Quantifying the benefits of stormwater harvesting for pollution mitigation

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Abstract

Stormwater harvesting (SWH) provides multiple benefits to urban water management. Other than providing water for human use, it also reduces the volume of polluted stormwater discharge to the environment. There are currently no methods available to quantify the additional environmental benefits, which could encourage greater uptake of the practice. This paper investigates a number of factors (climate and catchment characteristics, pollutant reduction targets, etc.) that could impact upon the benefits of SWH for pollution reduction through sensitivity analyses. A method was developed and tested for quantification of the pollution mitigation benefits by SWH under different scenarios. A novel indicator, Impervious Area Offset (IAO), was proposed to reflect the additional impervious area that can be left untreated to achieve the equivalent pollution load reduction targets due to the introduction of SWH. Results indicate significant correlations ($p < 0.01$) between IAO values and *extraction rate* (proportion of total annual runoff removed due to the harvesting system and water use substitution), system type, and pollutant reduction targets. The proposed linear empirical relationships between IAO values and *extraction rate* for different types of system configurations and pollution reduction targets were well represented by observed linear regression (average $R^2=0.98$ for all tested scenarios). Empirical relationships were validated successfully against different scenarios, with differences between predicted IAO and baseline IAO values being only $\pm 4.5\%$ for the majority of the validation scenarios. Using this simple and reliable method to rapidly quantify SWH benefits can further add to the growing business case of adopting SWH practices.

Keywords: pollution loads; catchment imperviousness; water sensitive urban design (WSUD); low impact development; sponge city.

1. Introduction

Due to rapid urbanisation, stormwater has become the major contributor to the deterioration of water quality in urban environments (Jeng *et al.*, 2005). In response, various solutions have been developed known as Water Sensitive Urban Design (WSUD) in Australia, Low Impact Development (LID) in the USA, and Nature Based Solutions (NBS) in Europe, among its many other common names (Fletcher *et al.*, 2015) and, more recently, as Sponge Cities in China (Jun *et al.*, 2017). Typical WSUD systems, e.g., stormwater bioretention systems and constructed wetlands, are usually effective in removing various types of pollutants in stormwater (Hatt *et al.*, 2009; Malaviya and Singh, 2012; Zhang *et al.*, 2015), and regulation has prescribed mandatory treatment requirements to reduce pollutant levels in stormwater (VSC, 1999). Indeed, current WSUD assets are predominantly implemented to meet environmental water quantity or quality targets (i.e., the main driver for these systems). Nevertheless, their additional multiple benefits are acknowledged, e.g., frequent flood mitigation (Zhang *et al.*, 2019), waterway health protection (Fletcher *et al.*, 2007), microclimate improvement (Wong *et al.*, 2013), and improvement of amenity values in urban landscapes (Polyakov *et al.*, 2015).

Stormwater is also regarded as a valuable water resource that can be harvested for non-potable uses, e.g., irrigation, car washing, and toilet flushing (Hatt *et al.*, 2006; Campisano *et al.*, 2017). The multiple benefits of stormwater harvesting (SWH) have also been reported (Mitchell *et al.*, 2007; Campisano *et al.*, 2017), e.g., supplementing water supply, which is an important driver for SWH, especially in water-stressed cities (Fisher-Jeffes L. *et al.*, 2017). Hammes *et al.* (2018) estimated that, by having a 45 m³ stormwater tank at a university technology centre (a total 5500 m² stormwater collection area) to receive filtered stormwater from porous asphalt pavements, potable water savings of up to 54% was achievable if the harvested stormwater were reused to flush toilets and urinals. Steffen *et al.* (2013) also found that SWH can reduce runoff volume of up to 20% in

semiarid regions in the U.S. Additionally, by harvesting stormwater, flows can be attenuated and restored to closer to pre-development hydrology (Ashbolt *et al.*, 2012; Anim *et al.*, 2019), which has significant ecological merits.

WSUD often plays a vital role in both stormwater pollution management and SWH, which are closely linked. However, for the purposes of design and planning in practice, they are often viewed as mutually exclusive and non-interacting objectives, which is counterintuitive to the principles of Integrated Urban Water Management (IUWM) (Mitchell, 2004). Often, urban developers tend to overlook the benefits of SWH for several reasons. On the one hand, they are perceived by asset managers (local councils and water authorities) to have increased maintenance due to the additional WSUD infrastructure required for SWH (e.g., storage tanks) (Campisano *et al.*, 2017; Kuller *et al.*, 2018b). Furthermore, the aesthetic inferiority of SWH infrastructure impedes the uptake of SWH (*i.e.*, low public acceptance), unless WSUD systems such as wetlands are used for storage, which, in fact, are used only in 5% of all SWH cases, according to Hatt *et al.* (2006). Most importantly, although it is widely acknowledged that extracting treated water from storage systems for reuse can further protect downstream water quality (Anderson, 2003; Fletcher *et al.*, 2007), this benefit is not easily quantified and there is currently no method available (unlike water quantity benefits that can be readily assessed with storage-behaviour and rainfall-runoff modelling, e.g., Mitchell *et al.* (2001)), and thus the business case is not easily justified (Kuller *et al.*, 2018a). Hence, for simplicity, SWH is often assumed to provide no benefit to water quality other than the initial treatment required by guidelines, which in many cases matches current prescribed best management practices for stormwater quality control. Overall, these aspects impede the willingness to pay for such infrastructure.

As such, although these impediments to implementing SWH appear daunting, the benefits of SWH should not simply be ignored; instead, they deserve a more meticulous investigation. Development of methodologies and algorithms to rapidly quantify these benefits, particularly for pollution mitigation (which has been driving the uptake of WSUD over the past decades) is necessary. Knowledge of these benefits would facilitate improved planning and design of these systems, including:

- (1) leveraging additional treatment capacity of existing treatment and harvesting systems in the event of increased urbanisation, thereby offsetting the need for new WSUD infrastructure,
- (2) decreasing the surface area requirement of WSUD assets through the provision of SWH within the system (a benefit to both the urban developer and the asset manager),
- (3) leveraging potential overtreatment to benefit existing downstream urban developments, which are space constrained (and most challenging for WSUD implementation from the developers' perspective), and
- (4) facilitating greater return on investment and general savings in infrastructure cost to both the developer and the asset manager (generally local councils) due to potential cost-sharing opportunities between multiple stakeholders (e.g., between utilities providers and the local council).

The first two quantifiable benefits are similar, with the second one less applicable to cases that already have WSUD implemented (i.e., it does not make sense to reduce the size/or remove the already existing systems). The two latter benefits can be estimated if we can better understand the first two benefits. As such, our focus in this paper will be on understanding the extent to which the addition of SWH to typical WSUD systems can provide additional treatment capacity. We hypothesise that this benefit can be expressed in terms of the additional impervious area it services (i.e., treats the runoff from) as a result of SWH, which in this paper we refer to as a new term - *Impervious Area Offset (IAO)*.

In order to develop a method for quantification of IAO, we must understand the impact of a range of factors on SWH in both pollution reduction aspects (e.g., WSUD treatment performance) and harvesting aspects (e.g., supply volume and demand pattern). Designing any WSUD systems is directly related to the targets of pollution reduction, and usually stricter targets correspond to larger systems (Zhang *et al.*, 2019). Furthermore, WSUD systems vary in pollution removal performance, e.g., it is usually easier to remove total suspended solids (TSS) than nutrients (Hatt *et al.*, 2009; Malaviya and Singh, 2012). Hence, investigating the effect of different pollutant types may reveal varying benefits of SWH. Similarly, WSUD technology type also matters, e.g., stormwater biofilters are often

more effective in removing pollution (Davis, 2007), but they may not have the storage capacity that constructed wetlands or ponds have. Various studies also show that system design parameters (e.g., filter depth, submerged zone depth, and detention time) significantly affect treatment performance (Hatt *et al.*, 2006; Afrooz and Boehm, 2017). In terms of harvesting, the yield (or, in our case, the volume extracted from the catchment), demand pattern of harvested water, and the requirements of supply can certainly influence the benefits of SWH. Additionally, in a broader context, climatic conditions (e.g., rainfalls) and catchment size (which determine the scale of SWH cases), whose impacts on WSUD are often studied (Bach *et al.*, 2013; Zhang *et al.*, 2019), also need to be considered.

