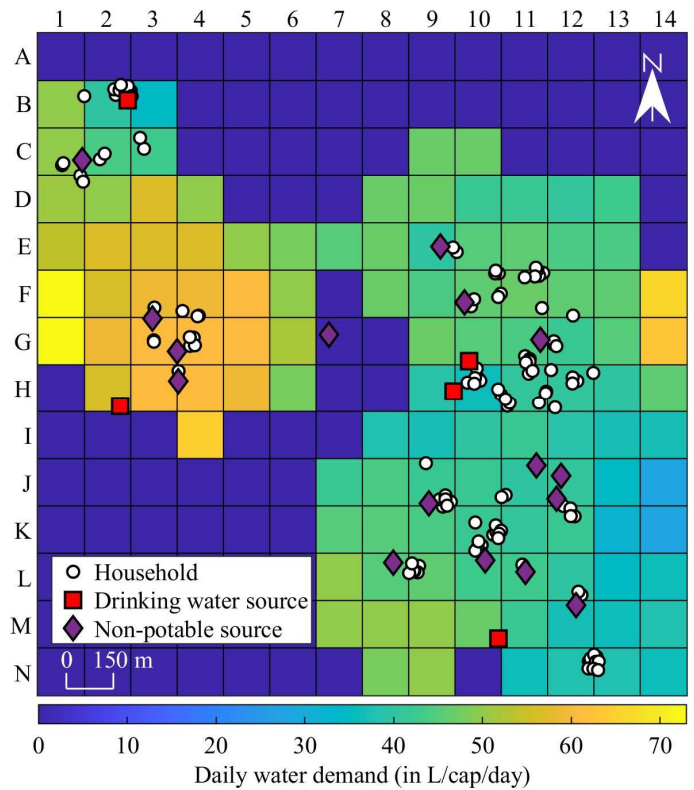
(a)



(b)



(c)



(d)

190 Figure 4 – (a) Map 1: spatial distribution of the households and the water sources; (b) Map 2: number of users of the new drinking water source  
 191 (c); Map 3: improvement of drinking water access; (d) Map 4: daily water demand per capita.

192 We assume here that a decision-maker wants to install a new drinking water source in Gogma. We illustrate here how the nine  
 193 steps of the decision support tool would apply for the case of Gogma.

194 *Step 1:* The four maps are introduced to the decision-maker. With the map 1, the decision-maker can have an overview of the  
195 position of households and water sources. The map 2 is useful to identify the areas where many people would fetch water from the  
196 new drinking water source. The map 3 is useful to identify where the new water source would improve drinking water access the  
197 most. At last, the decision-maker can use the map 4 to estimate the water quantity demanded.

198 *Step 2:* For the sake of the example, we assume that the decision-maker would like to place the new drinking water source on K10  
199 (in the southeast), where the most people would gain access to drinking water.

200 *Step 3:* The maps 2 and 4 are used to compute the daily water demand at the new drinking water source. On K10, the daily water  
201 demand is estimated to 11,300 L/day.

202 *Step 4 to 6:* Geophysical tests are performed to check the presence of water on K10. If confirmed, a borehole is drilled and  
203 pumping tests are performed to determine the maximum flow rate that can be pumped from the borehole. Then, physico-chemical  
204 tests are undertaken. If one of the previously mentioned tests is not satisfying on K10 (e.g. geophysical tests do not detect the  
205 presence of water, pumping tests reveal that the water demand cannot be met), the decision-maker selects another cell on the grid.

206 *Step 7 to 9:* The new drinking water source is sized. Finally, bacteriological water tests are performed on the water flowing out of  
207 the fountain. If the bacteriological water quality is satisfying, the water source can be opened for consumption. Otherwise, the  
208 decision-maker selects another cell on the grid.

## 209 4 Discussion

210 The application of the decision support tool in Gogma enables to provide drinking water access to 181 villagers. This is 8 times  
211 higher than the average result of a random positioning of the water source in this village (22 villagers), which is obtained by  
212 averaging the values of all cells of map 3. Random positioning corresponds to plan a project with poor on-field data on water use  
213 and available sources (MacDonald et al., 2005).

214 Regarding the influence of seasonality, for Gogma, maps 2 and 4 for the dry and wet seasons are similar as the yearly average  
215 maps shown in Figure 4b and Figure 4d. Regarding map 3, the number of people who gain access to drinking water is, for most  
216 locations, higher for the wet season than for the dry one. Indeed, more people were going to open wells during the wet season,  
217 according to the household surveys, as these wells were less dry (see Section 3.1). However, the location of most relevant areas is  
218 the same for the dry and wet season maps as for the yearly map shown in Figure 4c. Thus, we believe that this should not  
219 influence the choice of location by the decision maker, which is the main focus of this article. Finally, it is important to keep in  
220 mind that results regarding the influence of seasonality could differ for other villages.

