AGU ADVANCING EARTH AND SPACE SCIENCE

Water Resources Research

RESEARCH ARTICLE
10.1029/2021WR029621

Key Points:

- Multi-objective optimization is applied to explore competing water infrastructure trade-offs in coastal Bangladesh
- The analysis uses groundwater salinity measurements, an extensive household survey and an audit of drinking water infrastructure
- The findings reveal alternative scenarios to improve water security and the implications for budget allocation and policy delivery

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Roman, O., Hoque, S. F., Ford, L., Salehin, M., Alam, M. M., Hope, R., & Hall, J. W. (2021). Optimizing rural drinking water supply infrastructure to account for spatial variations in groundwater quality and household welfare in coastal Bangladesh. *Water Resources Research*, *57*, e2021WR029621. https://doi.org/10.1029/2021WR029621

Received 15 JAN 2021
Accepted 7 JUL 2021

Optimizing Rural Drinking Water Supply Infrastructure to Account for Spatial Variations in Groundwater Quality and Household Welfare in Coastal Bangladesh

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Abstract Achieving water security requires reconciling multiple objectives while prioritizing scarce resources for the provision of safe drinking water supplies. We examine decision-making to invest in drinking water infrastructure in coastal Bangladesh where increasing saline intrusion in aquifers intersects with high levels of poverty for the 20 million people living in the coastal region. Multi-objective optimization is used to explore the trade-offs between two public policy goals: (a) maximizing overall access to improved water supplies (the greater good) and (b) maximizing access for the population with the lowest welfare (the greater need). To elucidate this trade-off, we make use of groundwater salinity measurements, an extensive household survey and an audit of drinking water infrastructure in 1 out of Bangladesh's 139 polders, which is home to nearly 60,000 people. We quantify the costs of a variety of drinking water supply options including deep tube wells, desalination plants, and piped systems. The recommended solutions are sequences of investments in water supply assets that are optimized to specified locations within the polder. The method is potentially scalable and transferrable to inform investments to achieve the Sustainable Development Goal (Target 6.1) of universal access to safe and affordable drinking water.

1. Introduction

The 2030 Agenda for Sustainable Development, as articulated in Target 6.1, aims to achieve universal and equitable access to safe and affordable drinking water, using the proportion of population using safely managed drinking water services as the associated indicator (UN, 2015). Despite the progress in increasing "access" to technologically improved sources as part of the Millennium Development Goals (MDG), as of 2017, over 2 billion people lack safely managed drinking water and 785 million do not even have "basic" services (WHO/UNICEF, 2019). Progress to improve water security is most challenging in contexts where financial and institutional resources are limited and where water resources are threatened by chronic (e.g., groundwater contamination) and acute (e.g., floods and cyclones) threats. Bangladesh typifies these chronic and idiosyncratic water security risks, particularly in the coastal region, where around 20 million people live precarious lives with uncertain futures (M. A. Hoque et al., 2016; Shammi et al., 2017).

The financial resources that are available for investment of water supplies are inevitably scarce, so governments and development organizations face difficult prioritization problems. Should they adopt a utilitarian approach to maximize for the greater good for the greatest number of people or a Rawlsian social justice approach which prioritizes the "most in need" (Sen, 1974)? The question is complicated by the interaction between public works to provide water supplies and private actors who are willing and able to pay to satisfy their own water needs. In this case, actions by the state may actually crowd out private investments. These competing policy choices are not irreconcilable but present a sequencing and prioritization problem compounded by identification and measurement issues. Without information on the welfare or infrastructure distribution, information asymmetries can lead to perverse outcomes in the spatial distribution of infrastructure, as has been documented in arsenic affected areas in Bangladesh (van Geen et al., 2016). New high-resolution spatial datasets are providing opportunities to optimize the sequence of investments in public water supply infrastructure, in particular to address the needs of the poor who are often most exposed to saline drinking water while being least able to pay for alternative water sources.

The contribution of this article is threefold. First, we specify a spatial optimization model informed by a comprehensive set of infrastructure, environmental, and social data from coastal Bangladesh. Spatial optimization for site selection has been applied to a variety of problems, such as protection from natural hazards (Chen et al., 2001; Rincón et al., 2018), waste management (Babalola, 2018; Sharifi, 2004), and location of critical infrastructure (Bolouri et al., 2018; Zhang et al., 2016) including water supplies (Singh et al., 2017). However, no previous studies have examined the challenge of providing safe water supplies in a heterogeneous hydrogeological context with a variety of alternative infrastructure types with different spatial and economic characteristics. Second, we estimate and compare public policy goals to maximize drinking water infrastructure for the "greater good" and the "greater need." This reflects on the MDGs which focused on increasing first time "access" to improved water supply, compared to the SDGs that emphasize on providing safe and affordable "services" with particular attention to "leaving no one behind." Third and finally, we discuss the policy implications and application of the approach with a view to progress on the SDGs in Bangladesh and more widely.

We should emphasize from the outset that sustainable provision of water supplies should not simply be regarded as a technical optimization problem, even when welfare issues are central to the analysis. The many failures of drinking water supply projects to properly acknowledge local and culture context are widely documented as are issues associated with inadequate maintenance of assets resulting in failure of water supplies (Foster & Hope, 2016; Whaley & Cleaver, 2017). There will be local community and institutional considerations to take account of when designing an investment program. Thus, the results of any optimization should be regarded as providing guidance on possible efficient investment sequences rather than being in any way prescriptive. Nonetheless, the infrastructure prioritization problem in the context of heterogeneous population and aquifer characteristics, a large array of existing water supply infrastructure and a range of alternative supply options, is non-trivial. Decision makers, be they in government departments or development organizations, require analysis in order to understand how to navigate these complex interacting factors. This article seeks to demonstrate a methodology that provides that guidance, while recognizing that water professionals will have to account for several other factors when implementing investment programs.

2. Drinking Water Security in Bangladesh

Tubewells serve as the main source of drinking water in rural Bangladesh, with access to water for rural populations increasing from 65% in 1990 to 97% in 2015 (General Economics Division, 2015). In June 2019, the Department of Public Health and Engineering (DPHE), the national lead agency for provision rural water supply, reported a national coverage of 85 people per public water point, representing a total of 1.8 million waterpoints, of which 90.9% were functional. These waterpoints included 1.27 million shallow and 0.47 million deep tubewells, while the remaining are split between pond sand filters, ringwells and rain water harvesting systems (DPHE, 2019). However, the coverage increases significantly when private tubewells are taken into account. While there are no systematic records of private waterpoints, the number of private tubewells is thought to be eight times higher than public ones (MLGRDC, 2011), with estimated coverage ranging from 6.7 people per tubewell in areas with shallow freshwater aquifers to more than 12.4 people per tubewell in coastal areas exposed to high groundwater salinity (Fischer et al., 2020).

