Decision support system for economic assessment of water improvements in remote, low-resource settings

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A B S T R A C T

Since most people without access to safe water services live in remote areas of developing countries, assessing the economics of rural water developments poses a globally pressing challenge. This study seeks to: (1) outline the rural (non-networked) water development decision process in a systematic way; (2) incorporate that process into a modeling tool in order to conduct consistent economic analysis of developments across a wide range of contexts, and (3) assess the performance and potential applications of this tool. We introduce AWARE, a recently developed Decision Support System, to provide a generalized model of the processes and constraints related to the advancement of rural water services. AWARE enables robust comparisons to be made across a wide range of social, economic, physical, technical and management approaches. We demonstrate that it performs adequately, and propose that, despite its generalized approach, it will be useful for informing both development strategies and field projects.

Software availability

The AWARE software is available for download at no cost at: https://dl.dropboxusercontent.com/u/24352729/DSS.zip
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E-mail: dr.adam.abramson@gmail.com
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Hardware requirements: Microsoft Windows PC
Software requirements: Microsoft Excel, HYDRUS-1D
Program language: VBA
Program size: 8.1 MB

1. Introduction

Providing access to improved water sources in remote areas differs in important ways from such efforts in more urban settings: low population densities, together with a lack of centralized infrastructure, including grid electricity, prohibit the economies of scale associated with water networks from being achieved. As a result, expanding access within such communities involves many unique constraints, including a wide range of spatial dimensions further limited by a dependence on non-networked, local water sources, the economic challenges associated with a low willingness to pay in remote areas (as demonstrated, for example, by a meta-analysis conducted by Abramson et al., 2011), and the technological requirements of accessing and pumping water.

The dearth of sophisticated water infrastructures in remote areas attests to these challenges. Recent estimates suggest that only 24% of households in rural areas of developing countries use a tap in their home, compared to 73% of their urban counterparts (UNICEF and WHO, 2012). In regions with extremely low levels of infrastructure development, such as rural Sub-Saharan Africa where the rate of electricity access is less than one-fourth that of the rural developing world, this figure is proportionately reduced (OECD and IEA, 2012). As a whole, most (55%) remote communities fetch water from stand-pipes or hand-operated borehole pumps. The rest (20%) use unimproved water sources, including surface water.

With such a high dependence on non-networked, localized water services, providing insights into the economic dimensions of rural water improvements is a challenge, especially when extrapolating regional or global insights from a wide range of local
contexts. Indeed, assessing the costs and benefits of reaching global drinking water targets has been a primary objective of many studies since the United Nations Millennium Development Goals (MDGs) were formulated in 2000 (www.un.org/millenniumgoals; Cosgrove and Rijsberman, 2000; GWP, 2000; WHO and UNICEF, 2000; WSSCC, 2000; Devarajan et al., 2002; Smets, 2003; Winpenny, 2003; Mehta et al., 2005; Hailer et al., 2007; Hutton et al., 2007; Hutton, 2012). Due to the high variability of the technical, environmental, and managerial aspects of non-networked rural water services, various simplifications and assumptions were applied in these studies within vastly different social, political and economic contexts. A good example is the use of mean unit costs of past improvements to extrapolate the costs of developments for any given unreached population. These assumptions severely limit the ability of such assessments to align with the actual dynamics of the modeled communities, and prohibit the direct comparison of novel approaches with past efforts. Clearly, more robust approaches are needed.

Decision support tools offer a promising solution, since they are holistic, computerized frameworks for aiding decision-making involving multiple disciplines, constraints and objectives. Due to the complexity and multi-disciplinary nature of water resource management, such tools have yielded a high number of applications in this field (Keedwell and Khu, 2005; Makropoulos et al., 2008; Chung and Lansey, 2008; Liu et al., 2009; Pereira et al., 2012). For optimizing remote water services, one tool has been developed for a rural area in India by Olsen (2005) and another, only partially developed, for communities in South Africa (Sam and Murray, 1998). To our knowledge, however, no decision support tool has been developed to investigate remote, non-networked water services from a generalizable perspective, with potential for global application.

To develop an effective Decision Support System (DSS), all parameters relevant to the rural water development process should be simultaneously incorporated. While the above approaches include some relevant parameters (capital cost, economic demand, and water quantity requirements), they lack the following: (1) the ability to investigate groundwater-based sources – the most common water source in remote areas of developing regions—as well as a variety of feasible water pumping approaches; (2) spatial parameters, including population density, a water map outlining the spatial configuration of the community, and a water-fetching time target; (3) the ability to incorporate adequate economic data, including sound estimates of demand for water service improvements; and (4) a coherent water development algorithm that incorporates a wide range of parameters and moves logically through the water development process. In short, these multi-criteria approaches are useful for providing general assessments across various disciplines, but fall short in their ability to draw meaningful policy conclusions from robust, consistent, and disaggregated data and modeling mechanisms. Unlike the existing tools described above, the various social, environmental and economic dimensions of remote water configurations should be incorporated within a consistent modeling framework by a single (economic) metric, rather than by multiple criteria.

The major objectives of this study are: (1) to outline the rural (non-networked) water development decision process in a systematic way; (2) to incorporate that process into a modeling tool in order to conduct consistent economic analysis of developments across a wide range of contexts, and (3) to assess the performance and potential applications of this tool. This study presents the methodological framework of AWARE (Assessing Water Alternatives for Remote Economies), a DSS for exploring the economics of non-networked water developments for providing access to improved water services in remote areas. The application of the DSS is focused on cases where developing new water sources is more cost-effective than creating a water network. The tool is intended for (1) policymakers wishing to assess the economics of water improvements across a wide range of contexts, and (2) water practitioners needing to make preliminary assessments of field projects. Section 2 introduces the conceptual dimensions and components of the decision process. Section 3 outlines the integration of these dimensions into the DSS. Section 4 explores the validation of the framework through an example, and Section 5, through a parameter uncertainty analysis. Section 6 identifies and discusses potential applications of the DSS.

