

Article

Enhancing MUSIC's Capability for Performance Evaluation and Optimization of Established Urban Constructed Wetlands

Fujia Yang ^{1,2}, Shirley Gato-Trinidad ^{2,*}  and Iqbal Hossain ² 

¹ Yunnan Key Laboratory of Plateau Wetland Conservation, Restoration and Ecological Services, College of Ecology and Environment (College of Wetland), Southwest Forestry University, Kunming 650224, China; fujia_yang@swfu.edu.cn

² School of Engineering, Swinburne University of Technology, Melbourne, NSW 2150, Australia; ihossain@swin.edu.au

* Correspondence: sgatotrinidad@swin.edu.au

Abstract

The Model for Urban Stormwater Improvement Conceptualization (MUSIC) serves as a key hydrological tool for simulating urban stormwater runoff pollution and evaluating the treatment performance in Water-Sensitive Urban Designs like constructed wetlands (CWs). However, a significant limitation exists in MUSIC's current inability to model heavy metal contaminants, even though they are commonly found in urban stormwater and pose significant environmental risks. This eventually affects the model's utility during critical planning phases for urban developments. Thus, there is a need to address this limitation. Field investigations were conducted across established CWs in residential and industrial catchments throughout Greater Melbourne, Australia. Through systematic monitoring and calibration, an approach was developed to extend MUSIC's predictive capabilities to include several prevalent heavy metals. The results indicate that the enhanced model can generate plausible estimates for targeted metals while differentiating catchment-specific pollutant generation and treatment patterns. This advancement enhances MUSIC's functionality as a planning support tool, enabling the preliminary assessment of heavy metal dynamics alongside conventional pollutants during both design and operational stages. The findings underscore the value of incorporating metal-specific parameters into stormwater models, offering improved support for urban water management decisions and long-term water quality protection.

Keywords: MUSIC model; urban stormwater management; heavy metal mitigation; constructed wetlands; first-order decay model



Academic Editor: Ranjan Sarukkalige

Received: 14 July 2025

Revised: 8 August 2025

Accepted: 14 August 2025

Published: 18 August 2025

Citation: Yang, F.; Gato-Trinidad, S.; Hossain, I. Enhancing MUSIC's Capability for Performance Evaluation and Optimization of Established Urban Constructed Wetlands.

Hydrology **2025**, *12*, 219.

<https://doi.org/10.3390/hydrology12080219>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Rapid urban expansion due to the increasing population has created more impervious surfaces in urban cities, hence increased stormwater pollution. Protecting the natural environment and improving liveability requires the effective treatment and management of pollutant concentrations in stormwater runoffs. Currently, the concept of the treatment and reuse of stormwater is well adopted across the world. Water-Sensitive Urban Design (WUSD) in Australia, Green Infrastructure (GI) and Low-Impact Development (LID) in the US, or Sponge City in China, as well as Sustainable Urban Drainage Systems (SUDSs) in the UK are advocated in urban planning that utilizes diverse sources of water and stormwater for reusing and recycling [1,2].

When it comes to stormwater management and modeling, models such as SWMM, SUSTAIN, SWAT, and MUSIC are popular [3–6]. While each model has its merits, they also exhibit limitations in certain contexts. For example, models like SWMM and SUSTAIN, which calculate water storage based on catchment characteristics, typically only estimate the pollutant accumulation within the catchment, with the pollutant reduction being volume-based [5]. The Model for Urban Stormwater Improvement Conceptualization (MUSIC) serves as a conceptualization tool that integrates two components: the modeling of the water quality through a first-order decay model ($k-C^*$) and the modeling of the hydraulics of flow through a continuously stirred tank reactor (CSTR). The model looks beyond the complex pollutant interactions within WSUDs and uses empirical observations of how pollutants decrease in these systems [7,8]. Therefore, MUSIC has a higher accuracy in predicting the effluent quality compared to other models [5]. The simplicity and user-friendliness of MUSIC largely supported the planning and implementation of WSUDs not only in Australia [7,9], as the application of MUSIC in Singapore [4,10], China [5,11], and Malaysia [12,13] can also be observed. This empirical approach proves particularly valuable for heavy metal prediction, as demonstrated by MUSIC's strong agreement with observed removal rates in systems like waste tire permeable pavements (e.g., 69% TSS and 88% turbidity reduction) [14], a performance that many conventional models struggle to achieve without extensive calibration.

In comparison, SWAT, while widely used for watershed-scale heavy metal transport modeling through its integration with sediment dynamics, has its own limitations due to its simplified approach that treats metals as inert pollutants attached to sediments, neglecting transformations and subsurface leaching pathways [15]. Similarly, SWMM has become a standard for stormwater hydrology modeling [16] but relies on generalized removal rates from the literature (e.g., Zn: 89% in bioretention cells) rather than process-based algorithms. More critically, SWMM cannot simulate subsurface processes like adsorption or chemical transformations that govern heavy metal behavior in treatment systems [17], highlighting a key gap in conventional modeling approaches.

Although MUSIC remains a highly regarded conceptual design tool for CWs to assist decision-makers in making informed choices, MUSIC's predictions regarding pollutant reduction capabilities have been questioned. Several studies reported the unsatisfactory hydrological performance of the CWs related to overestimations in MUSIC. Specifically, Imteaz et al. reported an overprediction for TN treatments by MUSIC [9], and Fowdar et al. reported an underprediction of the TSS load and the overestimation of TP reduction rates [4]. While current practice studies have utilized MUSIC as a design conceptualization tool, there has been very limited research endeavoring to model the post-construction performance of CWs using MUSIC.

Given the empirical nature of the MUSIC model, the unsatisfactory prediction could be associated with the default parameters for the total nitrogen (TN), total phosphorous (TP), and total suspended solids (TSS) in various catchments. For instance, Dotto et al. suggested that the use of default parameters may be applicable only to highly urbanized areas, as the model calibration concluded that MUSIC is still a poor representation of reality [18]. Similarly, the use of default parameters can produce an inaccurate prediction of the TSS concentration, especially for residential catchments [19]. These previous studies primarily focused on calibrating catchment-related characteristics, such as the infiltration rate or impervious fraction, which contribute to rainfall and runoff generation. These studies did not address the issue of the pollutant generation and treatment prediction of any specific WSUD. Furthermore, Liu et al. reviewed 19 stormwater models and found that most are unsustainable for simulating changes in the WSUD over time [5]. Additionally, generic models often need refinement using field-measured parameters, a step rarely taken

before construction. Therefore, Wu et al. emphasized that research efforts should focus on developing predictive models for optimizing pollutant removal in CWs. Specifically, these models need to be resilient, as existing practices for common pollutants may not be directly applicable [20].

Compounding these challenges is the fact that a significant portion of the data used in deriving the default parameters in MUSIC is quite outdated. The rapid advances in clean manufacturing and pollution control technologies have rendered much of the historical stormwater quality data obsolete. This obsolescence, combined with the continuous release of new materials and chemicals into the environment, suggests that the identification of important stormwater runoff pollution sources and associated pollutants is an ongoing process. Therefore, the current study aims to address this gap by updating the MUSIC model with more recent data, particularly for heavy metals commonly found in urban stormwater runoffs. This update is crucial for improving the model's accuracy and applicability in predicting the water quality and treatment efficiency in different urban catchments.

Furthermore, another critical limitation in current approaches is that although the relevant pollutant contents were determined from multiple catchments in Melbourne, Australia, and the analysis of event mean concentrations (EMCs) is lacking in storm events. Specifically, many of these studies focused on pollutant levels in a specific area instead of EMCs [21,22]. For example, typical pollutant levels based on land use geographical characters are more accessible in the literature. As a result, it is a common approach to adopt typical values of pollutants, as practitioners often favor simple average concentrations over more complex and data-driven approaches [23]. This reliance on simpler methods and accessible data from the literature might have led to outdated knowledge regarding pollutant concentrations and loads in the study area.

These compounding limitations of the outdated parameter data and insufficient event-based analysis underscore why this study's focus on established wetlands with recent monitoring data provides valuable insights. This study presents a comparative assessment of MUSIC modeling applied to two established stormwater treatment wetlands situated in distinct catchments—one residential and one industrial—in Metropolitan Melbourne, Australia. The primary aim is to enhance the predictive accuracy of MUSIC by evaluating its performance against observed pollutant reduction rates. Specifically, the study compares modeled and measured pollutant removal efficiencies for each constructed wetland, thereby providing insights into MUSIC's reliability across varying land use contexts. The research then investigates the potential for predicting heavy metal reductions by incorporating empirical field observations from both types of catchments, which is a notable function that has not been previously achieved. While our two-case approach necessarily limits a broader generalization, it offers a crucial update to MUSIC's empirical foundation. Overall, this investigation endeavors to refine MUSIC's capabilities, ensuring it accurately reflects real-world pollutant reduction scenarios within CWs. The findings will provide valuable insights for designers and practitioners, enhancing the design and management of CWs to improve water quality and support resource conservation in urban waterways.