Despite the growth of public and private tubewells, achieving drinking water security remains a challenge due to naturally occurring arsenic and salts in groundwater. Located on the lower reaches of the Ganges-Brahmaputra-Meghna delta, Bangladesh has highly productive aquifers within the unconfined sediments of the Holocene age. However, these geologically young sediments are prone to developing and preserving high concentrations of arsenic, particularly within depths of 30–150 m that coincide with the optimum well depth (Edmunds et al., 2015). Groundwater arsenic, formally recognized by the government and media in 1993, was detected in concentrations above 50 μg/l in 29% of the shallow tubewells and 2% of the deep tubewells tested as part of a national blanket survey of five million tubewells conducted between 2000 and 2005 (Ahmed et al., 2006). In 2019, a national stratified random sample of households identified

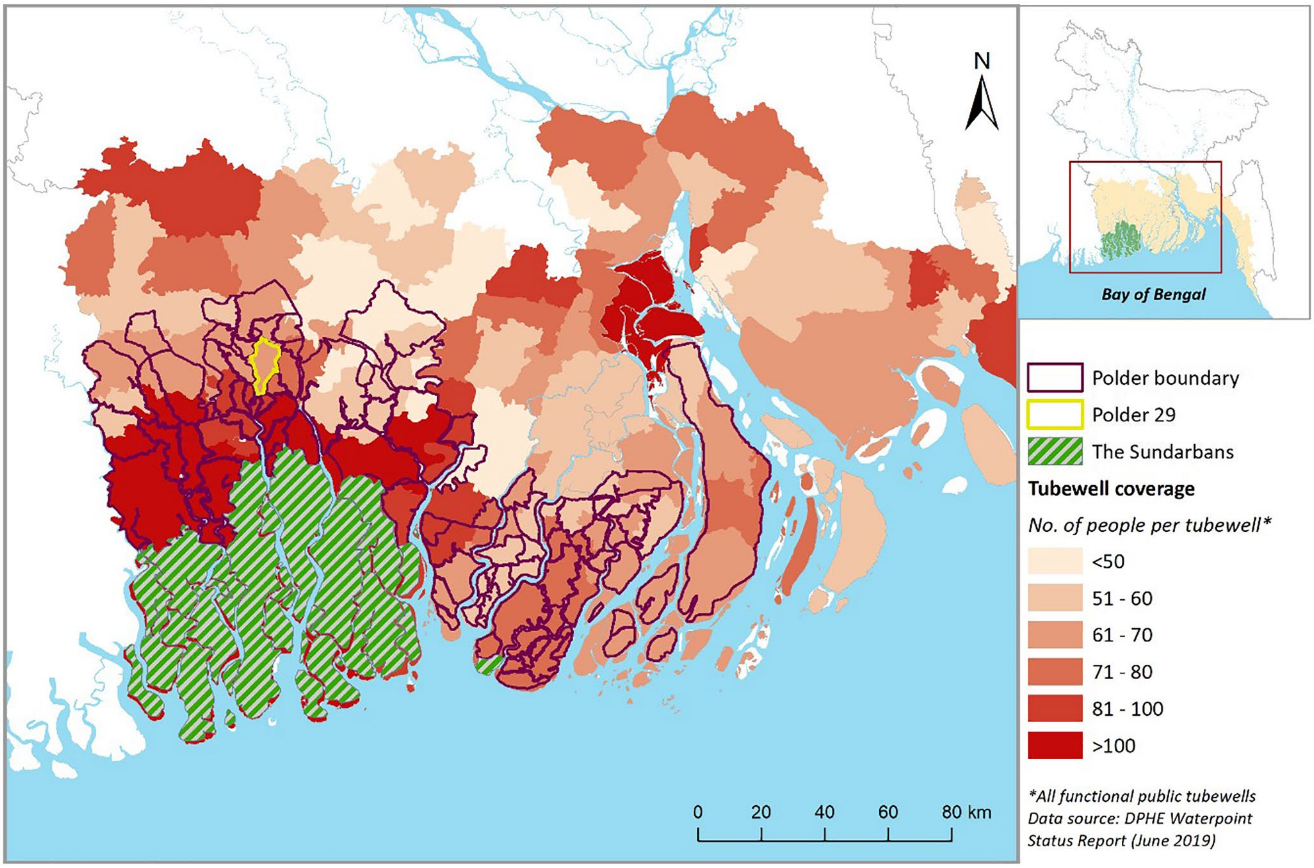

Figure 1. Coverage of public tubewells in the coastal region.

18.6% and 11.8% with arsenic above 10 μg/l and above 50 μg/l, respectively (UNICEF/MICS, 2019). This corresponds to approximately 31 million people with varying levels of risk, with the richest (top) welfare quintile having the lowest exposure, and limited difference being observed between the other quintiles (range: 18.2%–21.3%).

Besides arsenic, groundwater salinity is a major concern in the coastal zone, where the upper shallow (or first) aquifer (<90 m) is contaminated with varying levels of salinity, causing people to bore deeper tubewells, and draw water from the main (or second) aquifer (>90 m). However, salinity in coastal aquifers exhibit high spatial and vertical heterogeneity and potable water may not be available even at greater depths (A. Islam et al., 2013; Zahid et al., 2013). In Bangladesh, the official permissible threshold level of salt in groundwater for the coastal districts is set at 1,000 ppm or 1,500 μS/cm, which is higher than the standard set at 600 ppm for the rest of the country (MLGRDC, 2011). Tubewell coverage is very low in the south-western polders near the Sundarbans (Figure 1). Here, salinity in the first and second aquifers typically exceed 8,000 and 6,000 μS/cm, during the dry pre-monsoon season (Zahid et al., 2013). In the wet monsoon season, salinity levels usually are below 4,000 μS/cm, with the lowest values (<2,000 μS/cm) being recorded in Jessore, Narail, and Satkhira in the south-west and highest levels (>6,000 μS/cm) occurring in Pirojpur, Jhalokathi, Lakshmipur, and Noakhali in the south-central area (Zahid et al., 2013). Thus, alternative sources and technologies, including pond sand filters, rainwater harvesting, small-piped schemes, managed aquifer recharge, and reverse osmosis systems are widely used as well (Benneyworth et al., 2016; A. Islam et al., 2013). While rainwater harvesting and pond sand filters are two technologies that can be used in the saline areas, the former does not have the capacity to provide year-round supplies while the latter does not consistently meet water quality requirements.

The SDG Financing Strategy 2017 estimated an additional financial requirement of USD 9.34 billion to achieve SDG 6.1 and SDG 6.2 (General Economics Division, 2017). While the government has made progress on WASH financing, with allocations increasing from USD 309 million in 2007–2008 to USD 784 million in 2017–2018, the relative growth is disproportionately low compared to the substantial growth of GDP and the national budget during this period (Rahman et al., 2018). Moreover, there are significant spatial inequalities in budget allocation with metropolitan cities receiving 16 times more funds than the hard-to-reach regions (char lands, hilly areas, and the coastal belt) combined. Public sector funds accounted for about half of the WASH budget allocation in 2017–2018, with the remaining 30% from household contributions and 20% from development assistance (Rahman et al., 2018).

Distribution of public funds for water supply infrastructure development is not even, and usually not based on hydrogeological risk and poverty mapping, unless such areas are targeted by particular projects (van Geen et al., 2016). Allocation of funds from the government's Annual Development Program to the 492 upazilas (sub-districts/Tier-3 administrative boundary) is based on factors, such as the upazila's population size and area, regardless of its need and availability of other resources like tax revenues (JICA, 2015). The money provided to each upazila is then disbursed amongst the union parishads (Tier-4 administrative boundary)—the local government institutions legally mandated to deliver rural water services. In practice, however, limited fiscal autonomy and revenue discretion restricts the effectiveness of union parishads, which continue to rely on DPHE at the national level for planning and implementation (JICA, 2015). The union-wise division of funds also restrict implementation of large-scale projects that can benefit people, regardless of administrative boundaries.

