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A Planning Tool for Optimizing Investment to Reduce Drinking Water Risk to Multiple Water Treatment Plants in Open Catchments

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Abstract: Supplying safe, secure, and reliable drinking water is a growing challenge particularly in regions where catchments have diverse land uses, rapidly growing populations, and are subject to increasing weather extremes such as in the subtropics. Catchments represent the first barrier in providing ecosystem services for water quality protection and bulkwater suppliers are therefore investing in mitigation measures to reduce risk to drinking water quality for consumers. This paper presents an approach to combine data on erosion processes, pathogenic bacteria and protozoa from several sources, determine the highest risks from these hazards and identify an optimum portfolio of intervention activities that provide maximum risk reduction at water treatment plants (WTP) for a given budget using a simulated annealing optimizer. The approach is demonstrated in a catchment with six WTPs servicing small rural to urban populations. The catchment is predominantly used for agriculture. Results show that drinking water risk from protozoa can be reduced for most WTPs for moderate investment budget, while bacteria risk reduction requires significantly larger budget due to the greater number of significant source sites relative to protozoa. Total suspended sediment loads remain a very high risk to most of the WTPs due to the large extent of channel and gully erosion and landslides. A map of priority areas and associated suite of interventions are produced to guide on groundwork.

Keywords: decision support system; simulated annealing; optimization; total suspended sediments; pathogens; bacteria; protozoa; intervention; natural resource management

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1. Introduction

Bulk water suppliers and water utilities in Australia need to provide safe, secure and reliable water supply for consumers. They are regulated to implement the Australian Drinking Water Guidelines Framework for the management of drinking water quality (the ADWG Framework) which sets out a comprehensive, integrated approach for managing water contamination risks across all stages of water supply—from catchment to tap [1,2]. This represents a multi-barrier approach in which the catchment is the first barrier providing the ecosystem services for water quality [3], hence bulk water suppliers have a significant role as catchment managers.

In open catchments, land use changes for agriculture, forestry, industry, recreation and residential dwelling, have led to significant point and diffuse sources of water quality risks and degradation of ecosystem services the catchment once provided [4,5]. In southeast Queensland, Australia, where more than 90% of source water supply is from open catchments, the priority contaminants considered risks to water quality that have a direct impact on water treatment plants (WTP) capacity are pathogenic microorganisms [6] and total suspended sediments (TSS) [7]. The ADWG Framework highlights pathogens as the greatest risk to consumers of drinking water and catchment sources can include domestic onsite wastewater systems (OSFs), sewerage treatment plants (STPs), stormwater and animal waste from broadscale grazing and intensive animal industries [2]. Elevated levels of TSS can cause treatability issues at WTPs, through reducing the effectiveness of disinfection, increasing the requirement for chemical dosing [8] and reducing drinking water production rates.

Riparian rehabilitation projects [9–11] and other interventions to mitigate water quality risks such as OSF upgrades [12], intensive animal effluent treatment upgrades, hardening laneways and stream crossings, are essential to improve the first barrier or the ecosystem service the catchment provides [13]. However, catchment managers have been grappling with decisions regarding the location, type, and scale of these catchment interventions (mitigation measures and rehabilitation), particularly when finite resources have to be allocated across large catchment areas [14,15]. This poses the question: How can catchment managers or bulk water suppliers optimally allocate resources to effectively improve drinking water quality?

Many agencies use 'hotspot' or 'threat' maps to define the distribution, intensity and frequency of hazardous events to water quality. These maps can be helpful for identifying the location of risks, but they cannot always provide a robust method to allocate intervention resources, particularly when multiple objectives need to be considered [15,16]. Instead, the data and other information provided in the maps must be integrated into a structured, transparent and repeatable framework to develop intervention portfolios to provide the greatest return for a fixed budget [16].

The solution to providing this framework has been the development of the 'Decision Support System' (DSS). Typically, a DSS operates in a GIS environment and combines spatial datasets, non-spatial data (quantitative and qualitative) and other information to assess where contaminants arise, their mobilisation and their relative contribution to changes in water quality within a source water catchment. By linking the contaminant to a land use activity or catchment process through data analysis, a DSS can provide direction on where interventions should be targeted to get the best outcomes for water quality improvement [17,18]. The DSS and the underlying data must also be detailed enough to give an acceptable level of (un)certainty in the results [19]. Similarly, the concept of longitudinal connectivity has to be included in the planning process and has been successfully applied with DSSs designed for conservation planning [20,21], and for some catchment-based water quality models such as eWater Source [22].

In order to successfully manage multiple risks to water quality with catchment interventions, a DSS must be designed to evaluate alternative combinations of interventions and the trade-offs between them [16]. In many instances, agencies develop 'hotspot' or 'threat' maps from the outputs of catchment-based water quality models. A review of existing catchment-based water quality models and platforms was recently undertaken by Fu et al. [23], noting that main catchment models used across the peer-reviewed literature were the Soil and Water Assessment Tool [24], Hydrological Simulation Program—FORTRAN [25], Integrated Catchment Model (INCA) [26] and eWater Source [22]. While these models can be used to predict changes in water quality based on surrounding land use or catchment management, they cannot apply catchment interventions and link these to an optimisation algorithm so that a preferred set of catchment interventions (i.e., investment scenario) can be selected. Instead, the investment scenario must be developed a priori so that the input intervention portfolio includes pre-selected interventions. This means that the set of catchment interventions selected and their location and amount may not be the optimal for the given budget. Additionally, as running each scenario separately is very time consuming, this would limit the number of different interventions that can be used and therefore the number of portfolios generated.

Optimization algorithms can be used to select the optimal intervention portfolio for set targets, for example the largest reduction in risk to water quality for a given investment. A spatial optimization algorithm creates portfolios of interventions and compares the risk reduction between intervention portfolios to arrive at an optimal or near optimal portfolio.

This process of generating portfolios and calculating the risk reduction is computationally demanding when the number of spatial units and interventions is large and when there are multiple risks to trade off. There are several approaches to optimization which attempt to deal with a large solution space in order to reduce prolonged run-times.

Genetic algorithms have been successfully applied to optimize the location of best management practices to control of diffuse pollution sources [27,28], as well as many other parts of the water supply industry [29,30]. However, genetic algorithms do not handle multiple intervention options and spatial complexity well [31,32]. An alternative to complete optimization is multi-criteria analysis where pre-developed scenarios, prepared through general rules, that represent 'likely' optimal solutions are compared [33]. This approach is simple and supposedly not as resource demanding as implementing a full optimization process, but it is largely unknown what the cost/benefits are of the scenarios, how different these results would be to an optimized result and become very inefficient when considering complex models with multiple interventions [34].

Simulated annealing is an optimization routine that has been applied to resource allocation [35], conservation planning tools [20,21] and planning catchment erosion mitigation [15]. Simulated annealing is a probabilistic technique for finding the global optimum in a search space. The approach is to select a potential solution from the search space, compare it to the previously generated best performing solution and then reject the potential solution or replace the best performing solution with the potential solution. Subsequent solutions are based on minor variations of the current best performing solution. To avoid local minima, the simulated annealing approach initially explores the broader solution space before focusing on minima [32]. The approach is favoured due to its ability to deal with multiple intervention options and spatial complexity and also has the ability to reduce run-times in order to select an optimal set of interventions [31,34].

For DSSs to successfully improve catchment water quality, the DSS framework must be made relevant for the bulk water suppliers and provide interpretable and meaningful direction for those responsible for implementing the actions [35,36]. Environmental risk assessments have been used extensively to understand the relative impacts of multiple stressors on a selected environmental value. A relative risk framework was used to provide an estimate of the risk of contaminants from different catchment areas to the iconic Great Barrier Reef in Australia based on anthropogenic load score, reef condition score and reef exposure score [37]. Each parameter was given a score between 1 and 5 based on data ranges and assumed relationships between the value and degree of risk. This application allowed for the identification of suspended sediment, dissolved inorganic nitrogen and PS-II herbicides as most likely to pose a threat to the quality of run-off water entering the GBR ecosystem [37]. Given that data and resource limitations can lead to uncertainty of the absolute values of modelled contaminant loads [33,38], the strength of the relative risk assessment is that it can allow for the different sources of contaminants to be compared against particular land use types [37].

In southeast Queensland, there are over 30 WTPs supplying a population of over 3.4 million with a median growth rate of 2% [39]. Each of the WTPs has a different capability of treating bacteria, protozoa, virus and TSS. Given that determining precise loads of TSS and pathogens would be unrealistic for the 1.8 M ha of southeast Queensland water supply, a relative risk framework has been adopted to facilitate the identification and location of the sources of priority contaminants considered risks to water quality received at a specific WTP. Furthermore, the risk framework approach enables comparison between the contaminants for each WTP, as well as across the water supply region.

