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GIS-Based Multi-Criteria Decision Analysis for identifying water distribution points:

a case study in Lapilang & Suspa regions, Nepal

by

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A thesis submitted in partial fulfilment of the requirements of
the degree of
Master of Science (Geographical Information Science & Systems) – MSc (GISc)

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Dr. Stefan Kienberger

Vienna, 30.5.2018

Science Pledge

By my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used in my thesis and I have always indicated their origin.

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Preface

This framework describes work undertaken to fulfil the requirements of the degree of Master of Science (Geographical Information Science & Systems) – MSc (GISc). It consists of two main parts: first, a manuscript-based master thesis and second, a detailed report documents the empirical work.

Contributions of Authors

The manuscript was authorized by *Bassam Qashqo* (first and corresponding author) and by *Selene Silvestri* (second author). The contributions of the second author are of two folds: first, authoring and reviewing: section 2.2. Optimization Approach (mathematical programming) and the appendix and second, contributing to and reviewing section 2.3. GIS-MADM vs Optimization-MP and chapters 4 and 5. The remainder of the manuscript and the report were substantially authored by the first author.

Publication Statement

The topic of this research involves GIS-based multi-criteria decision analysis, optimization (mathematical programming) and water resources management. For that, we aim at publishing the manuscript in the journal of Water Resources Management (Springer). This journal has a significant impact factor (3.537 / 2016) and it is of high relevance to our study discipline. Another option might be the International Journal of Geographic Information Science (Taylor & Francis). In addition to its high impact factor (2.502 / 2016), this IJGIS is the leader among others in regards to the number of GIS-MCDA articles published (according to Greene et al. 2011).

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GIS-based multi-criteria decision analysis for identifying water distribution points: a case study in Lapilang & Suspa regions, Nepal

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GIS-based multi-criteria decision analysis for identifying water distribution points: a case study in Lapilang & Suspa regions, Nepal

ABSTRACT: Earthquakes can have catastrophic impacts on human life and on the environment. In Nepal 2015, two earthquakes severely affected the lives of several millions of people and destroyed vital infrastructure including water supply systems. In this context, the integration of the analytical tools of GIS and multi-criteria decision making techniques can provide a powerful means for enhanced recovery and long-term planning. In this paper, we present GIS-based multi-criteria decision analysis to identify potential areas to locate community water distribution points in Lapilang and Suspa regions in Nepal. The areas were evaluated based on trade-offs among two objectives: increasing water accessibility and minimizing cost. Through this study, two GIS-based models were introduced for calculating (1) cumulative vertical walking distance and (2) best near connection in a gravity-feed water system. As the same case study was examined using the Mathematical Programming (MP) approach, this paper also offers a comparison of philosophy, methods and results of both MP and GIS perspective on MCDM.

Keywords: GIS; multi criteria decision making; water distribution; vertical distance; optimization; mathematical programming

1. Introduction

An earthquake is considered one of the most devastating and dangerous disasters. Depending upon its magnitude, it may cause, to a large extent, deaths and injuries to people, direct threat to the environment and severe damage to man-made structures (Gautam 2008, p.1-13). Due to its geophysical nature and vulnerability to disasters, Nepal is the 11th most earthquake-prone country in the world (Baker et al. 2015; NPC 2015). In spring 2015, the Gorkha earthquake [magnitude (M) 7.8] and five aftershocks of ≥M 6.0 struck Nepal and it's neighbouring countries (Kargel et al. 2016). The earthquakes killed nearly 9,000, injured over 22,000 and affected the lives of approximately eight million people in Kathmandu and the surrounding districts in Nepal. Over half a million houses, livelihood, service and infrastructure facilities were destroyed. Additionally, according to the Nepali Department of Water Supply and Sewerage (DWSS), over 5,000 water supply systems suffered major or partial damage, including water sources, pipes and public tap-stands etc. (McNamara et al. 2017; NPC 2015).

At the beginning of 2016 following the immediate response, the Nepal Red Cross Society (NRCS) presented a Recovery Strategy. The Austrian Red Cross (AutRC) in cooperation with the Swiss Red Cross (SRC) and other Partner National Societies (PNSs) formed an Earthquake Recovery Operations (ERO) unit led by NRCS. The ERO covered the four sectors of humanitarian response; (1) shelter, (2) health and hygiene, (3) livelihood and (4) water, sanitation and hygiene (WASH) in Dolakha District. Dolakha, in northern Nepal, was where one of the strongest earthquake epicentres hit with a magnitude of 7.3 (OCHA 2015; Riedler et al. 2017).

As part of the ERO mission, the AutRC committed to the rehabilitation of 18 damaged community water supply systems (WSSs) in Dolakha. The WSS in that area is a gravity-feed system delivering clean water from the main sources to public tap-stands or, in some cases, directly to houses (ERO 2015a; Riedler et al. 2017). The lack of up-to-date data posed a challenge to rehabilitate and design water supply schemes. One of the recovery strategy's pillars was to 'build back better' and provide a well-documented basis for future interventions (NPC 2015). Therefore, the AutRC introduced its project as a case study for the research project EO4HumEn+[1]. One of the four main objectives of this study was to identify possible locations for community water distribution points (tap-stands) based on the NRCS WASH standards. The selection process was based on two main factors: (1) horizontal distance and (2) vertical distance, with maximum values of 150m and 50m respectively. As a result, the possible water distribution points[2] were 'manually' optimized according to a visual interpretation of both population density and 10m-interval contour lines (Riedler et al. 2017).

This issue has revealed the need for further advanced analysis, the aim of which is to recommend, in a systematic-manner, best "possible" areas to locate community water distribution points according to specific decision criteria. This study will thus extend the analysis of the EO4HumEn+ project to reach the aforementioned aim; however, the AutRC (with SRC) project has been suspended after designing and implementing only 8 out of 18 WSSs in Dolakha district.

Public tap-stands are an integral component of water distribution systems in rural areas (Wagner and Lanoix 1959, p. 217). The selection process of tap-stand sites involves often compromises on location and number of taps required per each stand. In addition to the technical and geographical aspects (incl. the ownership of lands), in Nepal, politicians or caste groups might also influence the siting of tap-stands (Jordan 1980, pp. 140, 141). This case is an ideal opportunity to integrate geographic information systems (GIS) and multiple-criteria decision making (MCDM) techniques, as it involves complex spatial decision-making based on trade-offs between several essential criteria.

1.1. Aim, challenges and structure of this paper

The main aim of this paper is to apply a GIS-based MCDM approach to identifying potential areas to locate community water distribution points (tap-stands). The selection of these areas will be based on (1) water accessibility, accounting for horizontal and vertical walking distances and proximity to points of interest (PoI) and vulnerable households (HHs), and (2) minimising cost considering distance to nearest feasible water source, potential target pressure and number of HHs covered.

[1] Extended EO-based services for dynamic information needs in humanitarian action. Project leader: Paris-Lodron University of Salzburg, Interfaculty Department of Geoinformatics – Z_GIS. In partnership with: Austrian Red Cross, Earth Observation Center (EOC) of the German Aero-space Center DLR and others. http://eo4humen.sus4.eu/projects/eo4humenplus

[2] These locations were identified for the community of Dorpa in Lapilang.

Wagner and Lanoix (1959) and Jordan (1980) mention several issues to consider in designing and locating public water tap-stands. In addition to the number, distribution and siting of tap-stands, few technical questions arise, such as the type of tap, the height of the loading platform, the drainage points around the tap-stands, adequate sun and shelter to encourage bathing, etc. Most of these questions can be answered, by water-supply engineer responsible and local authorities concerned, based on the local circumstances. This study does not engage with the detailed hydraulic design of the network and the exact implementation of tap-stands, neither with the socio-cultural and political factors; rather, it recommends to decision makers and water-supply engineers potential areas to locate water tap-stands according to the two aforementioned sets of conditions.

Beyond this recommendation, this paper improves upon standard MCDM studies by adding the following two components:

(i) As the same case study was examined using the Mathematical Programming (MP) approach, this paper offers a comparison of philosophy, methods and results of both MP and GIS perspective on MCDM.
(ii) This paper presents advanced spatial analysis and proposes two GIS-based models for calculating (1) cumulative vertical walking distance and (2) best near connection in a gravity-feed water system.

Following a concise review of literature, this paper is organized as follows: Chapter 2 presents and compares the GIS-based and the MP-based approaches in MCDM. Chapter 3 provides a detailed description of the project followed by comparative analysis of the results in Chapter 4 and conclusions in Chapter 5.

1.2. Literature review

The impacts of disasters have spatial dimensions which encourage finding new concepts and integrated approaches for sustainable rural development and for building back better (Kropp and Scheffran 2007). GIS offers a wide variety of tools to manipulate and analyse spatial data; however, the addition of MCDM analytical techniques provided a powerful means to handle the limitations of GIS when multiple complex criteria and objectives are involved (Carver 1991; Chakhar and Martel 2003; Jankowski 1995). Accordingly, the use GIS evolved into a “decision support system” (e.g. Eastman et al. 1995; Malczewski 2006a).

Since early 1990s, the integration of GIS and multi-criteria decision analysis (MCDA) has gained a growing interest for researchers (Greene et al. 2011; Malczewski 2006a). The field of land management, for example, has incorporated such methods as: land-use suitability analysis using fuzzy quantifiers via ordered weighted averaging (OWA) (Malczewski 2006b); land-use planning using OWA (Chen et al. 2011); multi-objective multi-criteria for land allocation using raster analysis (Eastman et al. 1995); spatial optimization techniques (Aerts et al. 2005); and mapping landslide hazard zones (Othman et al. 2012).

In the field of integrated water resources management, the MCDA was well documented by Bogardi et al. (1994). Hajkowicz and Collins (2007) reviewed 113 published papers and concluded that the multiple criteria analysis have been frequently used in water strategic planning and evaluation as well as in selection of infrastructure. For example, to prioritize the protection of drinking water facilities according to their vulnerability to contamination (Alvarado et al. 2016), to select potential areas for groundwater utilization (e.g. Kumar et al. 2014; Machiwal et al. 2011; Mukherjee et al. 2012), and to satisfy water demand with limited financial capabilities by prioritizing the execution of projects (Karnib 2004).

2. Approach

In this chapter we present the theoretical foundations behind the two approaches that have been applied separately to solve the water distribution points problem of Dolakha. First: the raster GIS-based approach using *multiple attribute decision making (MADM)* and second: the optimization approach using *mathematical programming (MP)*.

2.1. GIS-based Multi-Criteria Decision Analysis (MCDA)

Several approaches to solve multi-criteria decision making problems have been suggested in the decision analysis literature. Such problems involve a set of objectives and/or a set of attributes (Malczewski 1999). Selection of one MCDA method, or a combination of methods, depends much on the context of the problem (Greene et al. 2011).

In the context of our case study, two objectives need to be considered in nominating areas suitable for locating the water distribution points; (1) ensure water accessibility according to standards and (2) minimize costs. Each objective is operationalized by assigning three criteria/attributes. These criteria are perceived as *factors* that increase or decrease the suitability of alternatives (e.g. the shorter the walking distance the better) and as *constraints* to limit alternatives (e.g. distances longer than 250m are excluded) (Eastman 2009; Eastman et al. 1995). The alternatives here are represented as raster cells. The number of alternatives is also taken into account, which is relatively large in our case study: ~1 million.