Development of rural piped water schemes has almost always been project-based, with DPHE collaborating with donor organizations like UNICEF, DANIDA, UNDP, and the World Bank (Ibrahim, 2004). Small piped-water schemes target the safest source in the area and provide a centralized means of water quality control and treatment while remaining manageable by the community (Mink et al., 2019). Only 2% of the rural population in Bangladesh has access to piped water, mostly in locations with high arsenic or salinity (World Bank, 2018). These systems often encounter disinfection failures, intermittent supplies and low pressure, due to poor operation and maintenance caused by financial and socio-political issues (Ahsan et al., 2017). As per the Water Sector Development Plan (2011–2025), the government aims to increase rural piped water coverage to 10%–20% by 2025 (MLGRDC, 2011). Since 2005, the World Bank has been trying to leverage private sector funds through public-private-partnership models; however, low-cost recovery potential and lack of investor interest has been a major challenge. While many piped schemes have been constructed under this model, in practice, the private sector contributions have been paid by NGOs or wealthy individuals with charitable motives (World Bank, 2016).

Reverse osmosis-based desalination plants are gaining popularity in coastal Bangladesh, with both the government and NGOs promoting this technology since the early 2010s (Shamsuzzoha et al., 2018). These plants have a production capacity of about 20–60 m^3 per day and mainly purify brackish shallow groundwater by passing it through a semi-permeable membrane. Analysis of physio-chemical and bacteriological quality of 10 desalination plants in Satkhira and Khulna districts found that all plants met WHO and national drinking water standards for pH, calcium, magnesium, nitrate, sulfate, and fluoride concentration, with 10% and 20% exceeding the limits for total dissolved solids and electrical conductivity, respectively, due to high contamination in feed water (M. A. Islam et al., 2017). While technological solutions are available to deal with the salinity crisis, the uncoordinated public and private investments in infrastructure, in absence of data on hydrogeological risks and poverty distribution, are failing to reach the excluded pockets of unserved rural population (S. F. Hoque et al., 2019). Ensuring universal and equitable access to safe and affordable drinking water services, as articulated in SDG 6.1, requires investment decisions to be guided by timely and accurate local level information on aquifer availability and quality, existing water supply infrastructure, and household socio-economic characteristics.

3. Methodology

Here, we apply spatial multi-criteria decision analysis (MCDA) or GIS-based MCDA (Malczewski, 1999) to model the locations and sequences of investment in water supply infrastructure with a view to cost-effectively improve access to drinking water with salinity below 1,000 ppm. We focused on three objectives: (a) maximize the total population served with safe drinking water supplies, (b) maximize the number of low

Table 1
Primary Data Collection Methods (Refer to S. F. Hoque et al. [2019] for Details)

Method	Description
Water infrastructure audit	Recorded the locations, installation dates, technical specifications, ownership, maintenance, and usage patterns of 2,805 (all) tubewells in the middle and southern part of the polder, 354 (sample) tubewells in the north of the polder, 19 pond sand filters and three small piped systems
Water quality	Measured electrical conductivity *in situ* for all tubewells included in the water audit, using field kit CLEAN CON30 Tester, 0–20.00 mS/cm, with further tests in the laboratory using Ohaus ST300C-G Portable Conductivity Meter, 0–199.9 mS/cm. Values were converted from mS/cm to ppm using a conversion factor of 1 mS/cm = 500 ppm.
Household survey	Collected quantitative data on various indicators of multidimensional welfare and drinking/domestic water services for 2,103 households selected through a stratified random sampling technique

welfare people served (classified as households in the bottom welfare quartile), and (c) minimize the capital investment cost of providing drinking water supplies. Several geographic decision alternatives, or courses of action, are evaluated to find actions (what to do) and locations (where to do it). Mathematically, the problem is formulated as a development of suitability surfaces and a search for optimal infrastructure locations, to which households are assigned. This type of spatial MCDA is commonly known as an incapacitated facility location-allocation problem (Harris et al., 2009; Villegas et al., 2006; Zhang et al., 2016). While the demonstration is for a specific location in the coastal Bangladesh, with adequate data it could be applied to the entire coastal zone.

3.1. Study Site and Data Sources

The study is conducted in Polder 29 covering five unions across Dumuria and Batiaghata upazilas in Khulna district. It is 1 out of 139 polders in coastal Bangladesh, constructed in the 1960s and 1970s to promote agricultural production by controlling flow of saline tidal water through sluice gates. Polder 29 has more than 60,000 people (BBS, 2011) making a living from agriculture, aquaculture, and casual labor. The spatial optimization model used in this article draws on biophysical and socio-economic data from a water infrastructure audit, a household welfare survey, and water quality tests conducted in 2018. Table 1 summarizes these methods, the details of which are described in S. F. Hoque et al. (2019). The datasets can be found in S. F. Hoque et al. (2021) and Salehin et al. (2021).

The water infrastructure audit (Figure 2) was carried out as a complete census for the southern half of the polder, while a sample was available for most of the northern part of the polder where there is the greatest existing provision of tubewells. Only a portion of the northern region had a complete water infrastructure census, therefore, the sample of deep tubewells in the northern part of the polder was augmented using the following methodology: (a) a kernel density estimator was used to construct a continuous spatial density surface (Silverman, 1986) of deep tubewells and households in sampled and censed areas; (b) deep tubewells and households densities in censed areas were correlated using a spatial regression (ordinary least squares); (c) assuming some degree of uniformity in the northern region, the regression model for the censed areas was used to estimate the expected deep tubewells/household density in the sampled areas; and (d) the estimated deep tubewells were randomly allocated in the sampled area.

Analysis of the primary data, as published in S. F. Hoque et al. (2019) and S. F. Hoque and Hope (2020), revealed how spatial variation in groundwater salinity influenced water use behaviors. In the north and central parts of the polder, salinity in the shallow (<90 m) and deep (>90 m) aquifers was usually below 1,000 ppm and increased gradually toward the southern part of the polder where suitable deep aquifers were not found, as shown in Figures 2a and 2b. This, in turn, determined the different types of water supply infrastructure installed and its implications for household drinking water security. Of the 2,103 surveyed households, 58% used deep tubewells as their main source of drinking water, with 13% using shallow tubewells, 11% depending on pond sand filters, 9% using one of the three piped systems, 7% purchasing water