The aim of the paper is to outline a new approach for combining model and survey data on hazardous processes to drinking water quality (TSS, Bacteria, Viral and Protozoa) in open catchments using a risk framework and demonstrate how spatial optimisation of mitigation (intervention) measures are applied to reduce the highest risks to WTP intake based on intervention cost, efficacy and connectivity between the hazard source and WTP. Herein, the paper describes Seqwater's Catchment Investment Decision Support System

(CIDSS) and provides a case study of the Logan-Albert Catchment. Specific objectives of the case study catchment analysis are: (1) Can drinking water risk from Bacteria, Protozoa and TSS be reduced in the catchment and at what cost? (2) If so, where should funds be invested and what type of mitigation measures are required to achieve risk reduction for a given budget? (3) How does one prioritise the on-ground work program based on the optimal solution of mitigation measures? (4) What are the hazard treatment challenges when identifying new drinking water sources in highly developed catchments?

2. Study Area

The CIDSS is being applied to Seqwater's source catchments in southeast Queensland, Australia (Figure 1). The region has a subtropical climate with average summer and winter temperatures of 24 °C and 14 °C respectively. Annual and seasonal rainfall are variable with most rainfall occurring in Summer and autumn. As a result, river discharge regimes have very high hydrological variability [40]. Drinking water is sourced from seven coastal catchments each with one or more nested off-takes for water treatment located either along a river reach or within reservoirs. Additionally, there are two ground water bores and a desalination plant used for drinking water supply.

The combined catchment area for the surface source water is ~1.8 million ha of which Seqwater owns <5%. Approximately 70% of the source catchments is used for agriculture, dominated by livestock industries, and only 22% of the source catchments remains as natural environment. The catchments also include urban, peri-urban and rural residences where wastewater treatment varies from old OSFs (e.g., septic tanks) to high-capacity STPs for urban developments. Stormwater generally has low levels of treatment across the source catchment areas.

The CIDSS has been populated for all 30 WTPs and associated source catchments in SEQ. However, this paper focuses on a small subset (six WTPs) and their source catchments to demonstrate the application of the approach. The source water catchment demonstrated and discussed in this paper is the Logan-Albert catchment, which includes the Logan River and Canungra Creek (Figure 1C). Mean annual rainfall for mid (Beaudesert) and upper catchment (Lamington National Park) are 916 mm and 1580 mm respectively. Logan River currently has four off-take locations to supply WTPs to service communities along the catchment valley (Table 1). One-fifth of off-take is proposed in the Lower Logan River to accommodate growing water supply demand and water quality treatment challenges posed by the catchment. The proposed WTP would see the source catchment area increased by 996 km^2 and include a 102,884 ML reservoir (Wyaralong Dam). Canungra Creek has a single off-take for WTP to service the township of Canungra. The modelling scenarios detailed below consider water quality hazards impacting all six WTP (including proposed new WTP with an off-take at Cedar Grove Weir (CGW)). The catchment area across which interventions can be applied to reduce water quality risk is 2473 km^2 and comprises predominantly livestock grazing and also public lands for nature conservation in some headwaters, cropping on floodplains and residential areas (Figure 1C).

Table 1. Logan-Albert catchment water treatment plants (WTPs).

WTP	Supplies	Sub-Catchment Area (km^2)	Number of Planning Units	Planning Unit Area $\mu(\sigma)$(ha)
TMD	Maroon Dam	106	8	1323 (662)
TRA	Rathdowny	534	26	2052 (1849)
TKO	Kooralbyn	1035	47	2202 (1698)
TBE	Beaudesert	1385	61	2270 (1663)
CGW	Beaudesert, Water grid	2381	130	1832 (1446)
TCN	Canungra	92	4	2298 (1435)

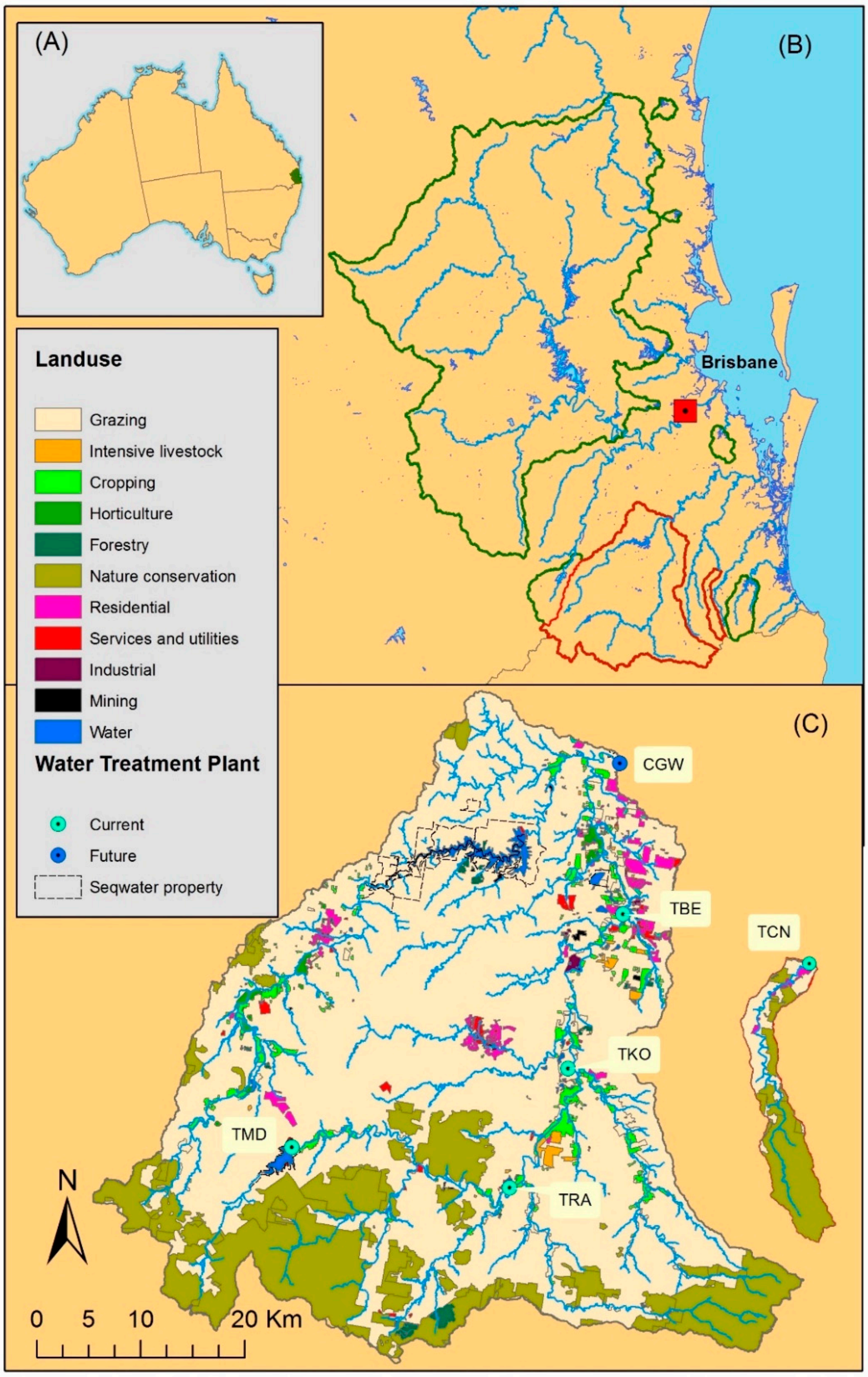

Figure 1. (**A**) Study area location on the east coast of Australia in Southeast Queensland. (**B**) Boundaries of the source water catchments with the case study catchment boundary shown in red. (**C**) Land use in the Logan-Albert catchment upstream of the WTP intakes.

3. Materials and Methods

3.1. Catchment Investment Decision Support System

The Catchment Investment Decision Support System (CIDSS) is a planning support tool that can identify hazardous processes and quantify their contribution to TSS and pathogen loads within source water received at downstream WTPs. The contribution from each of the hazardous processes to the overall TSS and pathogen loads are then assessed as the level of risk, which is based on the WTP treatment capability. A simulated annealing optimiser is then used to produce a portfolio of intervention activities (from a list of 63 different intervention activities with individual efficacies) across a given source water catchment area and is designed to provide the greatest reduction in drinking water quality risk for a given budget. The input hazards and solution interventions are specified at hydro-geomorphic units representing source water subcatchments containing similar land use and therefore processes generating hazards to water quality. These base spatial units are referred to as Planning Units and are typically 14 ha to 4000 ha (25th–75th percentile).

3.1.1. Inputs

The inputs to the CIDSS are (1) spatial data for solution visualization, which include catchment (defined by area contributing to the off-take point for WTP) and Planning Unit geometries, (2) Planning Unit physical attributes, (3) drinking water hazards, (4) interventions available, costs and efficacy, (5) upper limits of intervention that can be applied within each Planning Unit and (6) pathogen attenuation and TSS deposition and storage (loss) rates along the transport pathway.

