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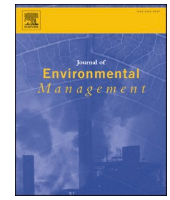

Research article

Optimising water storage for climate resilience: Geospatial targeting for small tanks rejuvenation in Sri Lanka

Fulvio D. Lopane [a,*], Sophie Ayling [a,b], Yi Rong Hoo [b], Mohammad Shamsudduha [c], Qiao Wang [b], George Joseph [b], Aroha Bahuguna [b]

[a] *Centre for Advanced Spatial Analysis, University College London. Gower St, WC1E 6BT, UK, London, United Kingdom*
[b] *The World Bank, 1818 H Street, NW Washington, DC, 20433, USA*
[c] *Department of Risk and Disaster Reduction, University College London. Gower St, WC1E 6BT, UK, London, United Kingdom*

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A B S T R A C T

In Sri Lanka, climate change and recurrent droughts pose significant threats to agricultural communities. Village water storage tanks have been used in countries in South Asia since the third millennium BC. According to the National Tanks Survey, Sri Lanka has some 23,000 small tanks of 80 ha or less; however, 21 percent are currently non-functional due to decades of neglect. This study designs a National Prioritisation Index for the rejuvenation of small tanks, employing a geospatial approach. Our research disaggregates district-level statistics at a 1 km resolution to map the demand from agricultural-dependent populations. We then construct several prioritisation indices that evaluate tanks from supply, demand, and utility for groundwater rejuvenation perspectives. Our findings highlight priority areas for tank rejuvenation concentrated in Kurunegala and Anuradhapura districts. The indices developed in this study provide a framework for targeting investments effectively, thereby optimising resource allocation for drought mitigation efforts. The approach can support enhancement of water security and resilience in vulnerable agricultural communities across Sri Lanka and in other parts of South Asia which are reliant on such infrastructure for water storage.

1. Introduction

Water storage is crucial for water security, especially in countries with monsoon driven climates (Anand et al., 2019). As a result, village water storage tanks have been used in countries in South Asia like India and Sri Lanka since as far back as the third millennium BC (Annandale, 2019) and are one of the oldest traditional water harvesting structures. They contribute to water security, particularly for agriculture dependent populations (Rodrigues et al., 2012) creating a buffer to mitigate the impact of floods in the monsoon months and providing additional supply for crops during water shortages and droughts (Anand et al., 2019). Given increased rainfall variability associated with climate change (Bayissa et al., 2022, IPCC et al., 2023), the role of water storage is becoming ever more important.

Recent developments in water storage and management optimisation have focused on integrating advanced technologies and sustainable practices to address the challenges posed by climate change and population growth. For example, Zhao et al. (2021) emphasise the importance of optimising ecosystem water consumption to balance land restoration and water resource conservation, highlighting the need for sustainable ecosystem restoration strategies; and Shuai et al. (2022) propose an equitable and effective water resource planning framework that handles competing regions and conflicting water departments, addressing uncertainties within water-stressed watersheds, which – like in our study – is relevant in the context of changing climates. Ding et al. (2024) investigate the impacts of climate change and land use change on water security, utilising the Soil and Water Assessment Tool (SWAT) to enhance water resource management at the watershed level; while Seitnazarov et al. (2024) discuss the use of expert systems for decision-making in agricultural water management, optimising water distribution and ensuring sustainable agricultural productivity, and Olatunde et al. (2024) underscore the necessity of integrating technology, policy, and community engagement in smart water management efforts. Finally, QU et al. (2024) establish a nonlinear multi-objective water resources joint optimisation model, employing a genetic algorithm to address complex water resource optimisation challenges in

* Corresponding author.
E-mail address: f.lopane@ucl.ac.uk (F.D. Lopane).

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urban settings. These advancements collectively contribute to more efficient, equitable, and sustainable water management practices, although the most advanced of these techniques and approaches require a significant amount of data, not always available, especially in the Global South.

Agriculture is crucial to Sri Lanka's economy, making up about 10 percent of GDP and 26 percent of employment respectively. Even for those not primarily employed in agriculture, it can be a supplementary income to non-farmer rural households (Department Of Census And Statistics, 2023a; Department of census and statistics, 2023b). There are three types of tank classification in Sri Lanka: minor, medium and large. This paper focuses on small tanks of 80 ha or less, which are classified as minor irrigation systems or minor irrigation works (Vidanage et al., 2022) (see Fig. 1 for an example of Sri Lankan tanks cascade system). Despite previous studies have used estimates between 18,000 (Jyothi and Panabokke, 2004) and 30,000 (Dharmasena, 2004), the Ministry of Agriculture of Sri Lanka provided us with their National Tanks Survey, which includes some 23,000 small tanks of 80 ha or less. 87% of these tanks are used for irrigation and 94% are used for some other agricultural purpose including fishing (22%) or livestock (40%). However, at least, some 21% are currently estimated to be non-functional (either damaged or abandoned) due to decades of neglect with the gradual advent of canal and groundwater systems of irrigation. Over the past few decades, there have been efforts to rehabilitate the tanks, but the magnitude of the challenge at hand is daunting. The Ministry of Agriculture with the support of organisations like UNDP and the World Bank are now attempting to revive some of these neglected tanks (Vidanage et al., 2022) to reduce the risk of crop failures due to climate fluctuations.

However, with so many tanks dotted around the country it is difficult to systematically identify where investment in rejuvenation should be targeted, and thus most efforts have been with smaller scale case studies to identify prioritisation criteria using qualitative analysis or analysis on small clusters of tanks. For example, Kalaiarasi and Arul (2022) developed a Tank Rehabilitation Index (TRI) for prioritising tanks to rejuvenate based on 24 indicators reflecting the physical, hydrological and socio technical aspects, but it looked at only four tanks of a cluster in Kiliyar sub basin, Palar basin, Tamil Nadu, India. Another study by Nagarajan managed to build an index for 89 tanks across two cascade systems in Addakkal, Hyderabad, India (Nagarajan, 2013). Other studies have identified some of the reasons for why some rehabilitation projects either succeed or fail, highlighting management issues (Sirimanna and Prasada, 2022), the utility that they serve indicating the demand they face, and the local capacity to manage them (CBOs etc.) (Dayal and Iyengar, 2006). In addition to providing water for agriculture, with timely desilting, the silt from tanks can also be used to improve agricultural land fertility (Anand et al., 2019).

Whilst these previous studies have been informative on a smaller scale, our study makes a rare attempt to build an index with a combination of available global, census and household survey datasets to take a wider lens across all the 23,000 small tanks in Sri Lanka. This study also identifies criteria to i) assess tank demand from the agriculture dependent population; ii) assess supply side constraints; iii) identify a means to decide which tanks to rejuvenate considering both factors in combination; and iv) when also considering groundwater rejuvenation capacity. The steps to construct this prioritisation index are substantially more computationally intensive than what has been attempted previously. The resulting methodology has potential application for other contexts, including even larger datasets across bigger countries in the region.

This paper seeks to address three research questions. Firstly, how do we identify the tanks in Sri Lanka that are most in need of rejuvenation? In other words, we first examine the problem from a supply perspective. Secondly, adopting a demand-based approach, how do we identify the areas of Sri Lanka that are most in need of small tank rejuvenation? Part of answering this question also means identifying where agricultural dependent populations live. Such data is not readily available from household datasets at any low level of spatial granularity, and therefore this paper presents a method designed to address this issue. Finally, once we had metrics for supply and demand indices computed, we asked one further question: how should we prioritise tank rejuvenation in Sri Lanka considering both supply- and demand-side constraints, as well as those which may hold the highest potential for groundwater recharge? This final piece on groundwater recharge prioritisation is considered as a sub-filter of those tanks already identified for prioritisation based on supply and demand factors. This paper presents is a novel study that addresses an unprecedented large-scale prioritisation analysis of water storage tanks in the region at a disaggregated spatial scale (down to single tanks level). Previous studies have been largely small-scale and/or qualitative in nature (Kalaiarasi and Arul, 2022; Nagarajan, 2013; Sirimanna and Prasada, 2022; Dayal and Iyengar, 2006; Anand et al., 2019), while this is the first national-scale data-driven attempt to systematically identify priorities in water tanks rejuvenation optimisation.

Our study provides a framework designed to identify priorities in the supply and demand (and their combination) for small water tanks, which is essential for informing policymakers in their decision-making processes. By utilising a geospatial approach and constructing detailed prioritisation indices, we generate numeric evidence at different spatial scales. This evidence supports effective policy development in climate resilience, particularly in optimising water storage and enhancing water security. The framework we present is instrumental in guiding targeted investments and resource allocation, ultimately contributing to the mitigation of drought impacts and the promotion of sustainable water management practices in vulnerable agricultural communities across Sri Lanka and potentially other regions reliant on similar infrastructure.

2. Data sources and sampling

We use a range of different data sources to conduct the analysis. For population modelling we use the WorldPop estimates at a 1 km resolution from 2020 (WORLDPOP & CIESIN, 2020). This data comes in the form of a global raster with 352,520 pixels. Secondly, we take the Global Human Settlement Layer (GHSL) (Schiavina et al., 2023) from the European Commission from 2023, which classifies land types at 1 km into eight different categories (Annex 3). From these we extrapolate which categorisations are urban vs. rural. Third, we use a land cover polygon provided by Sri Lankan Land Use Policy Planning Department which has 38 categories of land use. We classify these into agricultural and non-agricultural lands. The Household Income and Expenditure Survey 2016 (Department of census and statistics, 2017) is used to extrapolate the poverty rate at district and District Secretary's Division (DSD) level and then for calculations at district level of population dependent on agriculture as either a primary or secondary occupation. Two other global datasets which are used in the calculation of tank supply needs are the GLoSEM database on soil erosion (Borrelli et al., 2022) and the CHIRPS rainfall variability dataset (Funk et al., 2015), which gives the coefficient of variance for rainfall between 1983 and 2000 in the Maha season[1] at 100m resolution. For full details on the provenance of each data source see Table 1 in Annex 1.