The objectives considered are complementary (non-conflicting). This means that the solution should highlight the areas which satisfy both objectives to the maximum degree possible (Eastman 2009). This implies the application of MADM technique (also known as multi-criteria evaluation - MCE). MADM enables the trade-off between a set of discrete or feasible choice alternatives (Carver 1991; Figueira et al. 2005; Jankowski 1995).

After selecting and deriving criteria, the following steps are sequentially implemented (see full structure in Figure 1):

(i) Suitability maps are derived for each objective (i.e. for each criterion assigned to this objective), the so-called *standardization* process. With this process, since all factors are measured quantitatively, the alternatives are reclassified / ranked order on one common *interval* scale (Voogd 1983),

(ii) Weights are assigned to the suitability maps. The weights are derived using the *analytic hierarchy process (AHP)*, which is based on pairwise comparisons (Saaty 1987; Saaty 2008),

(iii) Finally, a *compensatory* decision rule is applied, the aim of which is to combine all maps into one single suitability map. We use one of the most common additive methods; *weighted linear combination (WLC)* (Carver 1991; Eastman 2009; Nyerges and Jankowski 2010; Voogd 1983). With WLC, the final suitability map S is derived by multiplying each factor by its relative weight followed by summation of the results; i.e.,

$$S = \sum w_i \ x_i \tag{1}$$

given w_i as weight of factor i, where $w_i \in [0, 1]$ and x_i as the standardized score of factor i where in our case $x_i \in \{0, 1, 2, 3, 4, 5\}$ (Eastman et al. 1995).

The MADM was fully implemented, based on (10mx10m cell size) advanced raster analysis, in ArcGIS v10.5 ESRI software. The project is further explained in the following chapter and the final results are illustrated and analysed in Chapter 4.

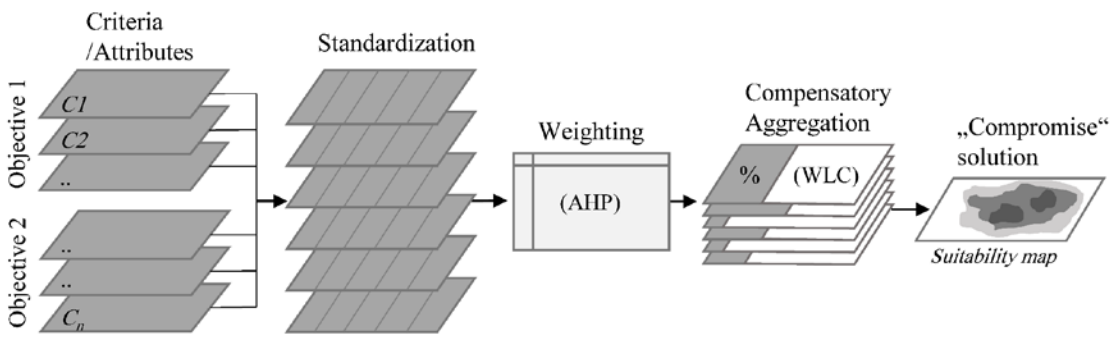

Figure 1: The structure of GIS-based multiple attribute decision making (MADM).

2.2. Optimization Approach (mathematical programming)

Mathematical Programming (MP) can be defined as an abstract representation of a problem, through mathematical equations, aimed at identifying the best (optimal) solution under a set of constraints imposed by the nature of the problem being studied. These constraints could represent financial, spatial, logistic, or many other factors. MP is one of the most developed and frequently utilized technique of Operations Research, which is the application of advanced mathematical methods to improve decision making (Bradley et al. 1977).

In mathematical terms, a mathematical programming model can be expressed as the minimization (or maximization) of an objective function, subject to a given set of *constraints*. If the mathematical representation uses only linear functions, the mathematical model is a *linear-programming model*. The first step in formulating a linear program is identifying the decisions, i.e. the elements that the decision-maker can control. These denote the decision variables of the problem, and their values define the solution. The objective function represents the criterion the decision-maker will use to evaluate alternative solutions, while the set of constraints represent the restrictions imposed by the characteristics of the studied problem.

MP can be used to solve many real-life problems, arising in different areas, such as transportation, scheduling, logistics, etc. The problem we aim to solve in this case study is a classical problem in the Operations Research literature named *Capacitated Facility Location Problem with Single Source (CFLPSS)*. Given a set of potential locations for facilities with fixed cost and capacity, and a set of customers, with demands for goods supplied from these facilities, the CFLPSS consists into identifying the subset of facilities and the assignment of customers to facilities that minimizes the total cost, without violating the capacity constraints (Sridharan 1995).

In our case study, the set of potential locations for facilities corresponds to the set of potential locations for tap-stands, while the set of customers are the HHs, and their demand is the daily demand of water they need to collect at the assigned facility. Note that HHs can be assigned only to tap-stand locations that are within a radius of the standard distances. Tap-stands are capacitated, as we set an upper bound of the number of HHs that each tap-stand can serve.[3] The MP approach is described in more detail in the appendix.

2.3. GIS-MADM vs Optimization-MP

Both approaches aim at solving one decision making problem, however, the disparity in formulating this problem between them is quite remarkable. In Table 1, we summarize the main characteristics of the two approaches. A decision explores choice among a set of alternatives and the basis for the decision is a criterion. In that sense, the criteria (as factors or constraints) are used to measure and evaluate the performance of alternatives.

In GIS MADM, the decision criteria are defined explicitly by a finite number of attributes which in turn are implicitly assigned to objectives. In optimization, the criteria are defined explicitly by predefined objectives. Using decision variables and constraints, the optimization approach evaluates alternatives by means of objective function. This means using mathematical equations to optimize (minimize or maximize) these alternatives in relation to objectives. The GIS aggregates the standardized attributes multiplied by their relative weights to finally obtain solution preferences (suitability map).

[3] This is an ongoing work and it has been presented at *Production and Operations Management Society (POMS)* annual conference 2018, Houston, May 4-7 and *Optimization Days (JOPT)* annual conference 2018, HEC Montréal, May 7-9.

Table 1: Comparison of GIS-based MADM and Optimization approaches.

	GIS-based MADM	*Optimization Approach*
Decision criteria defined by:	Attributes	Objectives
Objectives are defined:	Implicitly	Explicitly
Factors defined by:	Suitability maps	Variables
Constraints defined by:	Exclusion (values are set to 0)	Combination of parameters and variables
Alternatives are:	All possible outcomes of raster cells	All feasible solutions identified by the constraints
Weighting method:	Pairwise comparison (AHP) among criteria (attributes)	Straightforward among objectives
Decision rule:	Compensatory aggregation (WLC)	Objective function
Decision modeling:	Multi-criteria evaluation (raster-based)	Mathematical programming
Input	Raster (10m cell)	Tables (derived from GIS based on 25m raster cell)
Solutions provided:	Choice preferences (suitability map)	Optimal locations (ID and coordinates)
Visualization:	Fully supported	Unavailable (transformation of output coordinates into GIS is required)
Software used:	ArcGIS from ESRI	Cplex from IBM (coded using C++)

In both approaches, altering the weights affects much the final solution. However, the optimization approach is more concerned with the number of alternatives to be evaluated than the GIS MADM.

Sources: A combination of own observations (based on the case study) and adaptation from: Hwang and Yoon (1981) cited in Malczewski (1999 - p86), Eastman (1995) and Greene (2011).

3. Detailed Project Description

3.1. Study area

Raster GIS-based MADM was applied in two village development committees (VDCs): Lapilang and Suspa Chhamabati, situated in Dolakha district. The two VDCs cover a total area of 52.35 km² and are located approximately 70km east of Kathmandu, the capital city of Nepal (Figure 2).

As per the baseline survey conducted by NRCS in Dolakha, a total of 12,523 people (2,603 HHs) live in these two targeted VDCs, and their lives were severely affected in all aspects by the devastating earthquakes (Figure 3). Access to clean water was one of the most challenges, as water facilities, including main sources, were

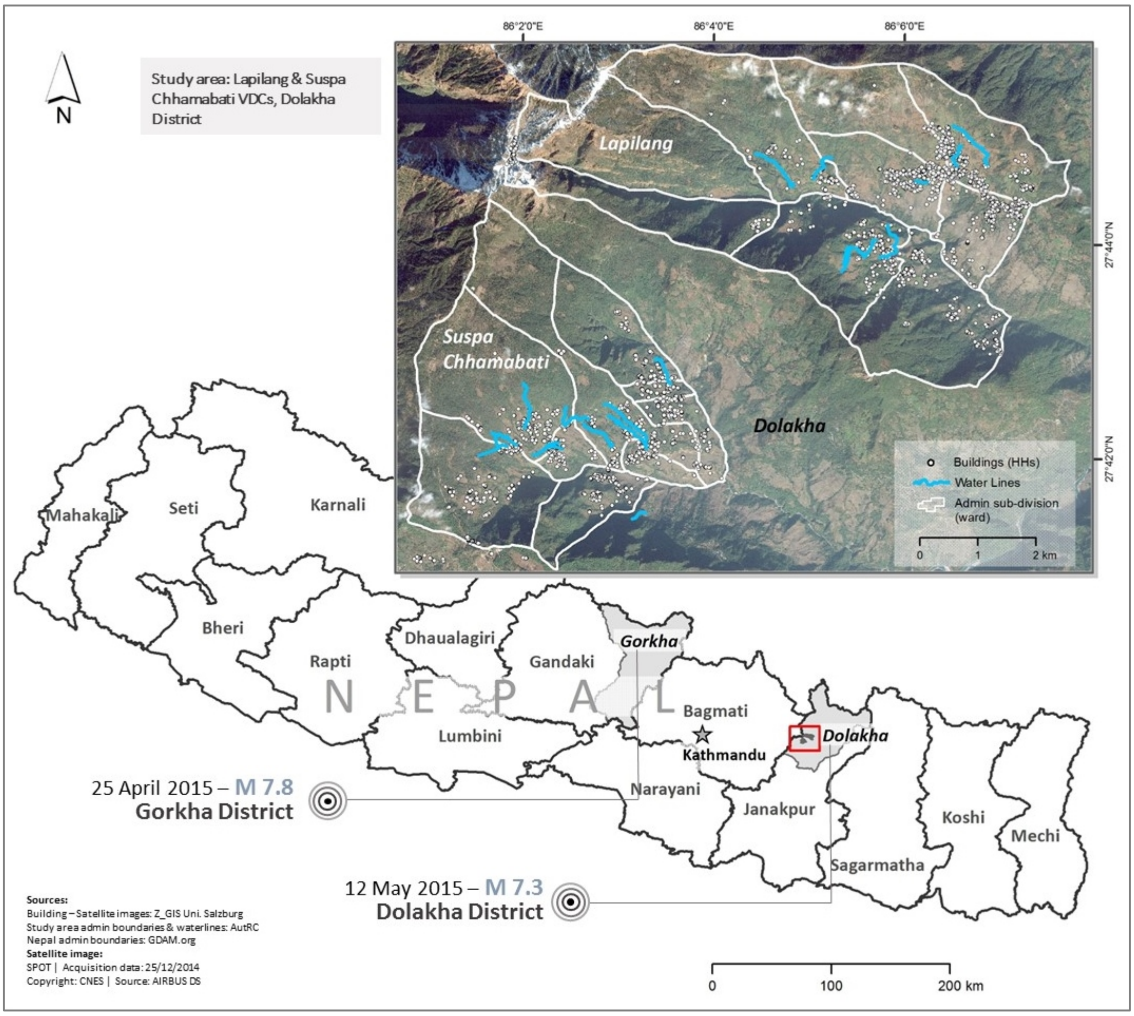

Figure 2: Map of Nepal shows the 2015 earthquakes and the study area; Lapilang and Suspa Chhamabati VDCs, Dolakha district.

damaged. In normal situation even before the EQ, the majority of the households of Lapilang and Suspa Chhamabati had to cover their daily water consumption needs by accessing public taps and in some areas, people had to walk long distances to fetch water. After the EQ, some households had to get water from unsafe sources, such as irrigation canals. Others had to walk much farther than before the EQ (SRC 2017).