Drinking water quality hazards considered in the CIDSS are TSS and pathogenic bacteria, protozoa and viral particles. These four water quality hazards are aggregated within the tool from 12 hazardous processes provided as input at the planning unit scale (Table 2). The derivation of the hazards through the hazardous process is described in the Supplementary Material S1 and briefly summarised here. The TSS sources are modelled independently of the CIDSS for diffuse hillslope erosion, landslides, gully erosion, channel (bank) erosion and point sources from intensive primary industries. The TSS loads are derived from empirical models and represent long-term annual averages from each source (erosion process) delivered to the outlet of each Planning Unit.

Table 2. Hazardous processes for each hazard to drinking water quality considered in the Catchment Investment Decision Support System (CIDSS).

Hazardous Process	Hazard			
	TSS	Bacteria	Protozoa	Viral
Hillslope erosion	✓	-	-	-
Landslides	✓	-	-	-
Gully erosion	✓	-	-	-
Channel (bank) erosion	✓	-	-	-
Unsealed roads	✓	-	-	-
Point source (instream sand and gravel extraction)	✓	-	-	-
Livestock grazing	-	✓	✓	-
Intensive livestock industries	-	✓	✓	-
Sewerage Treatment Plants	-	✓	✓	✓
On-site Sewerage Facilities	-	✓	✓	✓
Stormwater	-	✓	✓	✓
Aquatic recreation	-	✓	✓	✓

Pathogen sources are generated from livestock grazing, intensive livestock industries, STPs, OSFs and stormwater runoff from urban and residential areas. Pathogen source data are derived using the Sanitary Survey methodology [40–43] independent of the CIDSS.

The CIDSS currently includes 10 intervention programs containing 63 intervention activities that can be implemented in combination. A subset of the interventions applied in this case study is listed in Table 3. Each of the intervention activities (types) can impact any of the hazardous processes. The CIDSS allows for additional interventions to be added through updated input configuration tables.

Table 3. Intervention programs and available intervention types to mitigate source catchment water quality risks in the Logan-Albert catchment case study.

Program	Intervention	Efficacy
Channel erosion	Earthworks/rockwork/fencing—basic and complex	90%
	Revegetation and fencing	90% & 1 LRV
	Revegetation	60%
	Livestock exclusion fencing	75% & 1 LRV
Broadscale Livestock & Riparian Manag.	Earthworks basic	90%
	Revegetation	60%
	Livestock exclusion fencing	75% & 1 LRV
	Revegetation and fencing	90% & 3 LRV
	Fencing and off-stream watering	75% & 3 LRV
	Revegetation, fencing and off-stream watering	90% & 3 LRV
Gully erosion	Earthworks/rockwork/fencing—basic and complex	90%
	Revegetation with grasses	60%
	Livestock exclusion fencing	75%
	Revegetation and fencing	90%
Landslides	Earthworks complex	90%
	Earthworks simple swales or contours	90%
	Earthworks and fencing	90%
	Revegetation with woody species	75%
	Revegetation and fencing	90%
	Livestock exclusion fencing	10%
Point sources	Revegetation with grass filter strips	80%
	Revegetation and fencing	90%
	Sediment detention dam (small, large, complex)	50, 60 & 75%
Intensive livestock effluent manag.	Fencing to exclude calves from water course	60% & 1 LRV
	Laneways	60% & 1 LRV
	Stream crossings	60%
	Feedpad—hardening with basic or advanced drainage	10, 20% & 1,2 LRV
	Effluent pump upgrade and primary treatment (solids trap)	50% & 1 †,2 ‡ LRV
	Secondary treatment	60% & 1 †,2 ‡ LRV
	Effluent pump upgrade, primary treatment (solids trap) + irrigation	60% & 2 †,3 ‡ LRV
	Effluent pump upgrade, primary treatment (solids trap) + Secondary + irrigation	60% & 3 †,4 ‡ LRV

TSS efficacy in percent, pathogen efficacy in log reduction value (LRV). † is LRV specific to bacteria, ‡ is LRV specific to protozoa. Efficacy separated by comma indicate different values for the different level (e.g., small, large, complex) of the intervention.

Each intervention has a cost per unit specified as part of the input. These values are derived from Seqwater's historical investment programs that are based on commercial contractor rates for implementing the different activities across the region. Each intervention includes an efficacy for each of the hazardous processes (Table 3). The efficacy is used to scale the initial hazard load through the application of the intervention. The efficacy for erosion and sediment control is represented as a percentage reduction scaled by area of intervention applied. Efficacy values can be specified for different types of intervention. For example, where intervention requires stock exclusion fencing, complete exclusion will have a different response to partial exclusion which still allows concentrated stock access points. For pathogen hazards, intervention efficacy is based on log reduction values (LRV).

3.1.2. Computational Steps

A detailed description of the computational process is presented in the Supplementary Material S2. The key concepts are described here. The three main computational steps are data preparation, risk at plant conversion, and optimisation cost function.

Data Preparation

The data preparation step converts data from its input form to a table that represents the hazard at the planning unit for each input hazardous process. No transformation of TSS data is required. For bacteria and protozoa, the input data are consequence scores ($\log_{10}$ organisms (org)/day and $\log_{10}$ oocysts/day respectively) and likelihood scores (for connecting to waterways) and provided in the form of site-based tables, which list each site for each hazardous process within each planning unit. A modified score is calculated using Equation (1) to provide a score representative of org/day and oocysts/day (in log10 domain) delivered to a watercourse from the source. To sum the scores for each hazardous process and for each hazard, scores are converted to the natural domain summed and converted back to the log10 domain.

$$\text{Modified score} = \text{Consequence score} - (\text{5-Likelihood}) \tag{1}$$

Risk at Plant Conversion

There are multiple hazardous processes contributing to a single hazard. For example, hillslope erosion, gully erosion, instream sources, unsealed roads and landslides all contribute to the overall TSS load. Similarly, there are multiple hazardous processes contributing to the microbial hazards. The pollutant load generated by hazardous processes at the planning unit scale (input) is combined to produce a total hazard load at the planning unit scale.

To determine the risk at WTP posed by the hazards and hazardous processes from each Planning Unit, first the effective hazard at the plant is calculated by applying an attenuation factor to allow for distance travelled and dam capture. The second step in the procedure is to convert from the raw hazard units to a measure of risk at the WTP while noting each plant has different treatment capabilities.

TSS attenuation is based on a half distance approach (Equation (2)) to account for sediment loss from overland flow for Disconnected Planning Units and sediment deposition and long-term storage along channelized flow paths ($\geq$ 3rd-stream order).

$$TSS_{at} = TSS_{PU}\left(\frac{1}{2}\right)^{D/d} \tag{2}$$

where TSS_{at} is TSS load after attenuation, TSS_{PU} is TSS load at Planning Unit outlet, D is distance from Planning Unit outlet to watercourse ($\geq$3rd-stream order) for disconnected Planning Units and/or watercourse distance from Planning Unit to WTP excluding reservoirs for connected Planning Units. d is a parameter defining the distance at which 1/2 the TSS is lost to long-term storage and is set to 0.5 km for overland flow for disconnected Planning Units and 30 km for connected flow paths. D pertaining to Disconnected distance and Connected distance are input fields for Planning Unit attributes.

Reservoir trapping efficiency of TSS is a precalculated variable based on inflow to reservoir volume relationships [44] and is included as an input field for Planning Unit attributes. Further details of Trap efficiency calculation are provided in Supplementary Material.

Numerous factors influence pathogen attenuation rates [13]. Temperature and time are main factors, however there are limited empirical data for die-off rates for subtropical systems. Here, we use conservative attenuation rates based on temperate studies of 2 log reduction in large reservoirs (>1 GL), 1 log reduction per 10 km of low discharge channel and 1 log reduction per 50 km of high discharge channel [45]. Low discharge channel is defined as having daily flows less than or equal to $3 m^3 s^{-1}$ for more than 70% of days per year.

Hazard-to-risk conversion is applied to bring all hazards into a common unit for system evaluation and is done by a lookup table. Each WTP has thresholds of treatment capability for TSS (turbidity), bacteria, protozoa and viral loads (Table 4). Increasing from insignificant to catastrophic requires changes to operation and increased treatment cost until the plant either fails and/or needs to go offline due to not being able to treat the source water to a safe standard. Threshold values for pathogen are log scores directly related to the modified log scores. For TSS loads, turbidity thresholds (NTU) have been converted to annual load threshold based on (dis)aggregation methods using long-term ($\geq$10-year gauging station records) and TSS-NTU relationships established from regional monitoring programs.

Table 4. Example water treatment plant lookup table for treatment capability thresholds.