2. Materials and Methods

2.1. Overview of MUSIC

MUSIC was first introduced to Australian society in early 2000 [7]. In Australia, MUSIC is commonly utilized as a conceptualization design tool to meet the minimum reduction rate requirements for pollutants, especially TN, TP, and TSS. MUSIC can be simply described as a “source node” and a “treatment node”, where the “source node” encompasses the rainfall simulation, runoff, and pollutant generation, and the “treatment

node” reduces the pollutant concentrations through several treatment devices such as CWs or bioretention swales [24].

In 2020, MUSICX became available and eventually superseded the previous version, i.e., MUSIC. MUSICX offers additional functionalities and an improved interface compared to MUSIC. Notably, it allows for the modeling of multiple scenarios within a single interface. Nevertheless, the underlying modeling philosophy and default parameters remained unchanged.

2.1.1. Flow Simulation

During storm events, rainfall first fills up the surfaces and pores as an initial loss. Then, most of the runoffs are formed by stormwater flowing through impervious surfaces. Baseflow and groundwater exchange are often less significant in the urban catchment during a storm event. Therefore, in MUSIC the change in storage can be simply illustrated by the water balance model (Equation (1)).

$$ds/dt = \text{Precipitation} - \text{Evapotranspiration} - \text{Runoff} \pm \text{Groundwater} \quad (1)$$

Another major factor influencing runoffs is the effective impervious area in urban surfaces [25]. The estimation of runoffs on impervious surfaces is relatively simple in MUSIC because all stormwaters will become runoffs once the pores and depressions on the surface are saturated. In the meantime, runoff losses from pervious surfaces can be estimated through models that reveal the water storage (Equation (2)).

$$\text{Runoff} = r_{ci} \times A_i \times \text{Rainfall} + r_{cp} \times (1 - A_i) \times (\text{Rainfall} + \text{Water Use Outdoor}) \quad (2)$$

- A_i Fraction of effective impervious area;
- r_{ci} Impervious area runoff coefficient;
- r_{cp} Pervious area runoff coefficient.

In MUSIC, the simulation of flow is enabled for timesteps of 6 min or 24 h. Meteorological files including historical rainfall, evapotranspiration rates in different regions, and different timesteps are available in MUSIC, and the current version of MUSICX provides more options for customizing flow. A detailed description of the rainfall–runoff model can be found on eWater’s website [24].

2.1.2. Pollutant Generation

Following the generation of stormwater runoff, the pollutant load is empirically determined in MUSIC, where a certain number of pollutants are carried in the stormwater runoffs (stormflow) and groundwater (baseflow). For instance, the relationship between runoffs and gross pollutant concentration in the Melbourne catchment was derived from 192 gross pollutant traps, where regression analysis of the event mean concentrations (EMC) transformed the relationship between precipitation and pollutant load [24].

Similarly, the pollutant generation model is empirically determined in MUSIC. Duncan’s study investigated pollutant concentrations across different urban catchments ranging from roads, roofs, to highly urbanized areas [26]. Water quality data was collected from over 500 studies in Australia and overseas, and the logged forms of those values were moderated and embedded in the MUSIC model as default parameters [24]. In 2005, Fletcher et al. reviewed more studies in Australia on urban runoff qualities from different catchments ranging from roads and roofs to residential and industrial districts. An additional 17 international studies conducted between 1998 and 2002 were reviewed, and the typical values are summarized in Table 1 [27].

Table 1. Recommended typical values for runoff quality [27].

Pollutants	Residential		Industrial	
	Dry	Wet	Dry	Wet
TN (mg/L)	0.4~4	0.7~6	0.4~4	0.7~6
TP (mg/L)	0.04~0.5	0.08~0.8	0.04~0.5	0.08~0.8
TSS (mg/L)	5~50	40~500	5~50	40~500
Zn (mg/L)	N/A	0.05~0.5	N/A	0.1~1
Cu (mg/L)	N/A	0.02~0.3	N/A	0.02~0.3

2.1.3. Pollutant Treatment

When pollutants are carried along with the flow, the detailed behavior of the water parcels is often complex. Therefore, in the study region, the treatment of pollutants is simulated through a first-order decay model in MUSIC [24].

2.1.4. The First-Order Decay Model and Hydraulic Efficiency (γ) Estimation

The first-order decay model predicts the reduction at each treatment component at individual timesteps and is widely adopted in wastewater treatment facilities. It describes the trend of moving toward a more stable state where an equilibrium is reached. The process is expressed as the first-order kinetic equation (Equation (3)) below:

$$(C_{\text{out}} - C^*) / (C_{\text{in}} - C^*) = e^{-k/q} \quad (3)$$

- C^* Background concentration;
- C_{in} Input concentration;
- C_{out} Output concentration;
- k The rate of decay;
- q Flow rate per surface area (hydraulic loading).

The decay rate varies between different contaminants. Usually, the decay constant is higher for pollutants that have a larger particle size because they settle quite fast [7,24]. Moreover, the decay of pollutants is associated with the level of urbanization. For typical urban catchments, the impervious area ranges from 20% to 95%. However, when the imperviousness reaches 95%, there will be reductions in the removal of TN by 8%, TP by 10%, and TSS by 15% [27]. Specifically for CWs, the decay rate for TSS in wetland systems is approximately 5000 m/year, which is 10 times larger than k for TN (500 m/year), and the decay rate for TP is 1800 m/year.

In addition to pollutant decay rates, the hydraulic retention time significantly influences the performance of CWs, as greater water retention capacity leads to higher hydraulic efficiency and improved treatment performance. In MUSIC, hydraulic efficiency is determined by the CW's shape and vegetation layout, with increased efficiency achieved through a greater number of ponds that simulate the continuously stirred tank reactor (CSTR) rate [28]. The default number of CSTR cells in a CW is 4.

However, it should be noted that the above default parameters used in MUSIC were empirically determined in the late 1990s. Since then, rapid expansion in urban development and climate conditions has been experienced in Greater Melbourne. Therefore, fine-tuning these default parameters becomes crucial to ensure the accurate representation of CW performance [29].

2.2. Study Area

This study focuses on two free water surface (FWS) CWs located in Metropolitan Melbourne, Australia. Specifically for the Best Practice Management (BPM) guideline in

the study region [30], the functions of CWs heavily focus on annually reducing 45% of TN, 45% of TP, and 80% of TSS from residential catchments. These CWs, Marie Wallace CW and Jones Park CW, were selected to evaluate their performance in reducing key pollutants commonly found in stormwater runoff. Similarly to many other FWS CWs across the world, these two wetlands serve as representative examples of this type of stormwater management practice, which is widely implemented in urban settings globally.

Marie Wallace CW, indicated in red in Figure 1, was built in 2015 and primarily receives stormwater runoffs from an 11-hectare catchment area largely occupied by industrial activities. The CW consists of 154 m³ sediment pond followed by 2400 m² macrophyte zone. The macrophyte zone resembles a relatively straight and densely vegetated channel. Jones Park CW (denoted in blue in Figure 1) is situated in Brunswick East, Victoria, Australia. The wetland was constructed in 2019 and covers an area of 1479 m². To enhance connectivity between the sediment pond and the macrophyte zone, a rocky outfall was designed below a pedestrian boardwalk. The difference in elevation between the sediment pond and the macrophyte zone facilitates one-directional flow, creating a waterfall feature and simultaneously adding aesthetic value.