As mentioned earlier, since the RCs finished their rehabilitation project in Dolakha in summer 2017, collecting further field data (e.g. water schemes and the way each HH gets water) became difficult. This study, accordingly, is based on two hypotheses: (1) all buildings (HHs) have no access to water (neither via public taps nor via direct connection) and (2) the 18 water sources provided by the RC are the only existing and functioning sources of water for the population of the two targeted VDCs.

Figure 3: Photographs of (a) devastated houses viewed from a helicopter in the hills of Gorkha (AFP 2015), (b) a destroyed water scheme (SRC) and (c) a Nepali woman carrying water vessel - in normal situations, she had to walk 30 min to reach the water source carrying 15 liters water on each journey (Renewable World 2013)

3.2. Input data

Table 2 lists the input data considered in this study. The data have been manipulated in ArcGIS and structured in the form of Geodatabase file. The coordinate systems were unified to *WGS_1984_UTM_Zone_45N, Transverse_Mercator* projection.

Table 2: A list compiles the input GIS data that were used for the MCDM case study in Nepal.

Data	**Format**	**Source**	**Date** ***(delivered in)***
Digital surface model (DSM) *2m post-spacing - 10m spatial resolution*	raster *(.tif)*	Z_GIS	July.2017
Buildings *extracted from VHR satellite images in post-disaster situation*	vector *(.shp)*	Z_GIS	July.2017
Water schemes *18 schemes (intakes, main lines, tanks, safe yield...etc.) based on field collection*	vector *(various)*	AutRC	Feb-Sep.2017
Points of Interest (PoIs) *Schools, temples, health centers*	vector *(.osm - .shp)*	OpenStreetMap (OSM) & AutRC	Nov.2017
Administrative borders *VDCs and wards (division under VDC)*	vector *(.shp)*	AutRC - modified by Z_GIS	July.2017
Vulnerable HHs *15 buildings randomly selected*	-	-	-

3.3. Decision criteria

In the following paragraphs we present the six decision criteria that were considered in the evaluation of potential locations for community water distribution points in the targeted VDCs. We describe the methods, tools and models used or developed to derive each criterion.

3.3.1. Horizontal distance

This factor specifies the maximum horizontal distance that people should walk to fetch water. According to National Urban Water Supply and Sanitation Policy (MPPW 2009), basic water supply should be reachable within a maximum of 100m walking distance. The NRCS WASH standards recommend a maximum horizontal radius of 150m and in exceptional cases 250m (ERO 2015b).

Due to the topography of the study area (alpine area with steep terrain), we considered the actual travel distance or the so-called *Surface Distance* which extends the Euclidean (straight-line) distance over the type of travel surface (terrain) (ESRI 2016a). For that, we used *Path Distance* tool to generate the actual walking distance raster with buildings as input source data, DSM as an input surface raster and 250m for maximum distance. Additionally, we generated the *Backlink* raster to be used in calculating the cumulative vertical distance.

3.3.2. Vertical distance

Similar to horizontal distance, this factor defines the vertical distance d_V limits to access water supply. The NRCS defines a maximum vertical distance of 50m and 80m in exceptional cases (ERO 2015b).

From the description above it might seem that finding the vertical walking distances for all buildings simultaneously is a simple process. In geometry, it's commonly agreed that the d_V between two points a and b is defined as the absolute difference between the elevation Z values of these two points i.e. $d_V = |Za - Zb|$. However, in our case, this definition might be irrelevant, while it does not always necessarily express the vertical walking distance in an *accumulative* manner (see Figure 4), The cumulative vertical distance, referred to as $\bar{d}_V$, is rather expressed as:

$$\bar{d}_V = \sum_{i=1}^{n} |r_i| \tag{2}$$

where r here represents the *rise*.

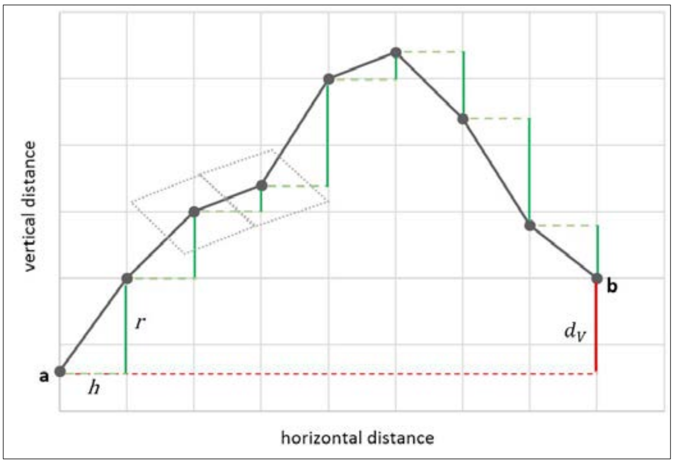

Figure 4: A simple graph illustrates the difference between the absolute and cumulative vertical distance.
In this example, $\bar{d}_V$ is almost 6 times the d_V.

We propose a GIS raster-based model to calculate the $\bar{d}_V$ to the nearest source (building) for each raster cell. The model is based on the following steps:

(i) Generating the rise r per cell raster, based on Equation (3). The r value here is derived from the basic formula of percent of slope which is also called *percent rise.*

$$r = \frac{r_P \times h}{100} \tag{3}$$

where r_P represents the percent rise per cell and h is the *run* (the *run* here equals to cell size = 10m).

(ii) Calculating the cost distance, referred to as c_d, with buildings as input source data and the resulting raster r as input cost raster.
The algorithm of c_d utilizes the node/link cell representation used in graph theory. In this representation, the node represents the center of a cell and each node is connected to its adjacent nodes by multiple links. The *cost* assigned to each cell of the output surface represents the cost per unit distance for moving through the cell. The *final value per cell* is the cell size multiplied by the *cost* with taking into account the directionality of travel between nodes to reach the source (ESRI 2016b).
To simplify this concept, we redefine the following:

- *final value per cell* is the total cumulative cost distance per cell, referred to as $\bar{c}_d$
- *cost* is the cumulative cost per cell $\bar{c}$ which in essence equals to $\bar{d}_V$ (since we used r as input cost raster), and
- h equals to the cell size.

Accordingly, we can estimate the $\bar{c}_d$ as:

for perpendicular travel: $$\bar{c}_d = \bar{c} \times h \tag{4}$$

for diagonal travel: $$\bar{c}_d = \bar{c} \times h \times \sqrt{2} \tag{5}$$

By using the backlink raster, referred to as b, we could distinguish between the perpendicular and diagonal node costs. The b raster identifies the directionality of traveling from each cell towards the nearest source using direction coding. The direction codes range from 0 to 8, where 0 represents the source cell, even numbers and odd numbers represent the diagonal and perpendicular directions respectively.

(iii) Based on the above incl. Equations (4 and 5), we can finally estimate the $\bar{d}_V$ by the following condition:

$$\bar{d}_V = \begin{cases} 0 & if\ b = 0 \\ \frac{\bar{c}_d}{h}, & if\ b \equiv 1\ (mod\ 2) \\ \frac{\bar{c}_d}{h \times \sqrt{2}} & otherwise \end{cases} \tag{6}$$

The conditional formula 6 was transformed into map algebra in ArcGIS to derive $\bar{d}_V$, the second criterion required. By examining the results, we find that the output raster reflects, in most cases, actual values of cumulative vertical distance. Nevertheless, these values were slightly overestimated in few random cases. Figure 5 compares two of the examined examples.

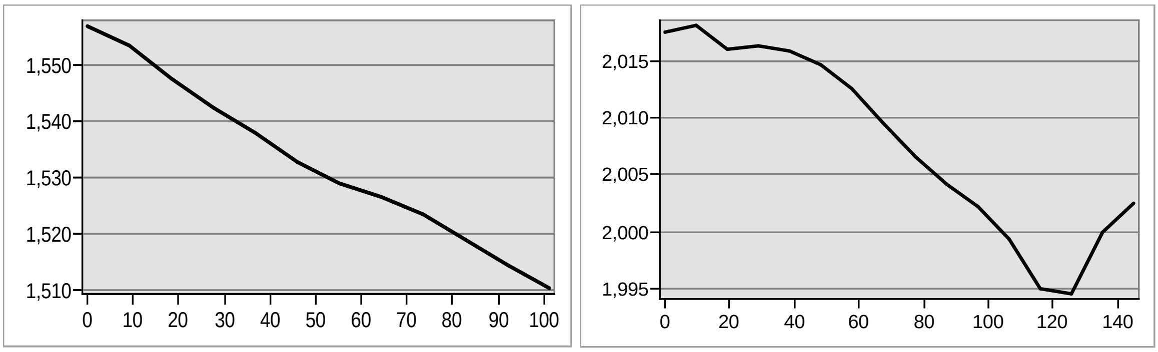

Figure 5: Two elevation profile graphs are interpolated on DSM using 3D analyst tool in ArcGIS to compare the accumulative vertical distance $\bar{d}_V$ with the absolute vertical distance $|d_V|$. In first example (left) $\bar{d}_V = |d_V| = 48.6m$ and in the second example (right) where $\bar{d}_V = 31.8m$ while $|d_V| = 17m$.

3.3.3. Proximity to PoIs and Vulnerable HHs

According to RC water accessibility recommendations, special attention should be paid to points of interest (such as schools, health centers and temples) and vulnerable households. That is, public tap-stands should be located at or as close as possible to these sites when the possibilities of a direct connection are least.

To include this factor in the final evaluation, we calculate the Euclidean distance considering a maximum distance of 100m from each of these sites.

3.3.4. *Coverage of buildings*

The average household size was estimated to 4.3 people as per a national population survey from Februray 2016 (ERO 2016) and to 3.7 people as per the study of Riedler et al. (2017). In this study, however, we adopted the RC estimation for 5 people per HH.

Wagner and Lanoix (1959) and Jordan (1980) agree that one public tap-stand should serve a maximum population of 200 persons. This means 40 HHs per tap-stand and around 7 per single tap, assuming the most practical design of tap-stands with 6 taps (WASH engineers' recommendation).

The point statistics analysis produced a raster, each cell of which indicates the exact number of buildings that could be covered per cell within a range of 250m horizontal distance.

3.3.5. *Best water connection*

We aim to ensure the best water connection possible considering the technical requirements for a gravity-feed WSS. To reach this aim, we included two main factors: the distance to the nearest feasible water source and the potential target water pressure.

With the available GIS tools of proximity and near analysis, it is possible to assign for each feature in a pre-defined search radius the "first" nearest feature found. However, to choose simultaneously the nearest and the most suitable feature, one might need to apply several processes (by using the available tools or by coding), depending on what "suitable" requires.