Finally, the tank data is drawn from three different databases. Our base data for the analysis is the national level database on the tanks from the Ministry of Agriculture of Sri Lanka. This dataset contains a record of 23,163 tanks in Sri Lanka with their command area, water height, and water level. Another associated database from the Ministry of Agriculture is then spatially joined to this dataset to add data on the functionality status of each tank. This brings us down to 21 thousand tanks for which this information was available on the functionality status. We then need additional information on the shape of each of these tanks

[1] The Maha season falls during the "North-east monsoon" from September to March and is one of two seasons when the crops are sown and harvested.

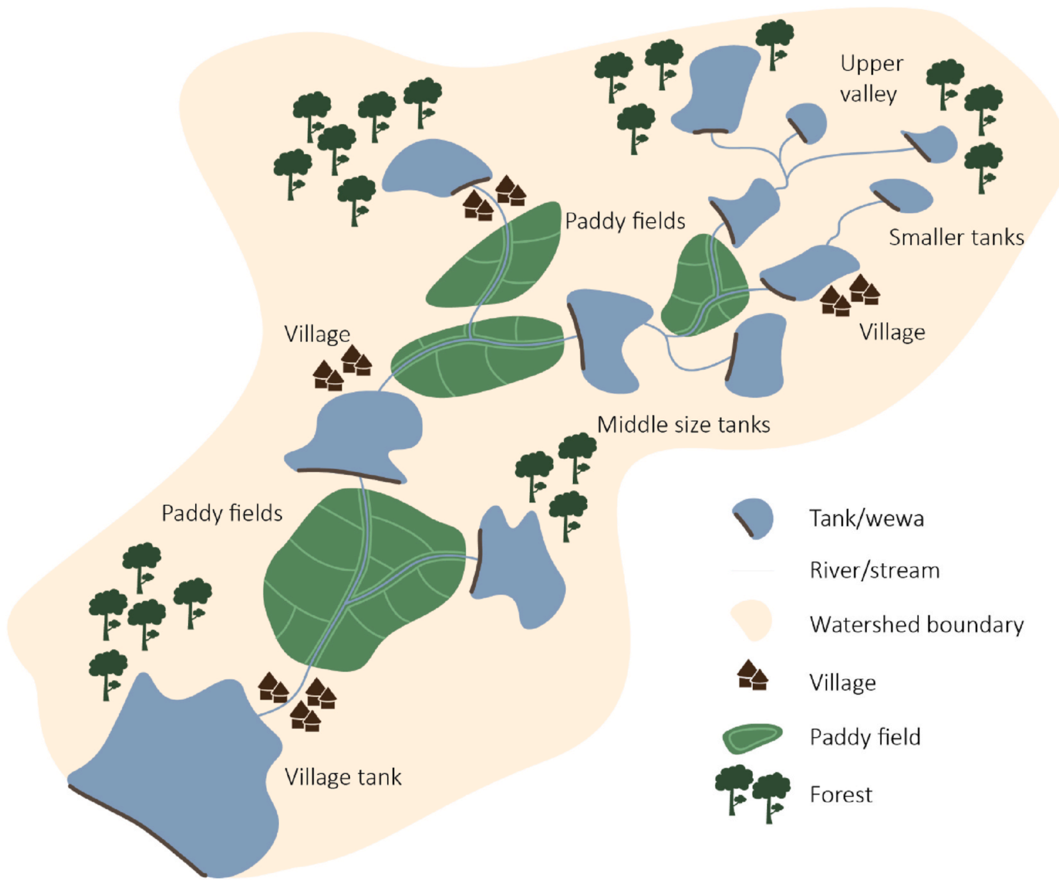


Fig. 1. Schematic representation of a typical Sri Lankan cascade system, illustrating the interconnected network of small tanks and reservoirs. This ancient irrigation system efficiently collects, stores, and distributes rainwater to support agriculture in dry regions. The design also promotes biodiversity by creating habitats for various plant and animal species.

(rather than just their GPS locations on the map). A survey by UNDP in 2018 (Annandale, 2019) uses satellite imagery to trace the outline of each of the tanks surveyed, but this is possible for 11,014 of the tanks in the country. A final constraint is that we are also seeking to gain siltation information from the tanks for computing the supply side index later in the methodology. However, only 6,938 of the UNDP tanks has such information in the survey. We used a machine learning technique (see section 3.2) to compute missing siltation information for the remainder, bringing back up the total to 11,014 tanks under analysis.

3. Methods

3.1. Design the conceptual framework

First, we developed a conceptual framework for criterion for prioritisation of tanks for rejuvenation. We group the factors under three thematic categories as laid out in the research questions. The first are *supply* related factors which consider the status of each of the tanks under study, such as the level of siltation measured in the tank at the time of the survey and the risk of soil erosion according to the global dataset Global Soil Erosion Modelling (GloSEM) from the European Soil Data Centre (Borrelli et al., 2022). In order to verify that siltation levels and soil erosion would be useful predictors of supply side malfunctions, we also conducted a linear regression with the functionality status of tanks as a dependent variable and identified a significant relationship between lower functionality, higher siltation and higher levels of soil erosion. Secondly, we consider *demand* related factors for tank rejuvenation. The UNDP survey (Annandale, 2019) revealed that 94% of the tanks that are included in the survey are used for some kind of agricultural practice, with 87% of them reportedly being used for irrigation by the community that are managing them. This led us to the importance of identifying the agriculture dependent population (ADP) for the tanks under study, in order to ascertain the level of demand they would cater to. This data is not readily available, and the computation process is described in detail below; it requires consideration of population counts as well as land use and household survey data on agricultural dependency at district level. We also consider rainfall variability as an important factor in determining the demand for tanks given that areas with a higher coefficient of variation of rainfall would be more likely to rely on the tanks for either drought or flood mitigation due to unexpected weather events. Finally, once the prioritised tanks from a supply and demand perspective had been identified, we add a final consideration on the additional utility of rejuvenation with respect to groundwater replenishment. To assess potential for contribution to groundwater replenishment, we consider the underlying aquifers on which each of the tanks are located. We assess their respective pump yields in ranking their utility for rejuvenation from a groundwater replenishment perspective (Fig. 2). More detail on each of these methods is now provided in the respective subsections.

All the analysis described below has been conducted in python. Scripts and corresponding public datasets are available on GitHub at https://github.com/fdlopane/SL-Tanks/.

3.2. Compute the supply side index

Computing the need for tank rejuvenation is the first part of the prioritisation index creation. This considers data from the tank survey and associated information on the functionality status of the tanks, their

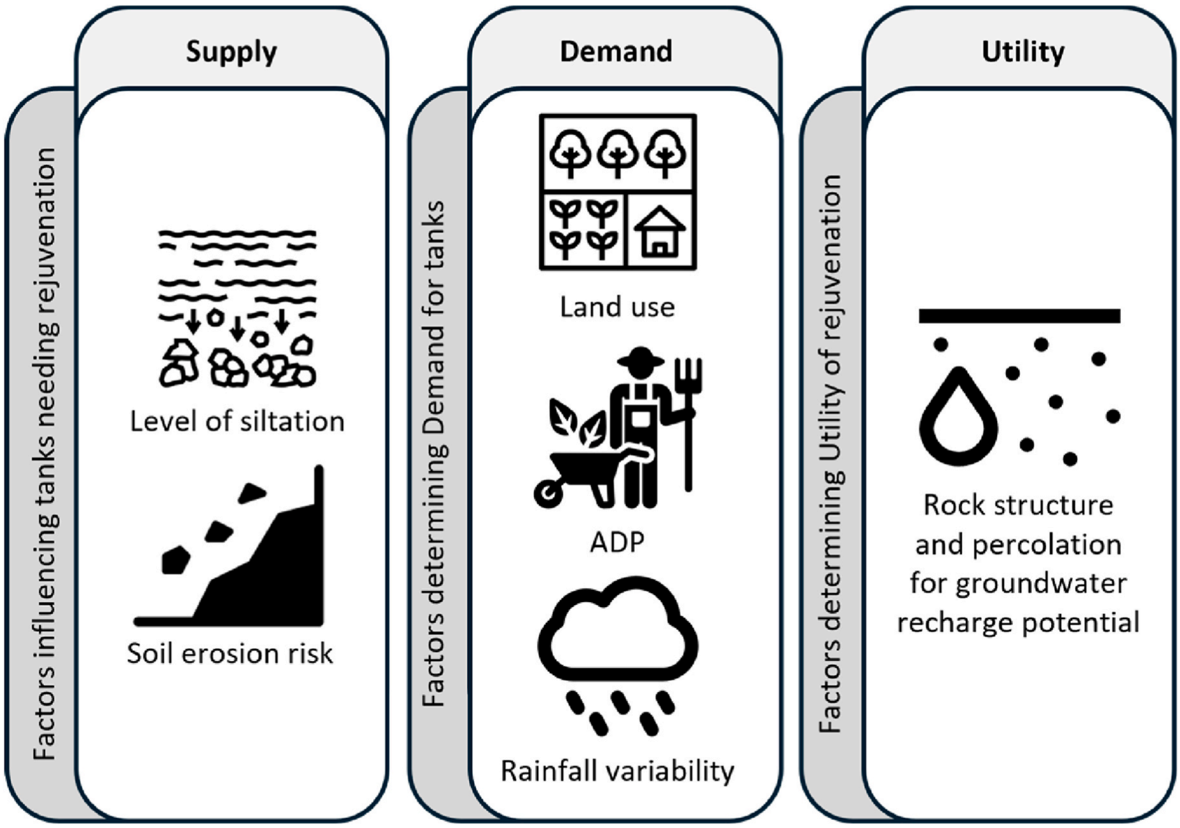


Fig. 2. Factors influencing supply, demand, and additional utility of small tanks rejuvenation.

level of siltation, and the soil erosion risk. Those tanks which will be prioritised are those that have high siltation levels and a high soil erosion risk, as emphasized by Dastagir et al. (2020) and Bebermeier et al. (2017). Each of these factors is normalised on a zero to one scale and the product of the two is computed to provide the index value for each tank in the dataset. Those with the highest scores in terms of both siltation and soil erosion are those which will rank highly on the index and be prioritised for supply side considerations. The formula for this computation is as follows:

$$S_i = SS_i \bullet E_i \quad (1)$$

Where S_i is the Supply-side index of tank *i*, SS_i is the normalised siltation score of tank *i*, and E_i is the normalised soil erosion score at tank *i* location.