To the authors' knowledge, there is no clear understanding to what extent SWH is beneficial for pollution mitigation and what are the most significant factors that impact the benefits. Furthermore, there is also no published method to quantify these benefits. Hence, in this paper, we introduce a useful quantitative indicator – the Impervious Area Offset (IAO) to describe the benefits of SWH on pollution reduction. IAO reflects the additional impervious area that can be left untreated to achieve same pollution reduction targets due to SWH. A simple approach was developed for the first time to quantify the IAO values under various scenarios through exploratory modelling exercises (which also contributed to a deeper understanding of the most important factors). Specifically, we focus on the following objectives:

- testing the sensitivity of pollution reduction benefits in relation to various factors that influence SWH,
- developing and validating empirical relationships between SWH and pollution reduction benefits, and
- discussing the tangible implications of these established relationships for practice.

We hypothesise that, due to the scalability of such decentralised systems, climate and catchment properties may be less sensitive to SWH benefits, while other factors, including harvesting aspects (e.g., supply reliability, extraction volume) and pollutant reduction aspects (e.g., treatment target, pollutant type, and system designs), are sensitive to SWH benefits. We showed that having an

empirical model is crucial to quantifying the real benefit of SWH, which can be used to estimate the tangible cost-benefit of SWH for different stakeholders and improve its business case or general viability, and encourage the uptake of the practice.

2. Material & Methods

In this section, we first propose an approach to quantify SWH benefits by calculating *Impervious Area Offset*, *IAO* (defined as the additional impervious area that can be serviced by the WSUD due to SWH) using the Model for Urban Stormwater Improvement Conceptualisation (MUSIC, by eWater, 2014) (Section 2.1). Over a hundred different scenarios were set-up to test the sensitivities of various climate, system design, and SWH variables to IAO (section 2.2). Based on the sensitivity testing, empirical relationships between IAO and the most sensitive parameters were proposed, with detailed calibration and validation methodologies introduced in Section 2.3.

2.1 Description of the quantitative approach

2.1.1 Selection of treatment and harvesting technologies

There are a multitude of WSUD technologies for stormwater treatment and harvesting, each with a variety of planning, design, and implementation considerations. Stormwater biofilters and constructed wetlands and ponds, which are currently the most widely used WSUD systems for stormwater treatment and harvesting (Hatt *et al.*, 2006), are the major focus of this study. Biofilters, known as rain gardens or bioretention systems, are often used for runoff reduction and pollution management and are highly scalable (Davis *et al.*, 2009; Afrooz and Boehm, 2017). Constructed wetlands and ponds, typically in moderate to larger scales, can provide benefits in flood mitigation and pollution reduction (Al-Rubaei *et al.*, 2016), as well as SWH (Mitchell *et al.*, 2006). Additionally, this study also looks into the treatment train approach, which is often the practice of SWH (Wong *et al.*, 2013), with the inclusion of vegetated swales (often used to provide flow collection, attenuation, and pre-treatment, Leroy *et al.*, 2016), and rainwater tanks (stormwater retention and fit-for-purpose water supply, Burns *et al.*, 2015). These technologies are currently the most widely used across Australia, as evidenced in several case studies in the literature (Hatt *et al.*, 2006; Mitchell *et al.*, 2006).

2.1.2 Basic model setup

In this study, MUSIC, which is the state-of-the-art WSUD modelling tool in the Australian urban water industry, was used to evaluate the treatment and harvesting performance of different WSUD systems and treatment trains (eWater, 2014). The rainfall-runoff simulation in MUSIC is based on the model developed by Chiew and McMahon (1997). Runoff can be routed using either simple translation only or the Muskingum-Cunge method (Cunge, 1969). Within WSUD systems, hydrologic routing is simulated using the modified Puls Method (Ball *et al.*, 2016), and water quality treatment employs first-order exponential decay over the length of the treatment systems and a series of continuously stirred tank reactors. The water storage tank modelling is based on a simple filling and spilling storage behaviour model with extraction from the tank according to constant or seasonal water demand pattern. A detailed description of MUSIC can be found in its user manual (eWater, 2014). To some extent MUSIC has been tested and validated against monitored data on a series of treatment measures (Wong *et al.*, 2002). Imteaz *et al.* (2013) also tested the accuracy of MUSIC in predicting flow conditions and removal efficiencies by stormwater treatment systems and found that MUSIC can simulate flow conditions with good accuracy but had varying performance of pollutant removal efficiencies prediction.

As with many other stormwater management models, *e.g.*, SWMM (Rossman, 2017) or SOURCE (Carr and Podger, 2012), MUSIC also has limitations, *e.g.*, it requires calibration and validation for a specific case study, as well as full uncertainty analyses. Nevertheless, apart from the fact that it is widely used in Australia, MUSIC was selected in this study as it enables long-term continuous simulations (with fine temporal resolution) and its water quality and WSUD treatment modules are more extensive than other similar models (Elliott and Trowsdale, 2007). It should be noted, however, that the same approach can be used by other models (preferably calibrated and validated for a local case study) to investigate the significance of relationships between SWH and pollution mitigation and develop the approach of quantifying the SWH benefits.

Figure 1 illustrates a schematic setup of the MUSIC model (based on a node-and-link-based user interface) to assess the pollution reduction benefits of SWH based on a typical treatment train

scenario. Briefly, runoff from a fully impervious catchment node (*Urban catchment*) drains into *Treatment systems* (in this case, swale and biofilter, which are coupled in series and designed to meet specific pollution reduction targets). Treated effluent from the treatment system is harvested in a storage tank (*Harvesting System*). The tank is set up to supply a specific water demand at a pre-defined volumetric reliability. The amount of water demand is adjusted (using Equation 1) such that the total guaranteed supply volume (defined by the system's volumetric reliability – see Equation 2) corresponds to a specific proportion of the harvested water (e.g., 25%, 50%, 75%, and 100%). The ratio of volume supplied to total runoff volume of the catchment is termed the *extraction rate* (percentage of water removed from the catchment for non-potable end uses). For example, if the tank receives a total inflow of 1000 m³, the required demand volume to guarantee an *extraction rate* of 25% for a tank that is 100% reliable would be 250 m³. For a tank that is 80% reliable, however, the required demand for the same *extraction rate* would be 312.5 m³ (i.e., requesting more demand, but only receiving 80% of it). The equivalent annual demand for a given *extraction rate* and target reliability is given by Equation 1.

$$V_{\text{demand}} = \frac{V_{\text{in}} \times p_{\text{ext}}}{R_v / 100 \%}$$
Equation 1

where:

V_{demand} – total annual demand (m³/yr)

V_{in} – total annual tank inflow (m³/yr)

P_{ext} – extraction rate (%), percentage of water removed from the catchment for end uses

R_v – volumetric reliability of the system (%), defined as:

$$R_v = \frac{\sum V_{\text{supplied}}}{\sum V_{\text{demand}}} \times 100\%$$
Equation 2

V_{supplied} – volume supplied by the harvesting system [m³]

Overflow from the treatment system is not directed into the storage tank, but is instead bypassed to the final downstream point. This is important as good practice dictates that only treated effluent

should be harvested (Wong *et al.*, 2013).

Figure 1 Basic MUSIC model setup for assessing pollution reduction benefits of SWH

The pollution reduction benefit is quantified in terms of the *how much untreated impervious area could be offset downstream such that targets were still complied with*: the aforementioned impervious area offset (IAO). Taking the SWH scenario shown in Figure 1 as an example, the **Treatment systems** (swale + biofilter) are designed to remove 45% of TN for the **Urban catchment** at the **Final downstream point** without considering the harvesting component; the **Harvesting system** (i.e., tank) in the same catchment removes additional runoff via harvesting water for reuse and thus results in greater than 45% TN loads at the **Final downstream point**. This means that x% of additional impervious area in the **Extra catchment** can be left untreated such that the TN reduction at the **Final downstream point** is still measured at 45% and therefore complies with treatment targets. The IAO is then defined as the ratio of x% of additional impervious area of the **Extra catchment** divided by the total impervious area of the **Urban catchment**.

