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# Performance Assessment of Low-cost Water Level Sensor for Water Sensitive Urban Design (WSUD) monitoring in the Tropics

## Évaluation des performances d'un capteur de niveau d'eau à faible coût pour la surveillance des ouvrages de gestion des eaux pluviales à la source (WSUD) sous les tropiques

Ning Ding \*, Perrine Hamel\*, Qingchuan Zhu\*\*, Frederic Cherqui\*\*, Jean-luc Bertrand-Krajewski\*\*

\*Asian School of the Environment, Nanyang Technological University, Singapore

\*\*INSA Lyon, DEEP EA 7429, F-69621, Villeurbanne cedex, France

Corresponding author: Ning Ding, DING0141@e.ntu.edu.sg, +65 89427121

### RÉSUMÉ

Les techniques alternatives deviennent un élément incontournable des stratégies de gestion intégrées des eaux urbaines. Bien que les projets de techniques alternatives se multiplient, les efforts de surveillance et de mesure de performance à moyen et long termes restent insuffisants, empêchant les agences publiques et développeurs privés de concevoir des ouvrages optimisés ou d'assurer la maintenance adéquate. Les efforts de surveillance des ouvrages sont généralement contraints par le manque de budget, en particulier dans les pays en développement. La flexibilité et les avantages économiques des technologies à bas coût sont donc particulièrement attractives pour les systèmes de surveillance. Dans cette étude, nous testons un capteur de hauteur d'eau bas coût (KIT0139) et le comparons à un capteur traditionnel (OTT PLS) en laboratoire, sous différentes conditions de température. Nos résultats suggèrent que le modèle de capteur bas coût étudié est robuste, les 6 capteurs testés donnant des résultats semblables (pas de différence significative dans les conditions expérimentales). Le capteur a démontré une précision acceptable, particulièrement pour les hauteurs d'eau supérieures à 0.2m. Nous établissons aussi des courbes de calibration en fonction de la température.

### ABSTRACT

Water Sensitive Urban Design (WSUD) has emerged as one of the most important sustainable strategies in integrated urban water management (IUWM). Though increasing WSUD systems have been implemented worldwide, there is relatively little attention paid to monitoring WSUD systems' medium- to long-term performance. The relatively limited monitoring efforts restrict the ability of public agencies and private developers to provide adequate maintenance for existing systems and to optimize the design of new systems in urban planning. The attempts of promoting monitoring are mainly limited by constrained budgets, especially in developing areas. With the huge economic advantages and flexibility for operation and communication, low-cost sensors (LCS) show great potential in establishing affordable monitoring systems. In this study, the performance of a LCS (KIT0139) was tested and compared to the counterpart traditional sensor (OTT PLS) in a laboratory under different . Results reveal that the LCS (KIT0139) has good robustness as there was no significant difference between the 6 individual LCS models under the testing conditions. Also, the LCS provides sufficient accuracy and precision compared to the traditional sensor tested, especially for water levels more than 0.2m. Calibration functions including the effect of water temperature were given since temperature in tropical cities is one main concern that would influence the performance of LCS.

### KEYWORDS

Low-cost sensor, Monitoring, Stormwater, Water level, Water sensitive urban design

# 1 Introduction

Urban hydrological processes have been considerably altered by rapid urbanization, which has resulted in the increase of water-related problems including floods and water pollution (Li et al., 2021; Reu Junqueira et al., 2021). Flood risk has significantly increased in urban areas due to the combination of intensifying stormwater events brought on by climate change (Chang et al., 2021; Rangari et al., 2021), highlighting the significance of Sustainable Urban Water Management (SUWM) principles in urban planning (Martijn Kuller et al., 2017). As a complementary approach to traditional human-engineered and centralized drainage systems, Water Sensitive Urban Design (WSUD) have been joined by including natural and semi-natural landscapes that are able to retain and purify runoff water (Gleason et al., 2021). WSUD integrates water cycle management with the built environment by retaining, filtering, storing, and utilizing runoff water resources in the urban area (Gleason & Flores, 2021). In addition to or in place of the conventional infrastructure, WSUD offers multi-functional landscapes (e.g., wetlands, bioretention basins, rain gardens, cleaning biotopes, green roofs) with numerous benefits (e.g., flood control, water purification, heat mitigation, carbon sequestration), making it the essential long-term strategy in integrated and sustainable urban water management (Keesstra et al., 2018; Tzoulas et al., 2007).