To generate index statistics at DSD and district level the supply side index values are summed. A decision was taken not to use the average as this would disproportionally favour districts with fewer tanks. Though computing the index itself is straightforward, due to the missing data on siltation for some 3,000 of the 11,000 tank polygons, sci-kit learn Random Forest Classifier was used to predict the missing siltation values before creating the index (Wang, 2024) (see Annex 5). Note that the soil erosion risk index considers a Digital Elevation Model (DEM) in its computation. The estimates for each of the components of the index were derived from the survey data at the tank level and the soil erosion risk was estimated by spatially joining the GLoSEM database to the tank outlines.

3.3. Compute a demand side index

Considering those tanks that are non-functioning will only provide a partial picture, as it is possible that some tanks are abandoned or in a state of disrepair simply because they are no longer needed by the surrounding population. Due to the increase in the provision of irrigation through canal systems, some abandoned tanks may no longer be needed. Further, over time, the surrounding population might have shifted away from agriculture and farm-based activities, thus reducing their dependence on tanks. With this in mind, we consider demand side factors and seek to compute the agriculture dependent population (ADP) for each tank using a combination of spatial datasets and the HIES household survey for calibration.

3.3.1. Compute the agriculture dependent population (ADP)

This step uses three data sources: the Land Use raster provided to us by the Sri Lankan Land Use Policy Planning department containing 38 categories of land use, the WorldPop population count raster (WORLDPOP & CIESIN, 2020), and the Household Income Expenditure Survey (HIES) (DEPARTMENT OF CENSUS AND STATISTICS, 2017) district level agricultural dependent population from 2016 (Fig. 3).

We first use HIES survey data to estimate the agricultural dependent population at the district level. Sri Lanka's HIES is a complex survey conducted in 2016 on a nationally representative sample to characterise important aspects and living pattern of people in different segment of population at a national and district levels, collecting detailed information on the income and expenditure patterns of households across the country, aimed at assessing living standards and informing economic and social policy decisions. Sri Lanka HIES 2016 (Department of census and statistics, 2017) covers all 25 districts in the country and a 20.7 million household population. These district level estimates of agriculture dependent population (AgDep[2]) estimated from the HIES take into account the population dependent on agriculture, not necessarily as the main occupation, but also considering it as direct or indirect source of

[2] Note that "AgDep" is the agriculture dependent population aggregate estimate from the HIES at the district level, while "ADP" is our disaggregate estimate at 100m resolution.

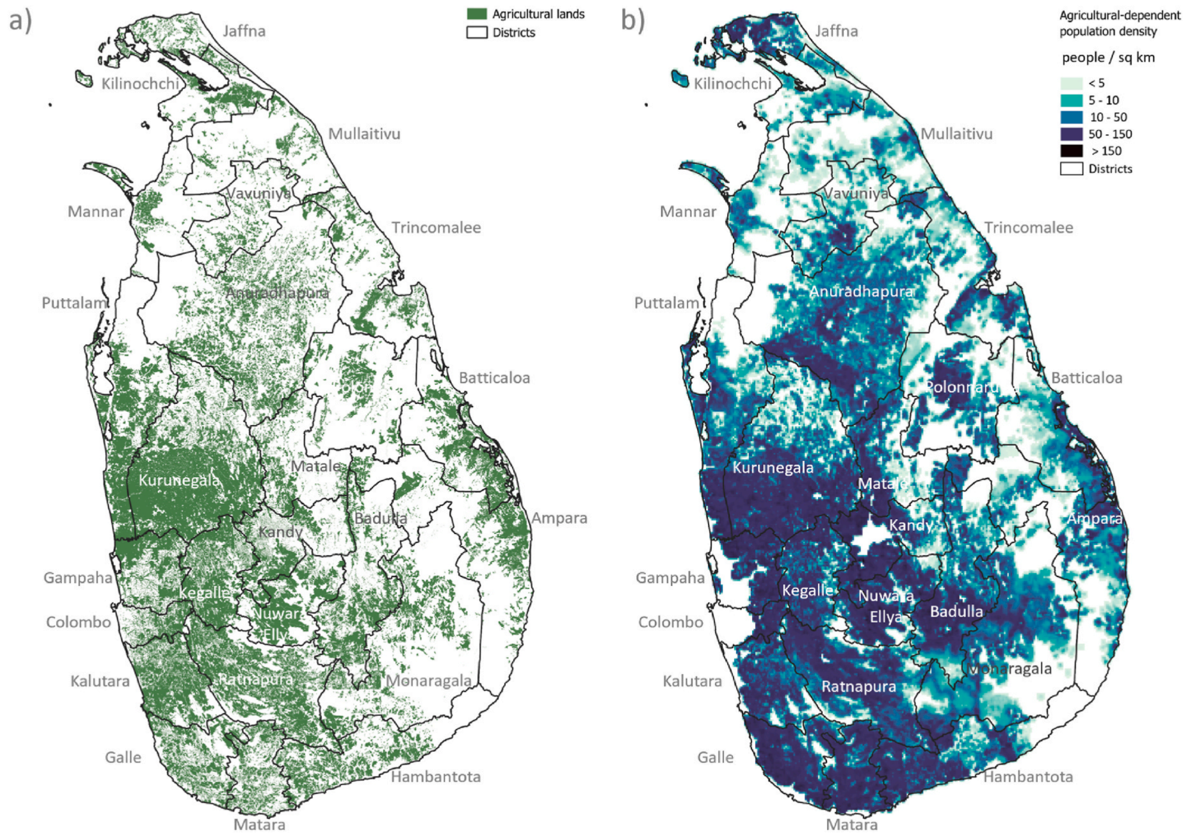


Fig. 3. a) Lands classified for agricultural use; b) Computed agricultural-dependent population (ADP).

secondary income. The AgDep estimates combines two pieces of information: first, the number of household members aged 15 years and over who are employed or working in the agriculture industry at the time of the survey interview, and second, the number of household members who have had income from agricultural activities, such as cultivating crops or livestock, as an employer or own account worker during the last year at the time of the interview. The first piece of information is obtained from the household demographic characteristics section (question 15 in the survey). A household is considered as an agriculture-dependent household if any household member is employed in the agricultural industry. The second piece of information is obtained from the household income section 5.2 and 5.3 in the survey: a household is considered as an agriculture-dependent household if any of the household members cultivate paddy, other seasonal crops, or other agricultural activities such as non-seasonal crops cultivation and livestock raising, as an employer or own account worker for sale or household consumption during the last year at the time of the interview.

However, this first step is only to provide us with some validation data, in order to come up with a method of estimating ADP at a much more fine-grained resolution (1 km). In order to produce a fine-grained estimate, we combine multiple raster datasets and conduct an estimation process (Fig. 4). This starts with using the 1 km resolution population count data from WorldPop. Though a 100m resolution WorldPop file exists we found it to be inaccurate with visual comparison with satellite imagery revealing heavily displaced human settlements at that level. We therefore used the 1 km resolution dataset and resampled it to 100m,

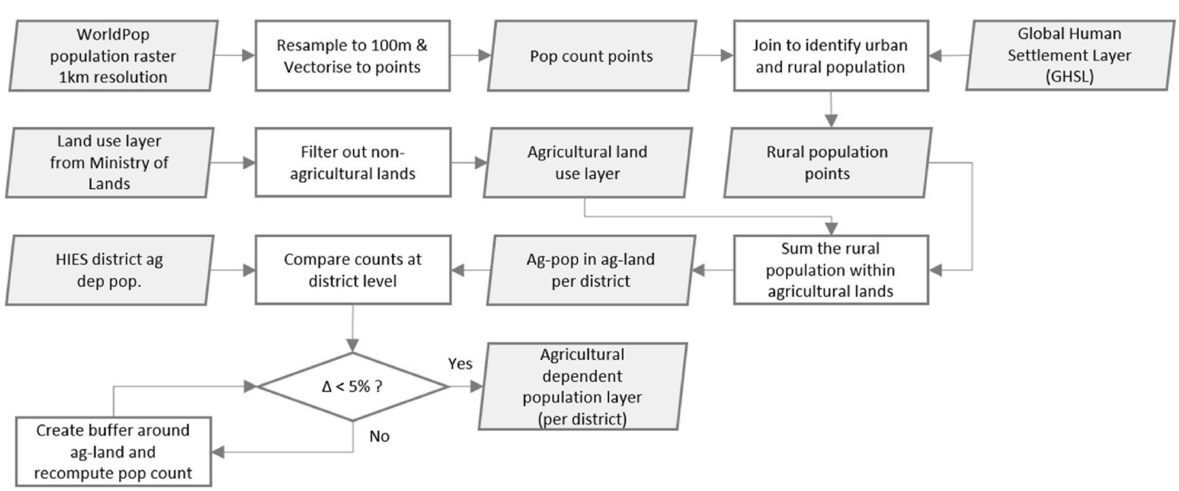


Fig. 4. Agricultural dependent population geocomputation workflow.

converted it to points, and joined it with the Global Human Settlement Layer (GHSL) raster (see Annex 4). This enables us to categorise the population as urban or rural depending on the grid cell on which they are located. We use the GHSL populations to mask out urban populations from the analysis by conducting a spatial join to identify where population points are located in GHSL pixels classified as urban. We then join this to the District Secretary's Division (DSD)[3] and district identifiers, enabling us to calculate the proportion of each district and DSD population that is rural. In parallel, we take the land use layer from the Ministry of Land and Land Development of Sri Lanka (MLLD Sri Lanka) (see Table 2 in Annex 2 - all the land classified as "Ag land" were considered in this study as land for agricultural purposes), which contains 38 land types and categorised into agricultural or non-agricultural (note that this does not consider whether the land is irrigated or not). For each district we take the 100m rural population point layer generated earlier and summarised the total population within each of the agricultural land shapes that is generated. As a result, for each agricultural land polygon we have the rural population of the district that falls within it, and those that fall outside of it. This results in a count of the total rural population for each district that falls within agricultural lands.