2.2 Scenarios for sensitivity testing

As discussed, SWH is influenced by various aspects, and all these variables are summarised in Table 1. Due to the large number of possible combinations that we could test in Table 1, we undertook sensitivity testing in two stages. In Stage 1, parameters, which were hypothesised to be least influential, including climate characteristics, catchment properties, and recycling patterns were first investigated based on the biofilter only and set to a constant value if their sensitivity was low or negligible. A total of 21 sensitivity scenarios were investigated. In Stage 2, two separate data sets were created to look into the sensitivity of *extraction rate*, pollutant type, reduction target and system design (Table 1):

- **“target-based” data set**, using fixed design parameters, with which we explored variable pollution reduction targets for three individual technology types, three pollutants of varying targets, and four different *extraction rates* – a total of 108 sensitivity scenarios;

- **“design-based” data set**, using a fixed pollution management target, with which we explored variable system designs for the three different technology types, with two contrasted design configurations and, additionally, two coupled designs, known as ‘treatment trains’, three pollutants (with the same management target), and four different *extraction rates* – a total of 96 sensitivity scenarios.

The results generated from sensitivity testing were plotted to illustrate the relationships between the IAO and the variables, accompanied by statistical analysis of the correlations using simple Pearson correlation and multiple regression.

Table 1. Summary of variables tested and their selected values

Category	Variables	Selected Values
Climate	City Rainfall Length (years) ¹⁾	Melbourne, Brisbane, Perth 1 year (1959), 10 years (2000 – 2009)
Catchment	Area [ha] Imperviousness [%]	1 ha, 10 ha, 100 ha 100%
Harvesting	Reliability of Supply [%] Demand Pattern <i>Extraction rate</i> [% of inflow]	60%, 80%, 90% Constant, Seasonal (scaled by Potential evapotranspiration) 25%, 50%, 75%, 100%
Treatment	Pollutant Type Reduction Target [%] ²⁾ System Type System Design Configuration Treatment train	Total Suspend Solids (TSS), Total Nitrogen (TN), Total Phosphorus (TP) TSS 95%, 85%, 60% TP 60%, 45%, 20% TN 55%, 45%, 20% Biofilter, Wetland, Pond Different designs for each system ³⁾ : <ul style="list-style-type: none"> • <u>Biofilter A</u>: extended detention depth (EDD) of 100 mm, filter media depth (FD) of 500 mm • <u>Biofilter B</u>: EDD - 500 mm, FD -300 mm • <u>Biofilter C</u>: EDD - 300 mm, FD -500 mm • <u>Wetland A</u>: EDD - 750 mm, detention time 72 hr • <u>Wetland B</u>: EDD - 250 mm, detention time 48 hr • <u>Wetland C</u>: EDD - 300 mm, detention time 48 hr • <u>Pond A</u>: EDD - 1000 mm, detention time 72 hr • <u>Pond B</u>: EDD - 2000 mm, detention time 72 hr • <u>Pond C</u>: EDD - 3000 mm, detention time 24 hr Treatment trains include (first two used for sensitive testing scenarios and the rest for validation scenarios): TT_1: wetland A+ storage tank TT_2: vegetated swales + biofilter A+ storage tank TT_V1_A: sedimentation pond + biofilter A + storage tank TT_V1_C: sedimentation pond + biofilter C + storage tank TT_V2_A: wetland A + pond storage TT_V2_C: wetland C + pond storage

¹⁾ To allow more robust testing of climate impact both spatially and temporary, for each city, two different rainfall series were used: 1-year rainfall data from Year 1959 (a typical year representing long term average in these cities), and 10-year rainfall between 2000 and 2009 (which had long term drought period; all 6-minute timestep). Refer to the supplementary document for the details and statistics of different climate types. ²⁾BPPEM guideline (VSC, 1999) requires load reduction of 85% for TSS, 45% for TP and 45% for TN, and the selected

targets in this study had a good coverage of what is required.³⁾ Details of the all the designs are given in Table S1- Table S3 of the Supplementary document. Both design A and B were used in the sensitivity testing of “design-based” data set, while only design A was used in the sensitivity testing of Stage 1, Stage 2 “target-based” data set, and the treatment train scenarios. Design C was only used in the empirical relationship validation scenarios introduced below.

2.3 Development and validation of empirical relationships for assessing IAO

2.3.1 Proposed empirical relationship

Having found significant correlation between IAO and variables from sensitivity testing, we proposed and tested an empirical relationship. As will become clear in the results, due to significant linear relationships observed between IAO and *extraction rates* (p_{ext}) for different types of pollutants, reduction targets, and system types, we proposed the following linear relationship:

$$IAO=f(p_{ext})=m\times(p_{ext}-b_{thresh}) \quad \text{Equation 3}$$

where:

IAO - the impervious area offset attained through harvesting (%), i.e., the percentage of additional impervious area (based on catchment area being treated), which can be left untreated such that pollution targets are still met due to harvesting.

m - the slope of the linear regression between p_{ext} and IAO; we refer to this as the *benefit coefficient*.

b_{thresh} – the *benefit threshold*, i.e., the minimum extraction required for an IAO to be noticeable.

It should be noted that this study did not intend to develop universal relationships that are globally transferable, but rather to understand what factors may be necessary to consider (in this case, p_{ext} and other factors that impact the m and b_{thresh}) if such relationships are to be developed elsewhere. Therefore, the findings of this study can guide planners or water managers in developing their own case-specific relationships, or if they simply assess IAO for a particular catchment, to understand how this IAO may be affected by different system types, pollutant types and harvesting requirements. Nevertheless, the relationships developed in this study can be used for the studied cities or other with similar conditions for rapid quantification of the SWH benefits (i.e., IAO).

2.3.2 Parameter estimation

Equation 3 was used to fit the acquired relationships between the IAO and the variables from sensitivity testing results to estimate m and b_{thresh} values. The goodness-of-fit (R^2) was estimated, and t-tests were conducted to check whether there was a statistical difference between baseline IAO (from our quantitative approach using MUSIC) and modelled IAO (from the proposed linear empirical relationship). The estimated m and b_{thresh} values were then summarised as look-up values for model validation/prediction.

2.3.3 Validation of the empirical relationships

In order to validate the empirical relationship, different and new hypothetical SWH scenarios were set up and simulated in MUSIC, which included three individual systems (biofilter, wetland, and pond) as well as treatment trains. Each individual system has two designs: Design A and Design C (see Table 1). New treatment trains that differed from those that were tested in sensitivity testings were also used: TT_V1_A (sedimentation pond + biofilter A + storage tank), TT_V1_C (sedimentation pond + biofilter C + storage tank), TT_V2_A (wetland A + pond storage) and TT_V2_C (wetland C + pond storage).

A total of 45 scenarios with different treatment targets and *extraction rates* were generated in MUSIC to model the IAO values (as the ‘Baseline IAO’). The empirical relationship was used to calculate the IAO value (as the ‘Modelled IAO’) for each scenario using the m and b_{thresh} values estimated from the sensitivity testings and validated against the ‘Baseline IAO’ values. For the treatment target and extraction rate that were different from sensitivity testings, linear interpolation was performed to derive m values since system designs were insensitive to IAO and significant linear correlation between treatment target and extraction rate to IAO values were exhibited. As Design C was not used in sensitivity testing but solely for validation, the values for Design A were taken. For treatment trains scenarios, parameters corresponding to the dominant treatment system type were used, e.g., biofilter for TT_V1 and wetland for TT_V2.

3. Results and Discussion

3.1 Influence of variables on SWH benefits

3.1.1 Impact of climate type and catchment and recycling demand on IAO

Table 2 summarises results from Stage 1 sensitivity testing, indicating the impact of climate characteristics, catchment properties, and recycling requirements on IAO. We found that climate conditions were less influential to IAO values, which were estimated to be around $1.0 \pm 0.5\%$ for all the three climate types (Table 2a). Furthermore, the difference in IAO between modelling results for 1-yr and 10-yr climate data was small, with a slightly lower IAO corresponding to the shorter period.