2. Components of the rural water decision process

This section outlines the main components of the decision process for rural water developments. This process consists of three main components: (1) parameters, both variable and constant, that are manipulated by (2) an algorithm to obtain (3) desired results. AWARE performs an exhaustive search of a combinatorial optimization procedure to identify the water service configurations that provide the lowest cost and highest net benefit under the technical alternatives and parameter values considered (Fig. 1).

The general relation of the social, physical, economic, management, technological and agronomic parameters to the decision process is shown in Fig. 1. A complete list of all 88 parameters is supplied in the supporting information, Tables A.1—A.6. The main process involves first describing the existing and targeted water service levels and then describing the array of technologies, along with their specifications, to be considered for reaching the targeted service level. Since the technologies are decomposed into their relevant attributes (i.e., pumping rate, cost, maximum yield), any technological solution, including water source, extraction and/or treatment method, that is defined appropriately, can be considered. AWARE then applies these technologies across all possible configurations in the given community, first by considering all feasible improvements to existing water services, and then, by developing the necessary number of new water sources to reach the water service target. The economic demand for the service improvement is compared with the cost under each water service configuration considered. The main results are the details of the configuration that achieves the targeted service level at: (1) the lowest cost, and (2) the highest net benefit.

2.1. Quantity, quality, and fetching time: existing and targeted service levels

In order to assess the improvement of water services, it is first necessary to define the current state of a community’s water services, as well as the target to be reached by the improvement. The most widely used and accepted target for drinking water is the notion of access to “safe” water, which is measured by the indicator of “access to an improved water source.” This is defined by the World Health Organization (WHO) and adopted into the MDGs (WHO and UNICEF, 2013). This serves as an important concept, therefore, for the rural water decision process. According to the WHO, this concept is defined by three primary attributes of a water source: the quality of the water, the quantity available and its distance in relation to the household. We, therefore, incorporate these attributes into the DSS framework. These align with previous studies of attribute-based economic demand for water service improvements (Hensher et al., 2005; Echenique and Seshagiri, 2009; Abramson et al., 2011), allowing such approaches to be incorporated into the decision process for demand estimation. We explore this in detail in Section 2.2.
While the quantity of supply and distance from the household (or fetching time) are determined in part by the technology investigated, their values vary by other factors as well, and must be calculated for each technological configuration. Quantity (L/d) is determined by the yield of the water source and the pump applied, assuming pump operation of at most 10 and 12 h daily for hand and motorized pumps, respectively. Fetching time (min/trip) is determined by the spatial configuration of the village (as described below). Water quality, however, is determined solely by the technology—water source and/or treatment—and does not vary. We introduce three categorical levels of water quality corresponding to low (not potable), mid (potable after treatment) and high (potable without treatment). These values enable the investigation of water quality improvements through both source and treatment improvements.

2.1.1. Water map

In order to determine current water service levels, the user must create a spatial approximation of the village layout. This “water map” serves to locate each household in relation to existing water sources that are potential candidates for being included in determining the optimal water service solution (either with or without improvements). Fig. 2 provides an example water map, with the relevant parameters derived from the corresponding table. Up to three existing water sources, S1, S2 and S3, can be considered at one time, where S1 is the most feasible source to be used for providing water, and S3 is the least feasible. These are defined by their pumping pressure head (m), quality, and the maximum source yield (L/d).

Since the decision process relies solely on the number of households within each sub-region in the water map, rather than on their exact location, precise spatial data is not required. Knowledge of household placement within these sub-regions and an estimate of population density serve as proxies for household spatial data. Thus, simple fieldwork or even locally available data may suffice for creating a water map. This approach also enables the user to prioritize existing sources to be considered for improvement, and categorizes the existing population within regions both within and beyond reach of such sources. The decision process thereby accounts for the population’s spatial layout by identifying three categories of households: (1) those currently served; (2) those to be served by improvements to existing sources, and (3) those to be served by new water source developments. This is described in Eqs. (A.3)–(A.11).

2.2. Economic parameters

The financial challenges associated with both developing and maintaining remote water service improvements are key constraints across the entire sector. Recent estimates suggest that the global costs of reaching universal access are more than 20 times greater than available development assistance (Hutton, 2012). Market-based mechanisms appear to fall short across the rural

<table>
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One emerging approach is to define economic demand for water service improvements by the attributes of the services. Having defined the marginal change in water services experienced under an improvement, the demand for such improvements can be determined. This is done by applying the household production framework of Lancaster (1966) to the field of water services. This theory asserts that individuals derive utility from the attributes of goods, rather than from the goods themselves. Accordingly, water services consist of various attributes, each associated with a certain level of utility. This utility can be modeled through a discrete choice experiment, or choice model. The conditional logit choice model applies when the indirect utility, \( v_i \), derived from choice attributes \( n \), is given by:

\[
v_i = \sum_i \beta_n X_i^n
\]  

(1)

where \( \beta_n \) is the choice model coefficient of attribute, with levels, \( X \), corresponding to those of an improved water service state, \( i \).