At this point we make a comparison between HIES household survey estimates on the agriculture dependent population (AgDep) at the district level and the computed estimates (ADP). Where the geospatially computed estimates of ADP are more than 5% lower or higher than the HIES estimates, we then iteratively compute a buffer in 100m intervals around the agricultural lands to get to within 5% of the estimate. The aim is to get to all estimates at district level within±5% of the HIES estimates. As a final stage to get the ADP country-wide, we merge back together each of the respective district level shapefiles with their corresponding ADP estimates into a single layer. This single combined polygon on agriculture dependent population can then be used to break down the rural population at DSD level if smaller levels of disaggregation are sought.

To estimate the ADP served by each tank, we generated a 1-km buffer around each tank and overlap each command area with the agricultural dependent population layer to get a final count of served population by each tank.

3.3.2. Generate the demand side index

To get the demand side index we need to consider the covariance of rainfall, as the ADP will be in greater need of the tank in areas where rainfall variability is higher, since rainfall variability during cropping seasons has been shown to have a significant and negative impact on smallholder farmers' income (Shumetie and Alemayehu Yismaw, 2018). Rainfall variability introduces risks such as late onset, early cessation, prolonged dry periods, and droughts of moderate-to-severe intensity. These factors adversely impact rainfed crop production by delaying planting, shortening the growing season, leading to lower yields, exacerbating household food insecurity (Sawe et al., 2018), and increasing the likelihood of crop failure (Bahiru et al., 2020; Mugalavai et al., 2008). While early rainfall onset may allow for early planting, it also raises the risk of seedling failure if followed by extended dry spells (Kipkorir et al., 2007), which can further hinder crop productivity if occurring during critical growth stages (Kipkorir et al., 2007; Mugalavai et al., 2008; Muluneh et al., 2017).

To get this estimate for each tank, we spatially join the CHIRPS data on rainfall variability (Coefficient of Variance) 1983–2020 Maha Season (Funk et al., 2015) to the tank polygons with the information on ADP above and normalise the values between 0 and 1. The higher the variability, the greater the demand (Kinda and Badolo, 2019; Habte et al., 2023).

Then to get the combined demand index value we multiply the normalised rainfall variability by the normalised ADP to get a final score for each tank where the higher the score the higher the demand, as show in equation (2).

$$D_i = ADP_i \bullet R_i \tag{2}$$

Where D_i is the Demand-side index of tank i, ADP_i is the agricultural dependent population served by tank i, and R_i is the normalised rainfall variability at tank i location. Similarly to the supply side index, to aggregate index statistics at DSD and district level the supply side index values are summed. Note that we would occasionally encounter populations that fell within the command area of more than one tank. In such cases, we decided these populations could be mapped to both tanks, given that they had the choice to go to either one (or both). This means that the numerical estimate of ADP is inflated beyond the population of the area, due to the overlap in populations dependent on multiple tanks.

3.4. Generate a combined supply-demand prioritisation index

Here we take the product of the supply side index generated in section 3.2 and the demand side index generated in section 3.3:

$$SD_i = S_i \bullet D_i \tag{3}$$

Where SD_i is the Supply-Demand index of tank i, S_i is the Supply index score of tank i, and D_i is the Demand-side index score of tank i. A weighted sum is then performed to generate index statistics aggregation at DSD and district level.

3.5. The combined index with groundwater recharge potential

There is some initial evidence that tanks could contribute to groundwater recharge: Van Meter et al. (2016) assessed the role of tanks as rainwater harvesters in agricultural landscapes within semi-arid regions of Tamil Nadu in southern India and found that shallow groundwater recharge increased by more than 40%. Another recent study (Brauns et al., 2022) in three catchments in the crystalline basement of the Cauvery Basin within Karnataka State of southern India looked at the impact of cascade of tanks on recharge to aquifers using groundwater chemistry and water-level data. They concluded that recharge contributions from tanks to groundwater are small and dependent on local geology and land-use practices. Brauns et al. (2022) cautioned that careful planning and monitoring of groundwater levels and quality are necessary as chances of groundwater contamination from agricultural chemicals and other sources (e.g., urban pollutants) are high. Van Meter et al. (2016) concluded that while recharge potential from rainwater harvesting in tanks could be seen as a 'nature-based solution' to water scarcity, it may lead to negative environmental consequences by dramatically reducing (up to 75%) natural runoff. Though the full impacts of tank rejuvenation on groundwater recharge in the Sri Lankan context are under-researched, we have included this element to the analysis as a theoretical exercise for when more information becomes available that re-inform the index structure in future research.

There are six main aquifers in Sri Lanka with an additional aquifer found throughout the weathered basement (Fig. 5). Geology and hydrogeology of these aquifer systems vary considerably across the country, which in turn affects the utility of tanks upon which they are situated. A final layer of this analysis is to consider the pumping yield of each of the respective aquifers in the prioritisation of tanks for rejuvenation.

Well-yield data from Sri Lanka's National Water Supply and Drainage Board (NWSDB) (Joseph et al., 2022) show that the highest yield aquifers are shallow alluvial (920 L/min), followed by deep confined aquifers (up to 585 L/min), next are shallow karstic aquifers found in the Jaffna peninsula which have considerable productivity (yield 400 L/min), shallow sandy aquifers have a yield of 225 L/min. Those with lower yields are basement regolith aquifers (150 L/min),

[3] District Secretary's Divisions (DSD) are one administrative level below a district (level IV administrative level) in Sri Lanka.

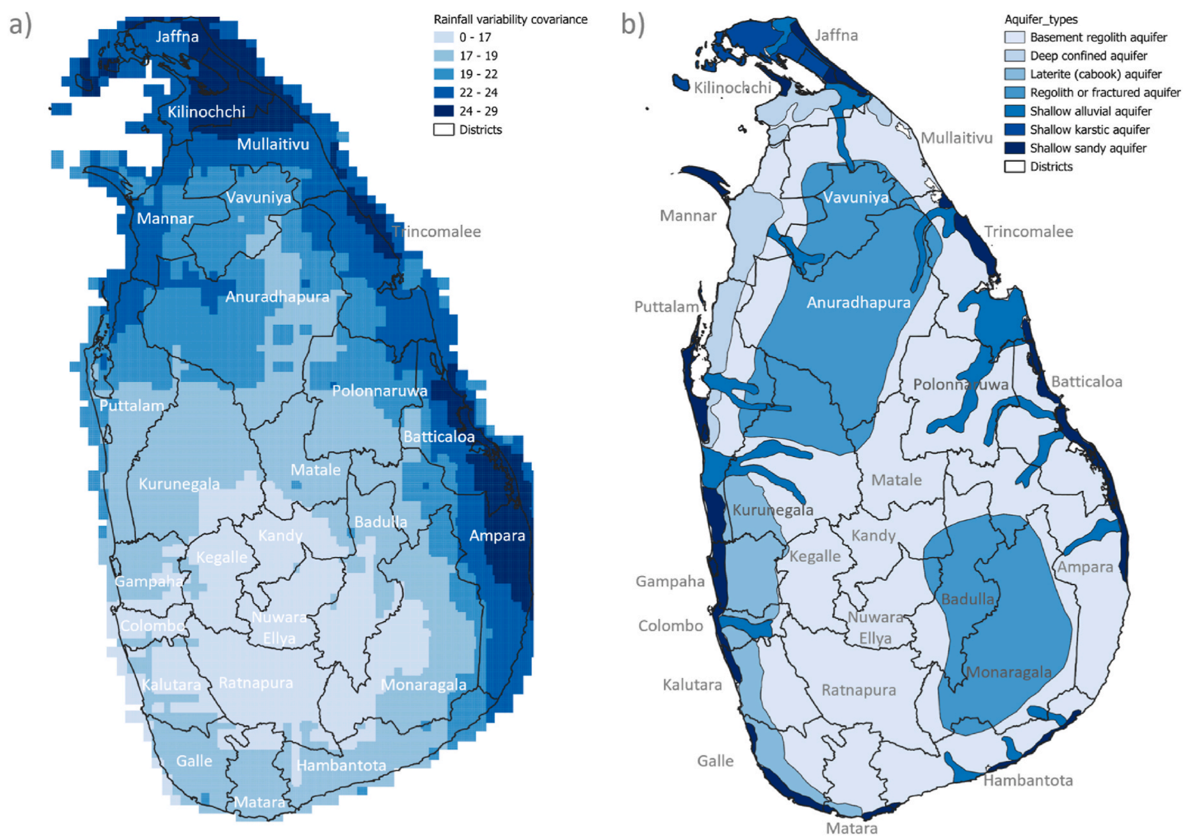


Fig. 5. a) Rainfall variability covariance in Sri Lanka; b) Geographic distribution of various aquifers in Sri Lanka.[41]

regolith or fractured aquifers (75 L/min) and laterite (Cabook) aquifers (70 L/min)(Joseph et al., 2022). Despite being low in productivity, focused groundwater recharge via leakage from tank cascades is highly likely in regolith or fractured aquifers in the north and southeast of the country.

With the tank demand, tank supply and tank utility indices all separately calculated, we then create a combined composite index. First of all, we rank the tanks depending on the supply-demand index score with the highest scoring being those that are most likely to require rejuvenation based on both sets of characteristics.