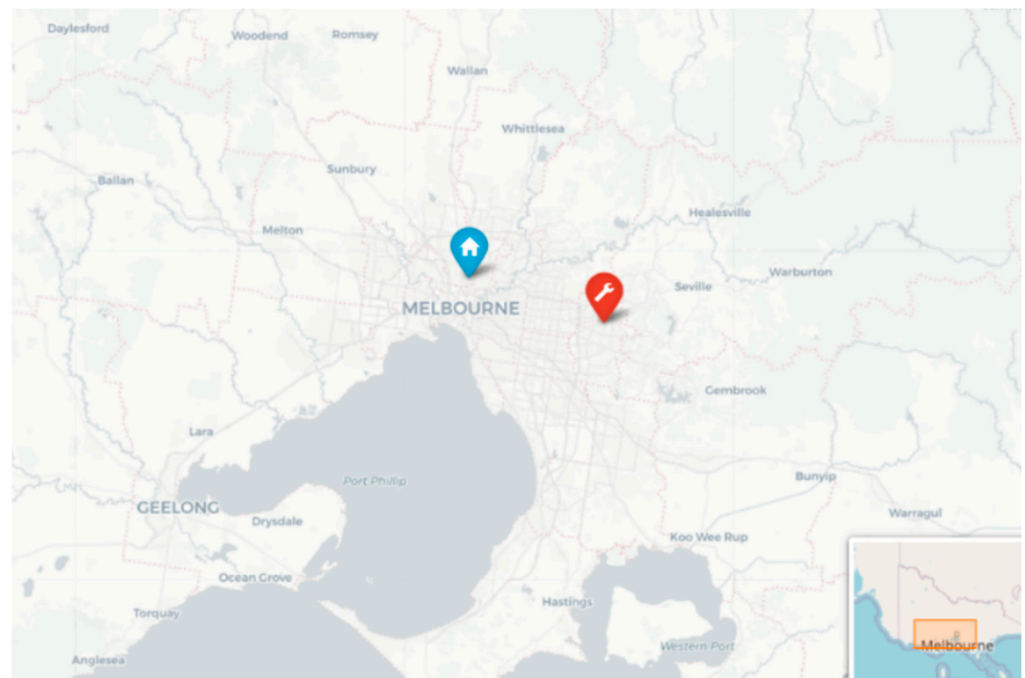


Figure 1. Locations of the investigated CWs in Metropolitan Melbourne.

Both CWs are designed to treat stormwater runoff through a series of processes including sedimentation and biological filtration within a macrophyte zone. The treated effluents are intended to support local ecosystems in the receiving water bodies (Figure 2).

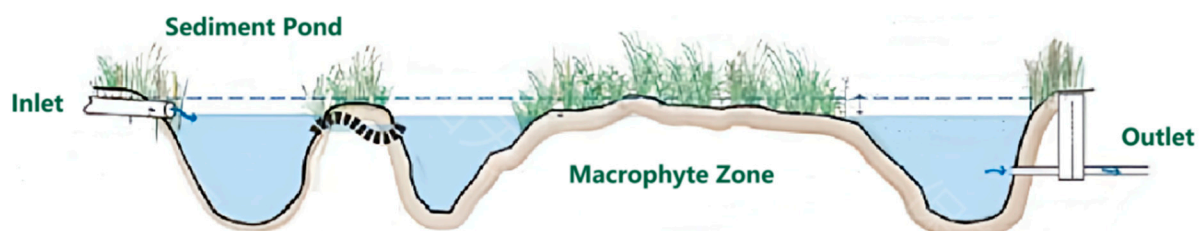


Figure 2. Schematic diagram of stormwater treatment in constructed wetland. The direction of water flow is indicated as blue arrow and black dashed line delineates the boundary between sediment pond and the macrophyte zone.

2.3. Water Sampling and Analysis

Water samples were routinely collected using grab sampling during dry conditions and automated samplers in wet weather from both the inlet and outlet of each CW to assess pollutant concentrations under different flow conditions. Sampling frequency was determined by seasonal rainfall patterns and operational constraints. During dry periods, grab samples were collected biweekly, while during wet-weather events, automated samplers collected time-proportional samples every 3 h over a 72 h period (totaling 48 samples per campaign). Supplemental grab samples were collected at the beginning (to capture first flush conditions) and end of each monitoring period. This approach provided high-temporal-resolution data during storm events while establishing baseline inlet/outlet conditions.

Each water sample was collected in a sterile 500 mL polyethylene bottle, which was rinsed three times with the sample water before collection. The samples were immediately placed on ice and transported to the laboratory for analysis within 24 h to ensure the integrity of the samples. Upon arrival, the samples were stored at 4 °C until analysis. A total of 188 water samples were collected over the study period.

Water samples collected in 2017 and 2019, as well as those collected in September 2022, were sent to ALS Environmental Services for testing. The remaining water samples collected in 2022 and 2023 were primarily analyzed using a HACH DR 3900 Spectrophotometer. A total of eight pollutants were analyzed within 48 h of collection, including three typical stormwater pollutants (TN, TP, TSS) and five heavy metals—Zinc (Zn), Copper (Cu), Aluminum (Al), Iron (Fe), and Manganese (Mn).

For trace metals, preservation with nitric acid was used to reduce the sample pH to less than two, ensuring the solubility of metals prior to analysis. This procedure prevents sorption to container walls or precipitation as metal oxides or hydroxides. The spectrophotometer was calibrated using standard reference materials. The specific wavelengths and methods used for each pollutant are detailed in Table 2 below.

Table 2. Analytical methods used for testing different pollutants through DR 3900 Spectrophotometer.

Pollutant	Analytical Method	Testing Range	Wavelength
Phosphorus, Total	Acid Persulfate Digestion Method	0.06 to 3.50 mg/L	880 nm
Nitrogen, Total	Persulfate Digestion Method	1 to 40 mg/L	345 nm
Suspended Solids	Photometric Method	5 to 750 mg/L	810 nm
Zinc	USEPA1 Zincon Method	0.01 to 3.00 mg/L	620 nm
Copper	Porphyrim Method	1 to 210 µg/L	425 nm
Aluminum	1,10-Phenanthroline Method	0.02 to 3.00 mg/L	510 nm
Manganese	1-(2-Pyridylazo)-2-Naphthol PAN Method	0.006 to 0.700 mg/L	560 nm
Iron	FerroZine® Method	0.009 to 1.400 mg/L	562 nm

2.4. Data Analysis

2.4.1. Pollutant Reduction Rates

Pollutant removal efficiency was calculated using two complementary approaches:

- (1) Event mean concentration (EMC)-based removal:

EMC represents the flow-weighted average concentration of a pollutant during a storm event, calculated as

$$EMC = \frac{\sum_{i=1}^n (C_i \times Q_i \times \Delta t)}{\sum_{i=1}^n (Q_i \times \Delta t)} \quad (4)$$

where

- C_i = pollutant concentration at time i (mg/L);
- Q_i = flow rate at time i (m^3/s);

- Δt = time interval between samples (s);
- n = total number of samples.

For stormflow conditions, the removal rate percentage was calculated using EMC values:

$$\text{Pollutant Removal Rate (\%)} = 100\% \times (\text{EMC IN} - \text{EMC OUT}) / \text{EMC IN} \quad (5)$$

(2) Instantaneous concentration-based removal:

For non-storm conditions or when flow data were unavailable where grab sampling was utilized, removal rates were calculated using discrete sample concentrations:

$$\text{Pollutant Removal Rate (\%)} = 100\% \times (\text{Concentration IN} - \text{Concentration OUT}) / \text{Concentration IN} \quad (6)$$

The EMC approach accounts for temporal variations in both flow and concentration during storm events, providing a more comprehensive assessment of wetland performance compared to using discrete samples alone. This dual-method approach ensures appropriate evaluation under different hydrological conditions.

2.4.2. Pollutant Generation Calibration

Assessing the treatment performance of CWs is essential, and equally important is the evaluation of the accuracy of pollutant generation estimates within MUSIC. The default natural logarithm values for pollutant generation in MUSIC originate from studies conducted by Fletcher et al. in the late 1990s [27]. These studies, which formed the basis for the current model parameters, did not establish reduction targets for heavy metals, and the MUSIC framework, as it stood, did not support the modeling of heavy metals.

To address this limitation and enhance the accuracy of pollutant generation estimates, a comprehensive assessment was conducted on inlet concentrations derived from water samples in both residential and industrial catchments. This involved calculating the logarithmic averages and standard deviations of pollutant concentrations under baseflow (dry-weather conditions) and stormflow (wet-weather conditions).

Analyzing data from these contrasting scenarios was aimed at developing a more precise understanding of pollutant generation and improving the modeling of heavy metals in MUSIC. Such an improvement is vital for accurately predicting pollutant loads and assessing the treatment efficacy of CWs across diverse settings.

2.4.3. Pollutant Reduction Calibration

Following the calibration of pollutant load generation parameters, the next step involves calibrating the treatment of pollutants by adjusting the background concentration (C^*) and decay rate (k , in m/year) based on field observations. The decay rates are derived across a range of background concentrations using the first-order decay rate equation (Equation (3)).

While newly constructed wetlands often assume a C^* of 0 mg/L for different pollutants [24], these values evolve as the wetland matures. Research indicates that pollutant concentrations near the outlet more accurately reflect true C^* values than an assumption of 0 [31]. Thus, average pollutant concentrations in the macrophyte zone towards the wetland's outlet are crucial for establishing a more accurate baseline.

Starting decay rates (k) were assumed based on literature and empirical observations, serving as a baseline for simulating pollutant reduction in CWs. The outputs were then compared with actual pollutant concentrations measured at the outlets of the CWs across different seasons and flow conditions. To establish appropriate ranges of k and C^* for MUSIC model calibration, the following scenarios were investigated:

- $C^* = 0$ (initial design assumption);

- C^* = MUSIC-recommended values (Table 1);
- C^* = dry weather average;
- C^* = average macrophyte zone concentration.