Risk	Descriptor	TSS (t/Year)	Viral (log_{10} Particles/Day)	Bacteria (log_{10} Organisms/Day)	Protozoa (log_{10} Oocysts/Day)
1	Insignificant	<343	<4	<4	<3.5
2	Minor	343 < 521	4 < 5	4 < 5	3.5 < 4.5
3	Moderate	521 < 906	5 < 6	5 < 6	4.5 < 5.5
4	Major	906 < 2070	6 < 8	6 < 8	5.5 < 7.5
5	Catastrophic	>2070	>8	>8	>7.5

In order to create a single objective function to control the optimisation, the four risk values (TSS, protozoa, bacteria, viral) are combined to a single overall risk value. The CIDSS creates the overall risk by applying a user specified weighting for the relative contribution of each of the four hazard risks (default to even weighting across hazards). The weighting approach requires the modeler to a priori determine the relative importance of each hazard for the WTP operation. The weighting also allows the consideration of hazards independently by scaling other hazards to zero.

Optimisation Function

The basic principle of the optimisation is to determine the overall reduction in risk from the initial base case and to compare that to the cost of producing the risk reduction.

The CIDSS uses a third-party simulated annealing computation library called Simanneal (see https://pypi.org/project/simanneal/). The simulated annealing process involves:

1. Randomly move or alter the state.
2. Assess the energy of the new state using an objective function.
3. Compare the energy to the previous state and decide whether to accept the new solution or reject it based on the current temperature.
4. Repeat until you have converged on an acceptable answer.

For a new scenario to be accepted, it must meet one of two requirements:

a. The scenario causes a decrease in state energy (i.e., an improvement in the objective function), or
b. The scenario increases the state energy (i.e., a slightly worse solution) but is within the bounds of the temperature. The temperature exponentially decreases as the algorithm progresses. In this way, we avoid getting trapped by local minima early in the process but start to hone a viable solution by the end.

The parameters required to control the simulated annealing process are:

- Tmax—the maximum starting temperature.
- Tmin—the ending temperature.
- Steps—the number of iterations in the simulation.
- Max_saturated_Steps—the maximum number of iterations to consider from a point determined to be close to a solution.

The key element of the simulated annealing approach is the logarithmic decline in 'temperature' and consequently the increased likelihood of accepting an improved scenario (lower energy) as the number of steps grows. The basic cooling formulas are:

$$\mathrm{Tfactor} = -\,\mathrm{math.log}(\mathrm{Tmax}/\mathrm{Tmin}) \tag{3}$$

$$T = Tmax \times math.exp(Tfactor \times step/Steps) \tag{4}$$

The energy is the cost function and the comparison as to whether to keep or reject a portfolio configuration of interventions is based on the change in energy (dE) divided by the temperature at that iteration step. The energy for a given iteration is the combination of the reduction in risk from the base risk and the deviation of intervention cost from the target budget:

$$Energy = ([interventionCost - budget])/([riskAfterIntervention - baseRisk]) \tag{5}$$

$$dE = energy\ for\ this\ portfolio - energy\ for\ previous\ best\text{-}case\ portfolio \tag{6}$$

In order to determine whether to accept a new portfolio, the energy must be lower than the previous best case and the exponent (base 10) of the $-$dE/Temperature must be greater than a random value between 0$-$1. The random value is selected from an even distribution. The temperature value decreased logarithmically across the iteration (creating a smaller math.exp($-$dE/T) value for a given dE as the optimization progresses. However, to ensure the method is not a simple hill climb strategy, this is compared to a random upper bound. As the optimization progresses there is a decreasing chance of rejecting an improved portfolio, and the optimization will approach a hill climb strategy.

$$Reject\ if\ dE > 0.0\ and\ math.exp(-dE/T) < random.random \tag{7}$$

The basic cost function of the CIDSS is to provide maximum risk reduction per dollar (cf = $/risk_reduction). However, there is an additional requirement that intervention portfolios should achieve a target budget. This is to allow for the common use case of 'what is the best collection of interventions for $x?'. If the optimisation focused purely on the risk reduction/$, then a likely and common outcome may be to do nothing or do a very small level of activity. In order to maintain an approach of maximum risk reduction per dollar for a given budget, the CIDSS applies budget 'cost penalty' to the portfolio. If the cost of the intervention portfolio is close to the target budget, then the cost penalty is low, however as the intervention portfolio cost deviates from the target budget an increasingly high penalty is applied. This high cost penalty will result in the scenario being rejected for one that is closer to the target budget. The implemented cost penalty approach is to affect the overall 'energy' (which in turn affects if the portfolio configuration is accepted or rejected).

Each iteration of the function applies the intervention, reducing the hazards load. Calculating a new set of raw hazards, their attenuation and risk after the applied intervention, then passing that data to the cost function, calculates the total portfolio cost to verify if the portfolio of interventions remains within the scenario budget assigned.

3.1.3. Interpreting Results

At the completion of the optimization process, the final portfolio of interventions is stored, as is the hazard load as well as the attenuated hazard load (both before and after interventions are applied). The associated total risk at the WTP is also stored. In order to visualise the relative spatial distribution of the initial risk and the risk after the portfolio of interventions has been applied, the CIDSS disaggregates the risk at WTP to provide a relative contribution to risk for each contributing planning unit.

3.2. Scenario Case Study

The Logan-Albert case study presented here demonstrates a nested design, whereby many planning units are upstream of more than one WTP. The CIDSS optimization process attempts to develop optimal portfolios of interventions to best achieve risk reduction across multiple downstream WTPs with varying treatment capacities. The case study area has four operational WTPs set along the Logan River and a proposed future WTP (CGW) located downstream to cater for growing demand and climate change resilience (Figure 1C). A sixth WTP is in the adjacent Canungra Creek subcatchment of the Albert

River. The collective catchment is divided into 135 Planning Units for assessing source water quality risk and possible combinations of 36 interventions, which are applicable in these catchments, are available for this scenario (Table 3). The example scenario has been designed to mitigate suspended sediment sources from catchment erosion processes and pathogen sources (point and non-point) from livestock industries. While pathogens from STPs, OSFs, stormwater and recreation sites are included to determine total risk to WTPs, this case study scenario excludes budget and interventions being applied to human pathogen sources and therefore only focuses on livestock pathogen sources and TSS. As only livestock pathogen sources and TSS considered in this scenario, the CIDSS hazard weightings are split evenly between TSS, bacteria and protozoa, while viral particles are given a zero weighting because livestock are not considered a viral source in the region.

4. Results and Discussion

4.1. Current State of Source Catchment Water Quality

The Logan-Albert catchment has very high loads of TSS, protozoa and bacteria. Figure 2 illustrates the modelled range of TSS loads at the Planning Unit scale with many Planning Units yielding in excess of 1000 t/year and Planning Units in Cannon Creek exceeding 10,000 t/year. Due to the nested WTP intake locations, a Planning Unit can deliver different TSS (and pathogen) loads to nested WTP due to different transport distances, hence deposition. For example, Figure 2B shows TSS loads delivered from Planning Units to CGW in contrast to the total yield from the Planning Unit (Figure 2A) and compared with TSS loads delivered to TBE (Figure 2C).

The dominant contributing hazardous processes to TSS risk at WTPs are landslides, channel and gully erosion (Figure 3). A study conducted in Knapps Creek subcatchment, which is 34.5 km upstream of the TBE (Figure 2A), predicted gully and channel erosion that contributes 5950 t/year to the watercourse [46,47] compared to 6211 t/y modelled for the CIDSS. The predicted load for this study is higher, but this can be attributed to additional gully presence in the catchment following the impact of Ex-Tropical Cyclone Debbie in 2017. A radionuclide and geochemistry study following a 2008 flood event also reported very high channel bank and gully erosion within the Logan-Albert catchment, particularly from the Knapps and Cannon Creek subcatchments, which had very high delivery rates to the Lower Logan [48], hence delivery to WTP intake locations. No studies have explicitly considered the landslides occurring in the Cannon Creek subcatchment that contribute the highest attenuated loads. The CIDSS attenuated sediment loads from Knapps and Cannon Creek were also amongst the highest in the catchment and therefore are in agreeance with past studies.