For the top 10% scoring tanks according to this ranking, we apply the groundwater recharge index so that we can sub-prioritise the tanks that score highly on supply and demand characteristics to consider groundwater recharge potential.

$$C_i = SD_i \bullet GWR_i \tag{4}$$

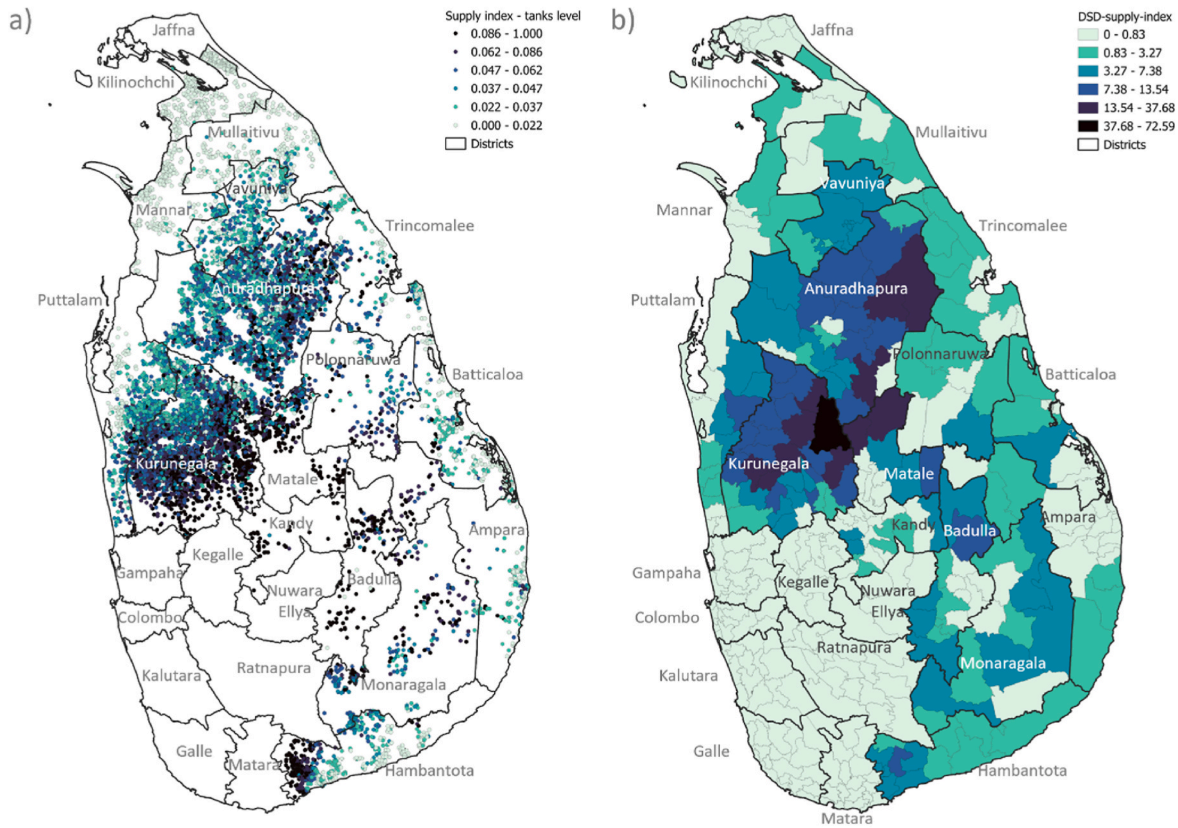
Where C_i is the Combined Supply-Demand index taking into account groundwater recharge potential of tank i, SD_i is the Supply-Demand index of tank i, and GWR_i is the groundwater recharge potential score of tank i location. A weighted sum is then performed to generate index statistics aggregation at DSD and district level.

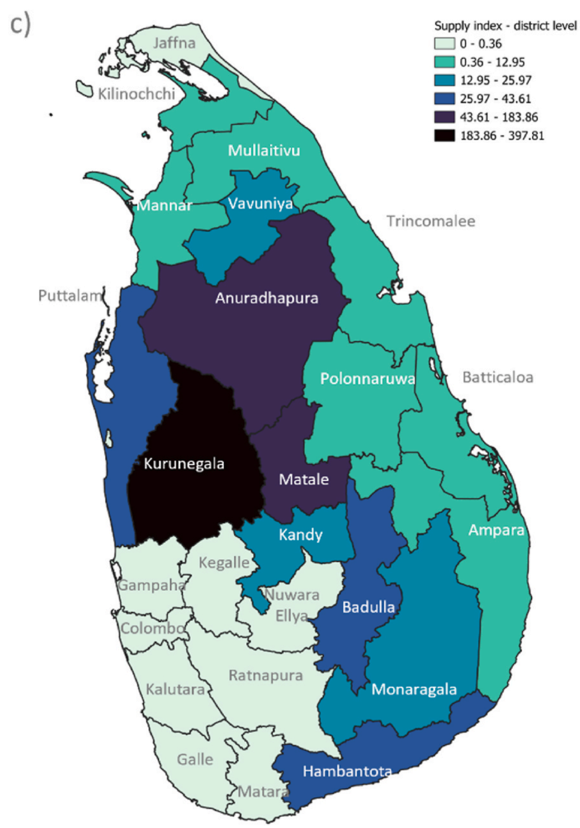
4. Results

Examining the visualisation of both supply (Fig. 6) and demand (Fig. 7) side indices, tanks in Kurunegala and Anuradhapura rank highest on both indices, partly because there is a large concentration of tanks in these two regions (4,434 in Kurunegala and 2,905 in Anuradhapura, with the remainder of the sample having under 1000 in each district).

With regards to the supply side index (Fig. 6) their siltation and soil erosion rankings cause Matale and Hambantota to rank third and fourth, though the difference is quite substantial when compared to the top two districts, in part due to the much lower agriculture dependent population. When we examine DSD level maps as opposed to District level, we see the level of variation within the priority districts. This is particularly notable in Hambantota on the supply index, where the targeted tanks are all in DSDs to the west of the district, whereas in Kurunegala and Anuradhapura the high ranking DSDs are more evenly distributed across the districts. The demand index (Fig. 7) also shows highest scores for Anuradhapura and Kurunegala, but Puttalam rather than Mutale comes third while Hambantota still comes fourth. Similar to the supply side index, there is a substantial drop in demand index scores for the third and fourth choices. The results at DSD level also show more of a stark difference between the top two districts and the rest of the country with many districts out of the top four not having any DSDs with a ranking over 0.85. For both supply and demand indices, Ratnapura ranks last, likely due to the very small number of tanks there (only 4 registered in the dataset used). When supply and demand indices are combined (Fig. 8), Matale and Hambantota also become prioritised though the top two districts remain consistent. Groundwater recharge potential consideration (Fig. 9) does little to change the ranking between the districts, though again, within the DSDs level maps it becomes evident where in each priority district the most attention should be focused when considering this third factor. Although the areas where groundwater recharge would be most effective are largely not in the priority districts, this was added as a sub-selection of the supply-demand targeted districts and hence by construction did not change the results greatly. It is worth noting that areas with higher numbers of tanks in general have lower pump yields in terms of aquifer recharge potential. The districts with some of the highest variance in rainfall do not see themselves at the top of many of the indices (Kilinochchi, Batticaloa and Ampara) because their tank numbers and agriculture dependent populations are relatively small.

Fig. 10 provides an overview of the ranking of different districts over the different metrics taken into consideration: the Supply index, the