221 Actually, in Gogma, a photovoltaic water pumping system, which is a drinking water source, was installed on K9 (Meunier, 2019;  
222 Meunier et al., 2019). This position was set by the village council without using a decision support tool. If the decision-making  
223 entity had used the decision support tool, more inhabitants would have improved their drinking water access in this village.

224 Indeed, according to Figure 4c, if the photovoltaic water pumping system had been installed on K10, the number of people who  
225 would have gained access to drinking water would have increased by 14%.

226 Using the measured water consumption at the photovoltaic water pumping system in Gogma (Meunier, 2019; Meunier et al.,  
227 2018), we are able to estimate the error when predicting the water demand. The estimated daily water consumption on K9 and the  
228 measured daily water consumption at the photovoltaic water pumping system for both seasons are shown in Table 2. We observe  
229 that the error is significant for both seasons. This might have two causes. The first one might be that the water source choice  
230 model (equation (2)) does not fully capture the behaviour of the inhabitants. However, this prediction error is low, which makes  
231 this reason unlikely. Indeed, we predicted that 241 people would go to the photovoltaic water pumping system on K9. At the  
232 moment, 259 people go there, according to the household surveys performed after the installation (Meunier, 2019). The second  
233 reason might be that the surveyed households had not accurately enough estimated their daily water volume consumed. Nauges  
234 and Whittington (2010) and Otter et al. (2020) underlined such discrepancies on households water consumption reported in  
235 surveys. In all cases, as the predicted water consumption is overestimated in comparison with the real water consumption, this is  
236 less of a problem as this leads to an oversizing of the photovoltaic water pumping system, which therefore allows to meet the  
237 water demand.

238 *Table 2 – Estimated and measured daily water consumption during the dry and the wet seasons in Gogma*

Season	Daily water consumption		
	Estimated (L/day)	Measured (L/day) (Meunier, 2019)	Relative error
Dry	10,600	8,600	23%
Wet	10,600	6,400	66%

239 The cost of applying the decision support tool must remain moderate to be applicable. We estimated that the data collection costs  
240 \$160/day (Meunier, 2019). Five days were required to gather GPS coordinates and perform the 90 household surveys in Gogma.  
241 Consequently, these maps cost ~\$800, which represents about ~2% of the lifecycle cost of the photovoltaic water pumping system  
242 installed in Gogma (Meunier, 2019) or 10% of the capital cost of a borehole equipped with a hand pump (Jeuland and  
243 Whittington, 2009). Thus, using the decision support tool in Gogma can be considered as economically reasonable in comparison  
244 with the cost of a water pumping installation.

245 For the case study, we assumed that the decision-maker uses the maps to maximize the number of people who would gain access  
246 to drinking water. This use of the decision support tool could be relevant for non-governmental organizations, policy makers or  
247 associations which aim at improving drinking water access. Another objective could be to maximize the economic profitability of  
248 the new drinking water source, which could be particularly interesting for companies. Indeed, as economies of scales usually  
249 occur for drinking water sources due to the high share of fixed costs (Harvey and Reed, 2004; Soenen et al., 2021), the  
250 profitability of the new source will likely increase along with the water demand at this source. Therefore, companies could use the  
251 maps 2 and 4 to identify the position where the water consumption at the new drinking water source would be the highest.

252 In Gogma, the budget that inhabitants can allocate to water is low, which is highlighted by the fact that the water cost at hand  
253 pumps is \$1/year. Thus, additional stakeholders (in this case crowdfunders and two associations) had to be involved in order to  
254 cover the installation costs of the photovoltaic water pumping system. Independently of this particular case, public authorities and  
255 non-governmental organizations could be interested to use the decision support tool to plan the budget of aid programs, as it  
256 provides information about the number of users at future improved water sources, which influences the water cost.

## 257 5 Conclusion

258 In this article, we used GPS data, survey data and a water source choice model to build a decision support tool to help place new  
259 drinking water sources in rural communities. We then considered a case study in which the decision-maker uses the decision  
260 support tool to improve drinking water access in a rural village of Burkina Faso.

