Longitudinal Water Pollution Monitoring and Retention Pond Capacity Assessment Using Smart Devices

Zhongzhe Shen[1], Mintai Kim[2]

[1]Virginia Tech, Virginia/USA · zhongzhes@vt.edu
[2]Virginia Tech, Virginia/USA · mintkim@vt.edu

Abstract: This study experiment uses low-cost smart devices to longitudinally monitor the level of common water pollutants, such as electrical conductivity (EC) and total dissolved solids (TDS), in a retention pond, and assess and quantify a retention pond's capacity for pollution reduction. Landscape performance (LAP) is an important and emerging topic that quantifies the impacts of design practices and helps to improve future designs. Although previous research has suggested that retention ponds can aid in cleaning surface runoff before water is discharged into downstream systems, most of this research has been theoretical, with few studies measuring the water cleaning capacity of retention ponds. In this study, the research team installs several smart devices with various sensors at each inlet and outlet of the retention pond water system. Environmental data is collected continuously and can be accessed by researchers at any time through an SD storage card. This research presents an alternative way for professionals to evaluate water quality and provides a method for quantifying a retention pond's pollution-reduction ability. The results of this study can potentially improve the existing environmental performance monitoring system, provide evidence-based data to guide future retention pond projects, and serve as a reference for landscape teaching to enhance the competence of future environmental professionals.

Keywords: Smart devices, water quality, retention ponds, landscape performance, longitudinal tracking

1 Introduction

1.1 Water Quality and Retention Ponds

In urban settings, water quality is influenced by various factors, including precipitation, climate, soil type, vegetation, geology, flow conditions, groundwater, and human activities. Activities such as mining, urban development, and agriculture can affect water quality. Nonpoint source pollution includes nutrients, sediments, and toxic pollutants (CHAUDHRY & MALIK 2017). Runoff is a major source of water pollution. As water moves along a surface, it absorbs trash, oil, chemicals, fertilizers, and other toxic substances. Sustainable stormwater management, such as the retention pond, aims to preserve and restore functional hydrology by using methods modeled after natural processes (LAF 2022). Sustainable stormwater management techniques lessen thermal pollution, minimize erosion, reduce floods, and reduce stormwater runoff. They can also enhance ecological and aesthetic value and help recharge the groundwater (LAF 2022).

Research on retention ponds and water pollution has shown that retention ponds can assist in cleaning and pure surface runoff before discharging polluted water into the downstream water systems. Retention ponds capture some microplastics in surface runoff and prevent them from being transported downstream (LIU et al. 2019). Retention ponds can provide a way to effectively and economically manage the quantity and quality of urban stormwater (WANG & SAMPLE 2014). However, most relevant studies do not quantify the capacity of retention

Journal of Digital Landscape Architecture, 8-2023, pp. 57-64. © Wichmann Verlag, VDE VERLAG GMBH · Berlin · Offenbach. ISBN 978-3-87907-740-3, ISSN 2367-4253, e-ISSN 2511-624X, doi:10.14627/537740007.

ponds to treat water pollution. Some studies have involved quantitative studies, but their data are usually derived from one or several data collections. Water quality change is a dynamic process influenced by other environmental factors such as temperature, humidity, weather conditions, and air quality. The fact that practically all measures are one-time snapshots is a limitation of the study methodologies (LUO et al. 2015).

1.2 Longitudinal Tracking

In a longitudinal study, researchers study the same subject repeatedly to detect any changes that may occur over a period of time. This longitudinal study greatly extended the time frame for data collection. Short-term studies do not reveal long-term ties, whereas long-term studies can follow short-term relationships. (GAILLE 2017). Although it is most commonly used in medicine, economics, and epidemiology, longitudinal studies can also be found and play an important role in studies related to design. Especially in the field of LAP, longitudinal studies are particularly indispensable. Research teams on LAP often work separately, and the quantitative methods used and documented landscape benefits differ from each other. All research methods share a common disadvantage: they are one-time observations (LUO & LI 2014). One-time observations can convey a cross-section of the benefits created by sustainable landscapes, and they are also useful for comparative studies of sustainable and traditional development. But if the goal is to accurately quantify LAP, the reliability and validity of many of these methods are open to question (LUO & LI 2014).

1.3 Smart Devices and Environmental Data Collection

Employing low-cost smart devices may be an alternative way to deal with this issue. With recent advances in technology, miniaturization of electronic equipment, and computing power, environmental sensors are becoming more innovative, reliable, compact, and cheap (GRIMMOND 2006, RUNDEL et al. 2009). More cheaply-made sensors are now able to be more numerous and densely spaced, with vastly improved temporal collection and rapid data transmission (MULLER et al. 2013).

