Creating a digital smart flood warning system for surface water flooding in West Yorkshire: Laboratory Report

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Contents

Introduction

Surface water flooding is a growing challenge across the UK, with more around 4.6 million properties in England currently in areas at risk of flooding from surface water. The Environment Agency's 2024 national assessment also reports that around 1.1 million properties are in areas at high risk of surface water flooding (Environment Agency, 2025b). Climate change is expected to exacerbate surface water flood risk, with UKCEH reporting that extended periods of extreme winter rainfall are now seven times more likely due to climate change while rainfall from extreme thunderstorms could increase by 25% in the UK by the 2050s (UKCEH, 2025).

Unlike fluvial flooding, surface water events are highly localised, driven by short duration rainfall, and difficult to forecast with existing modelling approaches (Environment Agency, 2025a; Speight et al., 2025). Forecasting surface water flooding in urban areas has been increasingly investigated in the past decade, however model confidence remains low, and lead time is limited to a few hours. As a result, risk management authorities including local authorities, flood wardens, and emergency responders, often lack monitoring and early warning systems capable of detecting surface water accumulation in real time. This leads to predominantly reactive responses, inefficient resource deployment, and limited capacity for coordinated multiagency flood management (Birch et al., 2021; Speight et al., 2021). Research highlights that surface water warnings need to meet the different spatial and temporal information needs of emergency responders, infrastructure providers, community groups and the public (Maybee et al., 2024; Ramsden et al., 2025). This reinforces the need for more localised and decision-relevant monitoring approaches that can support proactive flood management.

In 2023, the West Yorkshire Flood Innovation Programme (WYFLIP) undertook a scoping exercise, funded by the Local Digital Fund, to explore how smart technologies could transform regional flood resilience. Working with councils across Leeds, Kirklees, and Wakefield, alongside flood wardens and emergency responders, the WYFLIP investigated current flood management practice, challenges and opportunities for flood mitigation and response, and evaluated practical and accessible technology options for monitoring water level change in real time (Hargreaves & Bond, 2024; WYFLIP 2024). The research identified the need for, and opportunity to trial, an improved, proactive response to surface water flooding in West Yorkshire. The contemporary management for flooding was found to be reactive, resource inefficient, and prevented collaborative approaches between multiple organisations.

Long Range Wide Area Network (LoRaWAN) technology emerged as a promising data transmission mechanism, due to its ability to transmit low power, small packet data in real time across urban and rural landscapes (Zakaria et al., 2023). LoRaWAN is already widely used across the Yorkshire region for applications such as air quality monitoring, footfall analysis and light level measurement. LoRaWAN is increasingly being explored for flood related sensing applications in the UK and shows promise for enabling a targeted and proactive approach which facilitates infrastructure maintenance, flood incident response and pattern analysis of incidents over time (Hargreaves & Bond, 2024; Ragnoli et al., 2020). However, most activity to date has been supplier-led or reliant on commercial sensors (e.g. Previsico's flood-alert work with Whalley Flood Action Group; Andel Ltd.'s monitoring work with Aston Ingham Flood Group; Decentlab LoRaWAN river-level recorders used in Gwynedd; and AB Open-supported LoRaWAN river-level sensors through Things Calderdale), and there are relatively few documented examples of successful, operational deployment for flood mitigation or emergency response . Following WYFLIP's 2023 research, the recommended next step was a targeted pilot to evaluate suitable sensors and assess their performance in realistic conditions (Hargreaves & Bond, 2024).

In 2025, the University of Leeds, partnered with Wakefield Council through the WYFLIP, received funding to evaluate LoRaWAN-based water level sensors in a laboratory setting prior to piloting the sensors in real environmental conditions. The overarching aim of this collaboration is to establish a scientifically robust foundation for the future development of a regional LoRaWAN based flood monitoring network, informed by shared expertise and aligned with local authority operational needs (WYFLIP, 2024).

The objective of this research is to evaluate the performance of three commercially available LoRaWAN-based water level sensors - DecentLab Ultrasonic Level Sensor, ELSYS ELT2 MaxBotix Distance Sensor, and Milesight EM500 Ultrasonic Distance/Level Sensor (see Table 1) - under controlled laboratory conditions to assess their suitability for surface water flood monitoring. The sensors were chosen by WYFLIP members as three affordable options covering a range of desired properties. A summary of sensor properties as published in their respective data information manuals can be found in Table 1.

Sensor validation was conducted in both static and dynamic (moving water) scenarios to evaluate the sensors' accuracy, precision and reliability. These controlled assessments represent a critical first step in validating the suitability of each sensor type for deployment in real world surface water environments, where turbulent flow, debris and variable water levels present additional challenges which may mask fundamental sensor performance differences (Ragnoli et al., 2020; Zakaria et al., 2023).