261 The decision support tool:

- 262 • includes four complementary maps that make it visual for the decision-maker;
- 263 • helps the decision-maker to place any type of drinking water source (e.g. hand pumps, photovoltaic water pumping systems);
- 264 • can be used for different objectives such as improving drinking water access or increasing economic profitability;
- 265 • could be economically reasonable in comparison with the cost of a water pumping installation.

266 Even though the tool has been applied to a specific village in this article, it is generic and transferable to other villages. In  
267 addition, this decision support tool can be of interest to local authorities, governments, non-governmental organizations, and  
268 companies.

## 269 6 CRediT author contribution statement

270 **Sébastien Ferreira:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data  
271 curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Simon Meunier:**  
272 Conceptualization, Methodology, Validation, Resources, Data curation, Writing - review & editing, Visualization, Supervision,  
273 Project administration, Funding acquisition. **Matthias Heinrich:** Conceptualization, Methodology, Validation, Investigation, Data  
274 curation, Writing - review & editing, Visualization, Funding acquisition. **Judith A. Cherni:** Conceptualization, Methodology,  
275 Validation, Writing - review & editing, Visualization. **Arouna Darga:** Conceptualization, Methodology, Validation, Resources,  
276 Writing - review & editing, Visualization, Funding acquisition. **Loïc Quéval:** Conceptualization, Methodology, Validation,  
277 Resources, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

278 All authors approved the final version of the manuscript.

## 7 Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## 8 Acknowledgments

We thank the 280 contributors of the Turning Sun Into Water project, the associations Eau Fil du Soleil and Respublica that allowed to finance the photovoltaic water pumping system of Gogma and the data collection in 2019. We would like to thank the anonymous reviewers for their comments which allowed to improve the article.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## 9 References

- Aberilla, J.M., Gallego-Schmid, A., Stamford, L., Azapagic, A., 2020. Environmental assessment of domestic water supply options for remote communities. *Water Research* 175, 115687.
- Anthonj, C., Tracy, J.W., Fleming, L., Shields, K.F., Tikoisuva, W.M., Kelly, E., Thakkar, M.B., Cronk, R., Overmars, M., Bartram, J., 2020. Geographical inequalities in drinking water in the Solomon Islands. *Science of the Total Environment* 712, 135241.
- Bruno, G., Giannikos, I., 2015. Location and GIS, in: Laporte, G., Nickel, S., Saldanha-da-Gama, F., Location Science. Springer International Publishing, Switzerland, pp. 509–536.
- Caplain, V., 2018. Water demand and organization and payment schemes for solar pumping systems in emerging countries: a case study in Burkina Faso. Imperial College London, UK.
- Carlevaro, F., Gonzalez, C., 2015. Improved drinking-water supply technologies for low-income communities, in: Carlevaro, F., Gonzalez, C., Costing Improved Water Supply Systems for Low-income Communities: A Practical Manual. IWA Publishing, UK, pp. 11–18.
- Carrard, N., Madden, B., Chong, J., Grant, M., Nghiê, T.P., Bui, L.H., Hà, H.T.T., Willetts, J., 2019. Are piped water services reaching poor households? Empirical evidence from rural Viet Nam. *Water Research* 153, 239–250.
- Chaudhuri, S., Roy, M., 2017. Rural-urban spatial inequality in water and sanitation facilities in India: A cross-sectional study from household to national level. *Applied Geography* 85, 27–38.
- Church, R.L., 2002. Geographical information systems and location science. *Computers & Operations Research* 29 (6), 541–562.
- de Palencia, A.J.F., Foguet, A.P., 2011a. Water Point Mapping for the Analysis of Rural Water Supply Plans: Case Study from Tanzania. *Journal of Water Resources Planning and Management* 137, 439–447.
- de Palencia, A.J.F., Foguet, A.P., 2011b. Quality and year-round availability of water delivered by improved water points in rural Tanzania: effects on coverage. *Water Policy* 14, 509–523.
- de Palencia, A.J.F., Foguet, A.P., 2010. Building the role of local government authorities towards the achievement of the human right to water in rural Tanzania. *Natural Resources Forum* 34, 93–105.
- de Palencia, A.J.F., Foguet, A.P., 2008. Improving water access indicators in developing countries: a proposal using water point mapping methodology. *Water Supply* 8, 279–287.

312 Ferrer, J.P, de Palencia, A.J.F., Foguet, A.P., 2009. SAI: Aplicación de un SIG para el monitoreo de los programas de agua y saneamiento de  
313 ISF-ApD. Cuadernos internacionales de tecnología para el desarrollo humano, 8, 1–7.