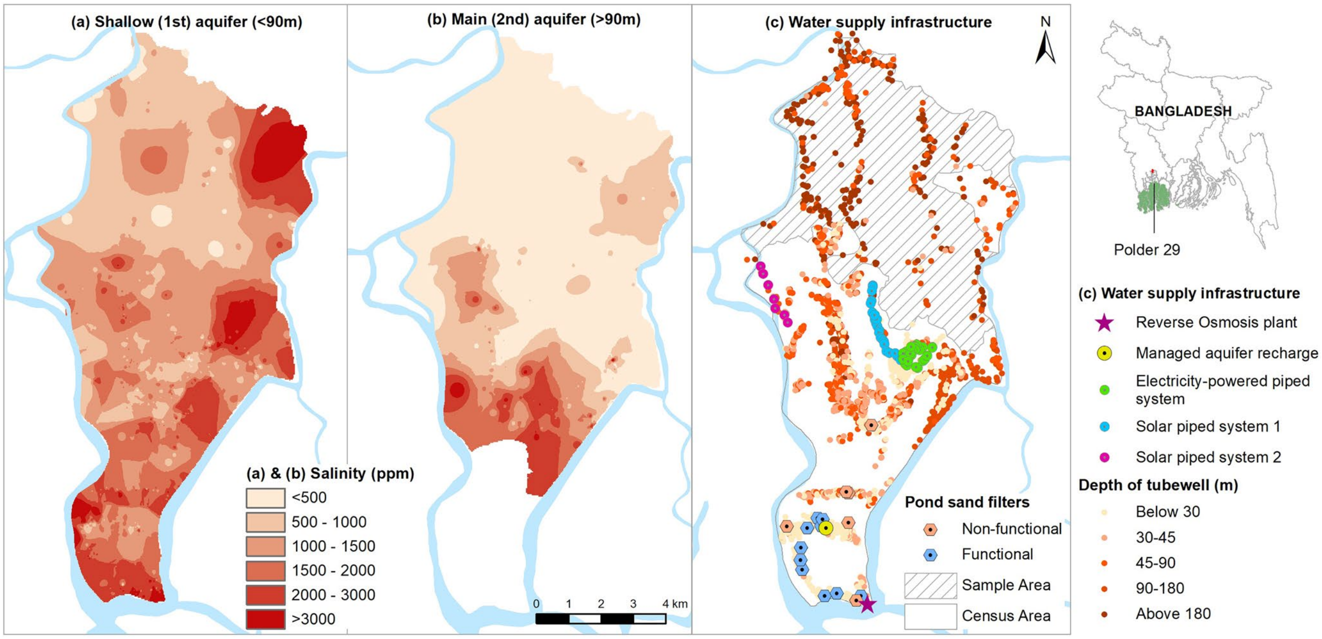

Figure 2. Maps of Polder 29 showing locations of (a) salinity measures in the shallow (first) aquifer, (b) salinity measures in the main (second) aquifer, and (c) censed and sampled drinking water supply infrastructure.

from informal vendors, and 2% using rainwater. Welfare inequalities were observed in type of source accessed and hence, collection time.

Table 2 shows the total number of tubewells in both the census and sample areas, disaggregated by depth and salinity. In the past decade, the number of privately funded tubewells quadrupled, comprising 78% of all tubewells in 2018. About 96% of the deep tubewells were used for drinking, compared to 15% of shallow tubewells, indicating people's preference of having a private source within their premises for non-drinking purposes.

Water salinity of shallow (<90 m) and deep (>90 m) tubewells were then used to map the spatial distribution of groundwater salinity in the shallow (first) and main (second) aquifers respectively using a natural neighborhood interpolation technique in ArcGIS 10.5. The main (second) aquifer has lower values of salinity

Table 2
Number and Salinity of Tubewells and Pond Sand Filters Used for Drinking in Polder 29

		No. and salinity of waterpoints used for drinking		
Infrastructure type	No. of functional waterpoints	<1,000 ppm	>1,000 ppm	Total
Pond sand filters (total = 19)	11	2	9	11
Tubewells (total = 3,159)	2,784	534	661	1,195
Deep (>300 ft)	**956**	**519**	**412**	**931**
Private	280	167	105	272
Public	676	352	307	659
Shallow (<300 ft)	**1,802**	**10**	**242**	**252**
Private	1,751	10	228	238
Public	51	0	14	14
Depth not known	**26**	**5**	**7**	**12**

Note. "Deep", "Shallow" and "Depth not known" are subcategories of Tubewells. "Deep" and "Shallow" are then subdivided in Private and Public, therefore the differentiation in bold is suggested.

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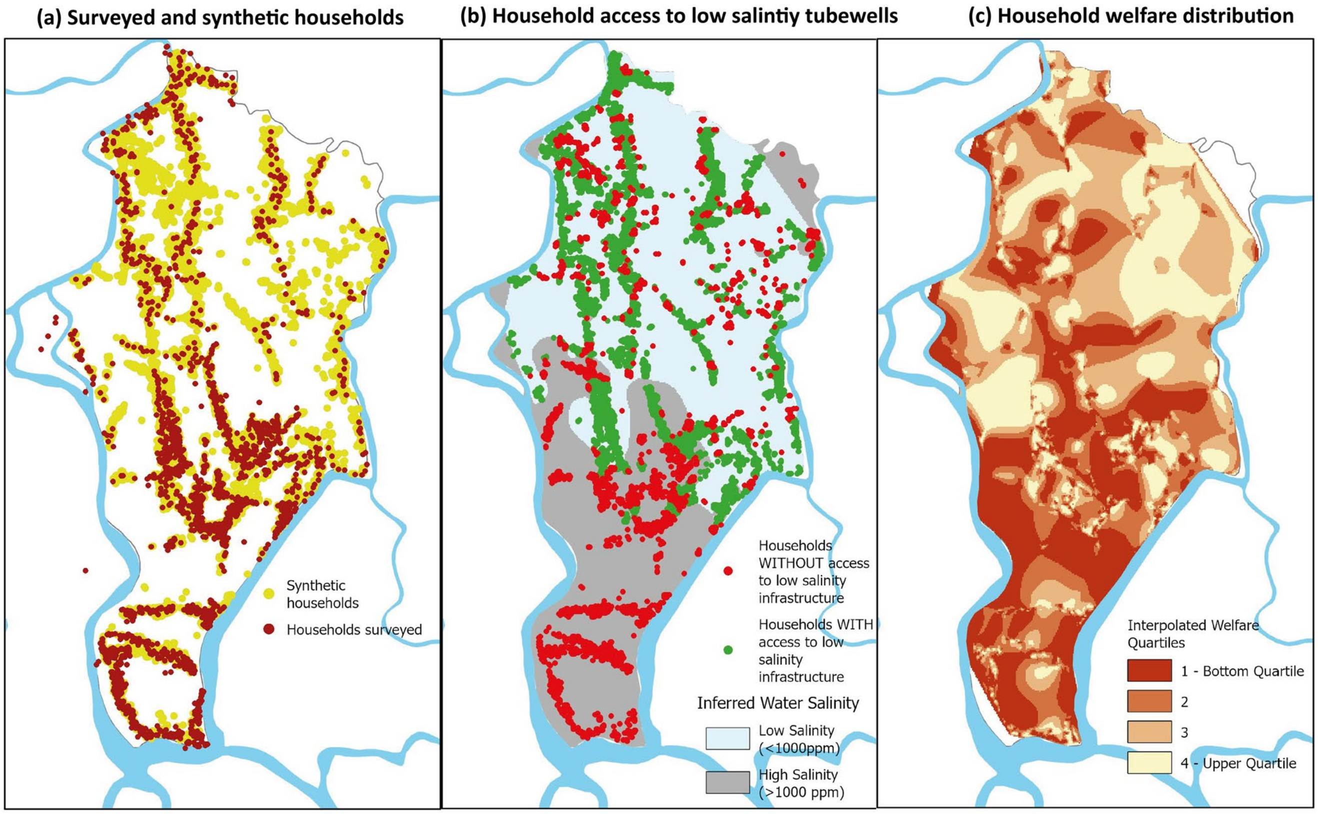

Figure 3. (a) Surveyed and synthetic households, (b) inferred water salinity and analysis of households with and without access to low salinity water supplies, and (c) interpolated welfare quartiles for households without access to low salinity water supplies.

other than in the southern part of the polder where salinity levels are high in both aquifers. Figures 2a and 2b show that the southern portion is characterized by brackish groundwater (salinity > 1,000 ppm). Therefore, tube wells are considered a suitable drinking water supply option for the north, while the south needs to rely on a different water source (rainwater) or water treatment technology (desalination). Data from the household survey was used to generate welfare indices through principal component analysis (PCA) of 10 selected variables (see Table S1). We extracted all components with eigenvalues >1, followed by a *k*-means cluster analysis of the factor scores of the first principal component (PC_1). This enabled categorization of households into welfare quartiles.