By establishing the relative performance of these sensors under repeatable laboratory conditions, this study provides essential evidence to inform the design of a pilot scale deployment across identified flood risk hotspots in West Yorkshire. The outcomes will support local authority teams in selecting appropriate sensor technologies, enhance regional capacity in LoRaWAN based environmental monitoring, and contribute to the development of a scalable, low-cost surface water flood warning system.

Table 1: A summary of sensor properties as published in their respective data information manuals.

Sensor name	**Decentlab Ultrasonic Level Sensor** SKU : DL-MBX-002-EU868	**ELSYS ELT2 MaxBotix Distance sensor** SKU : ELT2-MB7389	**Milesight EM500 Ultrasonic Distance/Level Sensor** SKU : EM500-UDL-868EU-W100
Sensor type	LoRaWAN-enabled non-contact ultrasonic distance level sensor	ELT-2 is a universal outdoor LoRaWAN device	Ultrasonic distance/level sensor within the EM500 outdoor LoRaWAN monitoring sensor series.
Measurement principle	Measures distance using ultrasonic time-of-flight, temperature compensated.	Measures analogue/digital signals and connect to external sensors, including a MaxBotix distance sensor input.	Ultrasonic non-contact distance/level measurement
Measurement range (vertical water level)	0.3–5 m	Depends on the specific MaxBotix sensor model connected. Typical range is 0.3-5m.	0.5–10 m
Accuracy	1% or better, factory calibrated.	1% or better, factory calibrated.	±1% full scale;
Resolution	1 mm	1 mm	1 mm
Cone angle	A specific cone angle was not found. The ultrasonic beam is a 'diffuse cone' and the greatest sensitivity is at the centre of the measurement beam.	A specific cone angle was not found. Typically features a narrow, focused beam designed to minimize interference from side objects, often referred to as having a 'small cone' or 'narrow beam'.	A detection cone angle of approximately 60^0 in front of the ultrasonic probe.
LoRaWAN connectivity range	Wireless range >10 km line-of-sight and approx. 2 km suburban.	Range stated as 8 km with actual range dependent on terrain/buildings.	up to 15 km communication range
Configuration method	Configurable via command line interface and LoRaWAN downlink command interface.	Configurable via NFC and over the air. Sampling rate, spreading factor, encryption keys, port and modes can be changed.	Configurable via NFC using Milesight ToolBox App or via USB/ToolBox software.
Battery power	2 x alkaline C batteries. Battery life estimate: 6.5 years at 10 min interval/SF7*	1x replaceable 3.6V AA 14505 Li-$SOCl_2$ battery Battery life estimate:	1x 19000 mAh replaceable battery Battery life estimate: Up to 10 years, low power consumption.

	3.5 years at 10 min interval/SF12 12.5 years at 60 min interval/SF7 10.5 years at 60 min interval/SF12 *SF= Spreading factor	up to 10 years, depending on the usage	
Operating conditions	Temperature: -20 to 50°C Humidity: 0–100% RH	Temperature: -40 to 60°C, -40 to 85°C with external power supply Humidity: 0–100% RH Pressure: 260–1260 hPa	Temperature: -30°C to +65° Humidity: 0% to 80% RH (non-condensing).
Enclosure	Polycarbonate enclosure; weatherproof, impact- and UV-resistant. Enclosure is IP66/IP67, sensor is IP67.	Enclosed in IP67 box; designed for extreme outdoor conditions.	IP67 waterproof enclosure for harsh environment applications.
Dimensions & weight	170 × 81 × 70 mm, 450 g including batteries.	94 × 59 × 35 mm, 100 g including batteries	156.1 × 71 × 69.5 mm, 370.4 g
Mounting / installation notes	Mount with ultrasonic horn facing target. Keep target centred in measurement beam, avoid interfering objects/sharp corners, mount on a cantilever away from poles/walls/tubes, protect from rain/direct sun where possible, and avoid metallic objects near the device for radio performance.	Mount using two side holes. Ensure cable gland and antenna connection are tightened to prevent moisture ingress. External sensors should use as short a cable as possible for best performance.	EM500 transceiver supports wall, pole and DIN rail mounting. For EM500-UDL, the device should sit vertically above the target/object, have a clear path, be more than 30 cm from side walls, and avoid internal obstructions, arched/circular container centres and inlet orifices.
Additional features/ parts required	N/A	Requires ANT868 OR ANT915C whip antenna & 2XER14500 batteries.	N/A
Price (August 2025)	£606.76	£384.45 including the whip antenna and batteries	£315.08

Methods

Laboratory testing was undertaken in the Sorby Environmental Fluid Dynamics Laboratory at the University of Leeds. Three LoRaWAN sensors - DecentLab Ultrasonic Level Sensor, ELSYS ELT2 MaxBotix Distance Sensor, and Milesight EM500 Ultrasonic Distance/Level Sensor (Table 1) – were evaluated.