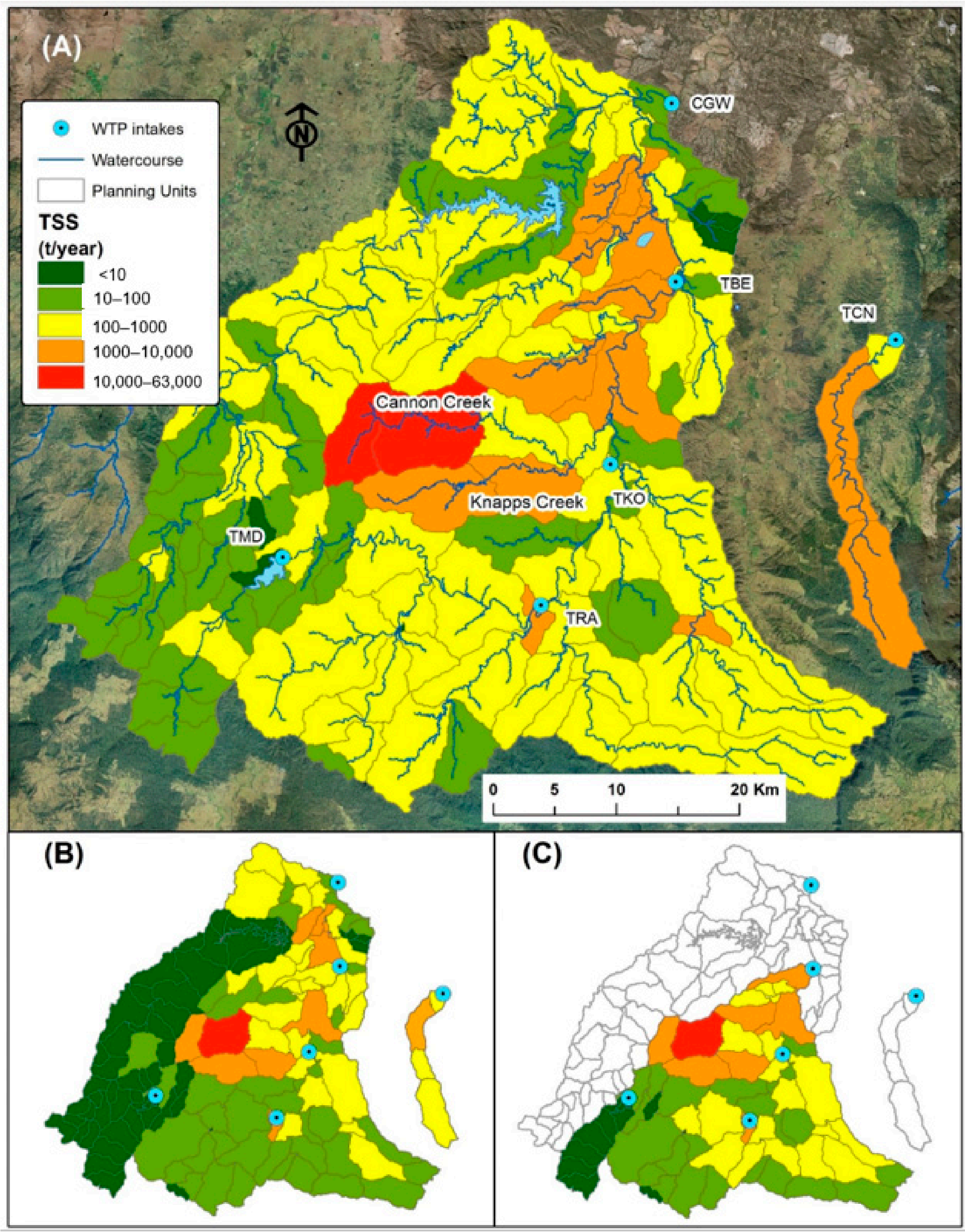

Figure 2. (**A**) Summed total suspended sediments (TSS) loads derived from all hazardous or erosion processes within each planning unit, (**B**) planning unit TSS loads delivered (less deposition/storage) to the proposed CGW and TCN water treatment plants, and (**C**) comparison with TSS loads delivered to the nested TBE, which has shorter transport distances and therefore less TSS deposition between planning units and the WTP. Cannon and Knapps Creeks are shown to highlight tributaries subject to previous studies due to high rates of erosion. See Table 1 for WTP names.

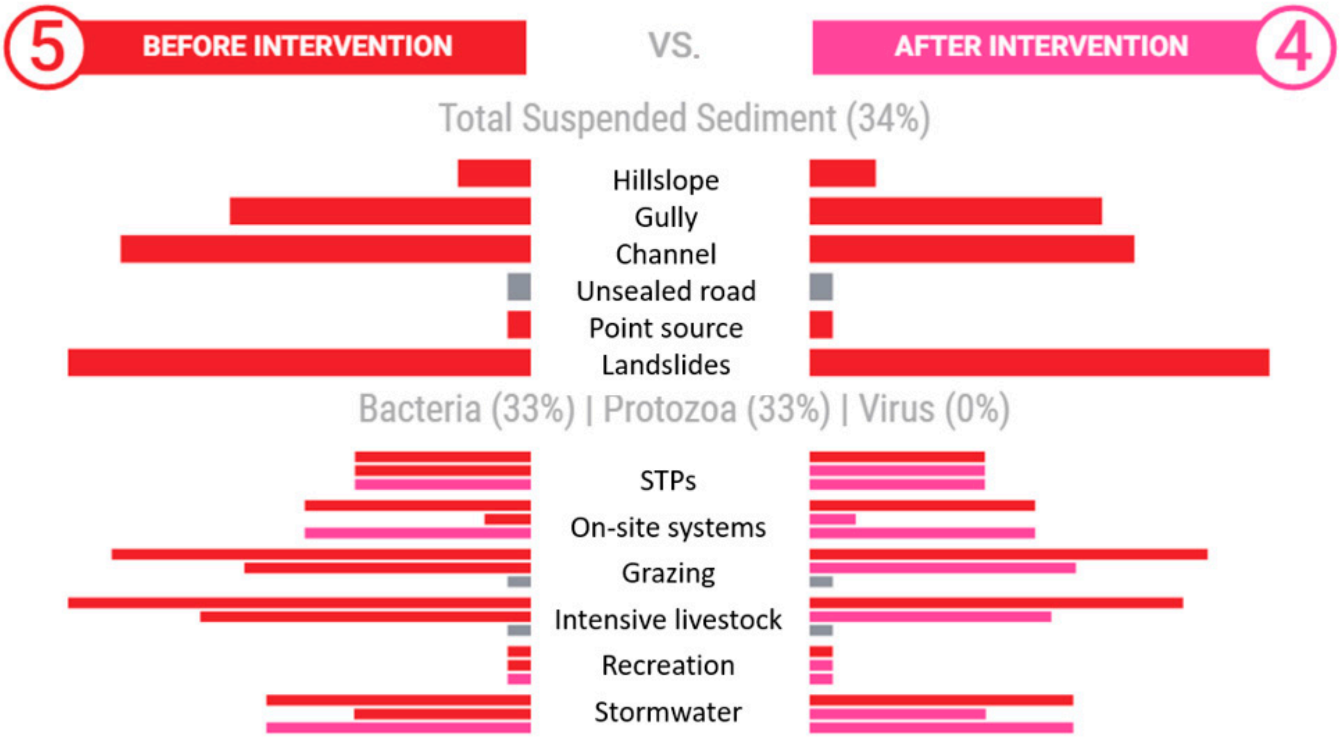

Figure 3. CIDSS graphical output for risk and hazardous process load for the current state (before intervention) and after intervention based on scenario's portfolio of interventions for reducing drinking water quality risk to CGW. Red bars represent very-high risk (5) and magenta bars represent high risk (4). Grey bars represent zero load. Here, grazing and intensive livestock are not a source of viral load. There are no data presented for Unsealed roads in this case study. Bar length is indicative of the size of load from the hazardous processes. For example, Landslides are the largest source of TSS. Intensive livestock is the largest source of bacteria and protozoa. The triplet bars for pathogens represent each hazard—bacteria (**top**), protozoa (**middle**) and virus (**lower**). The values in parentheses represent the weightings applied to each hazard in the optimization.

The hazardous processes contributing to the highest bacteria and protozoa risk are intensive livestock industries and cattle grazing in the catchment (Figure 3). CIDSS results for the current state (before intervention) show bacteria and protozoa loads are very-high risk, which implies the pathogen loads can exceed treatment plant capability to provide safe and reliable drinking water. That is, there is a potential shortfall between WTP capability to remove pathogen load compared to what is delivered to the WTP via the watercourses. A necessary but less than ideal WTP management strategy is to take the WTP off-line during the peak in contaminants typically associated with significant rainfall and runoff events. This strategy is dependent on being able to (1) effectively identify peaks in pathogen load and (2) have enough treated water available to meet demand while the WTP is offline. The effects of climate change on the magnitude and frequency of extreme weather events, hence on pathogen loading [49], may limit the effectiveness of this strategy, and there are numerous examples of the consequences of impact of treatment failure on the population [50]. Therefore, by targeting the livestock sources compared with human waste sources, this case study scenario is targeting the highest pathogen risk source with interventions.

4.2. Potential for Source Water Risk Reduction

A total of 35 simulations of the scenario were run to explore the solution space and derive risk reduction cost curves for budgets between $2,000,000 and $40,000,000. Based on the range of budgets considered in the simulations, risk reduction is achievable for a number of the WTPs (Figure 4). However, not all hazards have risk reduced at the WTPs. TSS cannot be reduced at CGW, TBE, TCN, and TKO below risk level 5 for budgets explored in the simulations and the range of interventions currently considered. Similarly, bacteria cannot be reduced at TBE, TRA, and TKO below risk level 5. While risk level reduction may be achievable for these hazards, the magnitude of investment required is not viable in the short to medium (5–10 year) term.