To further understand the role of WSUD in IUWM, the effectiveness of WSUD systems has been extensively studied at watershed and sub-watershed scales (Bellezoni et al., 2021; Gunnell et al., 2019; Ma et al., 2021; Meerow et al., 2021; Yau et al., 2017). However, such studies are mostly based on spatial models (e.g., SWMM, InVEST, MUSIC, MIKE, SUSTAIN) that focus on large-scale simulation, have ignored the real condition of WSUD systems at the site scale, and lack sufficient empirical data from field monitoring for the model validation and calibration (Hamel et al., 2021; Yin et al., 2021). The absence of field monitoring of WSUD systems is mainly due to the constrained budgets, especially in the developing areas such as Global South and most countries in Southeast Asia (Hamel & Tan, 2021). Since traditional monitoring systems can be costly and time-consuming, relatively few attempts were made for monitoring the medium- to long-term performance of WSUD systems in the Tropics (Bertrand-Krajewski, 2021; Hamel & Tan, 2021). The limited monitoring efforts restrict the ability of public agencies and private developers to provide adequate maintenance for existing WSUD systems and to optimize the design of new systems (M. Kuller et al., 2019).

Compared to traditional monitoring equipment, low-cost sensors (LCS) present great economic advantages by providing useful data at a considerably lower expense. Also, LCS often work on open-source platforms (e.g., Arduino), hence they are more flexible in operation and communication (Cherqui et al., 2020). Given their flexibility, LCS (Kumar et al., 2015). Currently, LCS technology has been emerging in many fields and showed reliable results, examples including air quality assessment (Ali et al., 2016; Morawska et al., 2018), air temperature measurement (Sun et al., 2019), water quality monitoring (Lambrou et al., 2014; Murphy et al., 2015), and agriculture (Valente et al., 2020). In this study, we aim to explore the potential of LCS in supporting the affordable and flexible monitoring network for WSUD systems, that can be promoted throughout the regional level for medium- to long-term monitoring. The main objectives are: 1) Testing the LCS with a traditional sensor (TS) in the laboratory. 2) Assessing the performance of this LCS in laboratory conditions. 3) Proposing calibration guidelines for the LCS tested for further field application.

As water level is one of the most essential parameters in water quantity monitoring, which indicates the performance of WSUD systems in stormwater retention, we first started the lab testing of sensors with the water level sensors. There are mainly two types of water level sensors: contact and non-contact sensors, including pressure transducer, ultrasonic sensor, laser sensor, capacitive devices, etc. (Loizou et al., 2016). Among them, the submersible pressure transducer and ultrasonic sensor are the most commonly used in the literature because of their good accuracy and flexibility (Zhu Q., 2021). Considering the field application, ultrasonic sensors are easy to be disturbed by the factors such as air temperature, wind, and rainfall (Ouychai, 2015; Zhang et al., 2019). Thus, the submersible pressure transducer with the anti-corrosion surface matches better with our requirements. Based on the literature and consideration of further field application, two water level sensors including a LCS (KIT0139 model, source: [https://wiki.dfrobot.com/Throw-in\\_Type\\_Liquid\\_Level\\_Transmitter\\_SKU\\_KIT0139](https://wiki.dfrobot.com/Throw-in_Type_Liquid_Level_Transmitter_SKU_KIT0139)) and a TS (OTT PLS model, source: <https://www.ott.com/products/water-level-1/ott-pls-pressure-level-sensor-959/>) were selected for lab testing. Both water level sensors are pressure transducers, which measure the water depth by converting the pressures at different depths of liquid into corresponding current or digital signals. In this study, we assessed and compared the performance of selected LCS and TS in laboratory conditions before further field application.