In some studies, smart devices have longitudinally collected environmental data in many design-related fields. In the field of smart buildings, studies focus on building occupants' thermal comfort and air quality, using feedback obtained from occupants through sensor networks (CORGNATI et al. 2008, CHOI & ZHU 2019). The optimum range is achieved by combining many sensors, including ambient temperature sensors, CO2 sensors, humidity sensors, volatile organic compounds, and particulate matter. The indoor air quality of buildings was examined (CHOI & MOON 2017, JIN et al. 2018). Smart sensors are also rooted in the urban study field. In 2013, Zeile, P., Resch, B., Loidl, M., Petutschnig, A., & Dörrzapf, L used sensors to identify places in the urban environment that were considered unsafe by cyclists. Specifically, physiological parameters such as ECG, skin conductivity, skin temperature, and heart rate variability are analyzed to determine the moment of stress (ZEILE et al. 2013). The results of the study show that the sensors can identify where there are emotional peaks, particularly fear and anger. This study provides urban planners with data to support, thereby reassessing and planning for those unsafe places in cities (ZEILE et al. 2013).

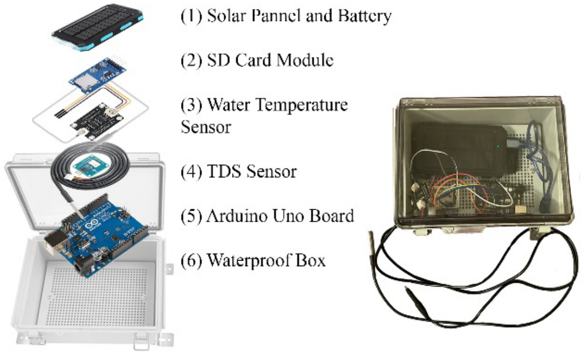


Fig. 1:
(Left) Exploded view of the low-cost smart device. (Right) A photo of the completed sensor nodes. These figures illustrate the development of the experimental water quality sensor nodes.

2 Research Hypothesis

This paper presents two particular study hypotheses that correlate to the aims, drawing inspiration from prior empirical research and Arduino-based sensors' capabilities:

i. Compared to traditional snapshot data collection methods, smart devices provide a more efficient and reliable way to monitor and collect water quality data longitudinally.
ii. Smart devices help professionals better analyze and evaluate retention ponds' capabilities by offering more precise, frequent, and high spatial resolution data.

3 Method

3.1 Overview

This study developed a low-cost water quality detection sensor node for collecting water quality data (i. e., water temperature, EC, and TDS). Several sensors and other supporting components constitute a low-cost smart water quality detection device for less than $100. Figure 1. shows the development of the experimental water quality sensor nodes. By minimizing the programming, installation, and cost, this smart device has the potential for further educational outreach and data collection in LAP and landscape architecture. The research process used in this study includes the following parts:

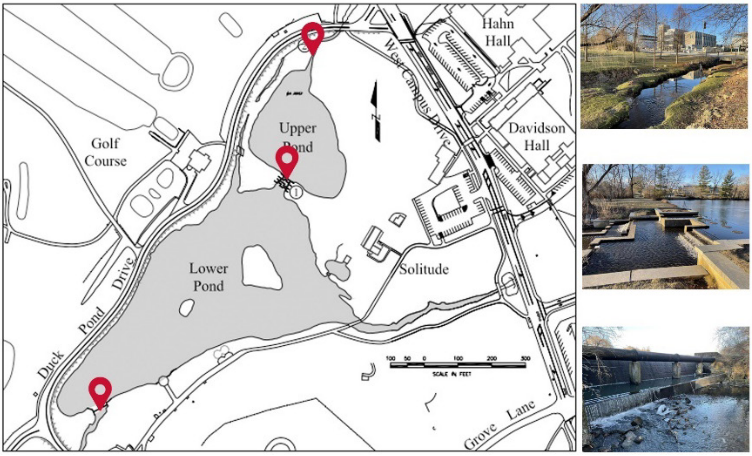
1) Selection of sensors according to the variables to be studied
2) Sensor nodes assembled to meet outdoor sensor requirements: achieving a certain degree of waterproofing, low power consumption and long battery life, effective data collection, and no environmental impact
3) Site installation of sensors and data collection for one week
4) Data analysis, results, and discussion

The method uses a longitudinal approach to provide a high level of validity. Additionally, the use of sensor-assisted longitudinal tracking provides high-precision data for research teams.