The total economic demand of any given water service level is a summation of each part-worth of the attributes of water service, which in turn, is a function of the population's inherent demand structure. This is defined by the beta value for that attribute in the choice model, and the delta or difference between current and improved service levels defined for that attribute. Willingness to pay for an improvement in water services across attribute, \( q \), is defined as:

\[
WTP = -\left[ \frac{\sum q \delta X_q + \delta_f}{\delta_c} \right]
\]

(2)

where \( \beta \) is the coefficient of the attribute, \( \Delta X \) is the attribute level change between current and improved water services, \( \beta_c \) is the coefficient of the cost, and \( \beta_f \) of the financing approach under the improvement. The financing approach consists of three alternatives derived in a previous discrete choice experiment by Abramson et al. (2011): Willingness to Pay (WTP), Willingness to Borrow (WTB) and Willingness to Work (WWT). The latter two are expressed as:

\[
WTB, WTW = -\left[ \frac{\sum q \beta X_q + \delta_f}{\beta_c + \beta_f} \right]
\]

(3)

where \( \beta_c \) is the coefficient of the interaction between the financing approach and cost. This accounts for the fact that the impact of water service cost on economic demand may differ by financing approach.

This choice model is integrated into the decision process to estimate the demand for water improvement \( f \) under financing arrangement \( j \). In this case, the attributes quantity, fetching time and quality are considered, the expression for determining economic demand, for financing approach \( f \), in these three scenarios is:

\[
\frac{\beta_{Quantity} \Delta Quantity}{\beta_c + \beta_{fc}} + \frac{\beta_{Time} \Delta Time}{\beta_c + \beta_{fc}} + \frac{\beta_{Quality} \Delta Quality}{\beta_c + \beta_{fc}} + \frac{\delta_f}{\beta_c + \beta_{fc}}
\]

(4)

The parameters for determining the economic demand for water service improvements, therefore, include the coefficient (beta values) for the three attributes, for the three financing approaches, the cost, and the three financing-cost interaction terms. These are integrated into AWARE, which calculates the demand for a given water service improvement, and applies it to the decision process.

This choice modeling approach requires a high level of understanding of local water service preferences and economic demand, which can be expected to differ across communities and socio-economic contexts. Water practitioners without such knowledge may apply synthetic demand data, or simply investigate the cost of improvements and apply a fixed household demand figure. In addition, other water service attributes not considered in this choice model may be adapted into AWARE's calculation of economic demand according to Eq. (2) above, for any attribute, \( q \).

2.2.1. “Water-for-work” program set-up

In order to assess the feasibility of community work commitments applied to irrigation as a financing approach for water improvements, a realistic “water-for-work” program must be defined. The core activities of such a program are: (1) the development of an improved community water source for multiple (domestic and productive) uses; (2) the provision of necessary agricultural investments, as well as marketing support and horticultural training; (3) the organization of all participating households to work together in a community garden to cultivate high-value, irrigated produce; (4) a contractual agreement between the program and participants outlining the commitments of each party and consequences for breaching the agreement; and (5) the marketing of the produce, which serves to amortize the loan for full cost recovery. In short, this management approach operates on the same platform as outgrower agriculture, which has played a prominent role in recent agricultural development in areas such as sub-Saharan Africa (Little and Watts, 1994; Porter and Phillips-Howard, 1997; Bingen et al., 2003), and may bridge the financing gap between local demand for water improvements and their costs. While various models exist for actually implementing such a program, these five activities constitute the core of a water-for-work program.

2.2.2. Other economic parameters

In addition to the modeled economic demand, the discount rate (%), and the economic timeframe (y) are considered. These influence both the economic demand as well as the water improvement costs, as discussed below.

2.3. Physical parameters

2.3.1. Water source

Two parameters are used to characterize the water sources in the decision process—source yield and pumping pressure head. Source yield (L/d) is input by the user for both existing and potential new sources. No mechanism for deriving this value exists within the DSS, but it represents the maximum amount of water that can be abstracted from a given water source before causing over-depletion of groundwater. Therefore, it is the responsibility of the user to ensure that sustainable pumping yield values are used. Pumping head (m) represents the dynamic elevated level of water during pumping (elevation head), along with any additional frictional head losses in the system. This is used to determine the output of a given water pump.

2.3.2. Demographic parameters

The average population density (households/km²) of a community is used in lieu of precise spatial data. This value serves to provide an estimate of the number of water sources needed under any given technological configuration. This parameter, along with...
the number of households considered in the decision realm, is derived from the water map (Fig. 2).

### 2.4. Water technologies

Reaching the intended water service target requires a specific array of water technologies. For non-networked systems, these technologies include source development (such as borehole drilling), water pumping and water treatment. As demonstrated in Fig. 1, two types of water improvements are investigated: 1) the improvement of existing water sources, through exchanging water pumping and/or treatment approaches and 2) the development of new water sources, through all three technological categories.

The user is responsible for quantifying the costs of these technologies, which may be expected to vary across or even within regions. One cost value is allowed for each new source, whereas treatment costs are input either per unit or per household (for household-level treatment approaches). Pumping costs are considered as capital and recurring (O&M) costs. Therefore, for water source and treatment technologies, O&M, replacement and capital costs must be integrated into one value. This may be done, for example, through calculating net present value (NPV). We discuss this further in Section 2.5.

#### 2.4.1. Water sources

In addition to the three existing water sources, S1, S2 and S3, up to six new water source types, {S4, ..., S6}, are considered for meeting the water target. These are also defined by their maximum yield (L/d), quality and total pumping head (m), and may be either improved or unimproved, depending on the targeted water service level. No costs are considered for existing water sources.

#### 2.4.2. Water treatment

The DSS allows up to three water treatment approaches to be considered for each water source in the decision process—including both existing and new sources. Each treatment method may be either source-based, such as a centralized slow-sand filter, or a point-of-use (POU) treatment, such as chlorination or household filtration. Source-based treatments may also include other modifications, such as the improvement of a traditional hand-dug well by constructing a concrete wellhead. It is assumed that every treatment approach results in high (potable) water quality. As above, one cost value is allowed, and costs are determined for each source for source-based treatments, and for each household for POU treatments.