As the household survey was not a complete census, household sizes and demographics were allocated synthetically to building locations using the methodology described in Rubinyi et al. (2021). This method involved (a) generation of synthetic households from the full census dataset and inclusive of selected attributes to the lowest reasonable level of aggregation; (b) spatial disaggregation of household units to small areas using dasymetric modeling techniques; and (c) pairing of synthetic households with location of household units based on the population distribution identified in the dasymetric model. Microdata from the 2011 National Census, led by the Bangladesh Bureau of Statistics, released through the Integrated Public Use Microdata Series for Dumuria Upazila were used to extrapolate household composition and attributes. Building locations were obtained from a "mapathon" in which volunteers mapped 22,000 building footprints from OpenStreetMap (https://www.openstreetmap.org). The resulting 14,903 household locations, representing 59,814 people are showed in Figure 3a, along with locations of the 2,103 surveyed households.

3.2. Characterizing the Population Without Access to Low-Salinity Drinking Water Supplies

The geolocated synthetic household data, including welfare attributes, was combined with the drinking water infrastructure location to estimate access to low-salinity drinking water. Deep tubewells with salinity below 1,000 ppm were selected and their coverage area was calculated using a radius of 150 m in accordance with the Bangladesh National Strategy for Water Supply and Sanitation (LGD, 2014). For the piped system coverage, the same radius of 150 m from each individual tap was used for coverage calculation. The population modeled for Polder 29 was 59,814 people, from which 41,827 have access to low salinity drinking water supplies (covered population; Figure 3b). For the remaining 17,987 people, who did not have access to low-salinity water (uncovered population), an interpolated mean surface of household welfare quartiles was developed (Figure 3c). Most of the total uncovered population (72%) and the uncovered population in the bottom quartile (83%) are located in the high salinity southern region.

3.3. Spatial Optimization

The decision variable is the set of water supply investments P, where each $p \in P$ is denoted by a triplet (x, y, s) where (x, y) are the cartesian coordinates of the water supply location and s is the type of water supply infrastructure, of which there are n different types. $c(s)$ is the fixed cost for implementing water supply s. There are m households in the polder each of which contains a_j people. If household j is within the designated distance of a low-salinity water supply, it is denoted the indicator variable $v_j = 1$; otherwise $v_j = 0$. If a household has access to more than one low-salinity water supply, it is allocated to the nearest supply. Each member of the household is given the same welfare indicator w_j, whereby $w_j = 1$ if household j falls in the bottom quartile of welfare, otherwise $w_j = 0$.

The objectives are formulated as follows:

Objective 1: Maximize overall access:

$$\max \sum_{j=1}^{m} v_j a_j$$

Objective 2: Maximize access to low welfare population:

$$\max \sum_{j=1}^{m} v_j w_j a_j$$

These objectives are applied subject to a cost constraint $c_{\max}$, which is the budget available for investment in water supply infrastructure:

$$c_{\max} \geq \sum_{p \in P} c(s)$$

The allocation problem is implemented on a discrete 30 m × 30 m grid over the entire model domain. In each cell, the number of additional (low welfare) households that would be served were a new supply to be located in that cell can be readily computed. This formulation was applied through GIS software using spatial analysis of suitability surfaces (raster data models) built as the objective functions.

To explore the trade-offs between Objectives 1 and 2, subject to a range of different cost constraints, we use the weighting method (Malczewski & Rinner, 2015), which scales between a set of single-objective problems by varying relative weightings for the objective functions. For our two-objective problem with objectives O_1 and O_2 and cost constraint $c_{\max}$, we construct the locus:

$$\max\left[qO_1 + (1-q)O_2\right] : q \in \{0, 1\}$$

where q was varied in intervals of 0.1 yielding 11 points on each Pareto frontier.

Table 3 summarizes the costs of drinking water supply options, which have been obtained through consultation with UNICEF and data collected during the field studies. An a priori examination of the costs indicates that deep tubewells are the most cost-efficient intervention for the areas with freshwater aquifers (i.e., the northern region). In the south where the aquifers have high salinity, other costlier options need to be considered: (a) reverse osmosis desalination plants, (b) piped systems from a deep tubewell source in a freshwater area (these systems should be located within 1 km of the fresh/saline boundary, and (c) piped systems from a desalination plant. The first two options already exist in Polder 29 with a good overall performance. The third option is a combination of the former two, with the intention to use the location

Table 3
Costs of Alternative Drinking Water Supply Infrastructure Options

	Modeled cost (USD)	Area of coverage (Ha)	Coverage geometry	Salinity
Deep tubewell	1,300	7	Circular with a 150 m radius	Low
Desalination	8,500[a]	7	Circular with a 150 m radius	High
Piped system from freshwater deep tubewell source	12,000[a]	25	Shape subjected to the optimization process	High within 1 km to the fresh/saline boundary
Piped system from desalination source	20,500	25	Shape subjected to the optimization process	High

[a]S. F. Hoque et al. (2019).

flexibility of desalination plants and the larger coverage area of a small piped system. Desalination plants can be fed from rivers (as currently in the Polder) or from shallow tubewells, increasing location flexibility and reducing source salinity (and consequently energy consumption).

4. Results

4.1. Low Salinity Area

In the northern region where water in the deep aquifer is below the acceptable salinity threshold, the optimization searched for the highest value locations through the area and a minimum distance of 300 m between neighboring deep tubewells (given the 150 m radius of coverage of each one). Figure 4 shows the construction of Pareto Frontiers for 8, 16, and 24 deep tubewells for the low salinity region. The dotted lines represent the paths developed for the range of different objective weights, each one of which represents an optimal investment sequence.

Table 4 summarizes the extreme alternatives: (a) maximizing access to low welfare population and (b) maximizing overall access. These extreme alternatives are called "maximize welfare" and "maximize access."