All collected data is analyzed using descriptive statistics, F-tests, and P-tests. Statistic analyses allow the research team to determine and quantify the difference among data gathered from sensor nodes and understand its statistical meaning.

3.2 Experimental Site

The research team chose the duck pond on Virginia Tech's campus, with two retention ponds as the experimental site to test their ability to reduce surface runoff pollutants. The research team installed three sensor nodes at the retention pond's inlets and outlets. Figure 2 shows the experimental site and the location of three sensor nodes.



(1) Sensor Node 1, Inlet of the first retention pond

(2) Sensor Node 2, Outlet of the first retention pond, as well as the inlet of the second pond

(3) Sensor Node 3, Outlet of the second retention pond

Fig. 2: This figure illustrates the experimental site, which includes two retention ponds, and presents the location of three sensor nodes

The upper pond area is about 5,684.52 m² (61,187.72 ft²) with approximately 2.2 m (7.2') average depth. The lower pond size is about 20,676.59 m² (222,561.01 ft²), and the average depth is about 3.8m (12.5').

3.3 Site Installation and Data Collection

At the test site, sensors have been placed at three locations – the inlets and outlets of the retention ponds. To ensure accurate readings, the sensors are installed close to the shore of the water body, while water quality probes are suspended in the water using wires. The installation ensures that there are no obstacles in the water that would affect the sensor readings, as well as no obstacles that would block the solar panels. The solar-powered sensor nodes operate continuously, 24/7, and collect longitudinal data on pollutant concentrations throughout the test period.

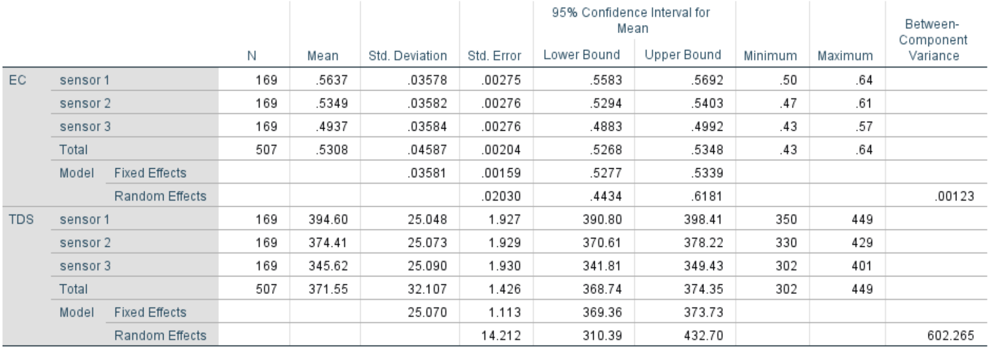
The sensors automatically collect data every hour, which is stored in TXT format on an onboard SD card. The data is later converted to CSV format for statistical analysis using SPSS. The researchers manually collect the data from the SD card every 48 hours to retrieve it.

4 Result

Statistical analysis of the collected data shows that there is a significant difference in the EC and TDS values among the three sensor modules. Table 1 presents the water quality data collected from the sensor modules between December 12 at 12:00 AM and December 18 at 11:00 PM, with a one-hour data collection interval. The data indicates that sensor 2 recorded TDS readings that were approximately 20 ppm lower than sensor 1, and sensor 3 readings were about 30 ppm lower than sensor 2.

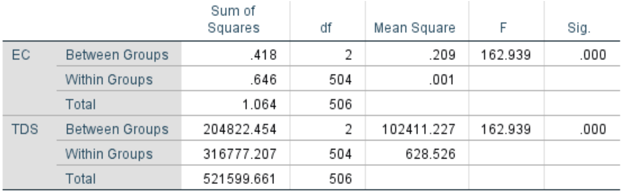
Table 2 presents the results of the ANOVA test, which show a statistically significant difference between the observed group data. The F value and sig. (P value) indicate that the null hypothesis (H0) should be rejected.

Table 1: Extracted data from water quality sensor modules on the experimental site



							95% Confidence Interval for Mean				
			N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum	Between-Component Variance
EC	sensor 1		169	.5637	.03578	.00275	.5583	.5692	.50	.64	
	sensor 2		169	.5349	.03582	.00276	.5294	.5403	.47	.61	
	sensor 3		169	.4937	.03584	.00276	.4883	.4992	.43	.57	
	Total		507	.5308	.04587	.00204	.5268	.5348	.43	.64	
	Model	Fixed Effects			.03581	.00159	.5277	.5339			
		Random Effects				.02030	.4434	.6181			.00123
TDS	sensor 1		169	394.60	25.048	1.927	390.80	398.41	350	449	
	sensor 2		169	374.41	25.073	1.929	370.61	378.22	330	429	
	sensor 3		169	345.62	25.090	1.930	341.81	349.43	302	401	
	Total		507	371.55	32.107	1.426	368.74	374.35	302	449	
	Model	Fixed Effects			25.070	1.113	369.36	373.73			
		Random Effects				14.212	310.39	432.70			602.265