Similarly, catchment size (1 ha to 100 ha) was also found to have minimal impact on IAO, with differences of $<0.3\%$ observed when different pollutant targets were set (Table 2b). However, initial sensitivity testing showed that pollutant type had considerable influence on the IAO, with the highest benefit achieved when TP was selected as the target pollutant (i.e., $IAO \approx 66.7\%$), followed by TN (i.e., $IAO \approx 29.0\%$) and TSS (i.e., $IAO \approx 1.0\%$).

Table 2: Impact of variables on Impervious Area Offset (IAO) – results from Stage 1 sensitivity testing

City	Climate length	Impervious area [ha]	Supply reliability [%]	Reduction target [%]	Reuse pattern	Impervious Area Offset (IAO) [%]
(a) Impact of climate variability						
Brisbane	1yr	10	80	TSS 85	Constant	0.48%
	10yrs					1.22%
Perth	1yr					0.92%
	10yrs					1.00%
Melbourne	1yr					0.93%
	10yrs					1.1%
(b) Impact of catchment size						
Melbourne	10yrs	1	80	TSS 85	Constant	0.9%
		10				1.01%
		100				1.03 %
		1		TP 60		66.7%
		10				66.7 %
		100				66.7%
		1		TN 45		28.9%
		10				28.9%
		100				29.2%
(c) Impact of demand pattern and supply reliability						
Melbourne	10yrs	10	60	TSS 85	Constant	0.94%
			80		Seasonal	0.93%
					Constant	0.93%
					Seasonal	1.00%
					Constant	0.93%
			90		Seasonal	1.10%

Note: All scenarios used an extraction rate of 100% for biofilter design A (Table 1).

Reliability and demand pattern were also less sensitive to the results (Table 2c), i.e., IAO values were always $\sim 1.0 \pm 0.07\%$ for different patterns and reliability requirements. It was expected that demand patterns would not be sensitive since our evaluation is based on annual statistics and demands may not necessarily be met by the system. As such, reliability, which is directly related to extracted volume (set by V_{demand} from Equation 1 based on extraction rate p_{ext}) is therefore believed to be a more direct indication of water removed from the system, and hence it needs to be included in further analysis.

Overall, these initial sensitivity tests support our hypothesis that climate type and catchment characteristics, recycling pattern, and reliability were least influential to SWH benefits. Hence, they were kept constant in further sensitivity analyses. Specifically, a catchment with an area of 1 ha (i.e., 10,000 m²) at Melbourne with a 10-yr climate series were selected, and the harvesting reliability was set as 80% at a constant demand pattern. These preliminary results also indicated that pollutant type was sensitive to the IAO, and its sensitivity is more thoroughly investigated in the next section.

3.1.2 Impact of extraction rate, pollutant type, system type, and reduction targets on IAO

Figure 2 illustrates the relationships between IAO and *extraction rates* for different pollutant types and treatment targets, with their statistical correlations also presented. Significant, positive and linear correlations between the *extraction rate* and IAO are observed ($R=0.35$; $p<0.01$, Figure 2). This was expected since the larger the volume of water supplied (i.e., *higher extraction rate*), the more benefits (i.e., higher IAO) can be gained through SWH. Although the strength of correlation is only low to medium (i.e., $0.3 < R < 0.5$), this was based on all different scenarios, and for a specific system design and pollution reduction target, the linear relationship is very strong (as shown in Figure 2).

Figure 2 Relationship between *extraction rates* and IAO for different system type, pollutant, and reduction targets: results from the “target-based” data set.

Applying SWH to treatment systems that specifically target different pollutants also exhibits variable levels of benefits. This observation is also extended to different system types and designs (Figure 2), e.g., for ponds and wetlands, the average values of IAO achieved from SWH were found to be TN (73.5%) > TP (25.0%) > TSS (5.59%), while for biofilters the order was TP (31.1%) > TN (16.9%) >

TSS (0.42%). These differences were attributed to the varying performance of these systems in removing pollutants. TN is usually more difficult to remove than TSS and TP by wetlands and ponds because of its highly soluble nature and because it is strongly influenced by variable operational conditions (Fletcher, 2004; Malaviya and Singh, 2012). TN removal in biofilters, however, can be improved through the inclusion of submerged zones, which can create anaerobic conditions that promote the denitrification process as per Zhang *et al.* (2011). Indeed, the treatment performance design curves generated for the tested systems (refer to Figure S1-S3 of the supplementary document) in this study revealed that the critical design pollutant for wetlands and ponds was TN, while that for biofilters was TP. Hence, stormwater harvesting would be most beneficial for additional TN removal in wetlands and ponds, and TP removal for biofilters.

System type also has significant impact on the harvesting benefits ($R=0.30$; $p<0.01$, Figure 2), ponds have the highest average IAO values (=42.9%, i.e., if we had 10,000 m² catchment with SWH using a pond, connecting an extra 4290 m² catchment to the system would still comply with pollutant reduction targets), followed by wetland (average 26.4%) and biofilters (average 16.1%) across different target pollutants. Among these treatment systems, ponds are least effective in removing pollutants, with sedimentation being the main mechanisms to trap pollutants of coarse to medium sizes (Fletcher, 2004), while biofilters are most effective (Davis, 2007; Hatt *et al.*, 2009). Additionally, wetlands and ponds are usually large systems and often have storage capacities of their own, hence they are regarded as more suitable for SWH systems (Hatt *et al.*, 2006). Therefore, to achieve the same treatment targets, ponds and wetlands are preferable to biofilters for the additional SWH benefits. However, system costs and available space should also be considered in practice as ponds and wetlands usually occupy significantly more space than biofilters for achieving the same treatment targets.

Pollutant reduction targets are negatively correlated to IAO values for TSS and TN in all systems ($p<0.01$, Figure 2), e.g., with a target to remove 60% TSS by ponds, the IAO value is estimated to be 11%, which is more than four times of the IAO when targeting 95% TSS removal (i.e., IAO=2.5%) at the same extraction rate of 50%. Indeed, lower treatment means higher levels of pollutant in the

treated water, which, if harvested for reuse, can lead to greater benefits. Results indicate that for a catchment with lower requirements of treatment on TSS and TN, SWH will lead to greater pollution mitigation benefits. TP, however, was once again an exception for biofilters. As they are the most effective treatment measure (Davis, 2007;Hatt *et al.*, 2009), their design sizes are extremely sensitive to the reduction targets of the critical pollutant, e.g., it is estimated that a biofilter system removing 60% of TP needs to be sized to 4.2% of the catchment impervious area, which is over 50 times larger than the system that treats 20% TP (i.e., only 0.08% of impervious area - Figure S1 of the supplementary document). Such a significant increase in system size due to the treatment requirement would allow significantly more water to be treated and stored in tanks for harvesting (consequently resulting in greater benefits). Nevertheless, it is not practical and cost-effective to design the biofilter for very high TP removal, and instead, a variety of WSUD systems could be selected (to form a treatment train) to meet the targets.

Figure 3 further confirms the linear and significant correlation ($p<0.01$) between *extraction rates* and IAO according to the analysis of the ‘design-based’ data set. Similarly, the relationships again vary according to different pollutant type, and pollutant reduction targets ($p<0.01$). Specifically, Figure 3 shows that for varying designs, clear differences were found, e.g., with a target to remove 45% TN, the IAO value was 30% for Wetland B and 45% for Wetland A at the same extraction rate of 75%. However, statistical analysis indicates that the system designs and IAO values are not significantly correlated ($p>0.05$). Additionally, the SWH benefits achieved using treatment trains are mainly due to the predominant treatment systems. In *TT_1*, for example, which uses a wetland as the treatment system and pond as storage (i.e., minimal further improvements), similar benefits were modelled as those for the individual wetland scenario (i.e., *Wetland A*).

Results from the multiple regression analysis further confirmed that the IAO could be predicted from the variables including *extraction rate*, pollutant type, system type and reduction targets, i.e., $R^2=0.90$ for the ‘target-based’ data set and $R^2=0.96$ for the ‘design-based’ data set.

Figure 3 Relationship between *extraction rates* and IAO for different system type and design, pollutant type, and reduction targets: results from the “design-based” data set. The same treatment targets were used for the figures (i.e., TSS 85%, TP 45% and TN 45%).