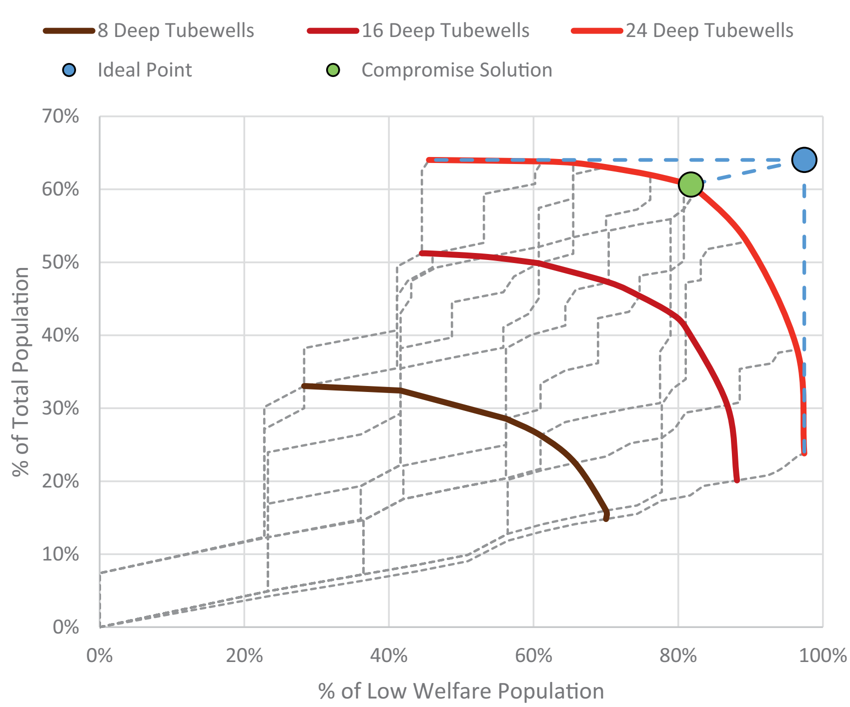

Figure 4. Trade-offs between maximizing access to low welfare population and maximizing overall access for constrained investments in deep tubewells in the low saline (northern region) area of the Polder 29.

Table 4
Three Cases of the Multi-Objective Optimization in the Northern Region of the Model Domain: (a) "Maximize Welfare," (b) "Maximize Access," and (c) Compromise Solution

No. of deep tubewells	Budget	Maximize welfare: Low welfare population served		Maximize welfare: Total population served		Compromise solution: Low welfare population served		Compromise solution: Total population served		Maximize access: Low welfare population served		Maximize access: Total population served	
8	$10.4k	572	70%	738	15%					231	28%	1,646	33%
16	$20.8k	720	88%	1,002	20%					364	45%	2,552	51%
24	$31.2k	796	97%	1,186	24%	668	82%	3,021	61%	372	46%	3,189	64%

For the "maximize welfare" alternative, the optimal 8 deep tubewell locations cover 70% of the people in households in the bottom welfare quartile without access to low-salinity drinking water while investment in 24 deep tubewell option can cover 97% of them. However, the latter covers less than 24% of the total population. The "maximize access" alternative to low-salinity drinking water demonstrates that there is some congruence with the objective to ensure that low welfare households are not "left behind" as the percentage of low welfare people served is similar to the total coverage for investments in 8, 16, and 24 deep tubewells. Table 4 illustrates diminishing returns for the investments in safe water supply infrastructure, as the optimization first selects the sites that serve the most people without access to low-salinity drinking water. The preferred trade-off between the two objectives, or compromise solution, is evaluated with reference to a goal or ideal point (Zeleny, 1982) combining the maximum values of the Pareto frontier. The best compromise solution is selected as the closest one to the theoretical ideal point (Carver, 1991). Compared with the "maximize welfare" alternative, the compromise solution reduced only 15% of low welfare coverage (from 97% to 82%) while gaining 37% of total coverage (from 24% to 61%). Compared with the "maximize access" alternative, the preferred alternative compromise only 3% of total coverage (from 64% to 61%) while gaining 36% of low welfare coverage (from 46% to 82%).

4.2. Entire Polder 29

The expansion of the model toward the south brings more complexity due to the variety of potential interventions and their cost and spatial characteristics. Desalination plants and piped systems were considered as viable options to provide low-salinity water supplies in this region.

For desalination plants, the optimization searched for the locations that would yield greatest benefit within 150 m. Current piped systems in the Polder cover areas between 20 and 30 Ha (based on 150 m coverage around each individual tap location), therefore, the proposed piped systems are assumed to cover 25 Ha and may be connected to deep tubewells in the low salinity region or to desalination plants. The shape of the coverage area was not established in advance but was optimized by searching for the pixels that would maximize drinking water supplies for the target population. The model navigate suitability surfaces built as each of the objective functions to find the highest value locations. In order to produce comparable metrics among the different interventions, the optimization results were combined, normalized, and ranked by cost-efficiency (i.e., using a (low welfare) people/cost index). Rival interventions (e.g., desalination plant and piped system covering the same area) were selected according to the cost-efficiency index in order to eliminate overlapping or double-counting of the population. Figure 5 shows the construction of Pareto Frontiers for portfolios of USD 50,000, USD 100,000, and USD 150,000 for the complete Polder 29. The dotted lines represent the paths developed using the range of different objective weights.

Table 5 summarizes the "maximize welfare" and "maximize access" alternatives and a compromise solution between these two objectives, for an infrastructure investment of USD 150,000 portfolio. The compromise solution is close to the maximum value of each objective without sacrificing significantly the other. Compared with the "maximize welfare" alternative, the compromise solution reduced only 4% of low welfare coverage (from 72% to 68%) while gaining 24% of total coverage (from 38% to 62%). In the same way, compared with the "maximize access" alternative, the preferred alternative compromise only 4% of total coverage (from 66% to 62%) while gaining 15% of low welfare coverage (from 53% to 68%).

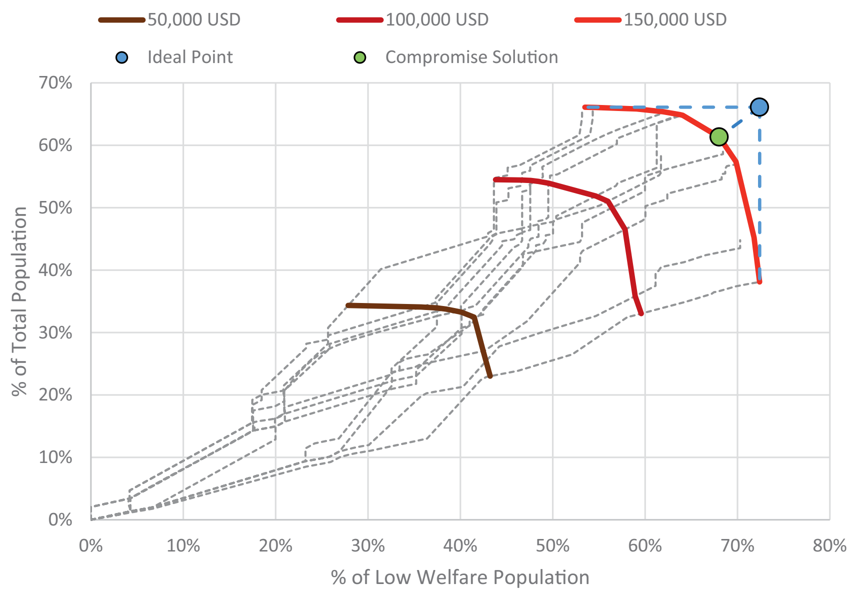

Figure 5. Trade-offs between total population served and low welfare population served for constrained investments in water infrastructure in Polder 29.