## 2 Methodology

### 2.1 Lab testing experiment

Seven water level sensors, including six LCS (KIT0139) and one TS (OTT PLS), were tested in the lab. The lab testing platform (Figure 2-1) mainly consists of one acrylic water column, seven water level sensors, one microcontroller (Arduino MKR1310 board), one water temperature controller (Heated Circulators machine), one water tank, two pumps and the online control platform (Arduino IDE software). To assess the influence of the variation in wetting and drying conditions which is common in flashy stormwater catchments on the sensors, the LCS was divided into two groups with three sensors in each group. As shown in Figure 2-1, group B of LCS was positioned at the 0m level (always submerged in water), while group A was at 0.3m level with a variety of dry and wet conditions. Additionally, testing three LCS of each group at the same time aimed to check if there is a distinct difference between the individual LCS models.

The sensors were tested for a measuring range of 0~1.7m, under three water temperatures (25°C, 30°C, 35°C). Each experiment included one complete cycle of filling the water column to the maximum height of 1.7m (upper limit) with an increment of 0.1m, followed by emptying to the minimum height of 0m (lower limit) with a decrement of 0.1m. After reaching each water level, there was a 10-second stabilization time before recording 100 readings from the LCS and 10 measurements from the TS. The reference water level was measured visually with a graduated ruler (1mm mark). In addition, the water temperature was recorded by OTT PLS during the water level measurements.

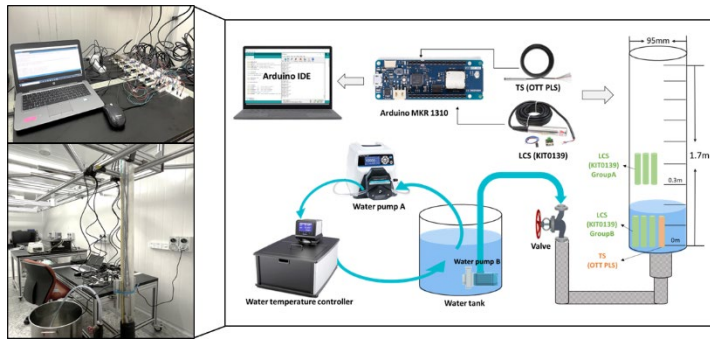


Figure 2-1. Lab testing experimental setup

## 2.2 Calibration of the sensors

Raw readings from the LCS (KIT0139) were selected and divided into two equivalent datasets, one dataset including 30 raw readings at each water level was used for generating the calibration function, while another 30 raw readings were used to obtain the calibrated water level measurements and assess the performance of LCS. Similarly, measurements by TS (OTT PLS) were divided into two datasets with each including 5 raw measurements at each water level to be used for calibration and validation, respectively.

A first order Ordinary least squares regression (OLS) method was used for the calibration of the sensors tested in this study. The OLS regression method requires the same amount of repeated measurements and the reference values, as well as the standard uncertainties of the reference values as inputs. All the calibration functions were generated by MATLAB (version R2021b).

## 2.3 Uncertainty assessment

Evaluating measurement uncertainties is a normal procedure in urban drainage and stormwater management. In this study, a method for uncertainty assessment by the law of propagation of uncertainties (Bertrand-Krajewski, 2021) was applied to evaluate the 95% confidence interval of the estimated true water level measured by the LCS (KIT0139). If the maximum uncertainty is calculated as  $u(\hat{h})$ , the final 95% interval for estimated true water level ( $\hat{h}$ ) is equal to  $[\hat{h} - 1.96 \times u(\hat{h}), \hat{h} + 1.96 \times u(\hat{h})]$ , where 1.96 is a constant coefficient used to approximate 95% coverage intervals with the hypothesis of the normal distribution.