#### 2.4.3. Water pumping

Water pumps are required for both improving existing sources and for developing new sources. For each case, up to six water pumps may be considered. Each pumping technology is defined by its rated discharge (L/d), which is dependent on the total pumping head (m). Thus, a table, including the total pumping head (m), maximum pump yield (L/d), and the cost and O&M costs ($) for each pump, is included in AWARE. The data for up to eighteen pumps can be stored in the input section of the DSS, which may be accessed while generating input parameters.

### 2.5. Costs

To account for both capital and operation costs, which differ across financing timeframes and discount rates, the net present value (NPV) is used. NPV is a common metric for cost—benefit studies of water development projects since it accounts for all costs and benefits accrued over a given period of time (e.g., Whittington et al., 2004). This includes construction, operation & maintenance and replacement costs, as are necessary for full cost recovery.

Alternatively, in order to analyze the net present cost and benefit values in terms of annual household amounts, divided evenly over the lifetime of the project, NPV values may be annualized:

\[
\text{Annualized Value} = \frac{d}{1 - (1 + d)^{-n}} \times \text{NPV}
\]

where \(d\) is discount rate (\(-\)), \(n\) is the project lifetime (y), and NPV is the Net Present Value ($). The selection of water abstraction approaches requires a rather complicated sizing scheme, which in turn, determines the cost. The total energy required to pump a given amount of water is inversely related to the pumping head and total water pumped. Likewise, both the pump’s capital and operating costs increase with total pumping head and water output. Commercial pump suppliers rely on charts or software, such as Grundfos® WebCAPS™, to determine the most appropriate pump for any given energy source, pumping head and output requirement (net.grundfos.com/App/WebCAPS). Of course, the end cost, performance and durability of any given pump is dependent on the actual pump supplier and model.

Besides the actual pump model, the output of the software includes the expected pump output (L/h) and the amount of power (W) consumed by the pump under the given conditions. Thus, it is possible to calculate the costs ($) of both the equipment (i.e., pump and accessories) and the operation under any given energy source.

In order to calculate operation costs, a power factor for grid and diesel pumps is necessary for converting the kWh of electricity into water supplied.

**Operation Cost, OpCost ($), is defined as:**

\[
\text{OpCost} = \text{RatedOutput} \cdot \text{EnergyCost} \cdot \text{PowFac} \cdot 365 \cdot \text{Timeframe}
\]

where \(\text{RatedOutput} (\text{m}^3/\text{d})\) is the manufacturer’s listed pumping rate at a given head, assuming 12 h of operation daily, \(\text{EnergyCost} ($/\text{kWh})\) is the unit cost of electricity, \(\text{Timeframe} (\text{y})\) is the project’s financial timeframe, and \(\text{PowFac} (\text{W}/(\text{L/h}))\) is the power factor defined as \(\text{RatedPower}/\text{PumpRate}\). In the default values, the power factor is defined as the \(\text{RatedPower} (\text{W})\) calculated by the Grundfos® WEBCaps software for any given pump, output and head, divided by the pump output, \(\text{PumpRate} (\text{m}^3/\text{h})\). This provides appropriate units (kW/m³) for converting to the unit cost of water supplied ($/m³). For diesel pumping, the generator converts diesel (m³) into power (kWh) at an average efficiency (m³/kWh). The efficiency of 0.00034 is used in the DSS and cost analysis as a default value, based on a diesel generator manufacturer’s empirical data (www.powderproducts.com/tools-fuel-consumption.php). The cost of energy supplied by a diesel gen-set, \(\text{EnergyCost}_d\), is defined as \(\text{DieselCost} \cdot \text{Efficiency}\), where \(\text{DieselCost}\) is the cost of diesel ($/L). In the DSS, these pumps are grouped by energy source and defined by output. For example, the user can choose a grid-powered pump capable of supplying 12 m³/d — without specifying the actual pump model.

Another important set of costs includes all agricultural inputs required for implementing a water-for-work program. In order to provide relevant information for the DSS agricultural module, the costs are divided by the size of the garden so as to allow an estimation of costs for any land area irrigated; all agricultural costs and benefits are adjusted to the units of $/m², since land area irrigated is a function of willingness to work, as described in Appendix A.
2.6. User input and default values

The user inputs parameter values on the “Input” worksheet of the AWARE file. Those requiring site-specific values are highlighted yellow, and include 35 water service parameters and 18 agronomic parameters. Default values are shaded brown, and include the costs and specifications of up to 18 pumps, including a selection of 15 Grundfos motorized pumps powered by grid, diesel and solar PV electricity, as well as several hand-operated pumping approaches. Other pumping technologies can be investigated by simply changing these values and selecting them in AWARE’s user interface.

Agronomic default values, including the maximum crop yield, relative yield function values, and irrigation work requirements, are based on authors’ fieldwork in Zambia and are described in detail in supporting information (Table B.1). In addition, the default beta values of attributes in the economic demand model are based on Abramson et al. (2011), and may be changed to reflect local water preferences.

Populating these parameter values into the model requires a good understanding of the local economic, social, hydrological and technical context. Our previous work demonstrates that all of the 13 main parameters investigated have substantial impact on the economic outcomes of water service improvements (Abramson et al., 2014). Some parameters are more difficult to estimate than others. Whereas technological specifications such as pump yield and fixed parameters such as population density are relatively straightforward, others such as economic demand, source yield and dynamic pumping head are particularly susceptible to estimate uncertainty. We explore the implications of this uncertainty in more detail in Section 5. Table 1 summarizes the user effort and complexity associated with populating values into each of the 14 main parameters.