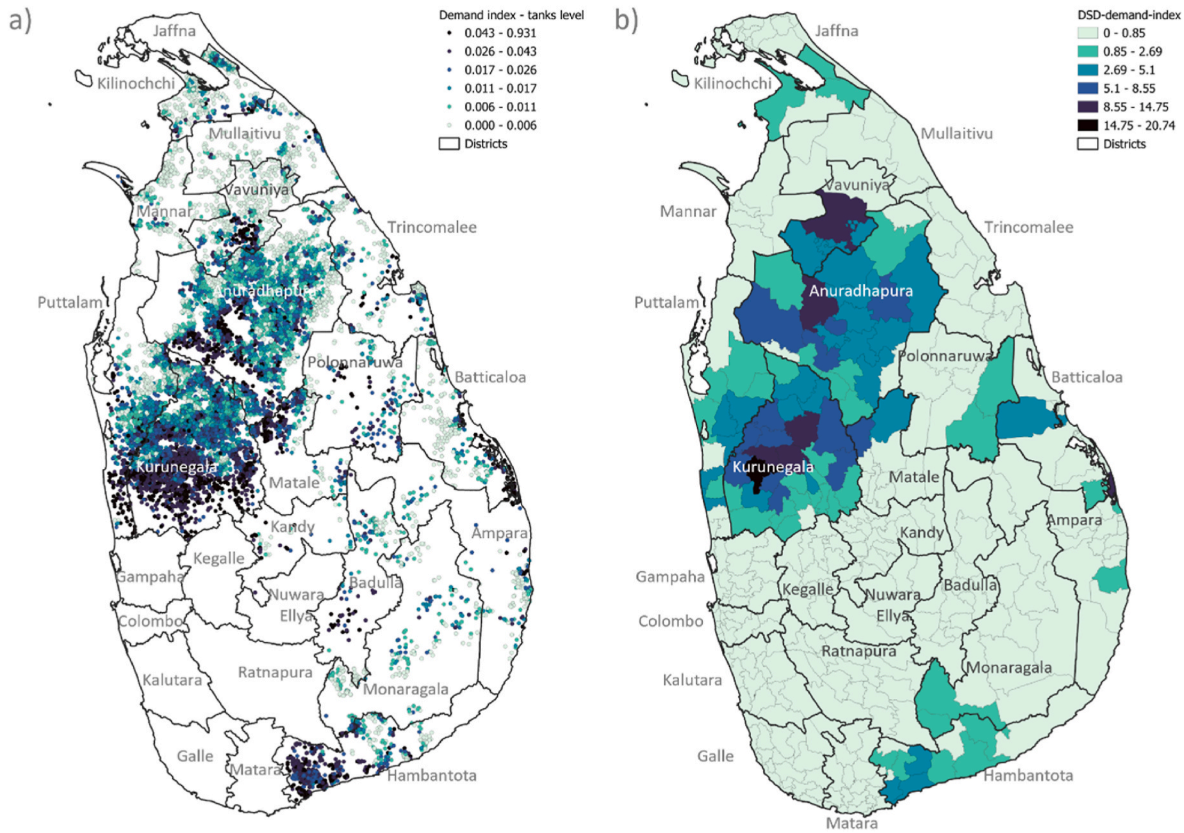


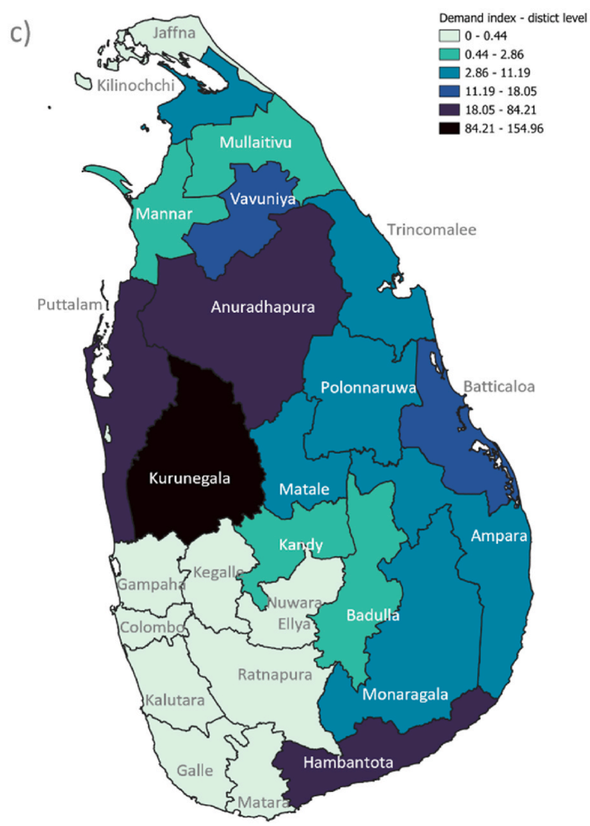


d)

District name	Rank	Supply index	ADP	N of tanks
Kurunegala	1	397.81	861,759	4434
Anuradhapura	2	183.86	518,678	2905
Matale	3	59.03	244,788	294
Hambantota	4	43.61	361,511	609
Puttalam	5	39.54	327,065	988
Badulla	6	34.87	472,792	180
Monaragala	7	25.97	306,732	281
Kandy	8	21.31	512,799	44
Vavuniya	9	18.59	72,084	532
Trincomalee	10	12.95	127,927	268
Polonnaruwa	11	11.38	208,821	162
Batticaloa	12	9.17	138,149	273
Ampara	13	7.41	213,973	164
Kilinochchi	14	5.40	21,874	466
Mannar	15	4.69	36,742	294
Mullaitivu	16	4.30	36,537	243
Ratnapura	17	0.36	579,676	4

Fig. 6. a) Disaggregated Supply index at individual tanks level; b) Supply index aggregated at District Secretary's Division (DSD) level (sum of individual tanks scores); c) Supply index at District level (sum of individual tanks scores). d) Rank of Districts based on Supply index scores.

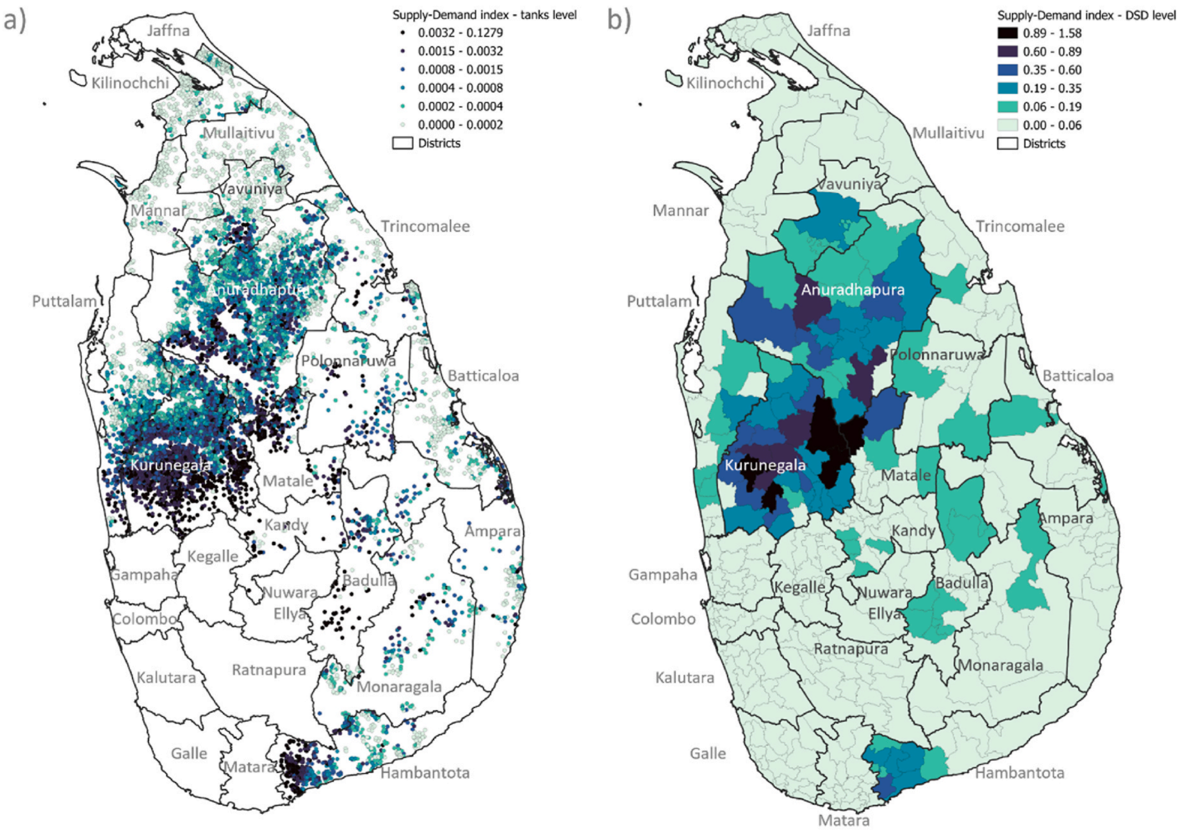


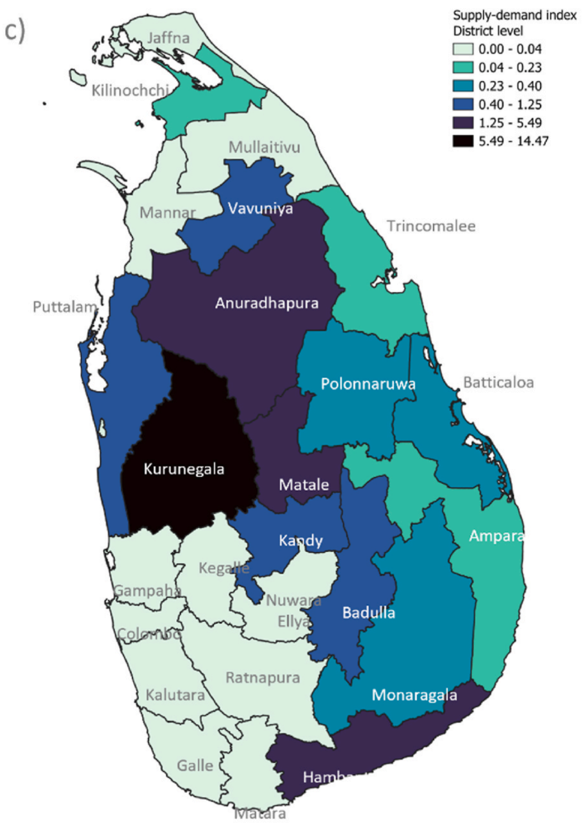


d)

District name	Rank	Demand index	ADP	N of tanks
Kurunegala	1	154.96	861,759	4434
Anuradhapura	2	84.21	518,678	2905
Puttalam	3	27.33	327,065	988
Hambantota	4	24.61	361,511	609
Batticaloa	5	18.05	138,149	273
Vavuniya	6	17.68	72,084	532
Matale	7	11.19	244,788	294
Kilinochchi	8	5.41	21,874	466
Polonnaruwa	9	4.32	208;821	162
Ampara	10	4.23	213,973	164
Monaragala	11	3.81	306,732	281
Trincomalee	12	3.44	127,927	268
Badulla	13	2.86	472,792	180
Mullaitivu	14	1.87	36,537	243
Mannar	15	1.64	36,742	294
Kandy	16	1.08	512,799	44
Ratnapura	17	0.44	579,676	4

Fig. 7. a) Disaggregated Demand index at individual tanks level; b) Demand index aggregated at District Secretary's Division (DSD) level (sum of individual tanks scores); c) Demand index at District level (sum of individual tanks scores); d) Rank of Districts based on Demand index scores.