To accomplish this, we propose one GIS-based model (tool) that performs all the processes needed to obtain the two required factors mentioned above. The model executes a total of 31 orders, the main ones being:

(1) Exclude from DSM raster all cells with an elevation higher than the highest water source within the study area. To minimize the number further, the DSM raster could be clipped using a *mask* raster.
(2) Transform the remaining cells into nodes (vector),
(3) connect each node with the near waterlines based on (user-defined) *search distance* and *maximum number of closest matches*,
(4) calculate difference in elevation between each node and its closest matches,
(5) calculate potential target pressure based on (user-defined) *linear loss/head*, considering here the elevation difference and distance,
(6) exclude all connections where elevation difference ≤ 1 *and* pressure < 0,
(7) select for each node the connection with the shortest distance,
(8) create final joins and finally, return to raster.

The basic inputs required for this tool are: waterlines and DSM raster. This results in three new raster surfaces: distance to nearest possible waterline, potential target pressure and the corresponding ID of waterline (to which the cell should be connected).

For Lapilang and Suspa VDCs, we used the following input parameters:

- water sources: 18 polyline features,

- DSM raster: 10mx10m cell size, clipped to horizontal distance raster (first criterion),
- search radius: 5 km,
- maximum number of closest matches: 5, and
- linear loss: 5% (as proposed by RC WASH engineers based on information available about the water schemes: type, length and diameter of pipes and safe yield).

Given these input parameters, the model evaluates over a million node connections/records in 45 minutes to produce the three raster surfaces.

3.4. Standardization

The derived criteria are measured in different scales and must be standardized before proceeding with weighting and combination (Eastman et al. 1995). In ArcGIS, using the reclassify module, we unify the mutually incomparable raw values for each criterion on one common scale from 0 to 5, where 5 is the best score, 1 is the worst, and 0 represents the values ruled out from the evaluation (Table 3).

The criterion scores were determined either:

(1) on a straight-forward manner based on the given standards of water accessibility; for example, in the case of walking distance, the worst values are assigned to the exceptional cases; or

(2) considering the hydraulic designs and thus, minimizing the costs. Taking coverage of buildings as first example, WASH engineers recommended the areas that serve many buildings at once while this allows several taps/tap-stands be connected with one main water line. Second example, potential target pressure where rank 5 is assigned to 10 – 60m of head; according to Jordan (1980), this pressure rating allows the use of Class III High-density polyethylene-HDP pipes, which is the standard pipe used in Nepal. The higher pressure ratings require other types (or combination) of pipes which are more expensive; Class IV HDP (rank 4) or Galvanized Iron (GI) pipes (rank 3).

Table 3: Standardization of criteria scores. Ranks are from 5 (best) to 1 (worst) and values under rank (0) are excluded. * indicates the maximum value of a criterion.

Criterion	unit	5	4	3	2	1	0
Horizontal walking distance	m	< 50	50 - 100	100 - 150	150 - 200	200 - 250*	-
Vertical walking distance	m	< 20	20 - 40	40 - 60	60 - 80	80 - 100	> 100
Proximity to PoIs and vulnerable households	m	< 10	10 - 25	25 - 50	50 - 75	75 - 100	> 100
Coverage of buildings	no. of bldgs.	127 - 193*	85 - 126	43 - 84	15 - 42	1 - 14	-
Potential target pressure (head)	m	10 - 60	60 - 100	100 - 250	250 - 350	350 - 554*	0.001 - 10
Distance to nearest possible water source	m	< 500	500 - 1,000	1,000 - 1,500	1,500 - 2,000	2,000 - 3,106*	-

3.5.Weighting

Each evaluation criterion considered in this study is explicitly correlated to one objective; however, reaching one solution that simultaneously meets and optimizes the two objectives is impossible. Thus, a compromise solution is required. To attain a compromise, trade-offs among the objectives are made by the use of weighting (e.g. Bogardi et al. 1994; Eastman et al. 1995).

Among several available weighting methods, we chose the pairwise comparisons method –known as the Analytical Hierarchy Process (AHP) –developed by Saaty in 1977 (e.g. Nyerges and Jankowski 2010; Saaty 1987). The comparisons in AHP are based on relative importance of each pair of criteria on the fundamental nine-point scale (Eastman et al. 1995; Figueira et al. 2005).

The weights were allocated on multiple levels to develop three scenarios of solutions:

- *first scenario:* using the AHP, more relative importance ratings were given to the water accessibility criteria than to those related to cost e.g. horizontal and vertical distances are extremely (9 times) more important than distance to water sources and for that, (1/9) would be in the reciprocal position.
- *second scenario:* the comparison matrix was re-evaluated favouring cost over accessibility (Table 4).

To our knowledge, there is no module in ArcGIS that calculates the weight values by the principle eigenvector; hence, the weights from these two levels were developed by adding each row for each matrix and dividing by their total. However, this way is considered by Saaty (2008) and Eastman et al. (1995), a good approximation of the principle eigenvector (Table 5).

- *third scenario:* the compromise solution weights were derived by averaging the weights from the first and second levels (Table 6).

Note: The final weights (shown in the following tables) were consistently rounded so they still sum to 1.

Table 4: First matrix of pairwise comparison for assessing the relative importance of factors. The derived weights prioritize the water accessibility criteria (first scenario).

Scenario 1: Water accessibility	Horizontal distance	Vertical distance	Proximity to PoIs and vulnerable HHs	Coverage of buildings	Potential target pressure	Distance to water source	***weights***
Horizontal distance	1	1	2	9	9	8	**0.35**
Vertical distance	1	1	2	9	9	8	**0.35**
Proximity to PoIs and vulnerable HHs	1/2	1/2	1	5	5	7	**0.16**
Coverage of buildings	1/9	1/9	1/5	1	1/2	1/4	**0.02**
Potential target pressure	1/9	1/9	1/5	2	1	1/2	**0.04**
Distance to water source	1/8	1/8	1/7	4	2	1	**0.08**

Table 5: Second matrix of pairwise comparison. The derived weights prioritize the cost-related criteria (second scenario).

Scenario 2: Minimize costs	Horizontal distance	Vertical distance	Proximity to PoIs and vulnerable HHs	Coverage of buildings	Potential target pressure	Distance to water source	***weights***
Horizontal distance	1	1	2	1/5	1/6	1/7	**0.05**
Vertical distance	1	1	2	1/5	1/6	1/7	**0.05**
Proximity to PoIs and vulnerable HHs	1/2	1/2	1	1/6	1/8	1/8	**0.03**
Coverage of buildings	5	5	6	1	1/2	1/3	**0.22**
Potential target pressure	6	6	8	2	1	1/2	**0.3**
Distance to water source	7	7	8	3	2	1	**0.35**

Table 6: The weights derived for the compromise solution. Averaging the weights of the established scenarios led to a fair allocation of weights among the two competing objectives.

Objective	***Criterion***	***weights***
Water accessibility	Horizontal distance	**0.2**
	Vertical distance	**0.2**
	Proximity to PoIs and vulnerable HHs	**0.1**
Minimizing the cost	Coverage of buildings	**0.12**
	Potential target pressure	**0.17**
	Distance to water source	**0.21**

3.6. Compensatory aggregation (Evaluation)

The final phase implies evaluating the suitability maps (factors and constraints) that have been developed in the previous steps. The evaluation is made simply by multiplying each map by its weight and adding up the results to produce one single map (Eastman et al. 1995). Among several methods available to aggregate compensatory factors (Greene et al. 2011), we applied the weighted linear combination (WLC) (Nyerges and Jankowski 2010; Voogd 1983).

In this empirical case study, there are no real DM preferences because, as mentioned earlier, the RC societies already implemented their rehabilitation project in Dolakha. For that, we proposed three solutions scenarios (suitability maps). These solutions were obtained using the *weighted overlay* function in ArcGIS.

4. Comparative results

Figure 6 shows the final results obtained from the two approaches. The maps show, for each scenario, high compatibility between the optimal locations of MP and the suitability maps of GIS. The majority of optimal points are distributed in rank 4 (second best): 93%, 48% and 71% for water accessibility, minimizing cost and compromise scenarios, respectively. These ratings are quite reasonable because, for example, the walking distance (as a water accessibility factor) was explicitly considered in the MP approach;

however, this was not the case for the distance to water source (as a cost factor). Since GIS MADM considered the proximity to PoIs and vulnerable HHs in the evaluation (which is limited to 100m buffer around each location), only few optimal locations are located in rank 5 (best). Figure 7 illustrates the distribution of optimal locations in the suitability maps per rank and for each scenario respectively.

Additionally, we compare the compromise solution of GIS with the initial results of the EO4HumEn+ project: the tap-stand locations that were identified manually based on a visual interpretation (Figure 8). The map shows 3 out of 9 identified points that do not fit with our results (due to their high altitude, the condition of gravity-feed WS is not respected).

Finding the ideal solution is almost impossible; however, the best compromise solution is defined by its minimum distance from the theoretical ideal (Carver 1991). In that sense, both approaches have obtained compromise solutions. However, which approach (solution) best addresses this problem, is still debatable accounting first for the complex siting factors of public tap-stands, not all of which were considered, and second for the special situation of Nepal, detailed in Chapter 1. The optimal locations of MP undoubtedly address the problem, but they do not allow for a good level of flexibility for hydraulic design in the field—which is, in contrast, well considered with the suitability map of GIS. On the other hand, altering the values assigned to factors/constraints is relatively easier in optimization than in GIS. In the same context, adding new factors/constraints is more straightforward and less time consuming in GIS than in MP.

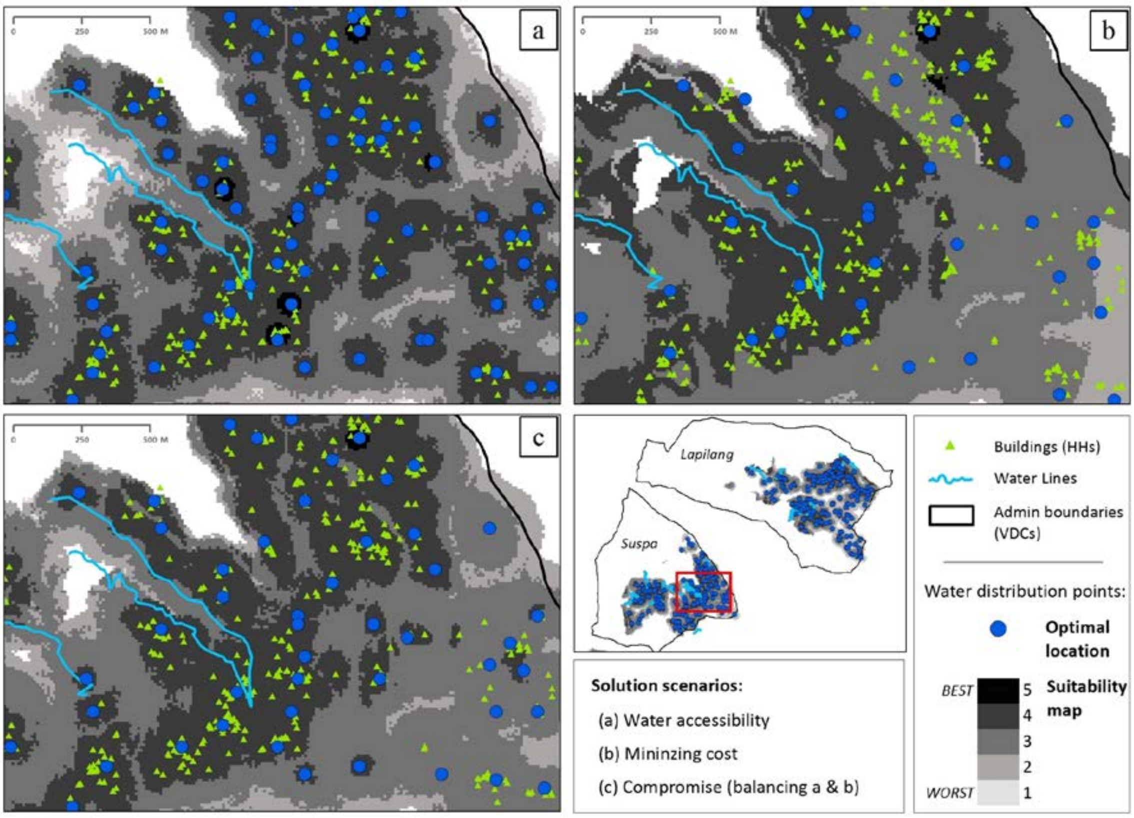

Figure 6: A map compares the final suitability maps of GIS-based MADM with the optimal locations of mathematical programming according to solution scenarios: (a) water accessibility, (b) minimizing cost and (c) compromise solution.