The decay rates were iteratively adjusted through a trial-and-error process within MUSIC, involving a series of adjustments and recalculations to fine-tune the rates for each pollutant under various scenarios. This process continued until the model outputs closely matched the observed data. Once the decay rates were refined, Student's t -test at a significance level of 0.05 was employed to statistically validate the differences between the observed and modeled pollutant reductions. This test ensured that the chosen background concentrations C^* and decay rates k were appropriate and that the model accurately represented the treatment performance of the CWs under diverse conditions.

3. Results and Discussion

3.1. Observed and Modeled Pollutant Reduction Rates

Figure 3 illustrates both the modeled representation of the CW in MUSIC and its real-life appearance. Table 2 presents the modeled and observed pollutant removal rates for the Jones Park CW across different seasons. The results indicate that the treatment percentages for the TN, TP, and TSS do not meet the required reduction targets of 45% for the TN and TP or 80% for the TSS, as shown in Table 3. It is important to note that neither MUSIC nor BPM currently provide reduction targets for heavy metals. This limitation highlights the need to update these models to include heavy metals, which are significant pollutants in urban stormwater runoffs. The absence of such targets in the current models underscores the importance of this study, which aims to address this gap by incorporating heavy metal reduction targets into MUSIC.



Figure 3. MUSIC representation of Jones Park CW. The direction of water flow is indicated in black arrow.

Table 3. Mean pollutant reduction rates and standard deviation for TN, TP, and TSS in different sampling periods (Jones Park—residential).

Pollutant	MUSIC-Modeled Reduction	Observed Average Pollutant Removal Rates (%) ± Standard Deviation in Different Seasons					
		2022 Summer	2022 Autumn	2022 Spring	2023 Summer	2023 Autumn	2023 Spring
TN	15.30%	20.03 ± 32.23	59.09 ± 0.00	18.18 ± 0.00	69.44 ± 19.44	69.79 ± 64.80	62.38 ± 83.76
TP	33.60%	−84.01 ± 147.56	18.52 ± 23.96	−18.06 ± 25.08	−8.78 ± 8.78	−13.18 ± 81.27	−28.94 ± 81.65
TSS	44.00%	−68.21 ± 72.24	−5.40 ± 90.47	23.33 ± 23.33	−149.26 ± 125.74	−258.29 ± 430.40	43.99 ± 49.07
Fe	N/A	−207.74 ± 284.81	−4.58 ± 28.41	9.57 ± 29.57	−88.54 ± 37.28	−289.21 ± 483.06	−407.81 ± 384.70
Cu	N/A	−58.63 ± 85.4	76.67 ± 20.55	−50.00 ± 16.67	55.00 ± 5.00	−40.12 ± 301.95	23.08 ± 109.88
Zn	N/A	−32.62 ± 32.10	27.66 ± 17.72	−31.25 ± 108.75	−366.18 ± 183.82	41.22 ± 52.72	32.73 ± 103.09
Al	N/A	−17.66 ± 66.31	1.58 ± 77.51	−7.50 ± 84.17	62.43 ± 7.26	9.50 ± 142.48	9.70 ± 62.39
Mn	N/A	−62.13 ± 3.89	26.33 ± 42.08	−13.22 ± 18.78	−41.25 ± 21.25	−125.12 ± 250.46	N/A

Overall, the mean removal rates of the TP in the Jones Park CW (residential catchment) consistently remained below 45%, often resulting in negative values, as seen in the Jones Park CW (Table 3). This finding aligns with Mitsch et al., who noted the constant transportation of TP in CWs under continued flows [32]. In contrast, the TN removal demonstrated a better performance, averaging over 60% in 2023. The TSS were primarily transported out during storm events, with the multi-stage design of the Jones Park CW likely influencing the treatment efficacy, as indicated by Jiang and Chui’s study [33].

The Marie Wallace CW (industrial catchment) also exhibited a suboptimal performance (Table 4), with pollutant removal rates (−153.65% to 0.54% for TN; −21.01% to 37.49% for TP; and −216.58% to 21.59% for TSS) that remained lower than those reported in the literature, such as Zhou et al.’s study (60% to 80% for TN, TP, and TSS) [34] and Vymazal and Krása’s paper (50% reduction in TN and 40% of TP) [35]. The negative TN/TP removal rates observed in the Marie Wallace CW can be attributed to the combined effects of clogging and hydraulic inefficiency. As documented by Wang et al., clogging occurs through both physical the sediment deposition and chemical precipitation of insoluble salts, progressively reducing the system’s treatment capacity [36]. This is particularly relevant for industrial wetlands receiving metal-laden stormwater, where the pollutant accumulation accelerates substrate degradation. Furthermore, as demonstrated by Ergaieg et al., clogging severely compromises the hydraulic retention time—a critical factor for effective nutrient removal [37]. During storm events, the reduced retention capacity leads to short-circuiting, where incoming flows bypass treatment zones and mobilize accumulated pollutants, resulting in elevated effluent concentrations that manifest as negative removal rates.

Table 4. Mean pollutant reduction rates and standard deviation for TN, TP, and TSS in different sampling periods (Marie Wallace—industrialized).

Pollutant	MUSIC-Modeled Reduction	Observed Average Pollutant Removal Rates (%) ± Standard Deviation in Different Seasons					
		2017 Spring	2019 Autumn	2022 Summer	2022 Autumn	2022 Spring	2023 Summer
TN	13.02%	N/A	−25.00 ± 54.01	−12.50 ± 119.82	64.99 ± 38.03	0.54 ± 73.81	−153.65 ± 236.38
TP	33.81%	N/A	−12.22 ± 8.75	46.75 ± 56.94	−21.01 ± 59.57	37.49 ± 16.58	11.35 ± 49.33
TSS	45.48%	N/A	21.59 ± 62.58	−37.30 ± 153.43	−56.42 ± 86.46	−19.99 ± 80.39	−216.58 ± 293.88
Fe	N/A	21.30 ± 49.50	−189.52 ± 110.53	−455.03 ± 631.99	−681.84 ± 798.87	−116.17 ± 209.53	−893.90 ± 876.51
Cu	N/A	6.25 ± 10.83	−58.33 ± 100.69	−51.92 ± 258.72	25.00 ± 75.00	68.75 ± 40.98	−428.77 ± 755.46
Zn	N/A	38.50 ± 28.76	−17.99 ± 52.71	80.56 ± 14.16	42.50 ± 43.29	72.55 ± 16.44	−81.53 ± 299.39
Al	N/A	−133.59 ± 304.94	34.36 ± 18.76	39.70 ± 64.90	−638.85 ± 1103.72	−188.54 ± 184.05	−322.41 ± 341
Mn	N/A	−4.69 ± 34.52	−355.86280.40	−327.07 ± 593.43	−319.81 ± 369.53	−17.96 ± 88.61	−284.26 ± 314.41

Regarding heavy metals, it is evident that more negative reduction rates appeared in 2019 with Fe (−189.52%) and Mn (−355.86%) and in 2017 with Al (−133.59%) (Table 3). The negative reduction rates for heavy metals suggest that the CW may have reached

capacity and experienced clogging over time, compromising the hydraulic retention and treatment efficiency time [38]. These findings further indicate a significant discrepancy between observed pollutant reduction rates and expectations, underscoring the need for calibrating MUSIC's default parameters to enhance the prediction accuracy.

3.2. Pollutant Generation (Default Parameters)

In addition to modeling the properties of pollutant treatment in CWs, it is paramount to evaluate the source node where pollutants are generated in stormwater runoffs. The concentrations of pollutants in the baseflow in the two investigated CWs are presented in Table 5. These concentrations are compared against the guideline values as well as those referenced in Duncan's study [26].

Table 5. Pollutant concentrations in baseflow and stormflow (log mg/L).