3. Decision process

AWARE conveys these user-input parameters through a decision process that iterates on the different configurations of improvements to existing water sources and the development of new sources, subject to the global constraint of the water service level to be achieved. Each iteration, therefore, corresponds to a unique water service improvement configuration. A combinatorial optimization procedure is run to identify all possible configurations for reaching a given water service level. An exhaustive search is performed on these configurations, and the results of the DSS include those achieving the lowest total cost and highest net benefit under the three financing approaches described above. For any given profile of initial parameters, AWARE can iterate up to 629,856 water service improvement configurations, depending on the number of technologies chosen by the user and the complexity of the village layout. A detailed description of the entire decision algorithm is given in Appendix A.

The decision process is divided into three modules (Fig. 3). The first two modules iterate on all possible permutations corresponding to the technological configurations of both improvements to existing (Module 1) and the development of new (Module 2) water sources. The methodology used to arrive at these configurations is described in Fig. 4 and in the appendix Eqs. (A.1) and (A.2). Fig. 4 presents an outline of the technological configurations considered in the DSS.

For the improvement of existing sources, up to 6 pumping and 3 treatment technologies (that is, 18 configurations) may be considered for each of 3 sources (thus, 183 configurations). For new source development, up to 6 source types, 6 pumping approaches and 3 treatment technologies (108 configurations) may be considered for the r replications needed to reach the required remaining household. In all, this results in 629,856 (183 × 108) possible water improvement configurations. These figures represent the maximum system complexity that can be modeled by AWARE.

It is important to note that in order for the null technological set to be considered, in which no intervention is investigated, N – 1 technological options may be chosen by the user from the above set limits. For example, five instead of six water pumping methods should be investigated in order to compare the option of leaving the existing pump in place at each existing source.

As the DSS progresses, three main parameters are modified under any given service improvement configuration: 1) the total cost; 2) the number of households served, and 3) the amount of extra water available for other uses at each source.

3.1. Module 1

In Module 1, the option to reach water service goals by improving existing water sources is considered. In each iteration, the DSS considers a unique technological array, and calculates and stores the variables mentioned above. For each existing source, starting with source S1, the program applies the iterated pump and treatment improvement configuration, and calculates the number of households served at that source.

According to these definitions, overlapping households, located within the fetching time of multiple sources, are considered to be served by a source only after all non-overlapping households have been served. Overlapping households within the fetching time target of source S1 are prioritized over those within S2, which are prioritized over S3. The number of households served at each source is determined under every improvement configuration considered, after Eqs. (A.3)–(A.11).

For each iteration in Module 1, the total households served by improvements are calculated. Likewise, the households remaining without improved services, according to the target, are calculated as the difference between those served by improvements under Module 1, and the total households within the decision realm. The total cost is simply the summation of all technological costs associated with that configuration, dependent upon the cost of each
technology and the number of replications of new sources needed to reach the water service target. The cost of treatment, as discussed above, may be calculated per unit served for POU treatment, or per source, if applied at the source.

The minimum total cost achieved under all improvement configurations serves as one of the primary objectives of the decision process, as given by Eq. (A.15). The result of Module 1 is the selected scenario, defined across each technology used in the configurations, that represents the lowest total cost for each unique value of total households served. This allows for an analysis of the incremental costs of expanding service reach through the improvement of existing sources. However, all configurations are passed to Module 2. For each configuration, extra water is calculated for each existing source as the difference between water demand and availability. The maximum amount of extra water from all three sources is also calculated, after Eq. (A.16).

### Module 2

The stored values are then sent to Module 2, which further iterates these results on every new source configuration, subject to the necessity that all households be served according to the given water service target. This is done by first calculating the minimal number of new water points necessary according to the spatial limit for any improvement configuration imputed in Module 1. This value is then further subject to a quantity limit, which determines how many sources are needed at each new point to satisfy the water supply target. In other words, if the yield of the new source is insufficient, then an additional source(s) must be developed for every new water point already developed to meet the fetching time target. The total number of households served by new water sources is then calculated, along with the total number of households served by both the improvement of existing sources and the

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**Fig. 3.** Overview of AWARE’s decision process. Modified variables, carried over between modules, are shown in the central lower box, surrounded by modules, inputs and results. First, existing water sources are considered for improvement (Module 1), then, new water sources are considered for achieving 100% service (Module 2). Last, net benefit is calculated under the financing arrangements introduced above (Module 3). The main output of the DSS is the lowest cost and maximum net benefit value, along with a description of the configuration used to achieve these outcomes.

**Fig. 4.** Schematic describing the creation of water improvement configurations in Modules 1 and 2. Shaded cells represent one demonstrative configuration in which the first option is chosen within each set of technical possibilities.
development of new sources. The total cost of each configuration, as well as the lowest cost configuration, is calculated. The amount of unused water for irrigation is assumed to be equal at all new sources. The maximum amount of water available at all sources is calculated in Eqs. (A.18)–(A.25).

The same parameters—number of households served, total cost, and maximum amount of unused water—are sent to Module 3. The results of Module 2 are the selected scenarios, defined across each configuration, that represent the 49 lowest unique values of total cost for providing all households with water service levels at or above the water service target.

3.3. Module 3

The main purpose of Module 3 is to incorporate the economic demand for reaching the water service target and to compute the corresponding net benefit. Economic demand is measured by three alternative metrics: (1) Willingness to Pay (WTP), (2) Willingness to Borrow (WTB), and (3) Willingness to Work (WTW). The first two are cash-based approaches and are modeled according to Eqs. (2) and (3). WTW is an expression of time commitments engaged in community work. We estimate the economic production from community irrigation by first modeling seasonal crop transpiration using the HYDRUS-1D modeling platform (Simunek et al., 2009). This public domain platform numerically solves the Richards equation and the advection-dispersion equations for modeling water flow, solute transport and root water uptake. We then apply these results to calculate the crop yield and revenue derived from irrigation.