314 Garriga, R.G., de Palencia, A.J.F., Foguet, A.P., 2015. Improved monitoring framework for local planning in the water, sanitation and hygiene  
315 sector: From data to decision-making. *Science of the Total Environment* 526, 204–214.

316 Garriga, R.G, de Palencia, A.J.F., Foguet, A.P, 2013. Water–sanitation–hygiene mapping: An improved approach for data collection at local  
317 level. *Science of the Total Environment* 463–464, 700–711.

318 Gross, E., Elshiewy, O., 2019. Choice and quantity demand for improved and unimproved public water sources in rural areas: Evidence from  
319 Benin. *Journal of Rural Studies* 69, 186–194.

320 Harvey, P., Reed, B., 2004. Financial issues, in: Harvey, P., Reed, B., *Rural Water Supply in Africa: Building Blocks for Handpump*  
321 *Sustainability*. WEDC, Loughborough University, UK, 95–120.

322 Howard, G., Bartram, J., 2003. Domestic Water Quantity, Service Level and Health. World Health Organization (WHO).

323 Jeuland, M., Whittington, D., 2009. Cost–benefit comparisons of investments in improved water supply and cholera vaccination programs.  
324 *Vaccine* 27 (23), 3109–3120.

325 Kelly, E., Shields, K.F., Cronk, R., Lee, K., Behnke, N., Klug, T., Bartram, J., 2018. Seasonality, water use and community management of  
326 water systems in rural settings: Qualitative evidence from Ghana, Kenya, and Zambia. *Science of the Total Environment* 628–629,  
327 715–721.

328 Keshavarzi, A.R., Sharifzadeh, M., Kamgar Haghighi, A.A., Amin, S., Keshtkar, Sh., Bamdad, A., 2006. Rural domestic water consumption  
329 behavior: A case study in Ramjerd area, Fars province, I.R. Iran. *Water Research* 40 (6), 1173–1178.

330 Kulinkina, A.V., Kosinski, K.C., Liss, A., Adjei, M.N., Ayamgah, G.A., Webb, P., Gute, D.M., Plummer, J.D., Naumova, E.N., 2016. Piped  
331 water consumption in Ghana: A case study of temporal and spatial patterns of clean water demand relative to alternative water sources  
332 in rural small towns. *Science of the Total Environment* 559, 291–301.

333 Logan, B.I., 1987. A micro-level approach to rural development planning: the case of piped water in Sierra Leone. *Applied Geography* 7 (1), 29–  
334 40.

335 MacDonald, A., Davies, J., Calow, R., Chilton, J., 2005. *Developing Groundwater: A guide for rural water supply*. ITDG Publishing, UK,  
336 pp. 77-96.

337 Martinez-Santos, P., 2017. Determinants for water consumption from improved sources in rural villages of southern Mali. *Applied Geography*  
338 85, 113–125.

339 Massachusetts Institute of Technology (MIT), 2008. *Water Quality Standards & Guidelines*.  
340 [http://web.mit.edu/watsan/methods\\_waterqualitystandards.html](http://web.mit.edu/watsan/methods_waterqualitystandards.html) (accessed 25 December 2021).

341 MATLAB, 2021a. Fit linear regression model. <https://fr.mathworks.com/help/stats/fitlm.html> (accessed 25 December 2021).

342 MATLAB, 2021b. Mapping Toolbox Documentation. <https://fr.mathworks.com/help/map/index.html> (accessed 25 December 2021).

343 Meunier, S., 2019. Optimal design of photovoltaic water pumping systems for rural communities – a technical, economic and social approach.  
344 Université Paris-Saclay, France.

345 Meunier, S., Heinrich, M., Quéval, L., Cherni, J.A., Vido, L., Darga, A., Dessante, P., Multon, B., Kitanidis, P.K., Marchand, C., 2019. A  
346 validated model of a photovoltaic water pumping system for off-grid rural communities. *Applied Energy* 241, 580–591.



347 Meunier, S., Manning, D.T., Quéval, L., Cherni, J.A., Dessante, P., Zimmerle, D., 2019. Determinants of the marginal willingness to pay for  
348 improved domestic water and irrigation in partially electrified Rwandan villages. *International Journal of Sustainable Development  
349 and World Ecology* 26 (6), 547–559.

350 Meunier, S., Queval, L., Darga, A., Dessante, P., Marchand, C., Heinrich, M., Cherni, J.A., Vido, L., Multon, B., 2018. Influence of The  
351 Temporal Resolution of The Water Consumption Profile on Photovoltaic Water Pumping Systems Modelling and Sizing. 2018 7th  
352 International Conference on Renewable Energy Research and Applications (ICRERA), 494–499.