Flow Type		Duncan (1999)	MUSIC Default Values	Jones Park (Residential)		Marie Wallace (Industrial)	
				No. Observa- tions	Concentration (mg/L)	No. Observa- tions	Concentration (mg/L)
TSS	Baseflow	1.55~2.19	1.2 ± 0.17	15	0.95 ± 0.38	8	0.84 ± 0.36
	Stormflow		2.15 ± 0.32	18	0.77 ± 0.28	15	0.85 ± 0.29
TP	Baseflow	−0.89~−0.40	$−0.85 \pm 0.19$	15	$−0.25 \pm 0.08$	8	$−0.36 \pm 0.43$
	Stormflow		$−0.6 \pm 0.25$	18	$−0.33 \pm 0.07$	18	$−0.51 \pm 0.55$
TN	Baseflow	0.33~0.42	0.11 ± 0.12	11	0.86 ± 0.54	7	0.47 ± 0.39
	Stormflow		0.3 ± 0.19	16	1.18 ± 0.44	16	0.54 ± 0.62
Cu	Baseflow	−1.62~−1.09	−1.10	15	$−1.50 \pm 0.25$	11	$−2.10 \pm 0.66$
	Stormflow			10	$−1.58 \pm 0.26$	15	$−1.80 \pm 0.51$
Zn	Baseflow	−0.80~0.57	−0.52	15	$−0.95 \pm 0.34$	9	$−1.38 \pm 0.31$
	Stormflow			10	$−0.97 \pm 0.13$	15	$−1.20 \pm 0.47$
Al	Baseflow	-	-	15	$−1.73 \pm 0.30$	11	$−1.26 \pm 0.77$
	Stormflow			10	$−1.62 \pm 0.17$	16	$−1.51 \pm 0.56$
Fe	Baseflow	0.20~0.74	-	15	$−0.39 \pm 0.29$	11	$−0.23 \pm 0.47$
	Stormflow			10	$−1.08 \pm 0.26$	15	$−0.48 \pm 0.46$
Mn	Baseflow	−0.63	-	15	$−1.27 \pm 0.22$	11	$−0.83 \pm 0.58$
	Stormflow			10	$−1.60 \pm 0.14$	16	$−1.20 \pm 0.47$

Regarding TN, TP, and TSS concentrations, it becomes evident (Table 5) that both CWs exhibit notably higher concentrations of TN during both the baseflow and stormflow, surpassing levels observed in MUSIC and Duncan's study. In contrast, the logged concentrations of the TP and TSS at both CWs are consistently lower when compared to the results obtained in Duncan's research and the default values employed in the MUSIC model (Table 4).

Concerning the heavy metals, it is noteworthy that MUSIC provides values exclusively for Cu and Zn (−1.10 and −0.52 mg/L), and in these cases, the concentrations in two CWs (Table 4) align with those observed in both Duncan's findings and MUSIC's default values. However, Fe and Mn concentrations in both wetlands are consistently lower in comparison to Duncan's research (Table 4). This could be attributed to Duncan's extensive review of pollutant concentrations in different WSUDs and different regions, as well as the reporting of numerical values within ranges rather than averages, as undertaken in this study.

3.3. Pollutant Treatment (Background Concentrations and Decay Rates)

3.3.1. Marie Wallace CW (Industrial Catchment)

The different background concentrations across seasons used for calculating the decay rates of pollutants of the Marie Wallace CW and the calculated decay rates are presented in Figure 4.

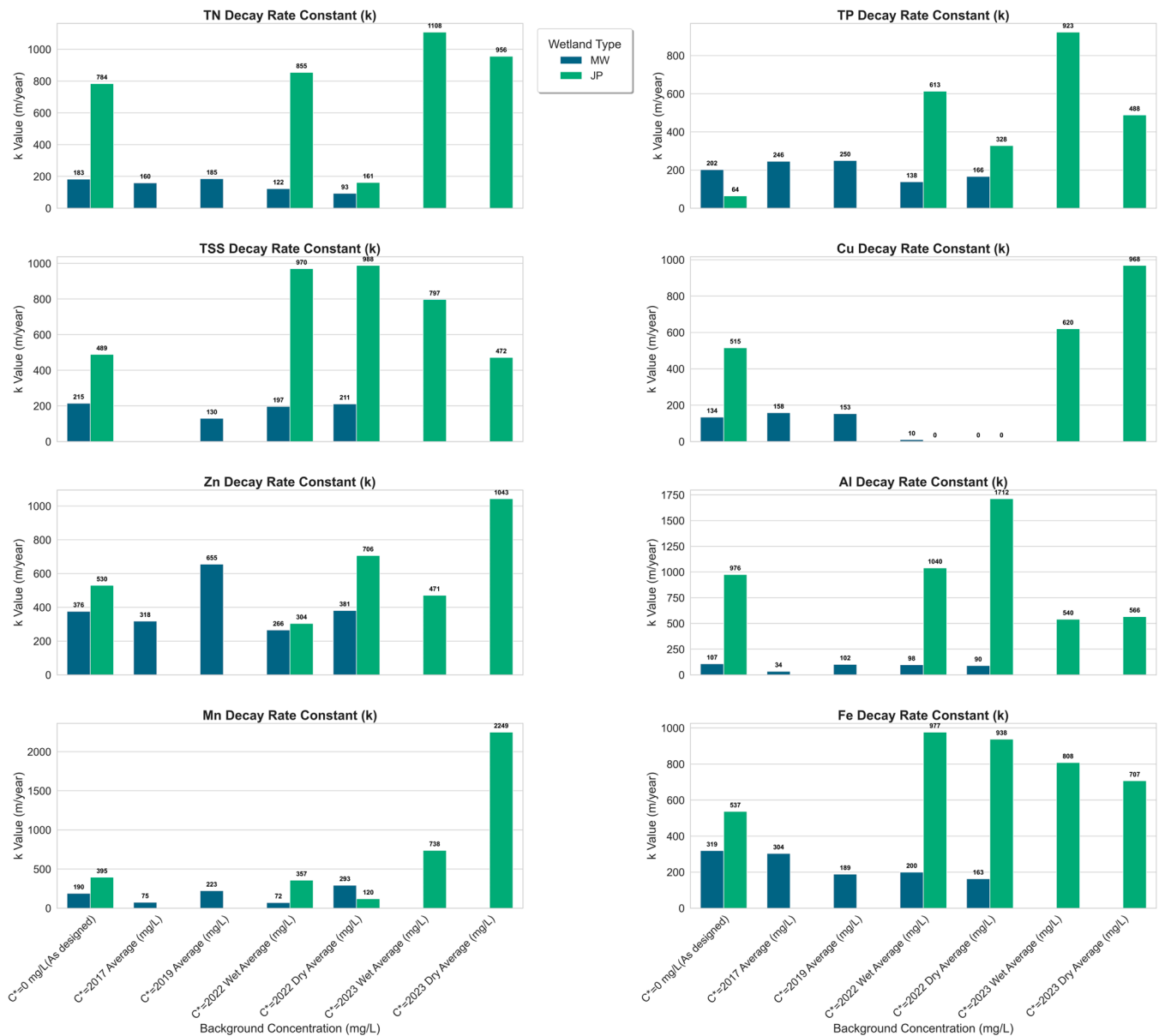


Figure 4. Background concentrations and corresponding decay rates of two investigated CWs.

The overall trend indicates that the background concentrations for the TN, TP, and TSS experienced an increase from 2017 to 2022, with the highest C^* occurring during dry weather in 2022, except for the TN. In 2017, the TN averaged 1.06 mg/L, which is within the MUSIC guideline range. However, in 2022 increased storm events from industrial catchments raised the C^* of the TN up to 6.18 mg/L (Figure 4). TP concentrations rose from 0.06 mg/L in 2017 and 0.07 mg/L in 2019 to 0.41 to 0.42 mg/L in 2022, which is well above MUSIC's lower bound of 0.03 mg/L (Figure 4). The C^* investigated in this research is more similar to Fletcher et al.'s research, where the mean TN concentrations in urban areas and road surfaces are 2.6 mg/L and 2.1 mg/L, and 0.13–0.4 mg/L of the TP, respectively [27]. Additionally, the TSS C^* in 2022 exceeded 10 mg/L, aligning with Kasper and Jenkins' study, which reported 15.3 mg/L background concentrations in a new stormwater wetland [39].

The decay rates for TN in the Marie Wallace CW range from approximately 100 to 200 m/year (Figure 4), which is significantly lower than the typical CW rate of 500 m/year and even below the 1000 m/year observed in sediment basins [24]. Similarly, k values for the TP and TSS are 138.29–249.51 m/year and 129.70–214.76 m/year, respectively, which

are again well below the common values for ponds and wetlands (200–2100 m/year for TP and 300–3200 m/year for TSS). This indicates that the Marie Wallace CW is not effectively reducing the TP and TSS, as detailed in Figure 4. Nevertheless, a suboptimal performance is common among CWs in Australia, with only 20% meeting design expectations, with the remainder of CWs either failing or performing unsatisfactorily [30].