3.2 Testing and validation of empirical relationship

3.2.1 Estimation of empirical model parameters

The linear correlation lines between the IAO and *extraction rate* shown in Figure 2 and Figure 3 were fitted to Equation 3 for estimation of *benefit coefficient* (m) and *benefit threshold* (b_{thresh}) values for different pollutants and systems types, thereby generating the look-up table of their values presented in Table 3. As shown, the fit of the IAO empirical relationships to the linear regression lines was generally good (average $R^2=0.98$). Comparison of the estimated IAO (from MUSIC) and the modelled IAO also showed no statistical difference (evidenced by high p values from t-tests), with the maximum different observed for Biofilter A targeting 95% of TSS ($\Delta\text{IAO}_{\text{max}}=2.5\%$ and $\Delta\text{IAO}_{\text{avg}\pm\text{std}} = 0.14\pm0.70\%$). Hence, these results show that the proposed linear empirical relationships appear to be a good representation of the actual correlations between IAO and the most sensitive parameters.

Table 3 Performance of the proposed empirical relationship: fitted parameter (m and b_{thresh}) values estimated and modelled IAO values from the sensitivity testing

System	Pollutant	Target	Modelled IAO [%]	m	b_{thresh}	R^2	Estimated IAO [%]	p value (t test)	$\Delta \text{IAO}^{(1)}$
Biofilter A	TSS	95	0.0%	0.025	0.507	0.956	2.5%	0.208	2.50%
	TSS	85	1.0%	0.009	0.246	0.663	0.9%	0.484	-0.10%
	TSS	60	0.7%	0.006	0.160	0.892	0.6%	0.380	-0.10%
	TP	60	61.2%	0.616	-0.020	0.996	61.6%	0.877	0.40%
	TP	45	56.3%	0.566	-0.015	0.999	56.6%	0.929	0.30%
	TP	20	27.0%	0.269	-0.017	0.999	26.9%	0.920	-0.10%
	TN	55	25.0%	0.257	-0.014	0.994	25.7%	0.933	0.70%
	TN	45	27.7%	0.276	0.004	0.998	27.6%	0.980	-0.10%
Biofilter B	TN	20	26.8%	0.267	0.000	0.997	26.7%	0.999	-0.10%
	TSS	85	1.8%	0.018	0.175	0.894	1.8%	0.332	0.00%
	TP	45	56.3%	0.570	-0.006	0.995	57.0%	0.970	0.70%
Wetland A	TN	45	27.7%	0.280	-0.004	0.994	28.0%	0.982	0.30%
	TSS	95	3.2%	0.032	0.000	0.999	3.2%	1.000	0.00%
	TSS	85	4.3%	0.043	0.014	0.998	4.3%	0.957	0.00%
	TSS	60	6.1%	0.060	-0.010	0.999	6.0%	0.969	-0.10%
	TP	60	21.8%	0.218	0.006	1.000	21.8%	0.983	0.00%
	TP	45	25.0%	0.254	-0.003	0.997	25.4%	0.990	0.40%
	TP	20	31.7%	0.308	-0.040	0.993	30.8%	0.876	-0.90%
	TN	55	72.4%	0.720	0.002	1.000	72.0%	0.995	-0.40%
	TN	45	89.2%	0.893	0.002	1.000	89.3%	0.992	0.10%
Wetland B	TN	20	127.1%	1.267	0.003	1.000	126.7%	0.992	-0.40%
	TSS	85	3.1%	0.031	0.006	0.999	3.1%	0.980	0.00%

Pond A	TP	45	19.6%	0.196	0.000	1.000	19.6%	1.000	0.00%
	TN	45	59.6%	0.597	0.009	1.000	59.7%	0.971	0.10%
	TSS	95	5.3%	0.053	0.004	1.000	5.3%	0.988	0.00%
	TSS	85	15.0%	0.152	0.022	0.998	15.2%	0.931	0.20%
	TSS	60	22.7%	0.232	0.014	0.998	23.2%	0.957	0.50%
	TP	60	48.5%	0.490	0.011	0.999	49.0%	0.966	0.50%
	TP	45	55.0%	0.557	0.009	0.999	55.7%	0.973	0.70%
	TP	20	55.5%	0.553	-0.010	0.999	55.3%	0.968	-0.20%
	TN	55	80.3%	0.804	0.015	0.999	80.4%	0.955	0.10%
	TN	45	117.5%	1.181	0.020	0.998	118.1%	0.939	0.60%
Pond B	TN	20	232.0%	2.340	0.013	0.999	234.0%	0.960	2.00%
	TSS	85	1.7%	0.017	0.034	0.995	1.7%	0.897	0.00%
	TP	45	79.5%	0.809	0.018	0.998	80.9%	0.943	1.40%
	TN	45	121.8%	1.219	0.015	0.999	121.9%	0.952	0.10%
TT_1 (Wetland A + Storage tank)	TSS	85	4.3%	0.042	-0.082	0.974	4.2%	0.754	-0.10%
	TP	45	24.9%	0.240	-0.080	0.975	24.0%	0.758	-0.90%
	TN	45	82.2%	0.805	-0.054	0.988	80.5%	0.834	-1.70%
TT_2 (Vegetated swales + Biofilter A + Storage tank)	TSS	85	1.0%	0.010	0.096	0.955	1.0%	0.714	0.00%
	TP	45	40.4%	0.396	-0.055	0.987	39.6%	0.830	-0.80%
	TN	45	26.8%	0.270	0.004	1.000	27.0%	0.989	0.20%

413 ¹⁾ $\Delta IAO = \text{Estimated IAO} - \text{Modelled IAO}$, where "estimated IAO" was from MUSIC simulation, and "Modelled IAO" was
414 from the proposed linear regression model

415 The estimated *benefit coefficient* (m) values indicate similar findings as observed in Figure 2 and
416 Figure 3. For example, m varies according to the type of target pollutants and the systems, with
417 $m_{TN} > m_{TP} > m_{TSS}$ for wetlands and ponds and $m_{TP} > m_{TN} > m_{TSS}$ for biofilters. Often, lower reduction targets
418 also correspond to higher m values (indicating more SWH benefits). Also, m values for ponds
419 (average 0.70) are usually higher than those of wetlands (average 0.38), followed by biofilters
420 (average 0.26). Different m values were found for two designs of each system. The differences,
421 however, were not significant, especially for the biofilter system (Table 3). Similarly, the m values
422 estimated for the treatment train scenario were close to those of the dominant treatment system (e.g.,
423 TT_1 versus Wetland A), indicating its significant impact on SWH benefits.
424 Theoretically, the *benefit threshold* (b_{thresh}) is generally taken as zeros for biofilters, ponds, and
425 wetland, because any minimum extraction from the systems (i.e., $p_{ext} \geq 0$) leads to noticeable benefits
426 (i.e., IAO values ≥ 0) according to Equation 3. This was confirmed by the very low values of
427 estimated b_{thresh} ($=0.002 \pm 0.041$, Table 3), except for using Biofilter A targeting TSS removal, which
428 is likely due to the low IAO values (thus small m and relatively higher b_{thresh} values calculated).
429 Although not tested in this study, for rain tanks, the b_{thresh} value is not zero if it is used as the only
430 WSUD system for both stormwater treatment and harvesting (e.g., household rainwater tank). This is
431 because rain tanks are not intrinsically designed to remove pollutants, unlike the other three systems.

As such, benefits are only perceived after a certain amount of extraction where pollution removal is achieved partly through sedimentation in the tank and direct removal of water from the system. This is the main reason why we recommend keeping the b_{thresh} term in the empirical equation, such that it can capture this kind of behaviour and is therefore applicable to all types of WSUD systems.

3.2.2 Validation of the Empirical relationship

Figure 4 presents the comparison between baseline IAO and modelled IAO values for the 45 various hypothetical scenarios with different system types and pollutant targets, with details of each scenario summarised in Table 4. The worst estimation was found for Biofilter C targeting TP reductions with estimated ΔIAO (=Baseline-Modelled) values of 16.8-25.9%, showing an underestimation of the stormwater harvesting benefits by the empirical relationship, i.e., it is a conservative method of estimating the SWH benefits. Overall, the proposed relationship predicted very close IAO values to the baseline IAO values, with the range of ΔIAO of between -3.80% (overestimation) and 4.20% (underestimation) and $\Delta IAO_{avg \pm std} = 0.00 \pm 1.83\%$. These results show that the proposed empirical relationships are transferable to different SWH cases for estimation of their benefits in pollution management.