## 2.4 Assessment of robustness, accuracy, and sensitivity

Three parameters were used to assess the performance of the LCS (KIT0139) tested in this study: 1) To represent if there is district difference between the individual LCS models, the robustness of the LCS was assessed based on the comparison between the six individual low-cost models. 2) Accuracy (represented by mean error) and precision (represented by the variance of measurements over the measuring range) of the estimated true water level measurements by the after LCS were assessed. 3) Sensitivity to water temperature was assessed based on the changes in sensors' accuracy and precision with the temperature increasing from 25 to 35 degrees.

## 3 Results

### 3.1 Robustness of LCS

The calibration functions and the maximum uncertainties for the LCS are shown in Table 3-1. For the uncertainty assessment, there was no significant difference between individual LCS models at 25~35 °C, except a spike for the LCS (KIT1) of the downward testing at 25°C. To further assess the difference between individual LCS models, the t-test was used to identify if there were statistical differences between the LCS models in terms of measuring water levels in different conditions. The Welch test was selected based on the variance assessment. Results gave fairly small t-values (close to 0) and the p-values were much higher than the significance level of 0.05, showing that the null hypothesis cannot be rejected. In other words, we can conclude that there was no significant difference between the individual LCS models in different testing conditions.

Table 3-1. Calibration functions generated based on the 1<sup>st</sup> order OLS method.

Temperature (°C)	Sensors	Water Up	Water Down	Max uncertainty (mm)	
				Water Up	Water Down
25	KIT1	Y=5919.3898+4.763X	Y=5987.0134+4.7252X	0.7234	1.1737
	KIT2	Y=5903.7339+4.7614X	Y=5975.5323+4.7234X	0.6030	0.5831
	KIT3	Y=5908.4382+4.7653X	Y=5977.8871+4.7265X	0.7611	0.7360
	KIT4	Y=5735.6588+4.6495X	Y=5792.4925+4.6385X	0.6294	0.3410
	KIT5	Y=5790.557+4.6699X	Y=5847.4237+4.658X	0.6734	0.7311
	KIT6	Y=5751.9771+4.6643X	Y=5818.5706+4.6473X	0.6326	0.6757
30	KIT1	Y=5730.2312+4.5483X	Y=5738.4677+4.5544X	0.7827	0.6850
	KIT2	Y=5731.5565+4.5434X	Y=5743.6962+4.5471X	0.6627	0.6327
	KIT3	Y=5722.6478+4.5443X	Y=5728.3871+4.5534X	0.6537	0.5469
	KIT4	Y=5613.1785+4.4757X	Y=5617.7993+4.479X	0.5774	0.5291
	KIT5	Y=5635.2208+4.4859X	Y=5643.3018+4.4881X	0.6223	0.8514
	KIT6	Y=5602.8043+4.4758X	Y=5618.9914+4.4703X	0.4755	0.6187
35	KIT1	Y=5753.3925+4.5448X	Y=5737.7419+4.5557X	0.6773	0.4709
	KIT2	Y=5754.0188+4.5479X	Y=5743.9731+4.5556X	0.4921	0.5216
	KIT3	Y=5740.621+4.5416X	Y=5726.2124+4.5534X	0.4775	0.4208
	KIT4	Y=5652.5964+4.4969X	Y=5648.0387+4.4868X	0.5267	0.6512
	KIT5	Y=5651.1642+4.4888X	Y=5637.929+4.486X	0.6627	0.6396
	KIT6	Y=5614.972+4.4794X	Y=5609.0523+4.4727X	0.4369	0.5519

### 3.2 Accuracy and precision of sensors tested

After calibrating the LCS (KIT0139) and TS (OTT PLS) based on the calibration functions generated by the 1st order OLS regression method, the accuracy and precision of the sensors were assessed. The accuracy distribution of the sensors over the measuring range at three water temperature degrees are shown in Figure 3-1.