Figure 6 shows the location of optimal infrastructure investments of USD 150,000 over the whole Polder 29 (i.e., low and high salinity regions). The solution that maximizes access for the greatest number of people is focused upon deep tubewells for the population without access to low-salinity drinking water in the north of the model domain. This portfolio includes 30 deep tubewells in the north, 5 piped systems close to the high/low salinity boundary, 2 piped systems in the high salinity region, and 1 desalination plant in the south. The "maximize welfare" solution has higher capital investment toward the south including seven desalination plants and three piped systems close to the high/low salinity boundary and other two piped systems from desalination in the south. The portfolio also includes 17 deep tubewells in the north. The compromise solution includes 30 deep tubewells in the north, 4 piped systems close to the high/low salinity boundary, and 3 piped systems from desalination in the south. Figure 7 shows the sequencing of interventions for this compromise solution and the number of (low welfare) people provided with access to safe drinking water supplies.

5. Discussion and Conclusion

Global progress to achieve and sustain safe drinking water services has shifted from a challenge of increasing infrastructure access (MDG era) to one of providing equitable and safe services (SDG era). Bangladesh has successfully achieved the former in 2015 and now is working to new and ambitious targets of water quality, non-discrimination, accessibility, and affordability by 2030. The contribution of this article

Table 5
Three Cases of the Multi-Objective Optimization in the Entire Polder 29: (a) Maximize Welfare, (b) Maximize Access, and (c) Compromise Solution

	Maximize welfare				Compromise solution				Maximize access			
Budget	Low welfare population served		Total population served		Low welfare population served		Total population served		Low welfare population served		Total population served	
$50k	1,925	43%	4,140	23%					1,240	28%	6,175	34%
$100k	2,653	60%	5,942	33%					1,951	44%	9,799	54%
$150k	3,224	72%	6,852	38%	3,029	68%	11,029	61%	2,381	53%	11,888	66%

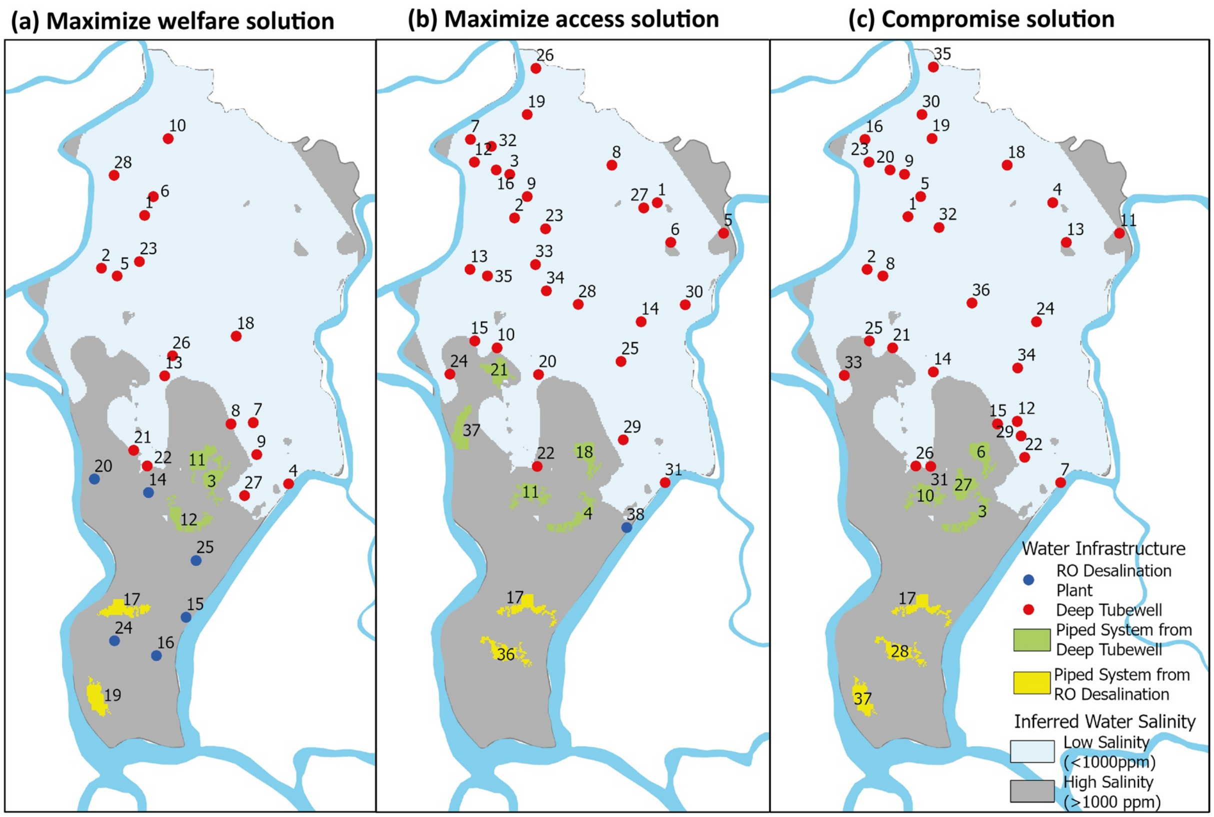

Figure 6. Location of optimal investments in drinking water infrastructure in the entire Polder 29 (a) maximize welfare solution, (b) maximize access solution, and (c) compromise solution.

has been threefold. First, we apply spatial optimization to a development policy challenge often limited by insufficient data to navigate competing trade-offs where water insecurity is amplified by social inequalities. Second, we explore the decision trade-offs in terms of the greater good (coverage) versus the greater need

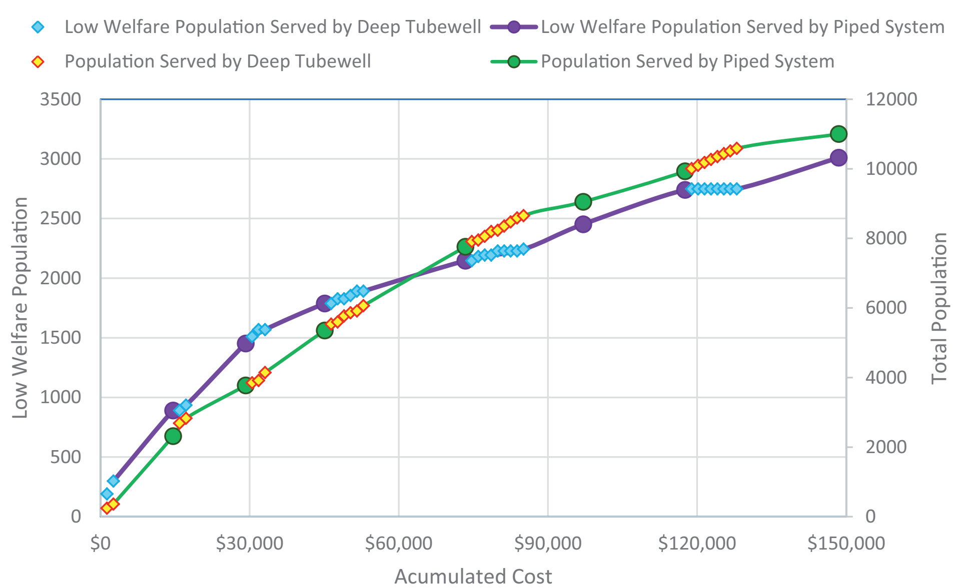

Figure 7. Marginal benefits (numbers of people served) for the sequenced investments for the compromise solution.