Table 4 Summary of the validation results

Scenarios	Pollutant	Target	P_{ext}	m value ¹⁾	b_{thresh} ²⁾	Baseline IAO [%]	Modelled IAO [%]	ΔIAO (Baseline – modelled)
Biofilter A	TSS	85	0.85	0.009	0.40	0.4%	0.8%	-0.4%
	TP	45	0.65	0.566	0.00	40.0%	36.8%	3.2%
	TN	45	0.55	0.276	0.00	13.0%	15.2%	-2.2%
Biofilter C	TSS	85	0.85	0.009	0.40	0.7%	0.8%	-0.1%
	TP	45	0.65	0.566	0.00	55.0%	36.8%	18.2%
	TN	45	0.55	0.276	0.00	16.5%	15.2%	1.3%
Biofilter C	TSS	70 ³⁾	0.85	0.007	0.00	0.3%	0.6%	-0.3%
	TP	30	0.65	0.388	0.00	51.1%	25.2%	25.9%
	TN	30	0.55	0.271	0.00	15.9%	14.9%	1.0%
Wetland A	TSS	85	0.85	0.043	0.00	3.7%	3.7%	0.0%
	TP	45	0.65	0.254	0.00	17.4%	16.5%	0.9%
	TN	45	0.55	0.893	0.00	50.2%	49.1%	1.1%
Wetland C	TSS	85	0.85	0.043	0.00	3.6%	3.7%	-0.1%
	TP	45	0.65	0.254	0.00	17.1%	16.5%	0.6%
	TN	45	0.55	0.893	0.00	48.9%	49.1%	-0.2%
Wetland C	TSS	70	0.85	0.053	0.00	3.0%	4.5%	-1.5%
	TP	30	0.65	0.287	0.00	16.5%	18.7%	-2.2%
	TN	30	0.55	1.118	0.00	60.1%	61.5%	-1.4%
Pond A	TSS	85	0.85	0.152	0.00	13.0%	12.9%	0.1%
	TP	45	0.65	0.557	0.00	37.4%	36.2%	1.2%
	TN	45	0.55	1.181	0.00	62.2%	65.0%	-2.8%
Pond C	TSS	85	0.85	0.152	0.00	12.2%	12.9%	-0.7%

Pond C	TP	45	0.65	0.557	0.00	38.9%	36.2%	2.7%
	TN	45	0.55	1.181	0.00	61.2%	65.0%	-3.8%
	TSS	70	0.85	0.200	0.00	16.0%	17.0%	-1.0%
	TP	30	0.65	0.555	0.00	34.4%	36.1%	-1.7%
	TN	30	0.55	1.876	0.00	99.6%	103.2%	-3.6%
TT_V1_A ³⁾ (Sed. Pond + Biofilter A + storage tank)	TSS	85	0.85	0.009	0.00	0.3%	0.4%	-0.5%
	TP	45	0.65	0.566	0.00	40.1%	36.8%	3.3%
	TN	45	0.55	0.276	0.00	12.2%	15.2%	-3.0%
TT_V1_C (Sed. Pond + Biofilter C + storage tank)	TSS	85	0.85	0.009	0.00	0.3%	0.4%	-0.5%
	TP	45	0.65	0.566	0.00	41.0%	36.8%	4.2%
	TN	45	0.55	0.276	0.00	14.7%	15.2%	-0.5%
TT_V1_C (Sed. Pond + Biofilter C + storage tank)	TSS	70	0.85	0.007	0.00	0.5%	0.4%	0.1%
	TP	30	0.65	0.389	0.00	42.1%	25.3%	16.8%
	TN	30	0.55	0.271	0.00	16.0%	14.9%	1.1%
TT_V2_A (Wetland A + Pond Storage)	TSS	85	0.85	0.152	0.00	12.5%	12.9%	-0.4%
	TP	45	0.65	0.557	0.00	35.7%	36.2%	-0.5%
	TN	45	0.55	1.181	0.00	63.1%	65.0%	-1.9%
TT_V2_C (Wetland C + Pond Storage)	TSS	85	0.85	0.152	0.00	12.9%	12.9%	0.0%
	TP	45	0.65	0.557	0.00	36.6%	36.2%	0.4%
	TN	45	0.55	1.181	0.00	67.1%	65.0%	2.1%
TT_V2_C (Wetland C + Pond Storage)	TSS	70	0.85	0.152	0.00	12.8%	12.9%	-0.1%
	TP	30	0.65	0.557	0.00	37.4%	36.2%	1.2%
	TN	30	0.55	1.181	0.00	68.3%	65.0%	3.3%

¹⁾ *m* values are looked up from Table 3 with the correspondence pollutant type and target. For systems with different design configurations (e.g., configuration C) from Table 3, the values for configuration A were taken as approximate as system design was found to be less sensitive. For the pollutant target that was not covered from sensitivity estimations, simple linear interpolations were conducted to derive *m* values.

²⁾ *b_{fresh}* values were set to zeros as according to the discussion in the last section (the main treatment systems are biofilters and wetlands).

³⁾ Sedimentation pond was only used for reducing TSS concentrations to 50 mg/L.

Figure 4 Results of validation of empirical relationships – baseline against modelled IAO values. Each dot represents one validation scenario in Table 4, with different colours indicating (a) different type of pollutants, and (b) different types of systems.

3.3 Implications for practice

This study shows that the SWH benefits (*i.e.*, IAO in this case) can be reliably quantified using a simple linear empirical equation based on *extraction rate* for different types of systems and reduction targets. For example, given a fully impervious catchment of 10,000 m², the required size of Biofilter A in Melbourne to achieve a 45% TP reduction is 72.0 m² (refer to design curve of Biofilter A in supplementary document) when SWH is not accounted for. With an extraction rate of 0.65 from the storage tank receiving treated stormwater (e.g., using the TT_V1_A scenario), the modelled IAO is 36.8% (Table 4). This indicates that an additional impervious area of 3680 m² can be left untreated or connected directly to the system while still meeting the treatment target (*i.e.*, 45% TP reduction). In Melbourne this means that a small neighbourhood of approximately 15 allotments (average lot size is 240 m², Melbourne Water, 2010) can be offset. Without this harvesting scenario, this additional

impervious surface may need 26.5 m² of additional system surface area to ensure that a 45% TP reduction can be achieved. Alternatively, in the original 10,000 m² catchment, only approximately 45.5 m² of biofilter A is needed instead of 72.0 m², to achieve the same 45% TP reduction if the same level of extraction is maintained. These thought experiments highlight the usefulness of such a relationship for investigating cost-benefit implications (*e.g.*, by coupling the empirical relationship with existing life cycle cost analysis tools), tackling on-site space constraints, and even leveraging the multi-functionality of WSUD infrastructure.

In this study, the extraction rates, system types and treatment targets were found to have significant correlations to IAO. However, although the other variables, *e.g.*, climate conditions and catchment characteristics, were not highly correlated to IAO, they cannot be simply ignored in the bigger picture in the design of WSUD systems, as well as the aspects of SWH. For example, Zhang *et al.* (2019) found that larger WSUD systems are recommended to account for the future climate variability to meet the same treatment targets and also to achieve same reliability of SWH. In addition, different catchment characteristics, such as land use that are not tested in this study, may lead to different levels of pollutions. This may consequently lead to different system designs (and even system types due to the availability of space for WSUD) and SWH requirements (*e.g.*, *extraction rates* under same harvesting reliability), thus impacting the SWH benefits.

WSUD planning is often undertaken based on water management targets (*e.g.*, pollution reduction, volume reduction, harvesting) (Deletic *et al.*, 2018), and/or other multiple objectives, such as cost (Xu *et al.*, 2017) and carbon sequestration (Moore and Hunt, 2013). These different factors are always accounted for independently in the planning of WSUD, creating some levels of redundancy for its implementation (especially for pollution reduction). With the developed empirical relationships, integrated planning of WSUD based on these two important aspects could be more effective in creating financial incentives for local government and developers in adopting and harnessing the multiple benefits of WSUD infrastructures. Further research could be undertaken to integrate all those benefits to enhance business cases of SWH through WSUD practices.