Regarding the heavy metal pollutants, the decay rate of Cu is particularly low, with k values ranging from 0 to 9.98 m/year in 2022 (Figure 4). This aligns with findings from Liu et al., who observed Cu's strong binding affinity in environmental systems, though their study focused on soil retention rather than aqueous decay. The slow attenuation of Cu in aquatic systems raises significant ecological concerns, as prolonged residence times increase the bioavailability and potential accumulation in aquatic food chains [40]. In comparison, a bioretention box with a 3-day detention period and an area of 0.72 m² achieves a Cu decay rate of 43.8 m/year [41]. The dramatic difference suggests that engineered systems may overcome the natural persistence of Cu complexes seen in both aquatic and terrestrial environments [42]. For Zn, while its decay rate is higher than Cu's, its tendency to form soluble complexes still poses measurable risks to aquatic organisms, particularly in systems with a limited dilution capacity [43]. Meanwhile, k values of Al, Mn, and Fe exhibit significant fluctuations, influenced by weather conditions, as the release and sink of trace metals are highly associated with weather conditions and the functionality of the CWs [44].

3.3.2. Jones Park CW

The background concentrations and decay rates in the Jones Park CW for different pollutants are recorded in Figure 3. The Jones Park CW exhibits higher concentrations of nutrients and sediments, with the average C^* for TN, TP, and TSS significantly exceeding the MUSIC guideline values and consistently surpassing those of the Marie Wallace CW, as shown in Figure 3. To illustrate this, the C^* for TSS in Jones Park (12–26.62 mg/L) is generally higher than the values reported in the literature, where Fletcher et al. found a 6 mg/L C^* of TSS [27], Wong et al. identified a 12 mg/L of TSS for the C^* [7], and Kasper and Jenkins reported a slightly higher level of a TSS C^* of 15.3 mg/L [39].

Due to its large catchment size (48.5 hectares), the wetland experiences significant nutrient wash-off. Hathaway and Hunt identified irreducible concentrations of 1.21–1.9 mg/L for the TN and 0.15–0.58 mg/L for the TP, indicating that stormwater infrastructure cannot reduce pollutant concentrations below these levels, which can be used as a reference for background concentrations [45]. This study found an average C^* exceeding 6 mg/L for TN and around 0.7 mg/L for the TP (Figure 4), these discrepancies may stem from pollutant accumulation in the sediment pond. Consequently, the high C^* indicates that the stormwater runoff from the Jones Park CW is likely to contribute to elevated pollutant levels at the outlet, rather than achieving significant reductions.

The decay rates for the TN in the Jones Park CW ranged from 161.40 m/year to 1108.06 m/year in different weather conditions (Figure 4). TSS decay rates on the other hand ranged from 488.75 m/year to 988.47 m/year, aligning with MUSIC recommendations. For the TP, decay rates in 2022 and 2023 remained at the lower end of MUSIC's recommended values (500–2800 m/year), attributed to a background TP concentration of 0.25 mg/L that limits the removal capacity during storm events, and stormwater events will result in greater exportation rather than the treatment of the TP [46].

In 2023, an increase in TSS concentrations at the outlet during storm events led to diminished decay rates. Similar findings were reported by Greenway, where TSS exportation is not uncommon, and factors such as sediment resuspension, wildlife disturbances, and temperature variations likely influenced these results [47]. In this study, the mean temperatures are 18.20 °C in 2022 and 14.27 °C in 2023, which impacted the TSS removal,

and the results align with Nayeb Yazdi et al.'s study, which reported a greater removal of the TSS in warm weather ($\geq 15^\circ\text{C}$) than in colder weather ($\leq 15^\circ\text{C}$) [48].

Regarding metallic pollutants, the overall decay rates were lower than those reported in the literature due to the catchment size and wetland characteristics. Chen et al. noted a k value of 1070.47 m/year for Zn in smaller, gravel-based CWs [49], while Walker and Hurl found a k value of 1930 m/year for Cu in larger wetlands [50]. Despite a similar mean reduction rate for Cu (50%), the Jones Park CW's lower decay rate (513.43 m/year to 968.39 m/year) is likely due to its smaller catchment size. Nevertheless, Cu concentrations averaging near 0 mg/L in 2022 showed no reduction, aligning with Knox et al.'s results when less than 0.01 mg/L of Cu is commonly reported for a matured CW that has been in operation for 20 years [51]. Increased Cu decay rates in 2023 correlated with greater rainfall, which is consistent with findings from Walaszek et al.'s research, which indicated enhanced metals levels introduced to the wetland from the stormwater runoffs, hence increasing the potential of the improved decay of Cu [52].

3.4. MUSICX Calibration Using Updated K and C^*

Following the analysis of the default pollutant generation values and the C^* and k values, this section focuses on aligning the modeled and observed pollutant reduction rates, evaluating the potential of MUSICX as a post-construction tool for predicting treatment performance. Adjustments to C^* and k values were made by incorporating pollutant concentration data from both the stormflow and baseflow (Table 5 and Figure 4). Iterations were conducted to assess the treatment effectiveness across various pollutant generation and treatment scenarios.

The analysis, performed at a significance level of 0.05, revealed no statistically significant differences. Therefore, it is recommended to adopt the k values presented in Table 6, which can be applied within the MUSIC model based on the catchment type.

Table 6. Recommended k and C^* values.

Pollutant	Marie Wallace CW (Industrial)			Jones Park CW (Residential)		
	k (m/Year)	C^* (mg/L)	t -Test	k (m/Year)	C^* (mg/L)	t -Test
TN	100–250	0.6–6	0.24	100–1000	2–10	0.25
TP	100–250	0.06–0.5	0.84	300–900	0.4–1	0.39
TSS	100–200	5–20	0.23	500–1000	10–30	0.46
Cu	10–150	0–0.03	0.35	500–1000	0–0.04	0.34
Zn	300–700	0–0.04	0.54	300–1000	0.05–0.3	0.44
Al	50–100	0–0.5	0.17	500–2000	0–0.02	0.25
Mn	70–300	0.1–0.7	0.09	100–2000	0.05–0.1	0.47
Fe	10–300	0.8–2	0.06	500–1000	0.1–1.1	0.37

A closer examination shows that the decay rates in CWs in residential areas are generally higher than those in industrial areas—except for Zn, which shows similar rates in both settings (Table 6). These variations are likely attributed to factors such as land use types, catchment and wetland sizes, the wetland age, or the extent of impervious surfaces. Thus, a cross-correlation analysis was performed. Notably, significant negative correlations are found between land use types and percentages of imperviousness, indicating that CWs in industrialized areas with higher impervious coverages exhibit lower decay rates for pollutants, including TN, TP, Cu, Zn, Mn, and Fe. The results also suggest that as CWs age, their decay rates tend to decrease. Similarly to this study, Sharley et al. found a direct link between the land use and metal concentrations in urban areas, indicating that CWs

in industrial areas are more susceptible to metal pollution and require modifications to existing WSUD measures. Thus, incorporating the land use type is essential [22].

The MUSIC model currently considers only three land use types—agricultural, forest, and urban—without differentiating between industrial and residential catchments [24]. While the k value reflects the removal processes (chemical, physical, and biological) within the wetland, these processes depend on pollutant characteristics, which are influenced by land use. Therefore, the Least Absolute Shrinkage and Selection Operator (Lasso) Regression is performed to address the current focus of CW design on residential catchments. This technique effectively eliminates the number of inputs when multicollinearity is presented. It also allows for adjustments to decay rates in both residential and industrial contexts, while the current model's moderate explanatory power ($R^2 = 0.52$) reflects that other factors, such as the wetland size and catchment imperviousness, may contribute but introduce multicollinearity, and the use of land use as the sole variable provides a foundational approach for improving decay rate estimations. This allows for the adjustment of different decay rates in CWs across various catchments. Thus, it is emphasized that further research, including the integration of additional variables or alternative modeling techniques, is needed to enhance the model's robustness and applicability.

Equation (7) below presents the prediction equation for the decay rate k . The calculation of the decay rate is based on various land use types, with “1” representing industrial and “0” representing residential areas.

$$k = 725.30 - 529.22 \times \text{land use} \quad (7)$$

The goodness of fit returns an R^2 of 0.52. Furthermore, the cross-validated scores for both the training and testing were 0.39 and 0.52, respectively. These scores suggest that the model exhibits an improved performance when new data is introduced and is less susceptible to noise present in the training data. While the current model's moderate explanatory power ($R^2 = 0.52$) reflects the limitations of using land use as the sole predictor, as other factors such as wetland size and catchment imperviousness may contribute but introduce multicollinearity, it nevertheless provides a foundational approach for improving decay rate estimations by allowing for the adjustment of different decay rates in CWs across various catchments. However, it is emphasized that further research, including the integration of additional variables or alternative modeling techniques, is needed to enhance the model's robustness and applicability.

4. Conclusions and Recommendations

This paper presents a refinement of the MUSIC model for predicting the pollutant reduction rates in CWs. The analysis revealed significant discrepancies between model-predicted and observed pollutant reduction rates, with MUSIC tending to overpredict pollutant reductions. It was found that pollutant removal rates vary across the seasons and land use types of the catchments. However, the reduction in the TSS and metals in both catchments in all seasons remained negative or low, highlighting the limitations of MUSIC's predictions.