Table 2: Result from the ANOVA test



		Sum of Squares	df	Mean Square	F	Sig.
EC	Between Groups	.418	2	.209	162.939	.000
	Within Groups	.646	504	.001		
	Total	1.064	506			
TDS	Between Groups	204822.454	2	102411.227	162.939	.000
	Within Groups	316777.207	504	628.526		
	Total	521599.661	506			

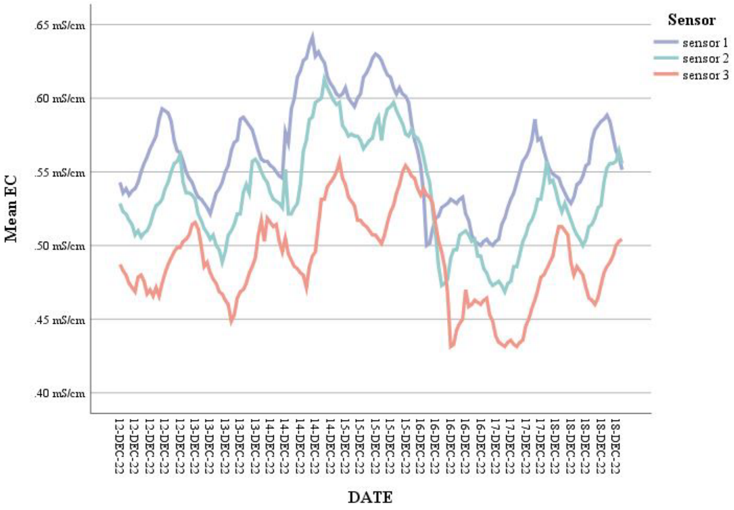


Fig. 3: EC concentration modification during the experimental period

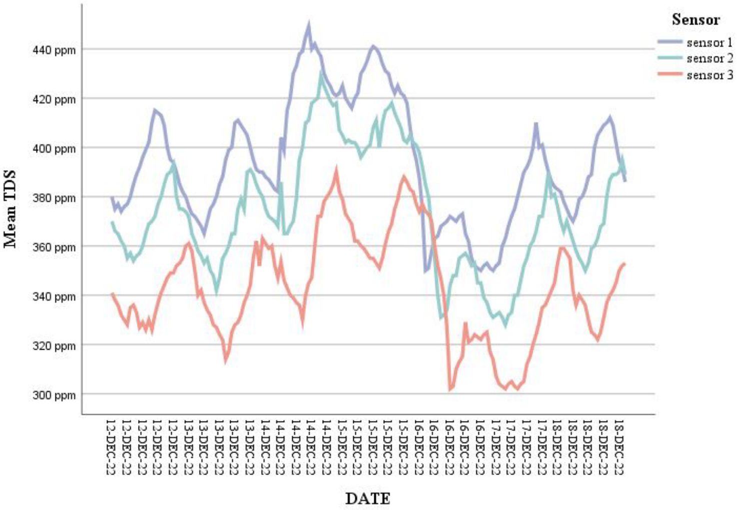


Fig. 4: TDS concentration modification during the experimental period

Figures 3 and 4 depict the variations in EC and TDS concentrations at the test site over time during the experimental period. The data collected by sensor 1 at the upper pond inlet indicates that the EC and TDS concentrations in the inflowing water begin to increase at 6:00 a.m. each day, reach their peak around 4:00 p.m., and then decrease from 6:00 p.m. onwards.

Images generated from data collected by sensor 2 and 3 show that the changes in EC and TDS concentrations at the upper and lower pond outlets are positively correlated with the data collected at the upper pond inlet, but with a delay of 2.5 hours and 5.5 hours, respectively.