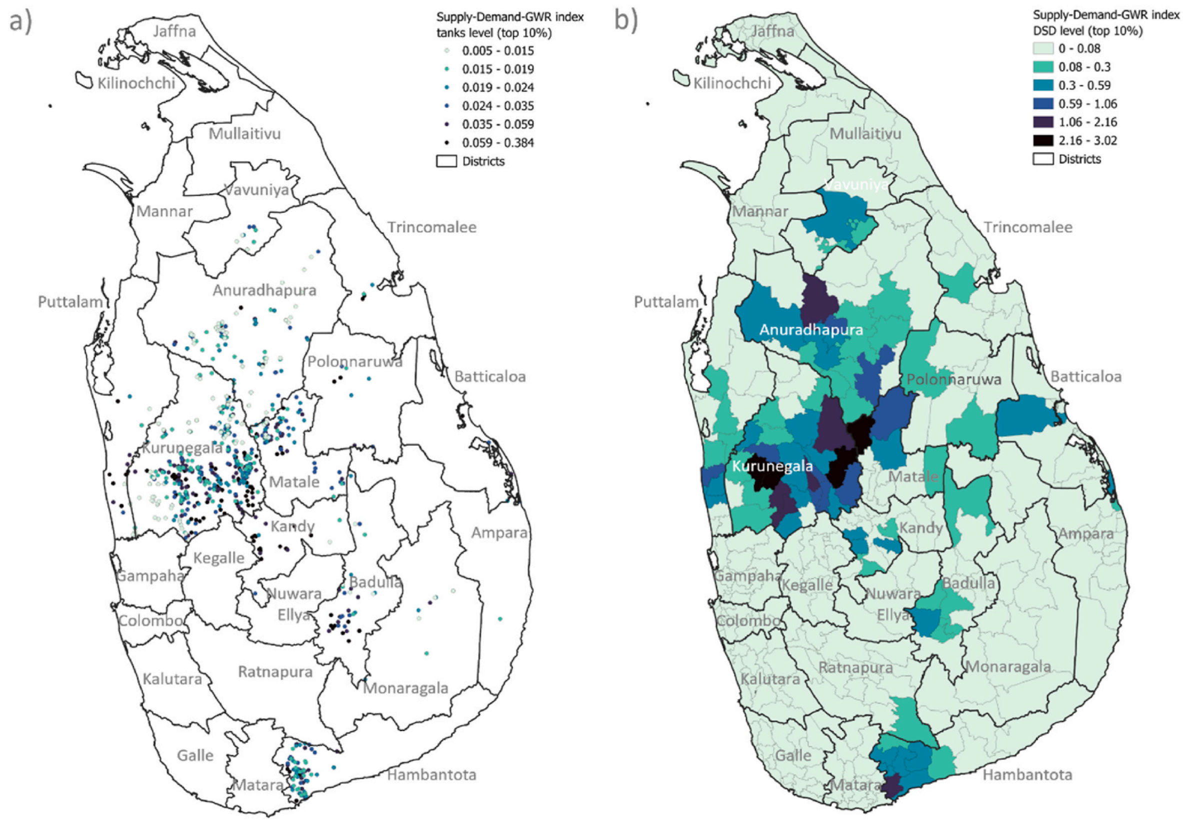


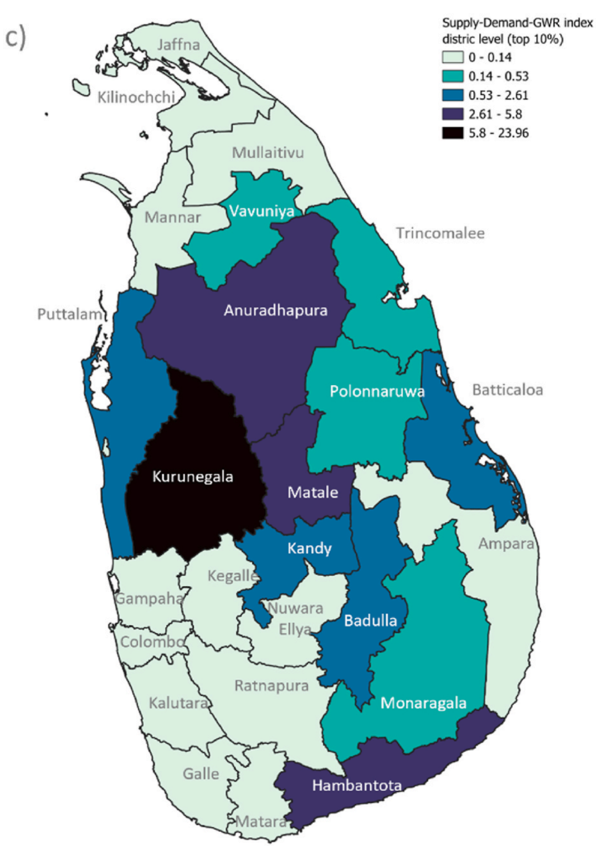


d)

District name	Rank	S-D index	ADP	N of tanks
Kurunegala	1	14.47	861,759	4434
Anuradhapura	2	5.49	518,678	2905
Matale	3	2.15	244,788	294
Hambantota	4	1.97	361,511	609
Puttalam	5	1.25	327,065	988
Badulla	6	0.79	472,792	180
Kandy	7	0.65	512,799	44
Vavuniya	8	0.63	72,084	532
Batticaloa	9	0.40	138,149	273
Monaragala	10	0.34	306,732	281
Polonnaruwa	11	0.31	208,821	162
Trincomalee	12	0.23	127,927	268
Ampara	13	0.13	213,973	164
Kilinochchi	14	0.07	21,874	466
Ratnapura	15	0.04	579,676	4
Mannar	16	0.03	36,742	294
Mullaitivu	17	0.03	36,537	243

Fig. 8. a) Combined supply-demand index at individual tanks level; b) Combined supply-demand index aggregated at District Secretary's Division (DSD) level (sum of individual tanks scores); c) Combined supply-demand index at District level (sum of individual tanks scores); d) Rank of Districts based on Combined supply-demand index scores.





d)

District name	Rank	SD-GWR Index	ADP	N of tanks
Kurunegala	1	23.96	861,759	4434
Anuradhapura	2	5.80	518,678	2905
Matale	3	4.64	244,788	294
Hambantota	4	3.91	361,511	609
Puttalam	5	2.61	327,065	988
Kandy	6	1.85	512,799	44
Badulla	7	1.59	472,792	180
Batticaloa	8	1.10	138,149	273
Vavuniya	9	0.53	72,084	532
Polonnaruwa	10	0.38	208,821	162
Monaragala	11	0.25	306,732	281
Trincomalee	12	0.24	127,927	268
Ampara	13	0.14	213,973	164
Ratnapura	14	0.12	579,676	4
Kilinochchi	15	0.00	21,874	466
Mannar	16	0.00	36,742	294
Mullaitivu	17	0.00	36,537	243

Fig. 9. Combined supply-demand with groundwater recharge (GWR) potential prioritisation at individual tanks level; b) Combined supply-demand with GWR potential prioritisation at DSD level (sum of individual tanks scores); c) Combined supply-demand with GWR potential prioritisation at District level (sum of individual tanks scores); d) Rank of Districts based on Combined supply-demand with GWR scores.

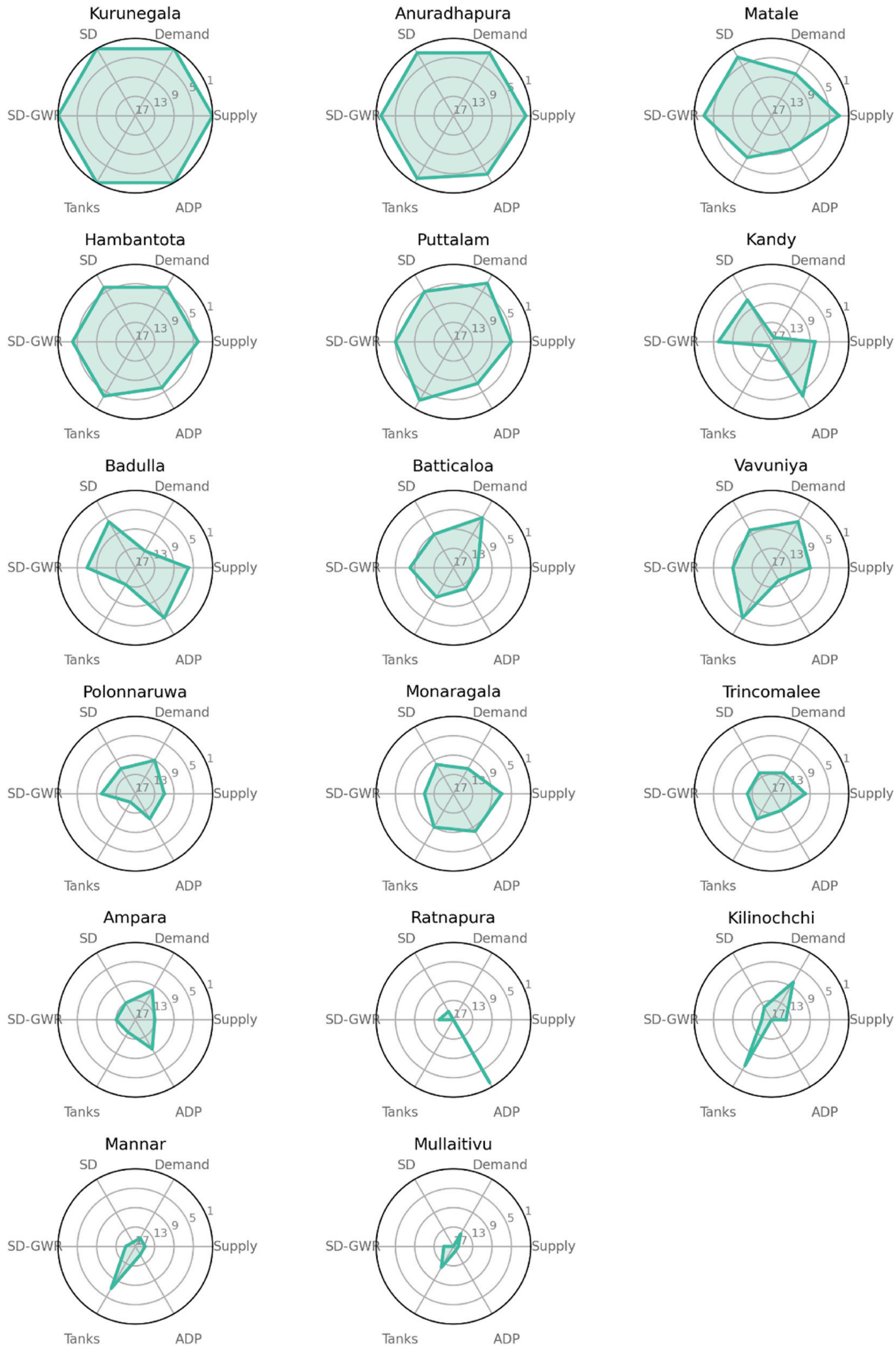


Fig. 10. Radar charts of Sri Lankan Districts ranked over six categories: Supply index, Demand index, Combined supply-demand (SD) index, Combined supply-demand with groundwater recharge (SD-GWR) potential, Number of tanks per District, Agricultural-Dependent Population (ADP) per District.