User inputs to Module 3 include the average daily potential evapotranspiration (mm/d), season length (d), minimum and maximum values to be investigated, along with the number of discretizations, for both relative irrigation (fraction of potential evapotranspiration) and salinity (expressed by electrical conductivity, dS/m) of the irrigation water. Then, the HYDRUS-1D modeling software is used to calculate transpiration. Transpiration is then converted to crop yield according to Hanks (1974), who outlined the linear relationship between actual and potential yield and transpiration, \( y = aT \) where \( Y \) is yield (kg) and \( T \) is transpiration (mm), \( a \) refers to actual and \( p \) refers to potential. This relationship is used to regress a linear equation to describe crop-specific yield as a function of relative transpiration. This is most often accompanied by a non-unitary slope term and an intercept term due to the relationship being not perfectly 1:1 in field conditions. Thus, the above relationship can be used to calculate the expected yields from modeled transpiration values (see Eqs. (A.32)–(A.34)).

These relative crop yield values (kg/m\(^2\)) are obtained for each discretization of irrigation and salinity values within each of the 49 lowest cost water service configurations. These are then used to calculate the actual yields (kg) obtained, which are subject to both lowest cost water service configuration and reaching the remaining households with a minimum quantity of 20 L per capita per day from improved water sources. Two water pumps are available, a hand-pump, \( P_h \), and an electric, submersible pump, \( P_p \). In addition, the community may choose to improve their traditional well by constructing a concrete headwall and drainage apron, \( T_h \). Fig. 5 summarizes this scenario, and further details are provided in supporting information (Tables D.1–D.4).

4. DSS example

Consider a rural community consisting of 80 households. Two water sources—an improved borehole, configured with a hand-pump (S1), and a traditional (unimproved) hand-dug well (S2)—serve 50 households in the village center, while 30 households live outside of the fetching time target (30 min/trip) of these sources. The average population density of the community is 10 households/km\(^2\). Suppose a water development program seeks to identify: (1) the most cost-effective and (2) the most profitable approach for supplying each household with a minimum quantity of 20 L per capita per day from improved water sources. Two water pumps are available, a hand-pump, \( P_h \), and an electric, submersible pump, \( P_p \). In addition, the community may choose to improve their traditional well by constructing a concrete headwall and drainage apron, \( T_h \). Fig. 5 summarizes this scenario, and further details are provided in supporting information (Tables D.1–D.4).

4.1. Example results

The results from Module 1 are presented in Table 2.

In this example, three unique values of households served by improvements, \( S_{\text{VA}} \), are reached by the various configurations. The lowest cost configurations are presented, along with their corresponding technical details. Since the existing hand-pump configured to source S1 is already serving the full number of households (40) within the targeted fetching time, replacing the pump is not cost-effective. At source S2, no households are served according to the water quality target. Providing treatment \( T_h \) allows eight households to be served, and in addition, replacing the existing pump with \( P_p \) allows another two households to be served.

The most cost-effective configuration for reaching all 80 households is represented as the output of Module 2 in Table 3. Configuration 3 from Table 2 above provides the most cost-effective approach, in combination with applying new source, \( S_{\text{NSB}} \) configured with pump \( P_p \), for reaching the remaining households. In this case, the highest amount of extra water is available at the new source.

Module 3 results consist of the 49 lowest cost configurations, along with the relevant measures of net benefit. Fig. 6 presents a visual summary of the total cost, maximum extra water available, and net benefit derived from drip irrigation.

This example indicates various trends in the water improvement decision process. The least cost approach, indicated by point (a), is reached by providing no improvement at the existing community borehole, and reaching the remaining households with a low-cost borehole (\( S_{\text{NSB}} \)) coupled to a hand-pump (\( P_h \)). In this case, there is very little extra water made available. Replacing the hand-pump with a submersible pump at the existing community borehole (shown by the diamond points in Fig. 5) results in an availability of roughly 20 m\(^3\)/d of unused water. The highest expansion, however, is reached by developing a new borehole (\( S_{\text{NSA}} \)) fitted with a motorized pump (\( P_p \)), which provides roughly 45 m\(^3\)/d of water for irrigation. This scenario, shown by point (c), creates the highest net benefit. In this case, a profit roughly four times higher than the
the remaining households with a new, low-cost borehole. Hamby (1994) distinguishes between (1) uncertainty analysis, in which uncertainty, to the exact values of those initial parameters. Therefore, it is important to determine the stability of the overall decision process, regarding and create instability in the predictions. Therefore, it is important associated with these parameters may perturb the optimization of the model, there is a possibility that the errors due to uncertainty. The factors in Module 1 identified to be most susceptible to error are the maximum source yield (MSY), the maximum pump yield (MPY), the total pumping pressure head (TPH) of all existing water sources, and the economic demand for water service improvements. Due to natural heterogeneity in aquifers, a 25% error is allowed for the estimated yield of each source. Pumping rates are perturbed by 10% due to deviations from manufacturer ratings in actual pumping performance. Seasonal fluctuations in groundwater levels, as well as natural heterogeneity in aquifer properties, may result in errors when estimating the total pumping head, so we perturbed this value by 15%. Economic demand for water improvements may be expected to vary considerably across both households and communities; we have allowed a 50% error with WTP, WTB, and WTW in our analysis.

In Module 2, the only factor considered subject to measurement error is the hydraulic yield of the new water sources (MSYN) and total pumping head (TPHN). We perturbed this to the same degree as in Module 1. For the sensitivity analysis, both Module 1 and Module 2 factors were simultaneously perturbed according to the decision process. This is because Module 1 is a prerequisite for Module 2.