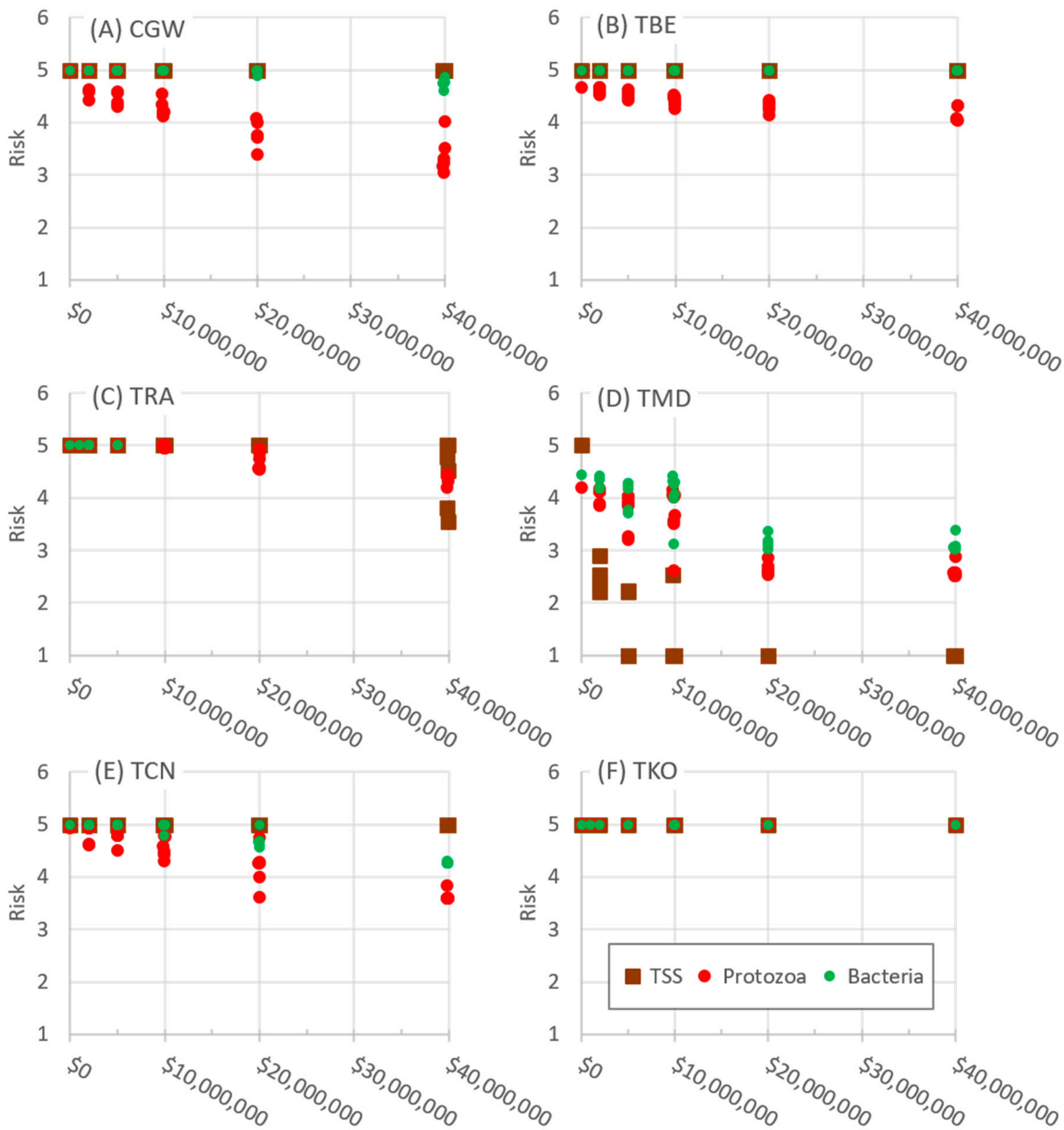

Figure 4. Variation in drinking water quality risk for each hazard (TSS, protozoa and bacteria) at each WTP based on 35 optimization simulations across budgets of $2M, $5M, $10M, $20M and $40M. Risk level 1 to 5 represents Insignificant, Low, Moderate, High and Very-high risk, respectively.

By considering the pareto front for the weighted mean risk reduction between hazards (TSS, bacteria and protozoa), the largest rate of change in mean risk relative to cost is evident for budgets up to $5,000,000 (Figure 5). While smaller budgets also have high rates of risk change, at individual WTPs, few hazards actually change risk levels (i.e., from risk level 5 to 4 or from 4 to 3). However, a pareto optimal solution for a $5,000,000 budget is on the inflection point of the pareto front curve and results in risk level change.

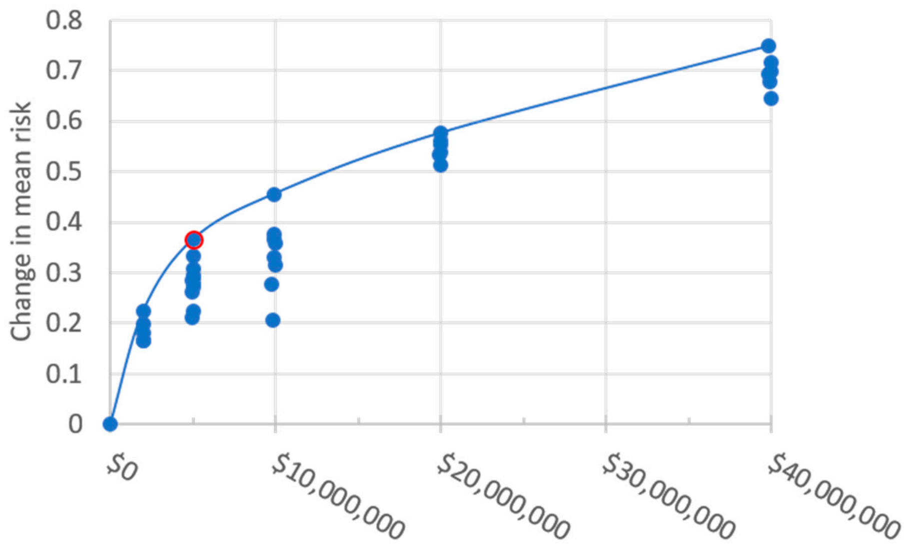

Figure 5. Pareto front based on highest weighted mean risk change for a range of budgets with the selected pareto optimal solution marked by a red circle.

4.3. Selected Scenario

The pareto optimal solution (Figure 5 red circle) is selected for the basis of planning catchment program of works. Based on the selected scenario and its portfolio of interventions, a reduction in risk level can be achieved at CGW and TMD while WTPs TKO, TRA, TBE, and TCN receive within-level risk reduction. That is, loads from hazardous processes are reduced but there are either too many sites requiring intervention and/or the loads are too high relative to the threshold required to change risk level.

The change between the current state (before intervention) and future state after the application of the intervention portfolio for CGW WTP is shown in Figure 3. The selected intervention portfolio reduces protozoa risk from level 5 to 4, which is due to a 2-log reduction in protozoa loads that can be achieved from interventions applied to intensive livestock industries (Figure 6). A 2-log reduction was also achieved for bacteria from intensive livestock industries, however bacteria loads are more than 2-log above the proposed CGW treatment capability threshold. In addition, bacteria from livestock grazing sources are a very high risk and only 0.4 log reduction is achieved. The reason for a small log reduction is due to the large number of grazing properties where livestock have access to watercourses. All high-risk grazing properties, which can be viewed in the CIDSS, will require interventions to better manage stock around watercourses before significant bacteria risk reduction can be achieved.

TSS sources to CGW were reduced by 3446 t/year primarily from interventions applied to channel erosion (Figure 6), despite landslides contributing the highest loads to CGW. An explanation for the intervention portfolio addressing channel erosion sources rather than the high landslide sources is due to the proximity of channel erosion to CGW combined with the higher longitudinal connectivity of channel erosion sources to the CGW relative to the landslide sources. However, similar to bacteria, TSS risk remained at level 5 due to annual loads being an order of magnitude higher than the threshold value required to change risk levels.