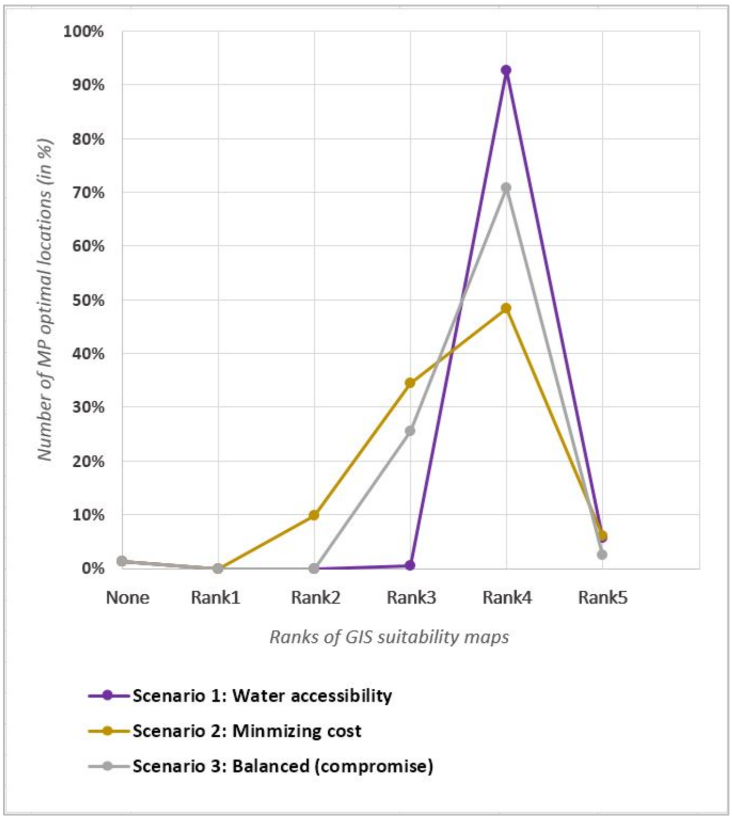

Figure 7: A graph shows for each solution scenario the distribution of optimal locations (MP results) in the suitability maps per rank (GIS MADM results).

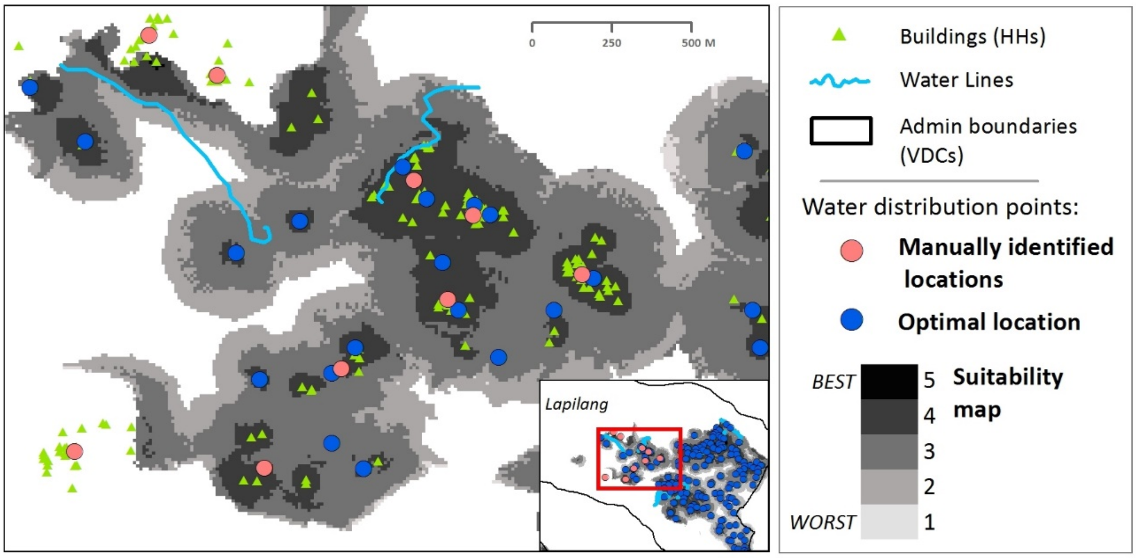

Figure 8: A map compares the water distribution points proposed initially for the community of Dorpa in Lapilang (these points were identified manually based on visual interpretation) with our automated results (the balanced scenario).

5. Conclusion

In this paper we presented the integration of GIS and multi-criteria decision analysis for finding potential locations of community water distribution points (tap-stands) represented by a case study in Lapilang and Suspa VDCs in Nepal. In fact, such cases could be ideally implemented when communities (and their politics) are involved in the decision making process, referring here to the selection of criteria and weights.

Additionally, two preliminary GIS-based models have been introduced to solve two analytical problems that were unveiled through this study; (1) finding the cumulative vertical walking distance and (2) finding the best water connection in a gravity-feed water supply system. However, further development is required to improve these models.

Furthermore, in the context of this study, we have had the opportunity to compare the raster GIS-based MADM with the mathematical programming approach, and we found that both used similar philosophy in structuring the problem and obtained comparable results, despite the variance in their deployed methodologies. The selection of approach and methods broadly depends on the context. However, the results confirm the need for further research and intensive efforts to integrate GIS and mathematical programming effectively in decision making support. This integration would be of great help in the humanitarian context, especially in the development of proactive measures in immediate response to disasters.

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APPENDIX

Optimization Approach (Mathematical Programming) continued…

The first step to model the problem was dividing the region of interest using a grid having cells of the same size. These cells were then divided into two sets (not separated). The set H of cells containing HHs and the group of cells L that are potential locations for tap-stands ($H \subseteq L$). Distances between cells are calculated using an algorithm that takes into account the geography of the region.

Sets

- L set of potential locations for tap-stands;
- H set of households;
- $A = \{(h, l): h \in H, l \in L,$ and the distance from h to l is within the standards$\}$.

Parameters

- f_l: cost of opening a tap-stand in l, for $l \in L$;
- c_{hl}: walking-cost from HH h to go collect water in l, for $(h, l) \in A$;
- d_h: daily demand of water from h, for $h \in H$;
- q: capacity of a tap-stand (max number of HHs that can be covered).

Variables

- $W_l, l \in L$: equal to 1 if a tap-stand is located in l, 0 otherwise;
  S_{hl}, $(h, l) \in A$: equal to 1 if HH h is assigned to tap-stand l, 0 otherwise.

The mathematical formulation for the CFLPSS is the following:

$$\text{minimize} \quad \sum_{l \in L} f_l W_l + \sum_{(h,l) \in A} c_{hl} S_{hl} \qquad (1)$$

$$\sum_{l \in L} S_{hl} = 1 \qquad h \in H \qquad (2)$$

$$\sum_{h \in H} d_h S_{hl} \leq q W_l \qquad l \in L \qquad (3)$$

$$W_l, S_{hl} \in \{0,1\} \qquad l \in L, (h, l) \in A \qquad (4)$$

Objective function (1) minimizes the costs of opening tap-stands and assigning HHs to opened water-tap locations. Constraints (2) impose that each HH is assigned to exactly one opened water tap. Constraints (3) ensure that capacities of tap-stands are respected.

Report: Empirical Work

REPORT: GIS-based multi-criteria decision analysis for identifying water distribution points: a case study in Lapilang & Suspa regions, Nepal

This report provides sufficient details on the empirical work and methodological steps that have been done to formulate the problem of this case study.

1. Input data manipulation

1.1. Data collection and manipulation

The input data was of different sources and formats and thus it was an essential step to process it and then transform it into a form of Geodatabase file of ArcGIS. We summarize the processing as follows:

- Administrative boundaries: the admin boundaries (of VDC and ward levels) were derived by georeferecing and digitizing two static maps (see Figure 9). These maps were produced by Survey Department – Government of Nepal and were eventually delivered through Nepal Red Cross Society. The final version was edited by Z_GIS.
- Water schemes: the spatial data (incl. sources, lines, tanks, break-pressure tanks, existing tap-stands…etc.) were provided mainly as KML and GPS files. Further information on these schemes (incl. safe yield and quality of sources, capacity of tanks, diameter /type of pipes, water demand...etc.) were combined from tables and reports of RC recovery project in Dolakha.
- Buildings (population distribution): were provided as shapefile format by Z_GIS. The final number of persons per household was suggested by AutRC.
- Vulnerable HHs: 18 buildings were randomly selected.
- PoIs (schools and hospitals): combined from OSM extraction and field collection by AutRC.
- Terrain model (DSM): as TIFF (.tif) format by Z_GIS.
- Potential water distribution points: as shapefile by Z_GIS (manually selected for Dorpa community in lapilang VDC based on visual interpretation).

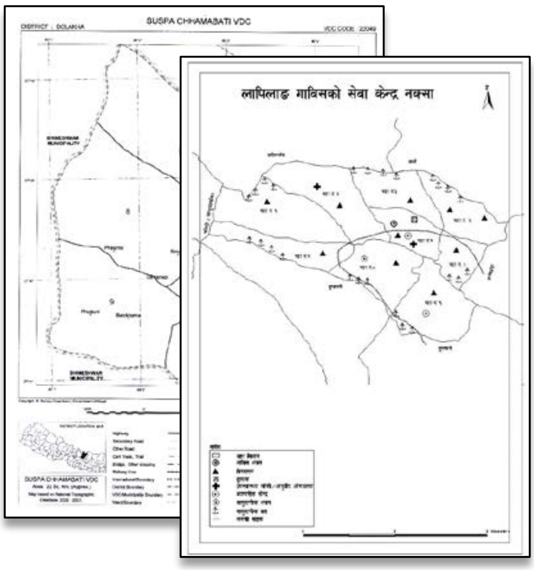

Figure 9: Maps of administrative boundaries of Lapilang and Suspa (VDC and ward division).

1.2. GIS data for Optimization

Several cell-statistics were performed in GIS and combined in a form of tables (tab-delimited .txt) to be used as input for the so-called *blackbox* in the optimization (mathematical programming) approach. The main steps are summarized as follows:

- Due to computational limitation that might be encountered in optimization process, the extent of the two regions was minimized (see Figure 10) and exported to raster of 25m cell size (instead of 10m, the case of GIS approach)
- For each region, export the 25m raster to points (i.e. base points)
- Perform spatial analysis: *Euclidean Distance* to calculate: 250m buffer of buildings and the distance to each water line in the study area - *Cell Statistics* to count per cell: the number of buildings, PoIs (incl. no of people for each) and whether or not it contains a vulnerable HH
- The output raster surfaces were extracted to the base points using the Spatial Analyst tool: *Extract Multi Values to Points* (see Figure 11):
- Finally export the attribute table of base points into excel and then tab-delimited text files (see the detailed content of tables in Figure 12).