The accuracy of TS was 1mm, 2mm, and 2mm over 0~1.7m under 25°C, 30°C, 35°C water temperature, respectively, indicating a high reliability of the TS in measuring water levels. Additionally, the precision of TS was high as the variance of the measurements by the TS in the lab testing was very small (approximately equal to zero). For the LCS, the accuracy was 14mm, 11mm, 10mm under 25°C, 30°C, 35°C water temperature, respectively, with a large variation over the measuring range of 0~1.7m. As shown in Figure 3-1, the accuracy of LCS seemed to be lower at the low water levels and become better at the medium to high water levels over the measuring range. The numerical results have proved that the accuracy of LCS was around 12~14mm at the 0.1~0.2m water level but can reach a much higher accuracy (1~5mm) over the range of 0.3~1.6m. Based on Figure 3-1 and numerical results, there was no statistical difference of LCS's accuracy for the water flow direction (water goes up and water goes down). In addition, the precision of LCS was relatively good as compared to the TS, since the variance of LCS in the lab testing was less than 0.2mm<sup>2</sup>.

### 3.3 Sensitivity of LCS to temperature

As temperatures in the Tropics can reach a level that may influence the performance of LCS in the field, the sensitivity of LCS to water temperature was assessed in the lab testing. The results of accuracy and precision of LCS did not show a significant change while the water temperature rising from 25 to 35 degree. But the calibration lines of LCS gave different coefficient under the three temperatures. Thus, we explored the relationship between the temperature and the coefficient in the calibration lines. As shown in Figure 3-2, the 2<sup>nd</sup> order of polynomial regression can fit the relationship between the two parameters well, this indicates that in the future field application, there could be a calibration function  $F(T, b_j)(j = 0,1)$  to involve the influence of temperature for calibrating the LCS (KIT0139) under the varying temperature conditions in Tropic cities. In this case, the estimated true water level (Y) by the LCS (KIT0139) should be expressed as:  $Y = F(T, b_0)X + F(T, b_1)$ , where X is the raw readings recorded from the LCS.

## 4 Conclusion

To explore the potential of low-cost sensors in Water Sensitive Urban Design (WSUD) monitoring, we conducted a lab testing experiment assessing the performance of the low-cost water level sensor KIT0139 and comparing it to the traditional sensor OTT PLS. Results indicate that the LCS (KIT0139) provides good robustness, sufficient accuracy and precision especially in measuring more than 0.2m water levels. Calibration functions including the effect of water temperature explored in this study can be the theoretical guidance for the LCS calibration in tropic cities. Future work will be the field application and calibration of LCS at WSUD system sites under real-world conditions as compared to the controlled lab conditions, as well as the real-time online data transmission based on LoRaWAN technology.

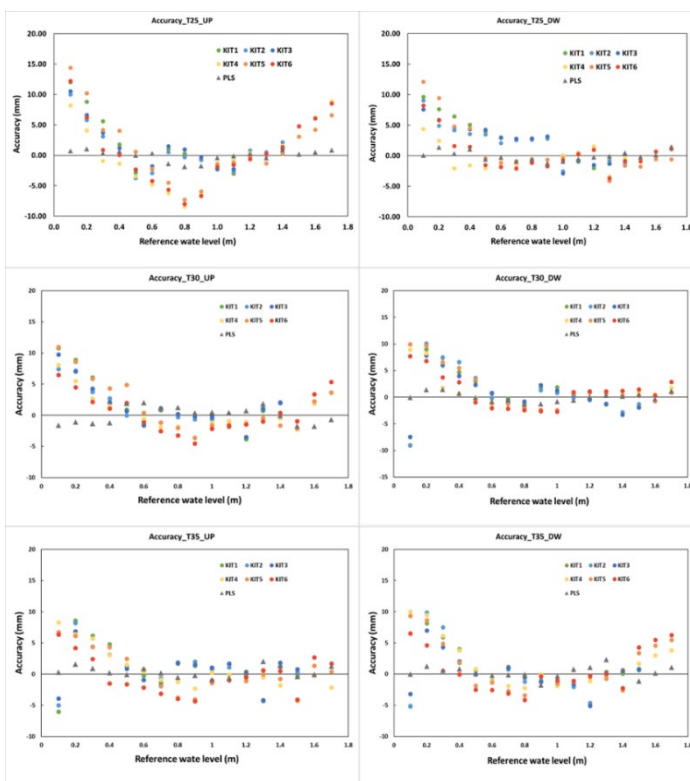


Figure 3-1. Accuracy of the LCS and TS tested. From top to bottom, and from left to right, the order is the accuracy of six LCS and one TS over the measuring range at water goes up and water goes down process under each water temperature (25, 30, 35 °C).