The proposed decay rates for the TN, TP, and TSS ranged from 100 to 250 m/year for industrial catchments and from 100 to 1000 m/year, while decay rates for metals varied from 10 to 700 m/year depending on the catchment type. These findings underscore the necessity for tailored guidelines and analyses for effective water management, illustrating that improving the accuracy of MUSIC not only enhances its predictive capabilities but also extends the lifecycle of CWs, thus achieving resource optimization.

These findings directly translate to three design imperatives for industrial wetlands: (1) a prioritized pre-treatment for metals/TSS to mitigate clogging risks, (2) land use-specific sizing

using validated decay rate thresholds (100–1000 m/year for nutrients; 10–700 m/year for metals), and (3) real-time monitoring to dynamically calibrate MUSIC with observed seasonal performances. For optimal resource allocation, it is recommended to adopt conservative decay rates (100 m/year nutrients; 10 m/year metals) and implement dynamic modeling that accounts for the demonstrated variability. Such targeted refinements will enhance MUSIC's accuracy while extending CW lifespans through science-based design optimization.

Future research should also expand validation efforts by applying this methodology to constructed wetlands across diverse climatic regions and catchment types. As more case studies become available, comparative analyses could establish regional adjustment factors for MUSIC's default parameters, particularly for heavy metals and emerging contaminants. Collaborative monitoring programs between researchers and water authorities would be particularly valuable for generating the standardized, long-term performance data needed to further refine the model accuracy while maintaining its practical utility for stormwater designers.

Author Contributions: Conceptualization, F.Y., S.G.-T., and I.H.; methodology, F.Y.; software, I.H.; validation, F.Y., S.G.-T., and I.H.; formal analysis, F.Y.; investigation, F.Y.; resources, S.G.-T. and I.H.; data curation, F.Y.; writing—original draft preparation, F.Y.; writing—review and editing, F.Y., S.G.-T. and I.H.; visualization, F.Y.; supervision, S.G.-T. and I.H.; project administration, S.G.-T. and I.H.; funding acquisition, S.G.-T. and I.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The research presented in this paper was conducted at Swinburne University of Technology, whose support and resources were instrumental to its completion. The authors wish to express their gratitude to Hume City Council, Knox City Council, Monash City Council, and Melbourne Water, who have generously contributed knowledge to this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MUSIC	Model for Urban Stormwater Improvement Conceptualization
CW	Constructed Wetland
WSUD	Water-Sensitive Urban Design
GI	Green Infrastructure
LID	Low-Impact Development
CSTR	Continuously Stirred Tank Reactor
TN	Total Nitrogen
TP	Total Phosphorous
TSS	Total Suspended Solids
EMC	Event Mean Concentration
FWS	Free Water Surface
BPM	Best Practice Management

References

1. Feng, W.; Liu, Y.; Gao, L. Stormwater treatment for reuse: Current practice and future development—A review. *J. Environ. Manag.* **2022**, *301*, 113830. [[CrossRef](#)]
2. Wang, Y.; van Roon, M.; Knight-Lenihan, S. Opportunities and challenges in water sensitive industrial development: An Auckland case study, New Zealand. *Int. J. Sustain. Dev. World Ecol.* **2021**, *28*, 143–156. [[CrossRef](#)]

3. Chhetri, S.; Ruangpan, L.; Abebe, Y.A.; Torres, A.S.; Vojinovic, Z. Review of environmental benefits and development of methodology for EUNIS habitat changes from nature-based solutions: Application to Denmark and the Netherlands. *Ecol. Indic.* **2024**, *165*, 112189. [CrossRef]
4. Fowdar, H.S.; Neo, T.H.; Ong, S.L.; Hu, J.; McCarthy, D.T. Performance analysis of a stormwater green infrastructure model for flow and water quality predictions. *J. Environ. Manag.* **2022**, *316*, 115259. [CrossRef] [PubMed]
5. Liu, Q.; Cui, W.; Tian, Z.; Tang, Y.; Tillotson, M.; Liu, J. Stormwater Management Modeling in “Sponge City” Construction: Current State and Future Directions. *Front. Environ. Sci.* **2022**, *9*, 816093. [CrossRef]
6. Lisenbee, W.A.; Hathaway, J.M.; Burns, M.J.; Fletcher, T.D. Modeling bioretention stormwater systems: Current models and future research needs. *Environ. Model. Softw.* **2021**, *144*, 105146. [CrossRef]
7. Wong, T.H.F.; Fletcher, T.D.; Duncan, H.P.; Jenkins, G.A. Modelling urban stormwater treatment—A unified approach. *Ecol. Eng.* **2006**, *27*, 58–70. [CrossRef]
8. Poozan, A.; Fletcher, T.D.; Arora, M.; William, W.A.; James, B.M. The influence of spatial arrangement and site conditions on the fate of infiltrated stormwater. *J. Hydrol.* **2024**, *630*, 130738. [CrossRef]
9. Imteaz, M.A.; Ahsan, A.; Rahman, A.; Mekanik, F. Modelling stormwater treatment systems using MUSIC: Accuracy. *Resour. Conserv. Recycl.* **2013**, *71*, 15–21. [CrossRef]
10. Tan, K.M.; Seow, W.K.; Wang, C.L.; Kew, H.J.; Parasuraman, S.B. Evaluation of performance of Active, Beautiful and Clean (ABC) on stormwater runoff management using MIKE URBAN: A case study in a residential estate in Singapore. *Urban Water J.* **2019**, *16*, 156–162. [CrossRef]
11. Zhang, K.; Manuelpillai, D.; Raut, B.; Deletic, A.; Bach, P.M. Evaluating the reliability of stormwater treatment systems under various future climate conditions. *J. Hydrol.* **2019**, *568*, 57–66. [CrossRef]
12. Idros, N.; Sidek, L.M.; Rahim, N.A.A.M.; Noh, N.M.; Abdelkader, A.M.; Mohiyaden, H.A.; Basri, H.; Zawawi, M.H.B.; Ahmed, A.N. Stormwater characterisation and modelling for Sungai Air Hitam in Selangor, Malaysia using model for urban stormwater improvement conceptualisation (music). *Ecol. Indic.* **2024**, *160*, 111850. [CrossRef]
13. Woon, K.L.; Goh, H.W.; Chang, C.K.; Juiani, S.F.; Zakaria, N.A. Bioretention Model for Urban Runoff Treatment in a Tropical Climate: A Case Study at the Universiti Sains Malaysia. *J. Water Manag. Model.* **2023**, *31*, C498. [CrossRef]
14. Raeesi, R.; Xue, Y.; Disfani, M.M.; Arora, M. Hydrological and water quality performance of Waste Tire Permeable Pavements: Field monitoring and numerical analysis. *J. Environ. Manag.* **2022**, *323*, 116199. [CrossRef]
15. Zhou, L.; Wu, F.; Meng, Y.; Byrne, P.; Ghomshei, M.; Abbaspour, K.C. Modeling transport and fate of heavy metals at the watershed scale: State-of-the-art and future directions. *Sci. Total Environ.* **2023**, *878*, 163087. [CrossRef]
16. Godyń, I.; Grela, A.; Muszyński, K.; Pamuła, J. The Impact of Green Infrastructure on the Quality of Stormwater and Environmental Risk. *Sustainability* **2024**, *16*, 8530. [CrossRef]
17. Gong, Y.; Li, X.; Xie, P.; Fu, H.; Nie, L.; Li, J.; Li, Y. The migration and accumulation of typical pollutants in the growing media layer of bioretention facilities. *Environ. Sci. Pollut. Res. Int.* **2023**, *30*, 44591–44606. [CrossRef]
18. Dotto, C.B.S.; Deletic, A.; McCarthy, D.T.; Fletcher, T.D. Calibration and Sensitivity Analysis of Urban Drainage Models: Music Rainfall/Runoff Module and a Simple Stormwater Quality Model. *Aust. J. Water Resour.* **2011**, *15*, 85–94. [CrossRef]
19. van der Sterren, M.; Hey-Cunningham, K.; Brennan, K. Modelling a residential catchment, an industrial catchment and a catchment under construction to evaluate the quality and quantity of stormwater discharges into a coastal salt water Lake. In Proceedings of the 34th Hydrology and Water Resources Symposium, HWRS, Sydney, NSW, Australia, 19–22 November 2012; pp. 536–544. Available online: <https://www.mendeley.com/catalogue/4ccf491c-7cff-31ab-8ab3-9bf98b51067b/> (accessed on 23 September 2024).
20. Wu, H.; Wang, R.; Yan, P.; Wu, S.; Chen, Z.; Zhao, Y.; Cheng, C.; Hu, Z.; Zhuang, L.; Guo, Z.; et al. Constructed wetlands for pollution control. *Nat. Rev. Earth Environ.* **2023**, *4*, 218–234. [CrossRef]
21. Okada, E.; Allinson, M.; Barral, M.P.; Clarke, B.; Allinson, G. Glyphosate and aminomethylphosphonic acid (AMPA) are commonly found in urban streams and wetlands of Melbourne, Australia. *Water Res.* **2020**, *168*, 115139. [CrossRef]
22. Sharley, D.J.; Sharp, S.M.; Marshall, S.; Jeppe, K.; Pettigrove, V.J. Linking urban land use to pollutants in constructed wetlands: Implications for stormwater and urban planning. *Landsc. Urban Plan.* **2017**, *162*, 80–91. [CrossRef]
23. Tuomela, C.; Sillanpää, N.; Koivusalo, H. Assessment of stormwater pollutant loads and source area contributions with storm water management model (SWMM). *J. Environ. Manag.* **2019**, *233*, 719–727. [CrossRef]
24. eWater 2023, Treatment Devices—MUSICX 1.0—Confluence. Available online: <https://ewater.atlassian.net/wiki/spaces/MX1/pages/56328461/Treatment+Devices> (accessed on 15 August 2025).
25. Chiew, F.H.S.; McMahon, T.A. Modelling runoff and diffuse pollution loads in urban areas. *Water Sci. Technol.* **1999**, *39*, 241–248. [CrossRef]
26. Duncan, H. Urban Stormwater Quality: A Statistical Overview. Cooperative Research Center for Catchment Hydrology. 1999, p. 134. Available online: <https://ewater.org.au/archive/crcch/archive/pubs/pdfs/technical199903.pdf> (accessed on 12 December 2023).