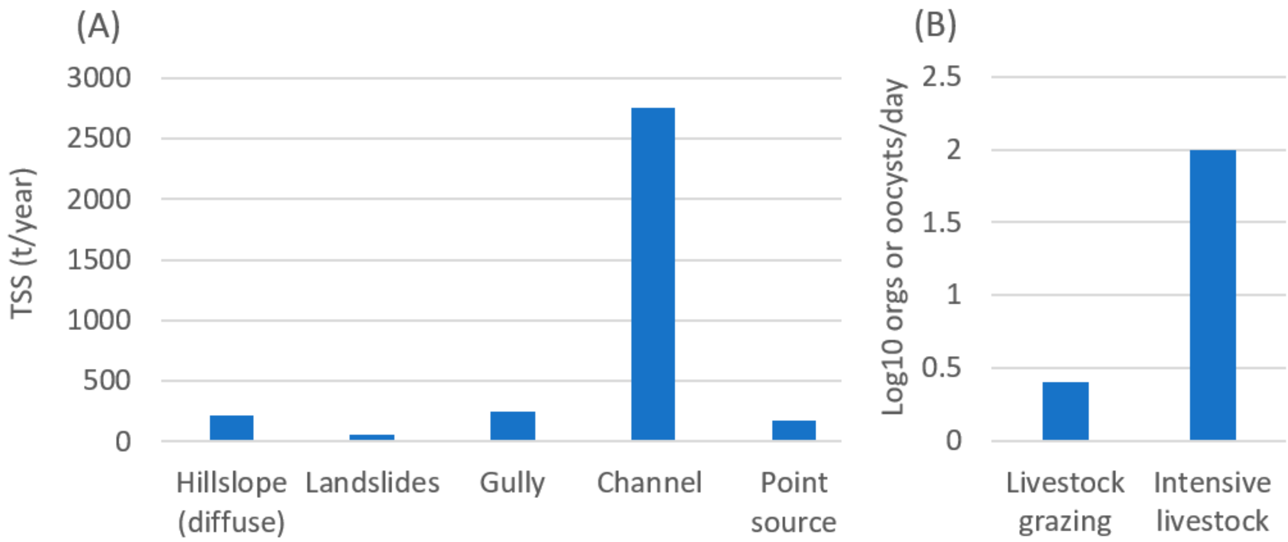

Figure 6. Reduction in (**A**) TSS and (**B**) pathogen loads to Cedar Grove Weir based on the selected solution portfolio of interventions. Intervention log reduction values for bacteria and protozoa are the same.

The intervention costs for each of the WTP subcatchments show 58% of the overall budget is allocated to Planning Units downstream of TBE to reduce risk to a future CGW if its treatment capability for each of the hazards is similar to TEB WTP (Table 5). Channel erosion and riparian management include interventions for managing cattle grazing and therefore pathogen risk as well as TSS risk account for 44% of the intervention solution while 46% of the intervention solution is allocated for the management of effluent from intensive livestock agriculture such as dairy (Table 6).

Table 5. Proportion of budget allocation to each subcatchment where 'Source catchment' represents total contributing area, and 'Excluding nested WTP' represents the proportion of catchment only contributing to the referenced WTP.

WTP	Source Catchment	Excluding Nested WTP
TCN	1%	1%
TMD	<1%	<1%
TRA	8%	7%
TKO	22%	14%
TBE	41%	19%
CGW	99%	58%

Table 6. Proportion of the scenario budget allocated to the different intervention programs.

Program	Percent of Budget Cost
Channel erosion and riparian management interventions	44%
Gully interventions	9%
Landslide interventions	1%
Intensive livestock interventions	46%

4.4. Prioritisation of CIDSS Solution

The selected scenario included intervention works to be applied across 111 Planning Units to achieve the identified risk reduction. The first step to prioritize on ground implementation of the optimized intervention portfolio is ranking the size of load reduction for each Planning Unit after accounting for load attenuation. For example, headwater interventions may reduce TSS load within the Planning Unit by 100 t/year, however this may only account for a reduction of 20 t/year at a downstream WTP. Mid or lower catchment interventions may reduce Planning Unit TSS load by 60 t/year, which may represent a 50 t/year reduction at the WTP. Thus, the second example with the mid to lower catchment Planning Unit would be ranked above the headwater Planning Unit. Additionally, because the attenuated load will vary between the nested WTPs, the prioritization is applied based on attenuation/deposition to the most downstream WTP. Thus, initial works programs can start targeting sites where the largest reductions in hazardous processes can be achieved. Figure 7 illustrates Planning Unit prioritisation for TSS load reduction. Here, the top 10 ranked Planning Units are located in close proximity to WTP intakes for CGW, TBE, TRA and TCN. Similarly, Planning Unit prioritisation mapping for protozoa and bacteria are produced to guide planning of the on-ground works to achieve the largest log reductions for these hazards in the early phase of the program rollout.

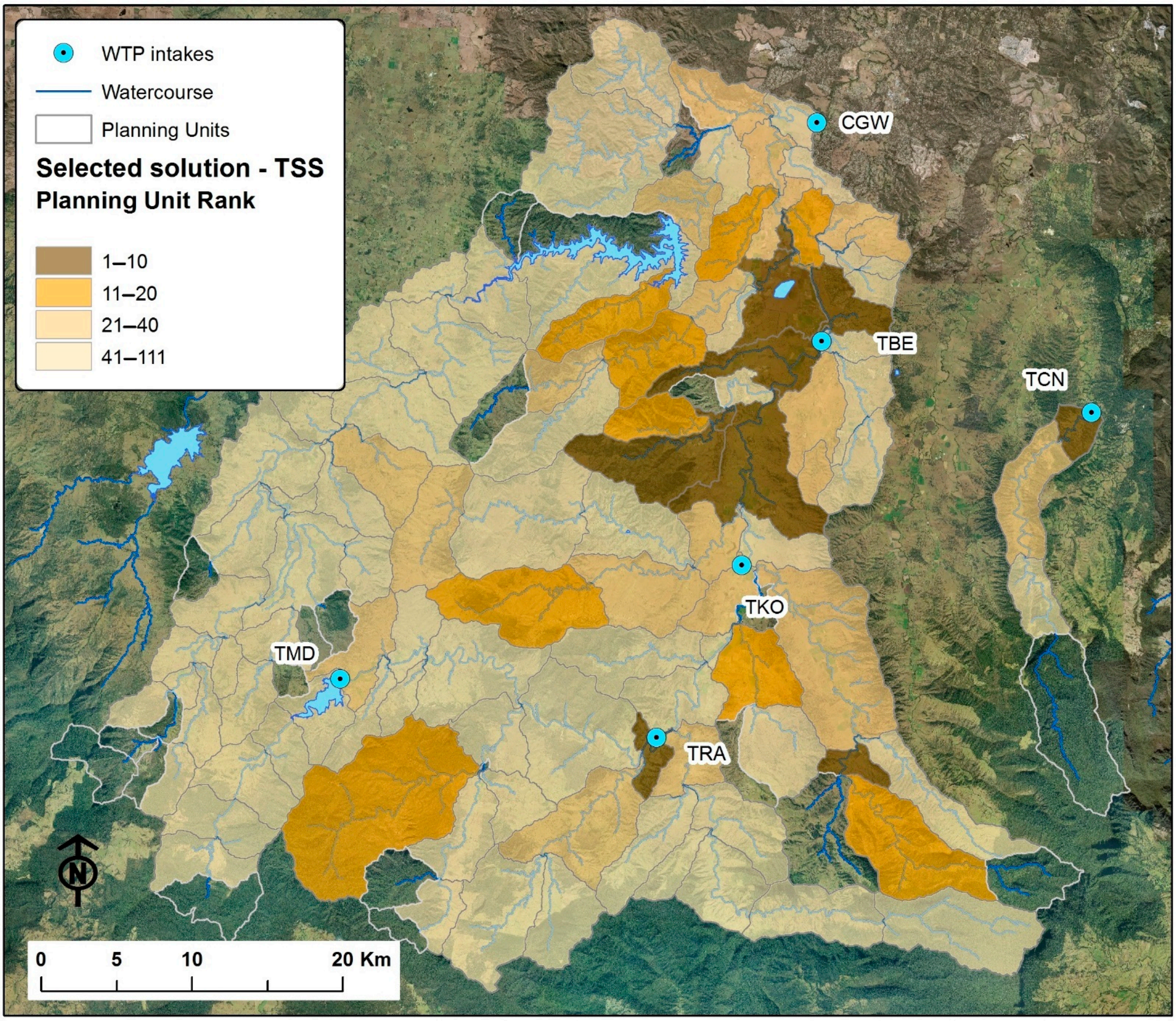

Figure 7. Prioritised Planning Units based on net TSS reduction at CGW. Planning Units without a rank (no colour shading) have no interventions applied in the scenario solution.

Notably, there are a large number of Planning Units requiring intervention for TSS and pathogen risk and the selected scenario budget for this case study yielded only modest risk reductions. This is indicative that the hazardous processes in the Logan-Albert catchment are chronic. There are no 'low hanging fruit' Planning Units where targeted interventions to a few Planning Units would result in significant risk reduction.

The CIDSS prioritized results present a significant refinement from previous studies in the region seeking to determine hazard sources and management options. Radionuclide and provenance studies had limited ability to attribute land use to the exact erosion process (e.g., channel bank, gully or landslide) and their specific location, and therefore such studies could not determine a fit-for-purpose intervention portfolio. Where radionuclide studies in the region have indicated that channel and gully erosion are the dominant erosion processes [46], subsequent assessment of channel condition has indicated 6350 km of watercourse require riparian revegetation to reduce channel erosion by 50% [10]. If considering both channel banks, then this equates to 12,700 km of riparian interventions and therefore little directional guide for catchment managers as to where to start. The prioritized Planning Units maps, when considered with conditional information on locations of previous intervention works, landowner willingness, site accessibility and practicality, provide a planning guide for implementing catchment interventions to contain the existing highest risk hazardous processes in a cost-effective process.