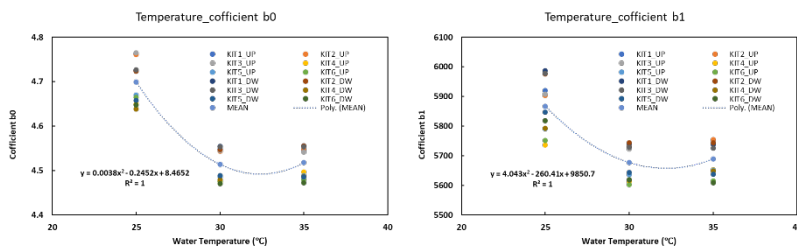


Figure 3-2. Relationship between the temperature and coefficients (b0 represents the slop, and b1 refers to the intercept) of the 1<sup>st</sup> order OLS calibration lines of LCS.

## BIBLIOGRAPHIE

- Ali, A. S., Zanzinger, Z., Debose, D., & Stephens, B. (2016). Open Source Building Science Sensors (OSBSS): A low-cost Arduino-based platform for long-term indoor environmental data collection. *Building and Environment*, 100, 114-126.
- Bellezoni, R. A., Meng, F., He, P., & Seto, K. C. (2021). Understanding and conceptualizing how urban green and blue infrastructure affects the food, water, and energy nexus: A synthesis of the literature. *Journal of Cleaner Production*, 289.
- Bertrand-Krajewski, C. L. (2021). *Metrology in Urban Drainage and Stormwater Management: Plug & Pray*. London (UK): IWA Publishing.
- Chang, H., Pallathadka, A., Sauer, J., Grimm, N. B., Zimmerman, R., Cheng, C., . . . Herreros-Cantis, P. (2021). Assessment of urban flood vulnerability using the social-ecological-technological systems framework in six US cities. *Sustainable Cities and Society*, 68.
- Cherqui, F., James, R., Poelsma, P., Burns, M. J., Szota, C., Fletcher, T., & Bertrand-Krajewski, J. L. (2020). A platform and protocol to standardise the test and selection low-cost sensors for water level monitoring. *H2Open Journal*, 3(1), 437-456.
- Gleason, J. A., & Flores, C. C. (2021). Challenges of Water Sensitive Cities in Mexico: The Case of the Metropolitan Area of Guadalajara. *Water*, 13(5).
- Gunnell, K., Mulligan, M., Robert A. Francis, & Hole, D. G. (2019). Evaluating natural infrastructure for flood management within the watersheds of selected global cities. *Sci Total Environ*, 670, 411-424.
- Hamel, P., & Tan, L. (2021). Blue-Green Infrastructure for Flood and Water Quality Management in Southeast Asia: Evidence and Knowledge Gaps. *Environ Manage.*
- Keesstra, S., Nunes, J., Novara, A., Finger, D., Avelar, D., Kalantari, Z., & Cerda, A. (2018). The superior effect of nature based solutions in land management for enhancing ecosystem services. *Sci Total Environ*, 610-611, 997-1009.
- Kuller, M., Bach, P. M., Ramirez-Lovering, D., & Deletic, A. (2017). Framing water sensitive urban design as part of the urban form: A critical review of tools for best planning practice. *Environmental Modelling & Software*, 96, 265-282.
- Kuller, M., Bach, P. M., Roberts, S., Browne, D., & Deletic, A. (2019). A planning-support tool for spatial suitability assessment of green urban stormwater infrastructure. *Sci Total Environ*, 686, 856-868.
- Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., . . . Britter, R. (2015). The rise of low-cost sensing for managing air pollution in cities. *Environ Int*, 75, 199-205.
- Lambrou, T. P., Anastasiou, C. C., Panayiotou, C. G., & Polycarpou, M. M. (2014). A Low-Cost Sensor Network for Real-Time Monitoring and Contamination Detection in Drinking Water Distribution Systems. *IEEE Sensors Journal*, 14(8), 2765-2772.