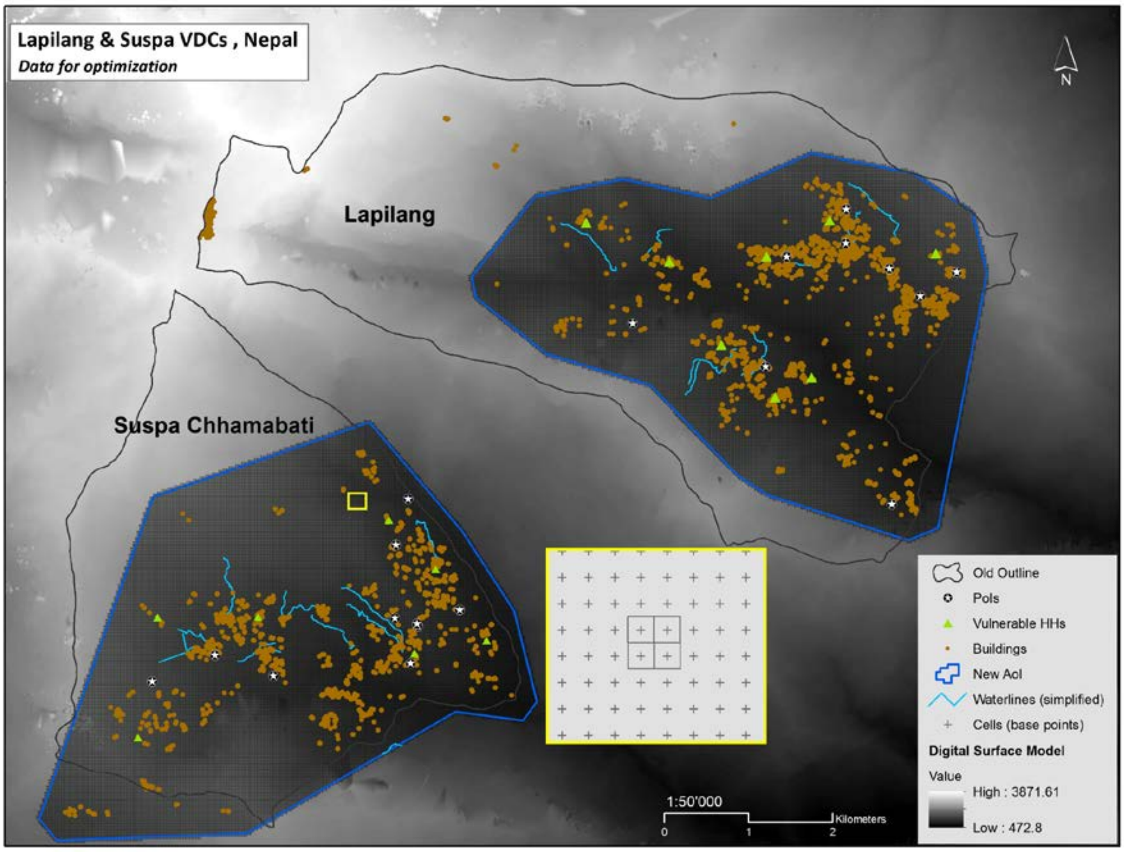

Figure 10: An explanatory map shows the GIS data that were delivered for the optimization approach.

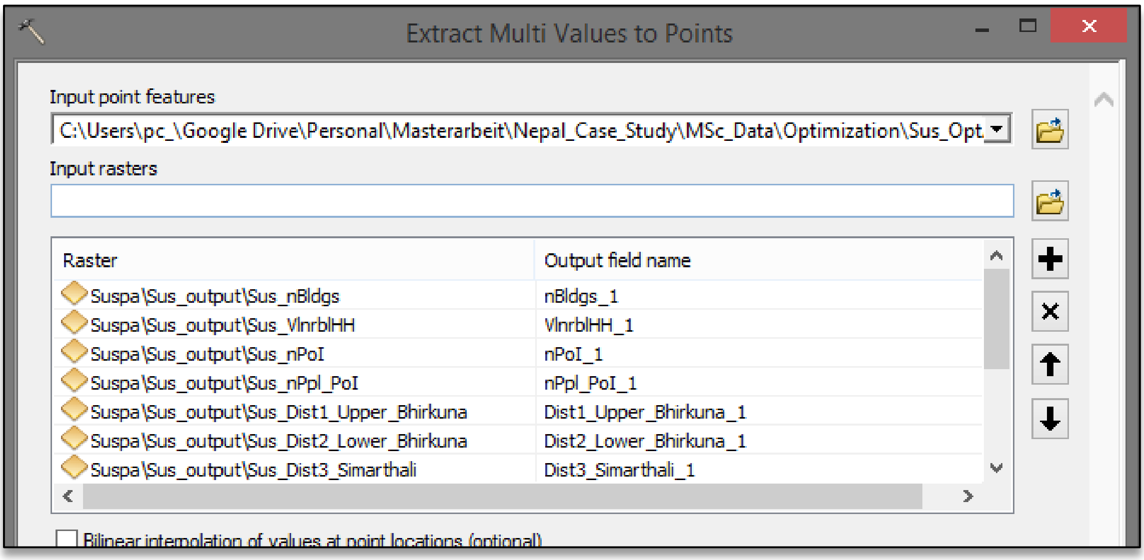

Figure 11: A screenshot shows the extraction of multiple raster values to the base points (example of Suspa VDC).

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Total nCells	Tot nBldgs	Min Coverage	Max Coverage	Horizontal Standards	Vertical Standards	Horizontal exceptions	Vertical exceptions	Tot nPipes	Num Closest Pipes to consider	Number People /HH	HH Daily demand/person	PoIs Coverage nPeople/tap	PoI Daily demand/person		
28307	1571	1	7	150	50	250	80	7	3	5	45	50	15		
SY1: Masipdojur	SY2: Simkomuhan	SY3: Terasung	SY4: Aaitabare	SY5: GhatteKhole	SY6: Dorpa	SY7: Suirekhola									
6220.80	24883.20	116640.00	103420.80	11664.00	124416.00	83203.20									
idCell	feasWT	X_coord	Y_coord	Z_coord	nBldgs	Contains Vulnerable HH	No. of PoI	nPeople in PoI	Dist1: Masipdojur	Dist2: Simkomuhan	Dist3: Terasung	Dist4: Aaitabare	Dist5: GhatteKhole	Dist6: Dorpa	Dist7: Suirekhola
1	0	411723.86	3070363.16	2253.06	0	0	0	0	1879.49	550.57	875.00	1311.73	2166.22	2688.52	2493.12
2	0	411673.86	3070338.16	2242.11	0	0	0	0	1823.63	575.54	886.71	1281.11	2126.76	2632.73	2452.04
3	0	411698.86	3070338.16	2244.41	0	0	0	0	1845.60	555.09	870.70	1283.79	2134.54	2654.36	2460.82
4	0	411723.86	3070338.16	2245.27	0	0	0	0	1867.65	535.02	855.13	1286.95	2142.57	2676.05	2469.82
5	0	411748.86	3070338.16	2248.07	0	0	0	0	1889.78	515.39	840.02	1290.59	2150.87	2697.80	2479.04
6	0	411773.86	3070338.16	2245.79	0	0	0	0	1911.97	496.24	825.38	1294.70	2159.43	2719.60	2488.47
7	0	411798.86	3070338.16	2238.47	0	0	0	0	1934.23	477.62	811.25	1299.28	2168.24	2741.46	2498.12
8	0	411823.86	3070338.16	2232.21	0	0	0	0	1956.56	459.62	797.65	1304.32	2177.30	2763.38	2507.99
9	0	411848.86	3070338.16	2231.22	0	0	0	0	1978.95	442.30	784.62	1308.63	2186.61	2785.34	2518.06

Figure 12: A screenshot of the final table (in Excel format) provided for optimization (example of Lapiland VDC). This table contains the extracted cell-based statistics and other information.

2. Implementation of MDCA in GIS

2.1. Derivation of criteria

2.1.1 Horizontal distance

As mentioned in the manuscript, due to the topography of study area, we found that: The difference between the Euclidean (straight-line) distance and the surface distance reached over 100m in cases where the terrain is immensely steep. This counts to over 40% of the total distance: 250m (see Figure 13). However, the surface distance was eventually used while it undoubtedly reflects more than the straight-line distance the actual distance that people have to walk.

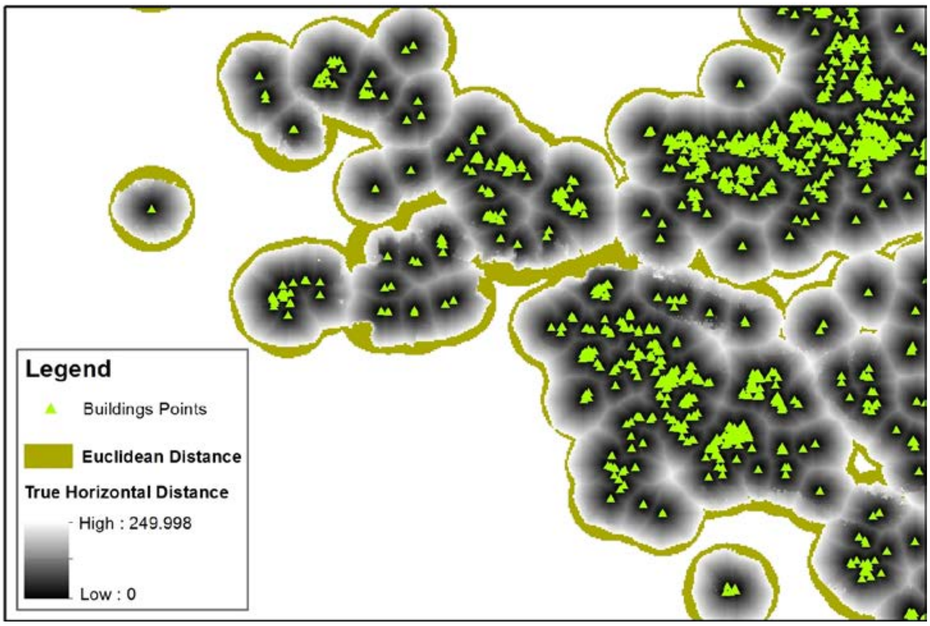

Figure 13: A map shows the difference between Euclidean and Surface horizontal distance in a mountainous area like Nepal.

2.1.2. Vertical distance

Several methods were initially examined to calculate the difference in elevation (absolute vertical distance $|d_V|$). We summarize two of these methods, as follows:

(1) Raster-based method:

- Using the inverse distance weighted (IDW) tool, we interpolated a surface from buildings using their elevation as Z value and these search parameters (search radius: fixed; max distance: 250m; min number of points: 30),
- We subtracted the interpolated surface from DSM (absolute value), and finally
- A condition was applied where the absolute values ≤ 80 (max value accepted for vertical distance).

By examining the results, we found that: the values of output surface (difference in elevation) are only comparable with the exact values of $|d_V|$ in the vicinity of buildings or in areas where the density of buildings is low (see Figure 14). These results were expected because it was based on interpolation.