4. Conclusion

In this study, we demonstrated for the first time that SWH has clear benefits in pollution reduction and an approach was developed to quantify these benefits. The IAO, our indicator of choice, reflects the additional impervious area that can be left untreated to achieve same pollution reduction targets due to SWH. A series of sensitivity analyses were conducted to explore the most important factors that impact IAO, and subsequently, SWH benefits. The results were used to develop and validate the empirical relationships to estimate IAO using the key independent variables. The main findings are:

- Significant correlations ($p<0.01$) were observed between IAO values and *extraction rate*, system type, and pollutant reduction targets. The impacts of climate conditions, catchment characteristics, and system design were found to be minimal.
- The proposed linear empirical relationships between IAO values and *extraction rate* for different types of systems and reduction targets were well represented by the observed linear regressions. The difference between estimated baseline IAO and modelled IAO was very small, e.g., $\Delta\text{IAO}_{\text{avg}\pm\text{std}}$ equals to $0.14\pm0.70\%$ with its maximum value of only 2.5%.
- The empirical relationships were validated successfully against various scenarios, with the ΔIAO values varied from -3.80% (overestimation) to 4.20% (underestimation) and $\Delta\text{IAO}_{\text{avg}\pm\text{std}}=0.00\pm1.83\%$.

Despite its simplicity, the developed relationships provide rules of thumb that can help strengthen the business case for stormwater harvesting and quantifiably demonstrate the multiple benefits of WSUD infrastructure. While this paper serves as one of the first studies to quantify the SWH benefits in pollution mitigation, investigation of the relationships between SWH benefits and pollution mitigation either more extensively (e.g., conduct model sensitivity analysis) or using other stormwater models as comparison would be interesting for future research.

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Table 1. Summary of variables tested and their selected values

Category	Variables	Selected Values
Climate	City	Melbourne, Brisbane, Perth
	Rainfall Length (years) ¹⁾	1 year (1959), 10 years (2000 – 2009)
Catchment	Area [ha]	1 ha, 10 ha, 100 ha
	Imperviousness [%]	100%
Harvesting	Reliability of Supply [%]	60%, 80%, 90%
	Demand Pattern	Constant, Seasonal (scaled by Potential evapotranspiration)
	Extraction rate [% of inflow]	25%, 50%, 75%, 100%
Treatment	Pollutant Type	Total Suspend Solids (TSS), Total Nitrogen (TN), Total Phosphorus (TP)
	Reduction Target [%] ²⁾	TSS 95%, 85%, 60% TP 60%, 45%, 20% TN 55%, 45%, 20%
	System Type System Design Configuration	Biofilter, Wetland, Pond Different designs for each system ³⁾ : <ul style="list-style-type: none">• <u>Biofilter A</u>: extended detention depth (EDD) of 100 mm, filter media depth (FD) of 500 mm• <u>Biofilter B</u>: EDD - 500 mm, FD -300 mm• <u>Biofilter C</u>: EDD - 300 mm, FD -500 mm• <u>Wetland A</u>: EDD - 750 mm, detention time 72 hr• <u>Wetland B</u>: EDD - 250 mm, detention time 48 hr• <u>Wetland C</u>: EDD - 300 mm, detention time 48 hr• <u>Pond A</u>: EDD - 1000 mm, detention time 72 hr• <u>Pond B</u>: EDD - 2000 mm, detention time 72 hr• <u>Pond C</u>: EDD - 3000 mm, detention time 24 hr
	Treatment train	Treatment trains include (first two used for sensitive testing scenarios and the rest for validation scenarios): TT_1: wetland A+ storage tank TT_2: vegetated swales + biofilter A+ storage tank TT_V1_A: sedimentation pond + biofilter A + storage tank TT_V1_C: sedimentation pond + biofilter C + storage tank TT_V2_A: wetland A + pond storage TT_V2_C: wetland C + pond storage

¹⁾ To allow more robust testing of climate impact both spatially and temporary, for each city, two different rainfall series were used: 1-year rainfall data from Year 1959 (a typical year representing long term average in these cities), and 10-year rainfall between 2000 and 2009 (which had long term drought period; all 6-minute timestep). Refer to the supplementary document for the details and statistics of different climate types. ²⁾BPBM guideline (VSC, 1999) requires load reduction of 85% for TSS, 45% for TP and 45% for TN, and the selected targets in this study had a good coverage of what is required. ³⁾ Details of the all the designs are given in Table S1- Table S3 of the Supplementary document. Both design A and B were used in the sensitivity testing of “design-based” data set, while only design A was used in the sensitivity testing of Stage 1, Stage 2 “target-based” data set, and the treatment train scenarios. Design C was only used in the empirical relationship validation scenarios introduced below.

Table 3 Performance of the proposed empirical relationship: fitted parameter (m and b_{thresh}) values
estimated and modelled IAO values from the sensitivity testing

System	Pollutant	Target	Modelled IAO [%]	m	b_{thresh}	R^2	Estimated IAO [%]	p value (t test)	$\Delta IAO^{1)}$
Biofilter A	TSS	95	0.0%	0.025	0.507	0.956	2.5%	0.208	2.50%
	TSS	85	1.0%	0.009	0.246	0.663	0.9%	0.484	-0.10%
	TSS	60	0.7%	0.006	0.160	0.892	0.6%	0.380	-0.10%
	TP	60	61.2%	0.616	-0.020	0.996	61.6%	0.877	0.40%
	TP	45	56.3%	0.566	-0.015	0.999	56.6%	0.929	0.30%
	TP	20	27.0%	0.269	-0.017	0.999	26.9%	0.920	-0.10%
	TN	55	25.0%	0.257	-0.014	0.994	25.7%	0.933	0.70%
	TN	45	27.7%	0.276	0.004	0.998	27.6%	0.980	-0.10%
	TN	20	26.8%	0.267	0.000	0.997	26.7%	0.999	-0.10%
Biofilter B	TSS	85	1.8%	0.018	0.175	0.894	1.8%	0.332	0.00%
	TP	45	56.3%	0.570	-0.006	0.995	57.0%	0.970	0.70%
	TN	45	27.7%	0.280	-0.004	0.994	28.0%	0.982	0.30%
Wetland A	TSS	95	3.2%	0.032	0.000	0.999	3.2%	1.000	0.00%
	TSS	85	4.3%	0.043	0.014	0.998	4.3%	0.957	0.00%
	TSS	60	6.1%	0.060	-0.010	0.999	6.0%	0.969	-0.10%
	TP	60	21.8%	0.218	0.006	1.000	21.8%	0.983	0.00%
	TP	45	25.0%	0.254	-0.003	0.997	25.4%	0.990	0.40%
	TP	20	31.7%	0.308	-0.040	0.993	30.8%	0.876	-0.90%
	TN	55	72.4%	0.720	0.002	1.000	72.0%	0.995	-0.40%
	TN	45	89.2%	0.893	0.002	1.000	89.3%	0.992	0.10%
	TN	20	127.1%	1.267	0.003	1.000	126.7%	0.992	-0.40%
Wetland B	TSS	85	3.1%	0.031	0.006	0.999	3.1%	0.980	0.00%
	TP	45	19.6%	0.196	0.000	1.000	19.6%	1.000	0.00%
	TN	45	59.6%	0.597	0.009	1.000	59.7%	0.971	0.10%
Pond A	TSS	95	5.3%	0.053	0.004	1.000	5.3%	0.988	0.00%
	TSS	85	15.0%	0.152	0.022	0.998	15.2%	0.931	0.20%
	TSS	60	22.7%	0.232	0.014	0.998	23.2%	0.957	0.50%
	TP	60	48.5%	0.490	0.011	0.999	49.0%	0.966	0.50%
	TP	45	55.0%	0.557	0.009	0.999	55.7%	0.973	0.70%
	TP	20	55.5%	0.553	-0.010	0.999	55.3%	0.968	-0.20%
	TN	55	80.3%	0.804	0.015	0.999	80.4%	0.955	0.10%
	TN	45	117.5%	1.181	0.020	0.998	118.1%	0.939	0.60%
	TN	20	232.0%	2.340	0.013	0.999	234.0%	0.960	2.00%
Pond B	TSS	85	1.7%	0.017	0.034	0.995	1.7%	0.897	0.00%
	TP	45	79.5%	0.809	0.018	0.998	80.9%	0.943	1.40%
	TN	45	121.8%	1.219	0.015	0.999	121.9%	0.952	0.10%
TT_1 (Wetland A + Storage tank)	TSS	85	4.3%	0.042	-0.082	0.974	4.2%	0.754	-0.10%
	TP	45	24.9%	0.240	-0.080	0.975	24.0%	0.758	-0.90%
	TN	45	82.2%	0.805	-0.054	0.988	80.5%	0.834	-1.70%
TT_2 (Vegetated swales + Biofilter A + Storage tank)	TSS	85	1.0%	0.010	0.096	0.955	1.0%	0.714	0.00%
	TP	45	40.4%	0.396	-0.055	0.987	39.6%	0.830	-0.80%
	TN	45	26.8%	0.270	0.004	1.000	27.0%	0.989	0.20%