After these iterations, additional factors from Module 3 were perturbed, and the module, including the HYDRUS-1D sub-routine, was executed. These factors included the potential evapotranspiration (PET) rate, which we assumed may diverge from yearly averages by 15%, the salinity of irrigation water (Sal), which we allowed to diverge by 5% from estimates, and household willingness to work (WTW), which, due to its susceptibility to various biases, was allowed to diverge by 50%, as mentioned above. The first two factors are embedded within the HYDRUS-1D software, and so were perturbed within the HYDRUS-1D iterations. Other agricultural parameters such as irrigation system configurations and costs were not included in this analysis, but are explored elsewhere (Woltering et al., 2011). The base values of the relevant factors,
along with the magnitude of their maximum perturbation, are presented in supporting information (Tables E.1–E.3).

5.2. Parameter uncertainty analysis methodology

A base scenario defined across these parameters (outlined below) was perturbed randomly along normal distributions according to Adar (1984) who defined the perturbed variable, $V^*$:

$$V_k^* = \sum_{k=1}^{K} \left[ 1 + \beta \left( -2 \log U_{1k} \right)^{0.5} \cos(2\pi U_{2k}) \right]$$

where $V$ is the perturbed variable, $k$ is the number of perturbations, $U$ is a randomly determined number between 0 and 1, and $\beta$ is the maximum allowed perturbation in the random function. For the first uncertainty analysis of Modules 1 and 2, $k$ is set at 100. For the second analysis of Module 3, $k$ is equal to 50, meaning perturbations to those parameters were executed for the first 50 previously perturbed scenarios.

5.3. Uncertainty analysis results

Fig. 7 presents AWARE results after random error perturbations. The total cost, net WTP and net WTB are perturbed to a similar degree as the uncertainty associated with the inputs, demonstrating that realistic levels of uncertainty do not create substantial instability in these modeled results. Total cost (base value: 29,070; mean after perturbations: 30,225; STD: 3821) varies upwards by 28% and downwards by 12%. This reflects less perturbations than would be expected if the effect of the 25% error associated with source yields were cumulative.

A multivariate regression of total cost by all parameters perturbed ($R$-square = 0.929) reveals that most of the variation in total cost can be explained by the perturbations to MSYN1, the yield of the new source, NS1. The total pumping head of the same source, TPHN1, is also statistically significant, but not nearly as important (Table E.4).

Net WTP (base value: $-18,420$; mean after perturbations: $-19,731$; STD: 4762) and net WTB (base value: $-670$; mean after perturbation: $-1219$; STD: 7962) must both be understood as the difference between total economic demand and cost, which explains the downward shift in perturbed outputs from original demand errors (gray box plots). Regression analysis, presented in Tables E.5 and E.6, demonstrates that most of the modeled

![Graphical representation of DSS results under the base scenario: Total Cost, Maximum Extra Water (MaxEW), and Net Benefit achieved with drip irrigation. For illustrative purposes, the figure shows the results sorted by total cost, among the lowest 49 total cost configurations, displayed by type of new source applied, and labeled by improvements applied to S1. Other configuration details not displayed here include whether or not the hand-dug well, S2, is improved, and the number of new sources required to meet the community needs.](image)

![Values of total cost, net WTP, WTB and WTW achieved with hand-watering both before (dotted line) and after (box plots and points) perturbations to Modules 1 and 2. For reference, the perturbations to original WTP and WTB values (gray box plots) are shown in relation to model outputs. Alongside this are the percent changes to the original net WTW values after perturbations to Module 3.](image)
responses can be explained by the uncertainty in the economic demand, with only one other parameter, NS1, having a statistically significant effect. This is confirmed in that the STD of economic demand error (2876 for WTP and 7342 for WTB) and perturbed outputs are comparable; most of the variations in results are a reflection of economic demand error. The physical parameters, which act on the total cost of the service improvement, account for much less of the variation, which is shown by the relative magnitude of their standardized coefficients against that of WTP and WTB.

The net benefit achieved under irrigation appears to be less stable in this analysis. Results shift downward after perturbations, with no perturbations creating higher values than the base scenario. Both hand-watering (base value: 44,899, mean after perturbations: 35,002, STD: 6298) and drip irrigation (base value: 37,835, mean after perturbations: 28,703, STD: 6276) respond similarly, with an 18–21% reduction in mean values after perturbations.

A closer look reveals a very clear correlation between these results and an intuitive factor: extra water available for irrigation, MaxEW. Where water is a limiting constraint to production, this parameter impacts the maximum amount of benefit achieved. When extra water available (m$^3$/d) and total benefit (thousand $) are linearly regressed, the relationship is statistically validated: R-square equals one for both hand-watering (y = 1.461x) and drip irrigation (y = 1.347x). Furthermore, a multivariate regression analysis of all perturbed parameters reveals that this effect is primarily due to variations in MSYN2, the yield of NS2 (Tables E.7 and E.8). Specifically, the ceiling observed in the net benefit value is correlated perfectly to the fact that the parameter’s base value identical to the yield of P1: the pump places an upper limit on the maximum net benefit achieved when perturbations are above baseline, whereas the yield of the source acts as the limiting factor when it is perturbed below.

This analysis demonstrates that considerable interactions and “trigger values” exist within the many parameters investigated. Thus, while there is an adequate level of stability observed in the model under levels of uncertainty anticipated under field conditions, small variations in the parameters whose base values lie near a threshold (i.e., act as the limiting factor), as demonstrated here, may produce one-sided impacts on the outcomes. Paired limits, in which one of two parameters interchangeably acts as a limiting factor, are common in the decision process: the yield of a water source may depend on either the source or the pump; the revenue earned from irrigation depends on either the amount of water or the amount of labor available, etc. These factors, especially, may produce an imbalance in output values in the presence of uncertainty. Regressions of both total cost and net benefit confirm this in our analysis.