- Li, C., Liu, M., Hu, Y., Zhou, R., Wu, W., & Huang, N. (2021). Evaluating the runoff storage supply-demand structure of green infrastructure for urban flood management. *Journal of Cleaner Production*, 280.
- Loizou, K., & Koutroulis, E. (2016). Water level sensing: State of the art review and performance evaluation of a low-cost measurement system. *Measurement*, 89, 204-214.
- Ma, Q., Li, Y., & Xu, L. (2021). Identification of green infrastructure networks based on ecosystem services in a rapidly urbanizing area. *Journal of Cleaner Production*, 300.
- Meerow, S., Natarajan, M., & Krantz, D. (2021). Green infrastructure performance in arid and semi-arid urban environments. *Urban Water Journal*, 18(4), 275-285.
- Morawska, L., Thai, P. K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., . . . Williams, R. (2018). Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? *Environ Int*, 116, 286-299.
- Murphy, K., Heery, B., Sullivan, T., Zhang, D., Paludetti, L., Lau, K. T., . . . Regan, F. (2015). A low-cost autonomous optical sensor for water quality monitoring. *Talanta*, 132, 520-527.
- Ouychai, I. P., Khoenkaw. (2015). A low-cost flash flood monitoring system. . *Proc. - 2015 7th Int. Conf. Inf. Technol. Electr. Eng. Envisioning Trend Comput. Inf. Eng., ICITEE 2015* 476-479.
- Rangari, V. A., Urmamahesh, N. V., & Patel, A. K. (2021). Flood-hazard risk classification and mapping for urban catchment under different climate change scenarios: A case study of Hyderabad city. *Urban Climate*, 36.
- Reu Junqueira, J., Serrao-Neumann, S., & White, I. (2021). A systematic review of approaches for modelling current and future impacts of extreme rainfall events using green infrastructure. *Journal of Cleaner Production*, 290.
- Sun, C.-Y., Kato, S., & Gou, Z. (2019). Application of Low-Cost Sensors for Urban Heat Island Assessment: A Case Study in Taiwan. *Sustainability*, 11(10).
- Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kaźmierczak, A., Niemela, J., & James, P. (2007). Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review. *Landscape and Urban Planning*, 81(3), 167-178.
- Valente, A., Silva, S., Duarte, D., Cabral Pinto, F., & Soares, S. (2020). Low-Cost LoRaWAN Node for Agro-Intelligence IoT. *Electronics*, 9(6).
- Yau, W., Radhakrishnan, M., & Liang. (2017). Effectiveness of ABC Waters Design Features for Runoff Quantity Control in Urban Singapore. *Water*, 9(8).
- Yin, D., Chen, Y., Jia, H., Wang, Q., Chen, Z., Xu, C., . . . Chen, A. S. (2021). Sponge city practice in China: A review of construction, assessment, operational and maintenance. *Journal of Cleaner Production*, 280.
- Zhang, D., Heery, B., O'Neil, M., Little, S., O'Connor, N. E., & Regan, F. (2019). A Low-Cost Smart Sensor Network for Catchment Monitoring. *Sensors (Basel)*, 19(10).
- Zhu Q., C. F., Bertrand-Krajewski J.-L. (2021). Station météorologique à bas coût pour le suivi de toitures végétalisées. In. Actes des 9<sup>e</sup> Journées Doctorales en Hydrologie Urbaine "JDHU 2020", Strasbourg, France, 26-27 mai, 4 p.