¹⁾ ΔIAO = Estimated IAO – Modelled IAO, where “estimated IAO” was from MUSIC simulation, and “Modelled IAO” was from the proposed linear regression model

Table 4 Summary of the validation results

Scenarios	Pollutant	Target	P_{ext}	m value ¹⁾	b_{tresh} ²⁾	Baseline IAO [%]	Modelled IAO [%]	Δ IAO (Baseline – modelled)
Biofilter A	TSS	85	0.85	0.009	0.40	0.4%	0.8%	-0.4%
	TP	45	0.65	0.566	0.00	40.0%	36.8%	3.2%
	TN	45	0.55	0.276	0.00	13.0%	15.2%	-2.2%
Biofilter C	TSS	85	0.85	0.009	0.40	0.7%	0.8%	-0.1%
	TP	45	0.65	0.566	0.00	55.0%	36.8%	18.2%
	TN	45	0.55	0.276	0.00	16.5%	15.2%	1.3%
Biofilter C	TSS	70 ³⁾	0.85	0.007	0.00	0.3%	0.6%	-0.3%
	TP	30	0.65	0.388	0.00	51.1%	25.2%	25.9%
	TN	30	0.55	0.271	0.00	15.9%	14.9%	1.0%
Wetland A	TSS	85	0.85	0.043	0.00	3.7%	3.7%	0.0%
	TP	45	0.65	0.254	0.00	17.4%	16.5%	0.9%
	TN	45	0.55	0.893	0.00	50.2%	49.1%	1.1%
Wetland C	TSS	85	0.85	0.043	0.00	3.6%	3.7%	-0.1%
	TP	45	0.65	0.254	0.00	17.1%	16.5%	0.6%
	TN	45	0.55	0.893	0.00	48.9%	49.1%	-0.2%
Wetland C	TSS	70	0.85	0.053	0.00	3.0%	4.5%	-1.5%
	TP	30	0.65	0.287	0.00	16.5%	18.7%	-2.2%
	TN	30	0.55	1.118	0.00	60.1%	61.5%	-1.4%
Pond A	TSS	85	0.85	0.152	0.00	13.0%	12.9%	0.1%
	TP	45	0.65	0.557	0.00	37.4%	36.2%	1.2%
	TN	45	0.55	1.181	0.00	62.2%	65.0%	-2.8%
Pond C	TSS	85	0.85	0.152	0.00	12.2%	12.9%	-0.7%
	TP	45	0.65	0.557	0.00	38.9%	36.2%	2.7%
	TN	45	0.55	1.181	0.00	61.2%	65.0%	-3.8%
Pond C	TSS	70	0.85	0.200	0.00	16.0%	17.0%	-1.0%
	TP	30	0.65	0.555	0.00	34.4%	36.1%	-1.7%
	TN	30	0.55	1.876	0.00	99.6%	103.2%	-3.6%
TT_V1_A ³⁾ (Sed. Pond + Biofilter A + storage tank)	TSS	85	0.85	0.009	0.00	0.3%	0.4%	-0.5%
	TP	45	0.65	0.566	0.00	40.1%	36.8%	3.3%
	TN	45	0.55	0.276	0.00	12.2%	15.2%	-3.0%
TT_V1_C (Sed. Pond + Biofilter C + storage tank)	TSS	85	0.85	0.009	0.00	0.3%	0.4%	-0.5%
	TP	45	0.65	0.566	0.00	41.0%	36.8%	4.2%
	TN	45	0.55	0.276	0.00	14.7%	15.2%	-0.5%
TT_V1_C (Sed. Pond + Biofilter C + storage tank)	TSS	70	0.85	0.007	0.00	0.5%	0.4%	0.1%
	TP	30	0.65	0.389	0.00	42.1%	25.3%	16.8%
	TN	30	0.55	0.271	0.00	16.0%	14.9%	1.1%
TT_V2_A (Wetland A + Pond Storage)	TSS	85	0.85	0.152	0.00	12.5%	12.9%	-0.4%
	TP	45	0.65	0.557	0.00	35.7%	36.2%	-0.5%
	TN	45	0.55	1.181	0.00	63.1%	65.0%	-1.9%
TT_V2_C (Wetland C + Pond Storage)	TSS	85	0.85	0.152	0.00	12.9%	12.9%	0.0%
	TP	45	0.65	0.557	0.00	36.6%	36.2%	0.4%
	TN	45	0.55	1.181	0.00	67.1%	65.0%	2.1%
TT_V2_C (Wetland C + Pond Storage)	TSS	70	0.85	0.152	0.00	12.8%	12.9%	-0.1%
	TP	30	0.65	0.557	0.00	37.4%	36.2%	1.2%
	TN	30	0.55	1.181	0.00	68.3%	65.0%	3.3%

¹⁾ m values are looked up from Table 3 with the correspondence pollutant type and target. For systems with different design configurations (e.g., configuration C) from Table 3, the values for configuration A were taken as approximate as system design was found to be less sensitive. For the pollutant target that was not covered from sensitivity estimations, simple linear interpolations were conducted to derive m values.

²⁾ b_{tresh} values were set to zeros as according to the discussion in the last section (the main treatment systems are biofilters and wetlands).

³⁾ Sedimentation pond was only used for reducing TSS concentrations to 50 mg/L.

Table 2 Impact of variables on Impervious Area Offset (IAO) – results from Stage 1 sensitivity

testing

City	Climate length	Impervious area [ha]	Supply reliability [%]	Reduction target [%]	Reuse pattern	Impervious Area Offset (IAO) [%]
(a) Impact of climate variability						
Brisbane	1yr	10	80	TSS 85	Constant	0.48%
	10yrs					1.22%
Perth	1yr					0.92%
	10yrs					1.00%
Melbourne	1yr					0.93%
	10yrs					1.1%
(b) Impact of catchment size						
Melbourne	10yrs	1	80	TSS 85	Constant	0.9%
		10				1.01%
		100				1.03 %
		1		TP 60		66.7%
		10				66.7 %
		100				66.7%
		1		TN 45		28.9%
		10				28.9%
		100				29.2%
(c) Impact of demand pattern and supply reliability						
Melbourne	10yrs	10	60	TSS 85	Constant	0.94%
					Seasonal	0.93%
					Constant	0.93%
					Seasonal	1.00%
					Constant	0.93%
					Seasonal	1.10%

Note: All scenarios used an extraction rate of 100% for biofilter design A (Table 1).

Figure 1

Figure 1 Basic MUSIC model setup for assessing pollution reduction benefits of SWH

Figure 2

Figure 2 Relationship between *extraction rates* and IAO for different system type, pollutant, and reduction targets: results from the “target-based” data set.

Figure 3

Figure 3 Relationship between *extraction rates* and IAO for different system type and design, pollutant type, and reduction targets: results from the “design-based” data set. The same treatment targets were used for the figures (i.e., TSS 85%, TP 45% and TN 45%).

Figure 4

Figure 4 Results of validation of empirical relationships – baseline against modelled IAO values. Each dot represents one validation scenario in Table 4, with different colours indicating (a) different type of pollutants, and (b) different types of systems.

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