5 Discussion and Conclusion

Initial findings suggest that a low-cost smart device is a feasible method for collecting water quality data and assessing the water purification capacity of the retention pond. The experimental results support both research hypotheses, showing that sensor modules can track the impact of human behavior on water quality in real-time and provide high spatial resolution water quality data that can be quantitatively analyzed. Compared to traditional hydrological data, which are typically measured at the river or watershed scale, the experimental smart device can provide more accurate and high-resolution data for landscape architectural professionals. The data collection interval in this experiment was one hour, but it can be adjusted to suit specific sites or projects, with a minimum interval of 2 seconds. The sensor modules can be powered by solar panels and batteries, allowing for longitudinal operation and remote data collection with low maintenance requirements. While the current experiment uses manual data collection every 48 hours, future research can be improved by adding a wireless network module to enable remote data collection via cellular networks. The prototype cost for this smart device is less than $100, and with a professionally printed circuit board (PCB) design, the cost can be further reduced in future development. Future studies could examine additional water quality parameters, but the cost of some sensors, such as nitrogen sensors, remains prohibitive. Balancing the cost of additional sensors against the necessary data is crucial. As the cost of sensor elements continues to decrease, more types of sensors may be deployed for future studies. Additionally, more sensor nodes could be placed in a more spatially dense configuration within the research site.

The experimental results indicate that retention ponds can effectively purify water, reducing TDS concentration by approximately 5.5 ppm and EC concentration by about 0.08 mS/cm in nearly 6 hours for every 10,000 m3 of retention water. However, other variables such as water flow, water channel depth, edge roughness, and aquatic life may influence the water purification capacity of retention ponds, and future studies should take these variables into account for more accurate results. Even though some errors might exist, this research, as a pioneering study, aims to provide data to support some empirical theories in landscape architecture. For example, in this study, the generally accepted theory that retention pond purify water is assisted by scientific data. The scientific data can be used to test, support, and complement some of the sustainability theories in the landscape architecture discipline. Landscape architecture is an evidence-based discipline that requires a sufficient basis to guide future design. In order to advance sustainable design practices, it is critical to gather scientific evidence to support the design and demonstrate performance. The results of this study can provide scientific data to support the development of the discipline.

This research has implications beyond the field of landscape architecture. With the increasing development of "smart cities," incorporating environmental data can enhance the efficiency of resource use and improve the quality of life for citizens. In cities where water resources are critical, water quality sensors can track and manage water resources across the city. Real-time monitoring can quickly identify and mitigate pollution leaks and improve resource use efficiency. Environmental sensors are not limited to water quality testing; similar technologies can be applied to air quality, soil analysis, and other areas. By mastering these technologies, landscape architecture professionals can become more involved in managing the entire city rather than being viewed as merely initiators and designers that some people think they are.

References

CHAUDHRY, F. N. & MALIK, M. F. (2017), Factors affecting water pollution: a review. J Ecosyst Ecography, 7 (225), 1-3.

CHOI, J. H. & MOON, J. (2017), Impacts of human and spatial factors on user satisfaction in office environments. Building and Environment, 114, 23-35.

CORGNATI, S. P., FABRIZIO, E. & FILIPPI, M. (2008), The impact of indoor thermal conditions, system controls and building types on the building energy demand. Energy and buildings, 40 (4), 627-636.

GAILLE, L. (2017, September 12), 13 advantages of disadvantages of longitudinal studies. Vittana.org. https://vittana.org/13-advantages-of-disadvantages-of-longitudinal-studies (09.04.2022).

GRIMMOND, C. S. B. (2006), Progress in measuring and observing the urban atmosphere. Theoretical and Applied Climatology, 84 (1), 3-22.

LIU, F., VIANELLO, A. & VOLLERTSEN, J. (2019), Retention of microplastics in sediments of urban and highway stormwater retention ponds. Environmental Pollution, 255, 113335.

LUO, Y. & LI, M. H. (2014), Landscape Performance of Built Projects: Comparing Landscape Architecture Foundation's Published Metrics and Methods. Landscape Architecture.

LUO, Y., LI, M. H., DUAN, S. L. & ZHANG, X. Z. (2015), LAP of Built Projects: Comparing Landscape Architecture Foundation's Published Metrics and Methods. Landscape Architecture.

MULLER, C. L., CHAPMAN, L., GRIMMOND, C. S. B., YOUNG, D. T. & CAI, X. (2013), Sensors and the city: a review of urban meteorological networks. International Journal of Climatology, 33 (7), 1585-1600.

RUNDEL, P. W., GRAHAM, E. A., ALLEN, M. F., FISHER, J. C. & HARMON, T. C. (2009), Environmental sensor networks in ecological research. New Phytologist, 182 (3), 589-607.

WANG, C. Y. & SAMPLE, D. J. (2014), Assessment of the nutrient removal effectiveness of floating treatment wetlands applied to urban retention ponds. Journal of Environmental Management, 137, 23-35.

ZEILE, P., RESCH, B., LOIDL, M., PETUTSCHNIG, A. & DÖRRZAPF, L. (2016), Urban Emotions and Cycling Experience – enriching traffic planning for cyclists with human sensor data. GI_Forum, 1 (2013), 204-216.