6. Potential applications of AWARE

The purpose of AWARE is to provide general policy and economic recommendations under assumptions appropriate for remote areas of low-income countries. It is a powerful tool for making comparisons across regions or studying the various elements of the rural water development process (Abramson et al., 2014). However, there are some important qualifications to make to its application in field projects. While it may provide a helpful preliminary comparison for a given water project, its results must be taken into further technical and planning assessments with more precise inputs before being implemented in the field. This is due to the various assumptions within the model, such as uniform population density as a proxy for spatial data, as well as its aggregation of household water uses and preferences.

6.1. Water distribution

The distribution of water from a water source to other locations, such as in a water network for in-home taps or community stand pipes, is not integrated into the decision process. As mentioned above, the DSS is focused on cases where developing new water sources is more cost-effective than creating a water network. A simple cost analysis demonstrates the implications for field application (Table F.1).

6.2. Other considerations

Since the DSS algorithm lacks precise spatial data, it is impossible to determine either the site-specific feasibility of new water developments or the exact optimal location of new water developments. Instead, users must infer the locations of recommended new sources. For most rural water sources, the exact location is dependent upon topography, and even localized heterogeneities. Thus, results must be interpreted under the assumption that the feasibility of any new source, So, is not spatially determined. Since the local geology will ultimately determine the actual locations of water sources, the discrepancy between modeled results and implementation will vary. Nevertheless, uncertainty exists even in carefully considered technical assessments, as evidenced, for example, in the high failure rate of borehole developments across many areas (e.g. Ball, 2004).

Second, only one new source type can be investigated at a time. This limits the output to general recommendations regarding new water sources. Users may minimize this limitation, for example, by grouping the village area investigated by each scenario investigated by the DSS into different areas according to source feasibility.

Third, the optimization scheme for finding the maximum net benefit achieved through irrigation is subject to the assumption that the maximum value is found within the 49 lowest cost alternatives, (B), as in Eqs. (A.35) and (A.36). Under complex scenarios, this assumption may be problematic, since a high number of configurations may result in many unique values of total cost. In such cases, the algorithm would need to be modified in order to perform a global maximization routine, rather than maximizing only this subset of results. However, this assumption holds for a sufficient complexity. In our companion study, for example, all scenarios investigated produced less than 49 unique values of costs (Abramson et al., 2014).

Fourth, the water-for-work program is considered for only the one water source with the highest amount of excess water. This provides an upper-boundary estimate under the assumption that all households would be able and willing to contribute work payments at that location.

Lastly, hydraulic processes are simplified in the current version of AWARE into total pumping pressure head and maximum source yield. This neglects the dynamic relationship between hydraulic head and yield, determined by hydraulic conductivity, k. For a more accurate model, it would be necessary to include hydraulic conductivity to determine the dynamic pumping head for any given yield. In addition, a dynamic variable to represent the relationship between drawdown and pumping output would need to be incorporated into the total pumping head of any source in order to fully account for all groundwater dynamics.

In light of these considerations, AWARE is capable of providing a robust economic comparison of a wide array of technical alternatives for meeting water improvement targets in remote, non-networked communities. While it has been developed primarily for providing more general comparisons—such as between solar and diesel-powered water sources or between the promotion of water treatment against new source development—rather than as a one-off project design tool, it is nevertheless useful for making
specific recommendations for field projects. For instance, it is capable of providing a preliminary assessment that may greatly assist water practitioners in narrowing their technological options, or in assessing a short list of options, before robust engineering assessments are made.

7. Conclusions

This study demonstrates the complexity involved in optimizing economic outcomes for remote, non-networked water service improvements. The AWARE platform offers users a robust decision support framework for modeling these outcomes while incorporating these complexities. Most notably, the DSS improves upon existing analytical tools and decision frameworks by accounting for a wide range of relevant parameters in order to gain economic insights that expand beyond unit cost assumptions.

As it is a first attempt at incorporating such a wide range of parameters into the rural water decision process, much improvement can be foreseen. Specifically, three strategic improvements would expand its current applications: (1) the hydrological component may be expanded to include other relevant parameters and processes; (2) a more robust spatial mechanism may be developed to account for village and water source layout, and (3) the simultaneous consideration of multiple water source types may be enabled. These improvements would further minimize assumptions within the decision process and would provide higher analytical resolution. In addition, incorporating other benefits, such as gains in health or savings in time, may expand its applicability into the realm of social cost–benefit analysis (Llamas et al., 1992; Hutton, 2012).

As we demonstrate, the decision process effectively identifies the total lowest cost and highest net benefit feasible under given inputs. Parameter uncertainty analysis indicates that the decision process may be unevenly impacted by errors in input estimates due to thresholds imposed by paired limiting factors. The off-centered responses to measurement errors, however, are within an acceptable range, with a deviation from base values of the same magnitude as the perturbations.

AWARE is a useful tool for providing both a preliminary comparative analysis for field projects and policy insights drawn from modeling regional or even global water development trends. By modeling and automating the rural water development decision process, AWARE enables robust comparisons to be made across a wide range of social, economic, physical, technical and management approaches. This makes rural water assessments substantially more efficient than case-by-case studies. In addition, the attribute-based approach of user inputs allows a wide range of development strategies, such as multiple-use water services and low-cost water development technologies, to be compared with more conventional approaches. Thus, rural water practitioners, development agencies and research entities may all find it useful.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2014.08.028.

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