27. Fletcher, T.; Duncan, H.; Poelsma, P.; Lloyd, S. Stormwater Flow and Quality and the Effectiveness of Non-Proprietary Stormwater Treatment Measures: A Review and Gap Analysis. Cooperative Research Center for Catchment Hydrology. 2005. Available online: https://xueshu.baidu.com/usercenter/paper/show?paperid=1v0q0ad0w6330pg0ev6a0v50xx784470&site=xueshu_se&hitarticle=1 (accessed on 15 August 2025).
28. Persson, J.; Somes, N.L.G.; Wong, T.H.F. Hydraulics efficiency of constructed wetlands and ponds. *Water Sci. Technol.* **1999**, *40*, 291–300. [[CrossRef](#)]
29. Hart, B.T.; Francey, M.; Chesterfield, C.; Blackham, D.; McCarthy, N. Management of urban waterways in Melbourne, Australia: 2—Integration and future directions. *Australas. J. Water Resour.* **2022**, *28*, 101–122. [[CrossRef](#)]
30. Victorian Stormwater Committee, EPA 1999, Urban Stormwater Best Practice Environmental Management Guidelines. Available online: <https://trid.trb.org/view.aspx?id=1159605> (accessed on 15 August 2025).
31. da Costa, J.F.; de Paoli, A.C.; Seidl, M.; von Sperling, M. Performance and behaviour of planted and unplanted units of a horizontal subsurface flow constructed wetland system treating municipal effluent from a UASB reactor. *Water Sci. Technol.* **2013**, *68*, 1495–1502. [[CrossRef](#)]
32. Mitsch, W.J.; Zhang, L.; Griffiths, L.N.; Bays, J. Contrasting two urban wetland parks created for improving habitat and downstream water quality. *Ecol. Eng.* **2023**, *192*, 106976. [[CrossRef](#)]
33. Jiang, L.; Chui, T.F.M. Performance and sustainability of a multi-stage free water surface constructed wetland under seasonal change and shock loading. *Ecol. Eng.* **2023**, *186*, 106834. [[CrossRef](#)]
34. Zhou, Q.; He, L.; Yuan, D.; Meng, R.; Zhao, H.; Zhao, H.; Zhang, Y.; Du, S. Pollutant-removal and DOM characteristics in an urban stormwater wetland. *Environ. Technol.* **2023**, *44*, 45–56. [[CrossRef](#)]
35. Vymazal, J.; Krása, P. Distribution of Mn, Al, Cu and Zn in a constructed wetland receiving municipal sewage. *Water Sci. Technol.* **2003**, *48*, 299–305. [[CrossRef](#)]
36. Wang, H.; Sheng, L.; Xu, J. Clogging mechanisms of constructed wetlands: A critical review. *J. Clean. Prod.* **2021**, *295*, 126455. [[CrossRef](#)]
37. Ergaieg, K.; Msaddek, M.H.; Kallel, A.; Trabelsi, I. Monitoring of horizontal subsurface flow constructed wetlands for tertiary treatment of municipal wastewater. *Arab. J. Geosci.* **2021**, *14*, 2045. [[CrossRef](#)]
38. Yang, M.; Lu, M.; Bian, H.; Sheng, L.; He, C. Effects of clogging on hydraulic behavior in a vertical-flow constructed wetland system: A modelling approach. *Ecol. Eng.* **2017**, *109*, 41–47. [[CrossRef](#)]
39. Kasper, T.M.; Jenkins, G.A. Measuring the background concentration in a constructed stormwater treatment wetland. *Urban Water J.* **2007**, *4*, 79–91. [[CrossRef](#)]
40. Liu, X.; Peng, C.; Zhou, Z.; Jiang, Z.; Guo, Z.; Xiao, X. Impacts of land use/cover and slope on the spatial distribution and ecological risk of trace metals in soils affected by smelting emissions. *Environ. Monit. Assess.* **2024**, *196*, 53. [[CrossRef](#)]
41. Kumar, S.; Nand, S.; Pratap, B.; Dubey, D.; Dutta, V. Removal kinetics and treatment efficiency of heavy metals and other wastewater contaminants in a constructed wetland microcosm: Does mixed macrophytic combinations perform better? *J. Clean. Prod.* **2021**, *327*, 129468. [[CrossRef](#)]
42. Ayyanar, A.; Thatikonda, S. Enhanced Electrokinetic Removal of Heavy Metals from a Contaminated Lake Sediment for Ecological Risk Reduction. *Soil Sediment Contam.* **2021**, *30*, 12–34. [[CrossRef](#)]
43. Elahi, M.; Rezaitabar, S.; Savabieasfahani, M. Ecological risk assessment of Toxic heavy Metal(loid)s in surface sediment of Zarivar International Wetland: An indices analysis approach. *Soil Sediment Contam.* **2022**, *31*, 405–422. [[CrossRef](#)]
44. Qin, C.; Xu, X.; Peck, E. Sink or source? Insights into the behavior of copper and zinc in the sediment porewater of a constructed wetland by peepers. *Sci. Total Environ.* **2022**, *821*, 153127. [[CrossRef](#)]
45. Hathaway, J.M.; Hunt, W.F. Evaluation of Storm-Water Wetlands in Series in Piedmont North Carolina. *J. Environ. Eng.* **2010**, *136*, 140–146. [[CrossRef](#)]
46. Sullivan, C.; McDonald, W. Hydrologic and water quality performance of a subsurface gravel wetland treating stormwater runoff. *J. Environ. Manag.* **2022**, *322*, 116120. [[CrossRef](#)]
47. Greenway, M. Stormwater wetlands for the enhancement of environmental ecosystem services: Case studies for two retrofit wetlands in Brisbane, Australia. *J. Clean. Prod.* **2017**, *163*, S91–S100. [[CrossRef](#)]
48. Nayeib Yazdi, M.; Scott, D.; Sample, D.J.; Wang, X. Efficacy of a retention pond in treating stormwater nutrients and sediment. *J. Clean. Prod.* **2021**, *290*, 125787. [[CrossRef](#)]
49. Chen, M.; Tang, Y.; Li, X.; Yu, Z. Study on the Heavy Metals Removal Efficiencies of Constructed Wetlands with Different Substrates. *J. Water Resour. Prot.* **2009**, *1*, 7. [[CrossRef](#)]
50. Walker, D.J.; Hurl, S. The reduction of heavy metals in a stormwater wetland. *Ecol. Eng.* **2002**, *18*, 407–414. [[CrossRef](#)]

51. Knox, A.S.; Paller, M.H.; Seaman, J.C.; Mayer, J.; Nicholson, C. Removal, distribution and retention of metals in a constructed wetland over 20 years. *Sci. Total Environ.* **2021**, 796, 149062. [[CrossRef](#)] [[PubMed](#)]
52. Walaszek, M.; Bois, P.; Laurent, J.; Lenormand, E.; Wanko, A. Urban stormwater treatment by a constructed wetland: Seasonality impacts on hydraulic efficiency, physico-chemical behavior and heavy metal occurrence. *Sci. Total Environ.* **2018**, 637–638, 443–454. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.