353 Meunier, S., Quéval, L., Darga, A., Dessante, P., Marchand, C., Heinrich, M., Cherni, J.A., de la Fresnaye, E.A., Vido, L., Multon, B., Kitanidis,  
354 P.K., 2020. Sensitivity Analysis of Photovoltaic Pumping Systems for Domestic Water Supply. *IEEE Transactions on Industry  
355 Applications* 56 (6), 6734–6743.

356 Mu, X., Whittington, D., Briscoe, J., 1990. Modeling village water demand behavior: A discrete choice approach. *Water Resources Research* 26,  
357 521–529.

358 Nauges, C., Whittington, D., 2010. Estimation of Water Demand in Developing Countries: An Overview. *World Bank Research Observer* 25  
359 (2), 263–294.

360 Nesbitt, R.C., Gabrysch, S., Laub, A., Soremekun, S., Manu, A., Kirkwood, B.R., Amenga-Etego, S., Wiru, K., Höfle, B., Grundy, C., 2014.  
361 Methods to measure potential spatial access to delivery care in low- and middle-income countries: a case study in rural Ghana.  
362 *International Journal of Health Geographics* 13, 25.

363 Otter, P., Sattler, W., Grischek, T., Jaskolski, M., Mey, E., Ulmer, N., Grossmann, P., Matthias, F., Malakar, P., Goldmaier, A., Benz, F.,  
364 Ndumwa, C., 2020. Economic evaluation of water supply systems operated with solar-driven electro-chlorination in rural regions in  
365 Nepal, Egypt and Tanzania. *Water Research* 187, 116384.

366 Senedak, S., Stangl, K., 2008. Groundwater Surveillance In the Vicinity of Mahoning County Landfills, 2006–2008.  
367 [https://www.mahoninghealth.org/wp-](https://www.mahoninghealth.org/wp-content/uploads/file/Documents/Documents/SpecialReports/Groundwater%20Surveillance%20around%20Mahoning%20County%20Landfills%202006-2008.pdf)  
368 [content/uploads/file/Documents/Documents/SpecialReports/Groundwater%20Surveillance%20around%20Mahoning%20County%20L](https://www.mahoninghealth.org/wp-content/uploads/file/Documents/Documents/SpecialReports/Groundwater%20Surveillance%20around%20Mahoning%20County%20Landfills%202006-2008.pdf)  
369 [andfills%202006-2008.pdf](https://www.mahoninghealth.org/wp-content/uploads/file/Documents/Documents/SpecialReports/Groundwater%20Surveillance%20around%20Mahoning%20County%20Landfills%202006-2008.pdf) (accessed 25 December 2021).

370 Soenen, C., Reinbold, V., Meunier, S., Cherni, J.A., Darga, A., Dessante, P., Quéval, L., 2021. Comparison of Tank and Battery Storages for  
371 Photovoltaic Water Pumping. *Energies* 14 (9), 2483.


372 The United Nations (UN), 2015. The 17 Sustainable Development Goals. <https://sdgs.un.org/goals> (accessed 25 December 2021).

373 Vezin, T., Meunier, S., Quéval, L., Cherni, J.A., Vido, L., Darga, A., Dessante, P., Kitanidis, P.K., Marchand, C., 2020. Borehole water level  
374 model for photovoltaic water pumping systems. *Applied Energy* 258, 114080.

375 World Health Organization (WHO), 2019. Progress on household drinking water, sanitation and hygiene 2000-2017: special focus on  
376 inequalities. <https://apps.who.int/iris/handle/10665/329370?locale-attribute=fr&> (accessed 25 December 2021).


377 World Health Organization (WHO), 2008. Regional and global costs of attaining the water supply and sanitation target (target 10) of the  
378 Millennium Development Goals. <https://apps.who.int/iris/handle/10665/204413> (accessed 25 December 2021).

379




**1. The decision-maker wants to place a new drinking water source in the village**

- What is the purpose of the decision-maker ?
- Is there water at the selected position ?
- Is the water quality satisfying ?
- What should be the size of the installation ?



**2. The decision support tool is introduced to the decision-maker**

- GPS and survey data are gathered.
- The water source choice model is applied.
- Four maps are used to select a position.
- Geophysical and water quality tests are performed.



**3. The decision-maker has found a suitable position for the drinking water source**

- The purpose of the decision-maker is met.
- Drinkable water flows out of the borehole.
- The installation fulfils the water demand.