4.5. Consequence of Increasing Water Supply in Open Catchments

The proposed new water treatment plant CGW increases source catchment area by 996 km^2 and includes a reservoir with a storage capacity of 102,884 ML. As such, CGW allows for longer travels distance and time, hence higher attenuation of hazards from the nested WTP catchments. The reservoir also serves to attenuate pathogens and trap sediment from a tributary. However, the additional source catchment area incorporates numerous erosion, bacteria and protozoa hazards in the lower catchment, which results in 58% of the intervention budget for the entire catchment needing to be spent mitigating the water quality risks from the new source catchment area (Table 5). Based on the scenario solution, a reduction in risk for protozoa is achieved while TSS (even with a reduction of 3660 t/year) and bacteria still present a very high risk to plant. The proposed new CGW WTP may need to be designed to treat higher loads of TSS and bacteria than the existing TBE WTP (upon which the future CGW capability was based for the scenario) to ensure the provision of safe drinking water based on both land use challenges and future climate changes [50].

4.6. Sensitivity Analysis, Uncertainty and Future Directions

The purpose of the CIDSS is to generate portfolios of interventions to provide a cost-effective return on investment. The CIDSS relies on a large range of input data and parameterization in order to apply the optimization process. Whilst the input data and parameterisation are the best available, they are not perfect. In order to assess the potential impact of parameterization (optimization settings, intervention efficacy, intervention cost, WTP risk thresholds, trap scaling), the CIDSS has a Monte Carlo runner. The Monte Carlo runner allows a scenario to be explored by setting upper and lower ranges and number of intervals for all parameters. The Monte Carlo runner repeats the scenario for every combination of potential parameter values to provide a distribution of results. The Monte Carlo runner provides guidance as to the most sensitive parameters (and focuses future data collection and refinement) and also demonstrates how sensitive or otherwise the selection of an intervention portfolio is to potential errors in the parameter values.

To demonstrate the Monte Carlo runner, global parameters and WTP catchment specific parameters were varied to evaluate scenario solution sensitivity. Increasing the simulated annealing parameter max_steps by an order of magnitude (1000 to 10,000) narrowed the range in the solution set in terms of change in mean risk and the budget used for the intervention solution. However, there was no overall improvement of the pareto optimal solution with only a single replicate scenario producing a slightly higher mean risk change (Figure 8). Similarly, increasing the increment (step = 0.2) size of intervention amount iteratively tried produced a solution set with the budget used very close to the budget available ($5M), but still yielded a solution range in mean risk change similar to the base parameter set. The increase in step size most likely enabled the optimizer to get closer to the global solution faster than with smaller step size and therefore enable more iterations of different intervention configurations close to the global optimum to minimize the cost penalty in the objective function. The scenario solution set was not improved (sensitive) to the remaining simulated annealing parameters S_Max_Steps (=500), Tmax (=250,000,000) and Tmin (=2.5).

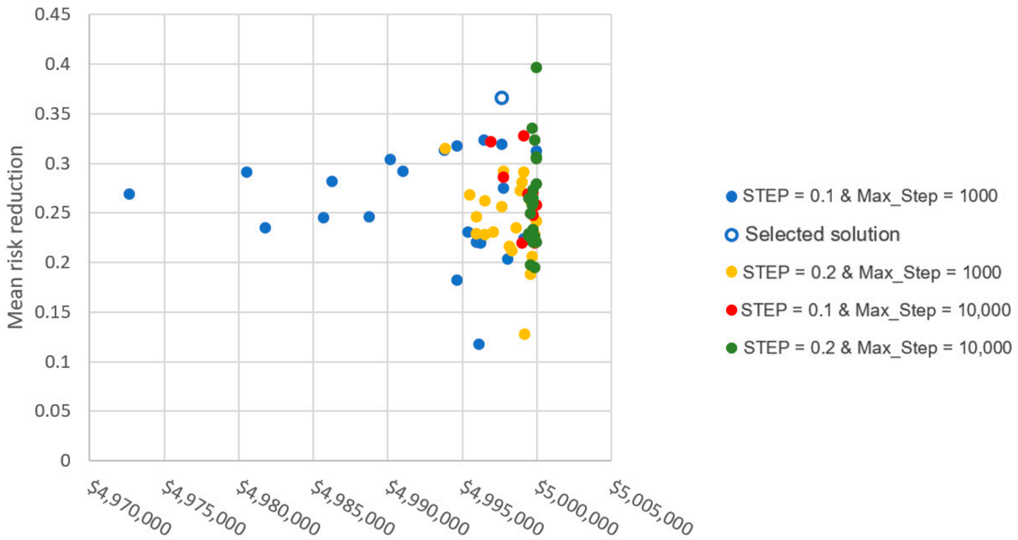

Figure 8. Variation in solution space for maximum risk reduction for a budget of $5,000,000 for varying global parameter Max steps and intervention increment step size.

Global intervention parameter values representing intervention efficacy and cost only influenced solution results where catchment risk/load was close to a threshold value for a particular hazard and therefore the solution result was not considered sensitive to intervention cost and efficacy values applied. Similarly, the solution had low sensitivity to risk at plant thresholds except for the TSS threshold for TMD. For example, Figure 9 shows no change in TSS risk for CGW whereas TMD varies from TSS risk 1 to 5 if TSS risk at plant threshold is decreased. This is because the TMD risk threshold is already very low (20 t/year), there is a narrow range between risk 1 to 5 in terms of TSS annual load, and the current modelled TSS load delivered to TMD (20.2 t/year) is just over the threshold. If the TSS threshold is lowered, then saving additional TSS becomes proportionally harder given the near background TSS loads from the catchment. Assessing the sensitivity of the risk at WTP thresholds helps determine solution sensitivity to the modelled hazard input data, which contain considerable uncertainty. Transforming the data into Risk has reduced solution sensitivity to modelled input values [37], however work is continuing to reduce input hazard data uncertainty via expanded water quality monitoring of TSS and pathogen concentrations across the hydrograph to better understand the rate and quantity of these hazards transported through the catchment. Additionally, ongoing catchment mapping research is also being used to identify the location and extent of landslide, channel and gully erosion, and combined with experimental field monitoring at specific sites to estimate rates of erosion before and after interventions have been implemented.

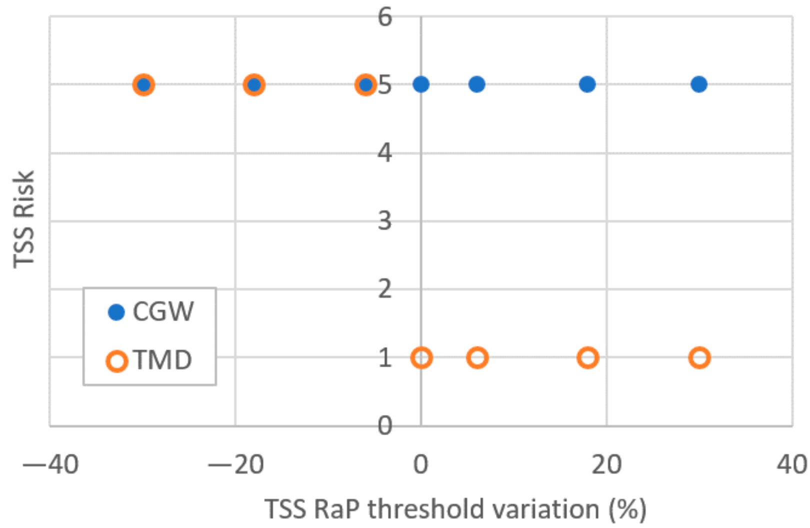

Figure 9. Influence of varying water treatment plant TSS risk thresholds on TSS risk level for the selected portfolio of interventions.

5. Conclusions

A CIDSS has been developed to support bulk water suppliers to supply safe drinking water by using a risk framework to identify and compare water quality hazards relative to WTP location in the catchment and WTP treatment capability. The CIDSS supports the development of catchment management plans to improve the first barrier in providing safe drinking water by identifying a near-global optimum solution set of interventions to reduce the highest risks relative to WTP treatment capability for the lowest cost using a simulated annealing optimizer. For the Logan-Albert catchment scenario with nested WTPs, a pareto optimal solution based on a budget of $5,000,000 was shown to reduce overall catchment mean risk. In the catchment dominated by agricultural land use, protozoa risk can be reduced at most of the nested WTPs based on the selected solution, however TSS loads and bacteria remain a treatment challenge. This study also illustrates how the CIDSS can be used to determine new WTP capability requirements by determining hazard loads and therefore potential risk at any point within the modelled catchment area.

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