(inequalities) and model the optimization problem in a coastal area with extensive groundwater salinity and significant social inequalities. The implications of the findings reveal alternative scenarios to improve water security and the distributional implications for budget allocation and policy delivery. Third, we discuss policy implications which could strengthen allocation and sequencing of investments given the large but uncoordinated funds from private households. This has wider implications for the capital investments required to provide safely managed drinking water services globally, which is estimated to be three times that of historical spending, with an annual financing gap of USD 37.6 million (Hutton & Varughese, 2016). Four out of five countries surveyed in the Global Analysis and Assessment of Sanitation and Drinking-Water (GLAAS) 2016/2017 cycle reported having insufficient finances for meeting their national targets, which are often less ambitious that those set by the SDG 6.1 (GLAAS, 2019).

Compared to many multi-objective optimization problems that have been reported in the water resources literature, the problem addressed in this article is relatively straightforward to solve. It contains just a few attributes (household location, welfare, salinity, and existing water supply infrastructure), objectives and constraints. The option space is potentially large but the suitability surface is easy to navigate, though the options became more complex when piped systems are considered. We regard this relative simplicity and transparency as a strength of the approach, particularly in the context of rural communities where technical capacity is limited. With modification the methodology could be applied elsewhere in Bangladesh where the drinking water challenges are different but still very significant, and possibly to other countries that have yet to meet their SDG targets.

High resolution spatial datasets are providing many new opportunities to target development assistance (Öhler et al., 2019). In this article we have made use of an innovative methodology geolocating synthetic households and have combined that with a new survey of drinking water supply infrastructure and water salinity. This crucial new information has been used to explore optimal strategies to new water supply infrastructure in a location where at present 30% of the population are using water supplies that are of high salinity. The methodology has been applied to a fairly large spatial domain (∼60,000 inhabitants), but this is still relatively small compared to the 20 million people living in the coastal zone of Bangladesh and more than 2 million Bangladeshis without access to safe drinking water supplies. The synthetic household geolocation methodology which we have used is potentially applicable at very large scales. Obtaining georeferenced drinking water infrastructure audits is more challenging, in particular when this entails water quality measurements, but the Joint Monitoring Program for Water Supply and Sanitation by WHO and UNICEF already surveys water supplies on a very large scale, which could be augmented with crowd sourcing and low-cost sensor techniques. The additional cost of providing surveys of drinking water infrastructure may be relatively low (e.g., the asset survey reported in this paper cost approximately USD 7,000) in comparison with the greater policy transparency in choosing policy pathways with greater transparency on the likely outcomes for different social groups, particularly the more vulnerable and marginalized.

The article has highlighted the particular challenges of providing safe drinking water supplies in areas where the aquifer is too saline to provide safe drinking water. Under these circumstances, we explored the possibility of piping water from deep tubewells where the aquifer is tolerably saline, which is a technology currently in existence in coastal Bangladesh. We also explored the option of connecting piped systems to reverse osmosis desalination plants, which combines two currently used technologies in a new way. Experience of using these technologies will provide evidence about operating costs (for desalination and pumping) which can be onerous and should be incorporated into the optimization for further refinement. Moreover, proper operation and maintenance will help sustain the optimal investments during their lifespan. Desalination plants produce brine effluents, whose environmental impacts need to be considered. Some available options for brine disposal in rural environments are discharged to rivers (already saline), evaporation ponds, or landfills (Boden & Subban, 2018).

This reflects our second contribution in how the use of multi-objective optimization has enabled the exploration of the trade-offs between the target to achieve universal access to safe drinking water and the imperative to "leave no one behind." We framed this trade-off in terms of the tension between a Benthamian approach to deliver the greatest good (low saline water) to the most people and a Rawlsian approach to maximize benefits (low saline water) to the most in need. While there is some congruence between the objectives of maximizing overall access and maximizing access for the low welfare population, these two objectives result in different spatial and social outcomes. Notably, maximizing overall access skews investments to areas with low salinity and away from areas where provision of safe drinking water supply infrastructure is more expensive and where there is a larger proportion of low welfare people. By combining infrastructure, environmental, and social parameters, the "optimal" infrastructure decision framework reflects a more realistic and interdisciplinary understanding of water security and inequality trade-offs.

Revealing these trade-offs has policy implications as the methodology provides the optimum sequence of investments so that the investments that yield the most benefits can be targeted first. In a situation of uncertain budgets for infrastructure investments, it is attractive to achieve the highest marginal benefits first. However, in practice there may be cost efficiencies to be gained through a construction program that deals with whole neighbourhoods sequentially. To achieve this a two-scale optimization could be implemented, at the scales of individual assets and at a neighborhood scale, or a more sophisticated cost function could be employed.

A second policy implication is to recognize the recent dominant role of private investment in private tubewells in meeting the MDG of improved access, and the potential to explore synergies with public expenditure (Fischer et al., 2020). While shallow tubewells are not part of public infrastructure investments because of known water quality concerns, household investments reveal an unmet demand for more convenient (closer) infrastructure to serve multiple household needs (cooking, washing, bathing, and as well as drinking). An optimization could be carried out given assumptions about the potential for future private investment in deep tubewells, in particular in higher welfare areas of the polder, which would release public and donor funds to target the low welfare population. Indeed our framing in terms of the greater good (Bentham) versus the greater need (Rawls) provides the basis to consider how public and private finance may be combined. For example, donors with mandates to benefit the poor may pursue and support the Rawlsian path with government agreeing to a Benthamian path, but in coordination with appropriate sequencing.

The results of this large-scale optimization should be regarded as a guide to decision makers, who will bring other considerations into program design and delivery. Detailed technical designs for recommended water supply infrastructure will be needed, which will have to account for specific topographic, hydrogeological, and social issues. The optimization does not incorporate the long-term changes that are taking place in the coastal zone in Bangladesh, in particular demographic change and the impacts of sea level rise on saline intrusion. Though our previous research has looked extensively at these issues (Lázár et al., 2020), given the urgency with which the SDG target 6.1 is being pursued in Bangladesh, we do not think that these longer-term considerations would significantly change our recommendations, though they could in principle be included in our methodology through use of future projections and scenario analysis. It is nonetheless important that investments are resilient to current and future climatic extremes, notably cyclones and floods which intermittently hit the coast of Bangladesh. Responding to this increasingly complex decision space to account for climate, financial, environmental, and social interactions is suited to optimization models which can identify spatial and social inequalities to improve water security decision-making for those most in need.

Data Availability Statement

Datasets for this research are placed in the ReShare online Data Repository (https://reshare.ukdataservice.ac.uk/) and are available from: S. F. Hoque et al. (2021) and Salehin et al. (2021).

Acknowledgments
This document is an output from the REACH program funded by UK Aid from the Foreign, Commonwealth and Development Office (FCDO) for the benefit of developing countries (Programme Code 201880). However, the views expressed and information contained in it are not necessarily those of or endorsed by FCDO, which can accept no responsibility for such views or information or for any reliance placed on them.

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