Demand index, the Combined supply-demand (SD) index, Combined supply-demand index with groundwater recharge (SD-GWR) potential, and also the number of tanks per district, and the Agricultural-Dependent Population (ADP) per district. This overview demonstrates

[4] Aquifer map compiled and digitised from several sources including Dissanayake and Chandrajith (2018); Dissanayake and Weerasooriya, 1985; Karuratne, 2007; Panabokke, 2007; Panabokke and Perera (2005).

how simultaneously taking into consideration several factors and combining supply and demand into an integrated index allows a more nuanced and comprehensive analysis: for instance, it is evident how Ratnapura ranks very highly in ADP count, but due to the low rank in number of tanks, it also ranks low in the combined indexes, or how despite the high number of tanks in Kilinochchi, its combined score is low due to the absence of ADP. The visualisation presented in Fig. 10 summarises the detailed results of Fig. 6–9 and allows a comprehensive analysis at the district scale.

5. Discussion

This paper has outlined a novel approach for identifying village water storage tanks in Sri Lanka that are most in need of restoration, considering supply side constraints, demand side pressures as well as their potential for offering a tertiary support to recharging the groundwater sources on which they sit. The estimates of agriculture dependent population for computation of tank demand at 1 km resolution show their concentration in the Southwest of the country. For tank demand and supply, the highest scoring tanks and DSDs for prioritisation consistently appear in Anuradhapura and Kurunegala districts, but these more granular estimates enable us to identify where - in those districts - the greatest benefit for rejuvenation would be. With respect to groundwater recharge, most high yield aquifers are not in districts scoring highly on supply and demand indices. The analysis therefore took the groundwater recharge potential on the subset of top scoring tanks on the other two indices. Hambantota is the district which sees the fourth highest ranking at district level when considering all three factors. We would like to highlight that the potential for tanks to contribute to groundwater recharge is understudied and requires further investigation for this final metric to be fully utilised.

This study is the first known study to attempt a systematic large-scale prioritisation of such tanks in the region at a disaggregated spatial scale down to tank and DSD level, with previous studies having been largely small-scale and/or qualitative in nature. For instance Kalaiarasi and Arul (2022) define a tank prioritisation index based on 24 indicators, but they only apply it to 4 tanks in the Madurantakam tank cluster (India). Also Nagarajan (2013) defined a tank rehabilitation index and applied it to only 5 tanks in two cascade systems in Pedda Mungalcheda and Addakkal (India). Anand et al. (2019) use remote sensing and GIS for the identification of 4 potential locations of small tanks rehabilitation in Bhadrachalam catchment from the Godavari river basin (India). On the other hand, it is possible to find studies at bigger scales (national level), however they are aggregate in nature, and do not consider single tanks features at a granular level; for instance Sirimanna and Prasada (2022) conduct a meta-analysis on tanks' rehabilitation performances measured through a benefit-cost ratio in India and Sri Lanka. They perform a regression analysis to identify factors that have positive impacts in rehabilitation projects like farmers participation, and operation and management activities in addition to the physical tank rehabilitation. Also Dayal and Iyengar (2006) conducted a large-scale study, however, they did not consider single tanks characteristics at scale, rather they examine the effectiveness of different tank rehabilitation models implemented in Tamil Nadu, Karnataka, Pondicherry, and Orissa. Their objective is to develop a protocol for future rehabilitation projects, with an emphasis on improving rural livelihoods and ensuring equitable access to water resources.

Meanwhile, the estimates provided in our study are intended to be used at a lower spatial scale and as the analysis demonstrates the statistics that are produced at district level can be misleading when compared to those at a higher spatial resolution. Water storage, both large and small reservoirs, is crucial for water security in countries with monsoon driven climates (Anand et al., 2019). They contribute to water security, particularly for agriculture dependent populations by creating a buffer to mitigate the impacts of floods in monsoon months and providing additional water supply for crops during water shortages and droughts in the dry season (Rodrigues et al., 2012). The method presented here for calculating high resolution estimates of agriculture dependent population is novel and holds potential to be applied to other countries around the world, with the replicable code provided. The indices themselves present an innovative perspective in their consideration of multiple characteristics that contribute to both supply and demand for tanks including rainfall variability and levels of siltation and soil erosion. The fine-grained estimates can be useful at the tank level but also their availability for aggregation at the DSD and district level can offer a useful tool for policy makers.

For what concerns the economic dimension of our analysis, our research provides a framework that generates numeric evidence at various spatial scales, which is crucial for informing policymakers and guiding strategic economic resource allocation. The economic significance of our framework lies in its ability to identify priority areas for the rejuvenation of small water tanks, which are critical for water storage and climate resilience. By mapping the demand from agricultural-dependent populations and evaluating the tanks from supply, demand, and utility perspectives, our prioritisation indices enable policymakers to allocate resources more effectively. This targeted approach ensures that investments are made in areas where they will have the most significant impact, thereby optimising the use of limited financial resources. Furthermore, our analysis provides a foundation for conducting cost-benefit evaluations to assess the potential economic benefits of tank rejuvenation against the costs involved. By incorporating economic metrics such as cost savings from reduced water scarcity, increased agricultural productivity, and improved livelihood security, policymakers can make use of the outcomes of our study for a comprehensive understanding of the financial implications of small tank rejuvenation. This economic insight supports the development of robust policies that not only enhance water security but also promote sustainable economic growth in vulnerable agricultural communities. In summary, the numeric evidence produced by our study serves as a critical tool for policymakers. It aids in the strategic allocation of economic resources, ensuring that investments in water storage infrastructure are both effective and efficient. This approach ultimately contributes to the resilience of agricultural communities, fostering long-term economic stability and sustainability.

Though the study offers useful methods and results, there are also some limitations that largely relate to data limitations in terms of quality and availability. Firstly, the study does not consider the way in which tanks are connected to one another as cascade systems due to a lack of available data on the connections. Further research could either collect data on the ground on connections between tanks (which could be challenging due to the scale of the study), or potentially seek to detect cascades by using AI assisted image processing of high-resolution satellite imagery. The consequence of not having information on cascades is that this analysis will be biased towards rejuvenating tanks around which more people are living in the demand index. This may obscure the possibility that in a cascade of tanks, those higher up in the cascade may need rejuvenation and are having knock-on impacts on those further down, even if they see less direct human interaction. We provide the supply and demand side indices separately as well as combined in this analysis, so it is possible to distinguish the need for prioritisation on e.g. tanks that are in disrepair, even if they do not immediately serve a large population nearby. Secondly, for the estimation of the agriculture dependent population, we assumed that agriculture dependent populations would live close to agricultural lands, in the same way as we assume that users of tanks live close to tanks. Furthermore, due to the lack of information on the command area of each tank, we assumed a 1 km buffer around each one. Empirical information on the command areas for each tank may in turn change the agriculture dependent populations we assume to be reliant on them in each administrative unit. And although the calculation of agriculture dependent population at the administrative unit level reflects the population, calculations of ADP at the tank level do not consider overlaps where a single user may be within the catchment of two or more tanks. Thirdly, we do not account for the areas where major irrigation systems are now accessible in this analysis. In some places the tanks may supplement irrigation systems, while in others they may not be necessary if they are completely replaced. If there are no irrigation systems available, the reliance on small tanks will be much greater. We have not been able to include this due to lack of available data at national scale, but would recommend this as an area for future work if data on major irrigation systems becomes available. Fourth, the groundwater recharge analysis should be taken with caution as we should also consider that too much recharge may affect environmental flows as described earlier in the text. Finally, the overall quality of the input data necessitated a large amount of pre-processing that was needed to combine information from across multiple sources before analysis begun. Siltation estimates were imputed for a portion of the sample as described in the methods section and it would be advisable to replace the imputed values with real data with future data collection efforts. We would recommend some further qualitative research to corroborate the findings presented here, and better understand the reasons for the results that we see here. The main contribution of the study is to provide the framework for analysis when input data is available, but it is nonetheless a large-scale effort with available information.

6. Conclusions

This paper has outlined an approach for prioritisation of village water storage tank restoration from a database of 11,000 considering supply, demand and utility factors. This is crucial, as these tanks are likely to be in higher demand in the coming decades, due to increasing climate variability. Some novelty aspects include the provision of fine-grained estimations of both agriculture dependent populations and tank prioritisation criteria, together with scale of the case study. It has also created a code base and methodology that can be replicated in similar contexts, such as in peninsular India where similar village tank systems have been in operation for thousands of years, and the scale for application is even greater. The paper also intends to be a useful policy tool by offering estimates at more aggregated DSD and district levels that highlight where different types of targeting could take place. Although the resulting estimates could benefit from improved data availability, particularly around tank cascades, this paper aims to also motivate the collection and collation of such information for applied usage.

CRediT authorship contribution statement

Fulvio D. Lopane: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Sophie Ayling:** Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Yi Rong Hoo:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Mohammad Shamsudduha:** Writing – review & editing, Methodology, Investigation. **Qiao Wang:** Writing – review & editing, Methodology, Investigation. **George Joseph:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Aroha Bahuguna:** Supervision, Conceptualization.

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Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.124031.

Data availability

Data will be made available on request.

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