(2) Vector-based method:

- A small extent of DSM was transformed to vector (point feature-class),
- In *Model Builder*, we used the *Feature selection* iterator to select one building, then compare its elevation with the elevation of each point within 250m buffer, and delete the points that have elevation values of 80m higher/lower than of the building's elevation.
- Using the *Feedback loop,* the second building is compared with the remaining points after first deletion and so on.

The results of this method are irrelevant, although they ensure the required range of $|d_V|$ for each building within a 250m buffer. (the resulted point feature is illustrated in Figure 15).

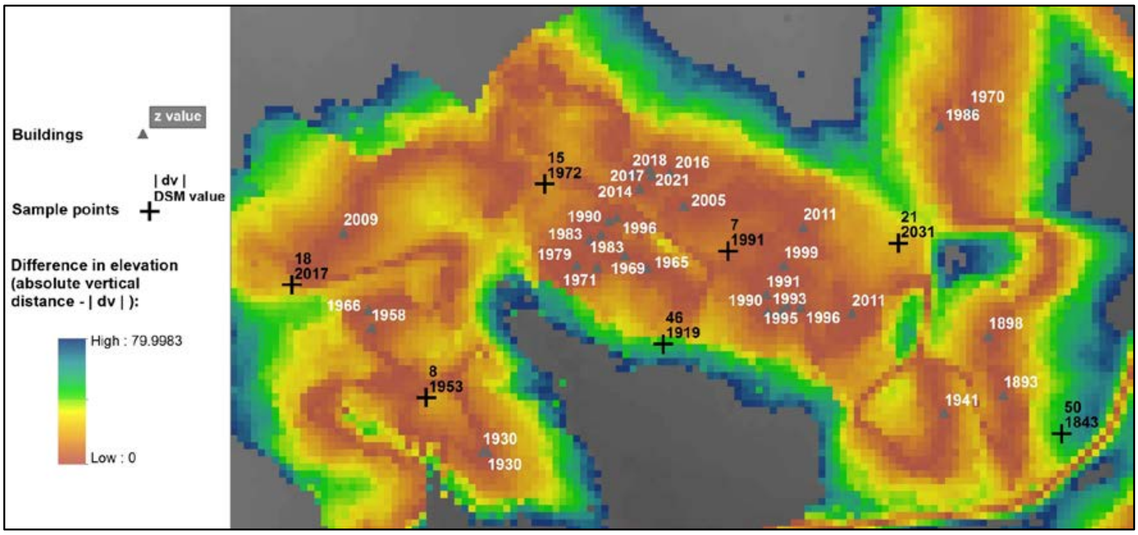

Figure 14: A map shows the results of raster-interpolation method to calculating the vertical distance.

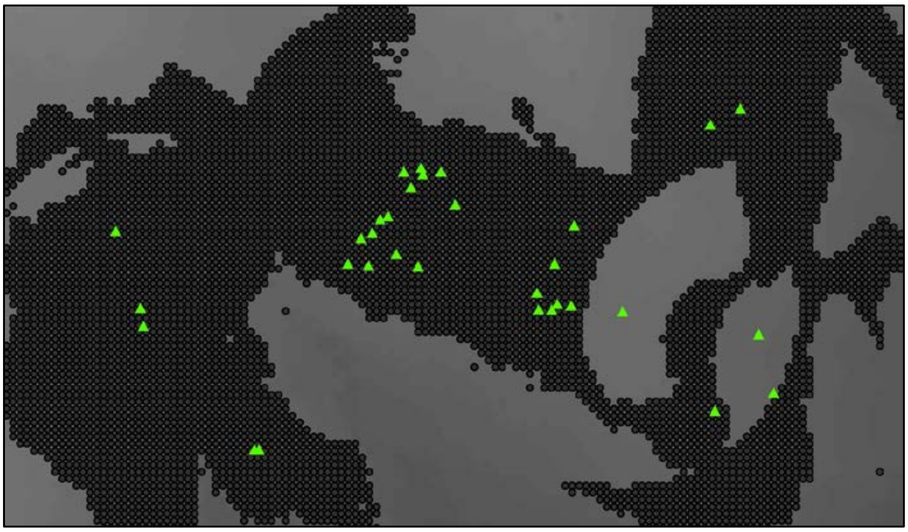

Figure 15: A screenshot shows the results of vector-based method to calculating vertical distance.

These methods in turn had led to finding the 'cumulative' vertical distance model. This model has been elaborated in Paragraph 3.3.2. of the manuscript. However, we present here the design of the model (model builder) and the resulted tool (interface) in Figure 16.

The criteria: Proximity to PoIs and vulnerable HHs & Coverage of buildings, were described in detail in the manuscript under Paragraphs 3.3.3. and 3.3.4. respectively.

2.1.3. Best connection model

Since this model was elaborated in in this paragraph, we only illustrate here the design of this model (Figure 17) and the resulted tool (Figure 18).

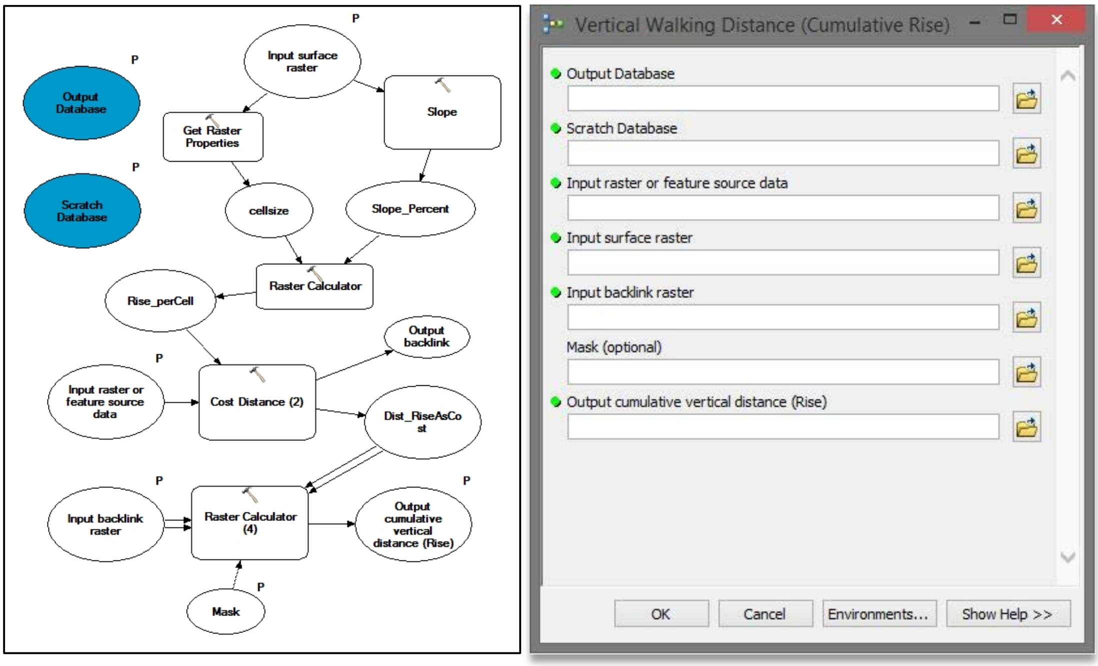

Figure 16: C*umulative vertical distance:* model design (left) and tool interface (right) – model builder, ArcGIS.

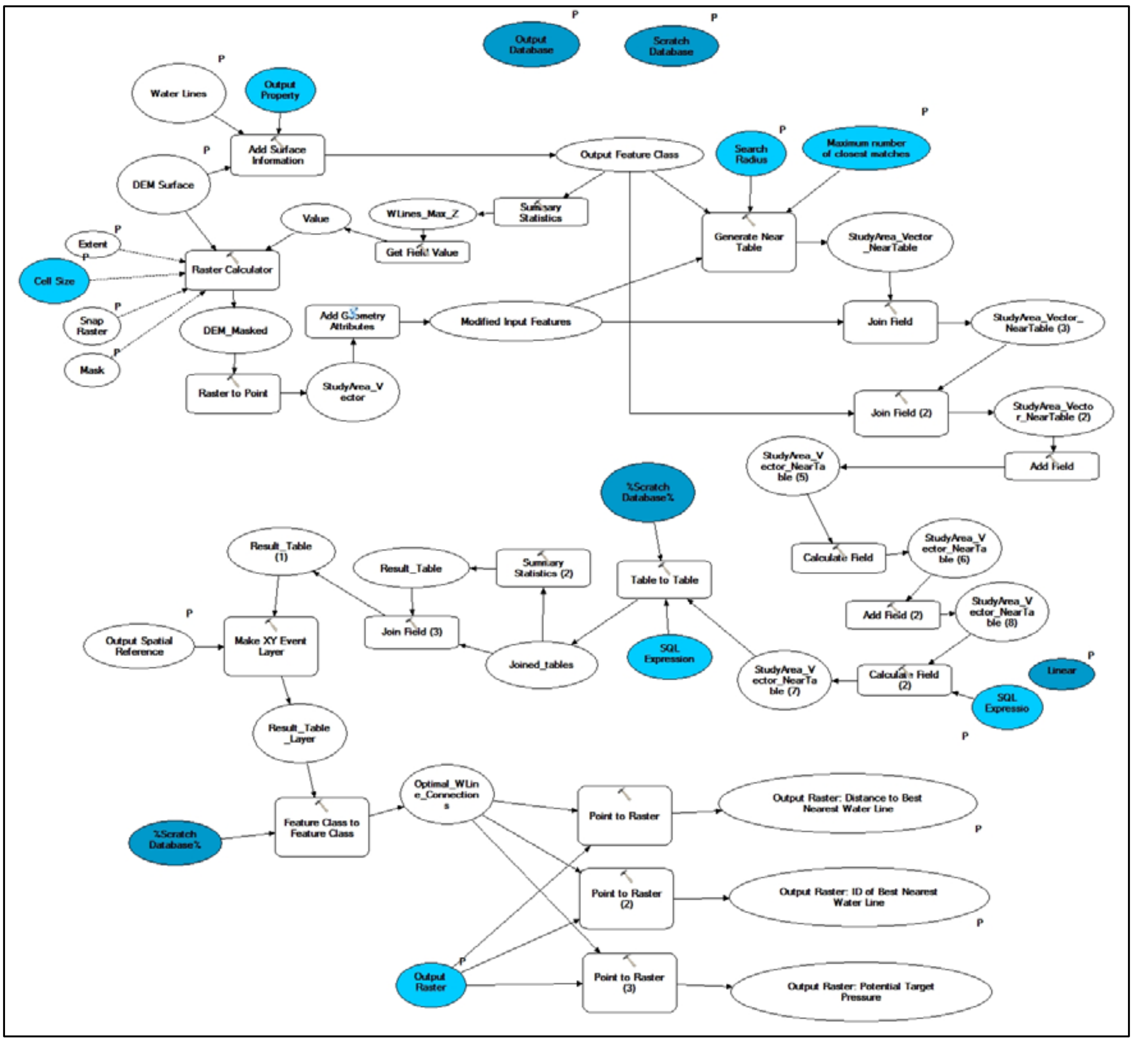

Figure 17: The design of *best water connection* model - model builder, ArcGIS.

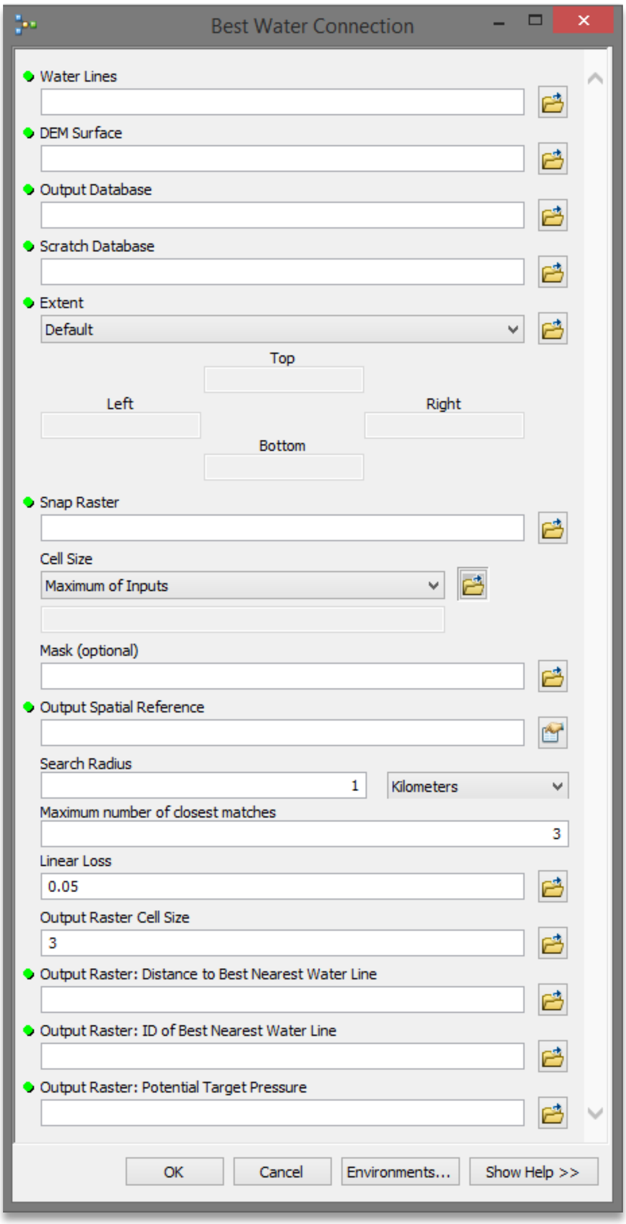

Figure 18: The tool interface of best water connection model.

2.2. Reclassification, weighting and aggregation of criteria

In this chapter we present the following figures:

- Figure 19: the derived criteria (pre-standardization),
- Figure 20: the standardization process (reclassification) – An example of horizontal walking distance,
- Figure 21: the aggregation (weighted linear combination – WLC) of the standardized criteria using *weighted overlay* tool. An example of water accessibility scenario.
- Figure 22: A model that organized the reclassification, assigning the weights (weighted overlay), and deriving three solution scenarios: Water accessibility, minimizing Cost and the best-fit which balances the two objectives.

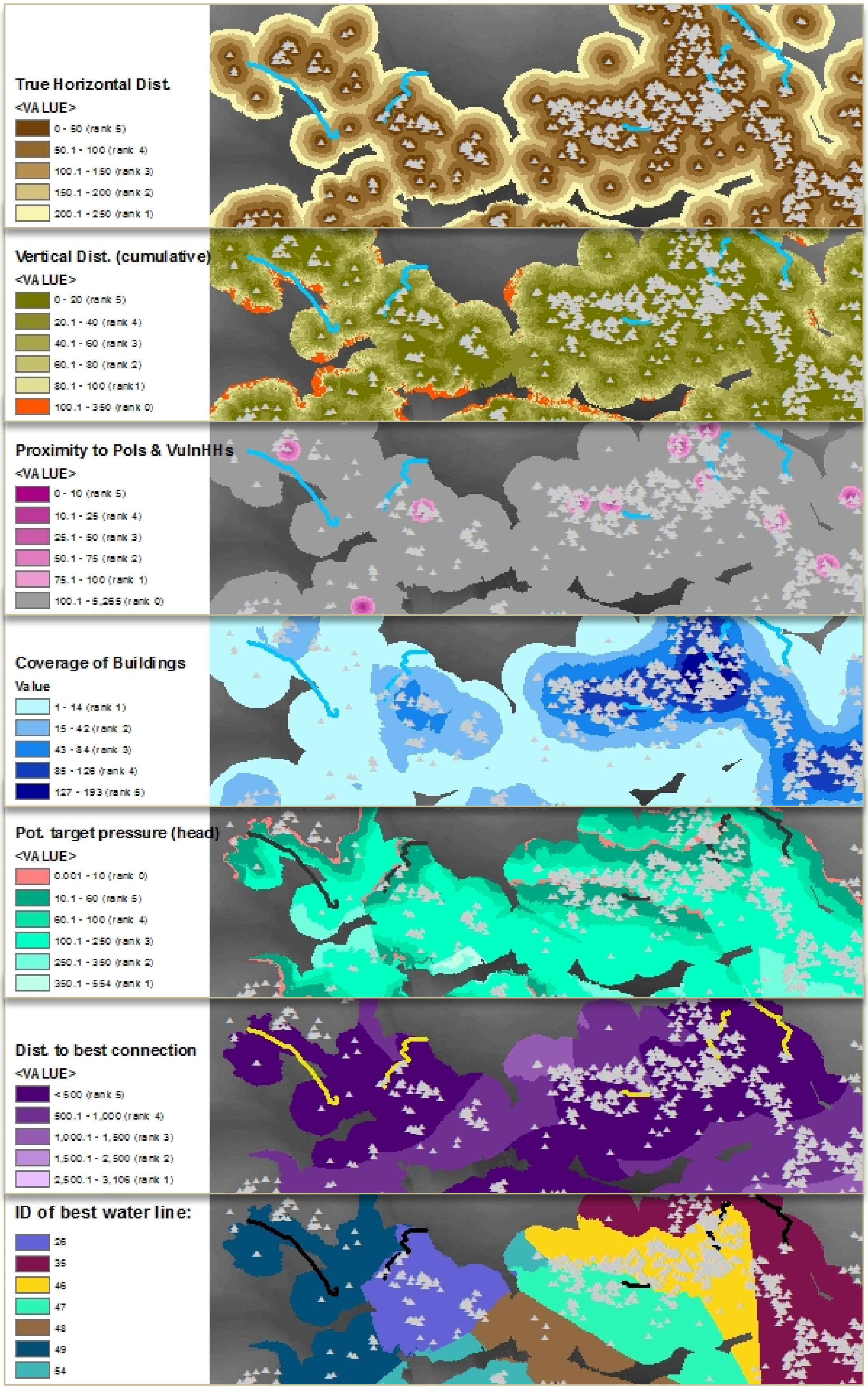

Figure 19: Derived criteria (first six layers from top) and the ID of the best nearest water line (last).

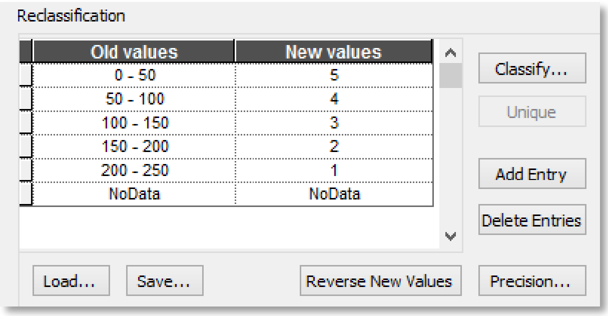

Figure 20: Reclassification - An example of horizontal distance.

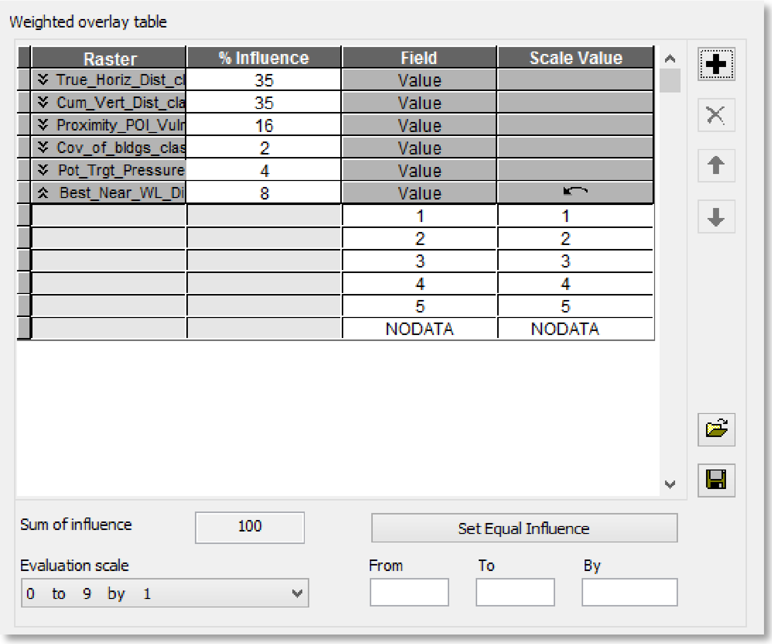

Figure 21: Weighted Overlay - An example of water accessibility scenario.

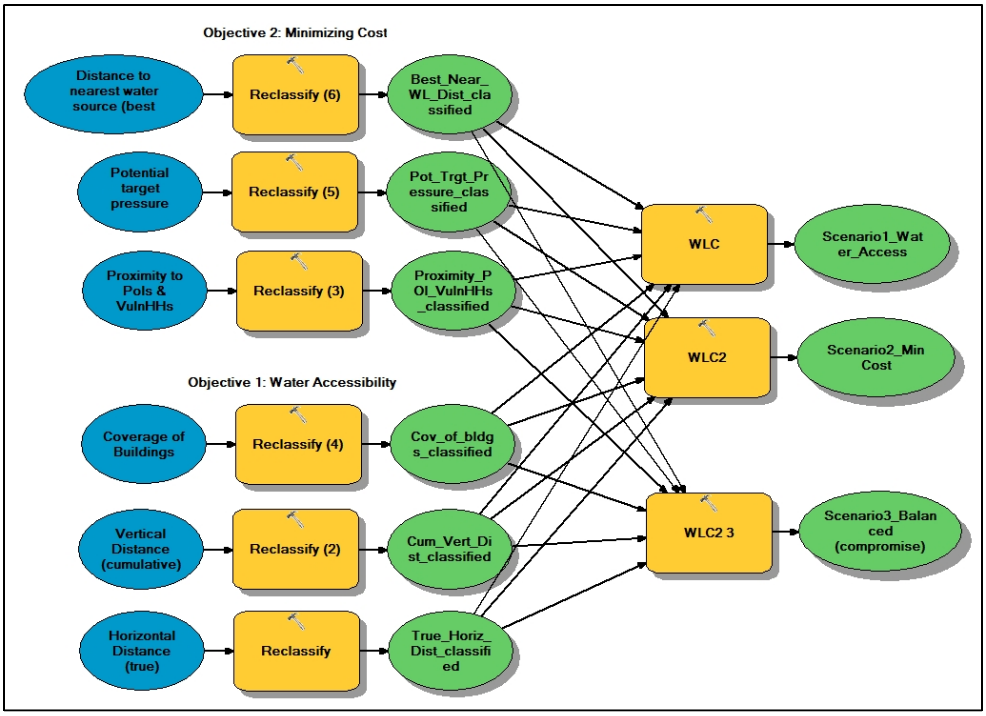

Figure 22: Reclassification and aggregation are organized in one model - model builder, ArcGIS.

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Vienna, 30.5.2018