All sensors used factory default settings and configured to record water level at regular 2-minute intervals, chosen to conserve battery in advance of field deployment. Strict timestamp synchronisation between sensors was not employed; however, all sensors recorded measurements within 30 seconds of one another. As sensors were spatially offset and therefore did not measure the same point on the water surface, and as the water surface exhibited small-scale temporal variability even under nominally static conditions, sub-second synchronisation was not considered necessary for comparative performance assessment.

Sensor performance was evaluated using two laboratory facilities: 1) a 1.6 m^3 'T'-shaped density current tank, designed for density-driven flows and used here for static water change only, and 2) an 8.5 m long, 0.30 m wide and 0.30 m deep, tilting, recirculating hydraulic slurry flume capable of both static and dynamic water flow. In separate experimental phases, sensors were mounted centrally above the tank or flume, oriented perpendicular to the water surface, and positioned at heights appropriate for their specified measurement range (Table 1).

The density tank was used to test all three sensors under static water conditions. Three sensor readings were obtained at each of five reference water levels: 2.98 m, 2.88 m, 2.78 m, 2.68 m, and 2.56 m.

The hydraulic slurry flume was used to test the Maxbotix and Decent lab sensors under both static and dynamic water conditions. The Milesight sensor was not tested in the flume because its 60° cone angle exceeded the flume width (0.30 m), preventing reliable water level measurement due to interference from the flume walls. Five sensor readings were taken per reference water level under both static and dynamic conditions. Static reference water levels were recorded at 0.241m and 0.220m. Dynamic water conditions were measured at three pump frequencies - 15, 25, and 35 Hz - corresponding to 0.12 m s^{-1}, 0.20 m s^{-1} and 0.28 m s^{-1} flow velocities, respectively. Reference water levels under dynamic conditions were 0.191 m at 15 Hz and 0.243 m at both 25 Hz and 35 Hz.

All data were recorded in real time via The Things Network. Measurements obtained during transitional periods, including changes between static water levels and prior to stabilisation of dynamic conditions, were excluded from analysis to ensure data quality.

Sensors were mounted at varying heights above the density tank and slurry flume to accommodate laboratory setup requirements. To enable direct comparison between sensors, all measurements were normalised to water depth using the known vertical distance between each sensor and the top of the tank or flume. For each sensor, reference water level, and pump frequency, the mean and standard deviation of normalised sensor-derived water depth were calculated. Measurement error was defined as the difference between the mean sensor-derived water depth and the corresponding reference water level. Sensor precision was quantified using the standard deviation of the water-level difference across repeated measurements.

Results

The objective of this study was to evaluate the performance of three commercially available LoRaWAN-based water level sensors by comparing sensor precision and measurement error under static and dynamic water conditions.

Static water level performance

All sensors recorded water level with a precision of < 1.15 mm (Table 2). For individual static water levels in the density tank, the mean standard deviation of sensor-measured water level was 0.12 mm for Decentlab, 0.26 mm for Maxbotix, and 0.30 mm for Milesight. The maximum standard deviation recorded was 0.58 mm for Decentlab, 0.71 mm for Maxbotix, and 0.82 mm for Milesight. All three sensors recorded a minimum standard deviation of 0.00 mm for at least one water level. Across the five static water levels investigated in the density tank, Decentlab recorded a standard deviation of 0.00 mm for four levels, while Maxbotix and Milesight each recorded a standard deviation of 0.00 mm for three levels.

Standard deviation was higher for static measurements conducted in the slurry flume, although fewer water levels were investigated (Table 2). Individual standard deviation values of 1.11 mm and 1.13 mm were recorded for Decentlab, while Maxbotix recorded a standard deviation of 0.79 mm for both measurements.

Mean measurement error - defined as the difference between sensor-derived water depth and the corresponding reference water level - was 1.17 mm for Decentlab, 0.17 mm for Maxbotix, and 1.25 mm for Milesight in the density tank (Table 3). Both Decentlab and Maxbotix exhibited instances of under- and over-estimation relative to the reference water level. Measurement error for Decentlab ranged from −1.33 mm to 3.00 mm, while measurement error for Maxbotix ranged from −1.83 mm to 3.00 mm. In contrast, the Milesight sensor consistently overestimated water level relative to the reference water level, with measurement error ranging from 0.50 mm to 2.00 mm.

Only one measurement error value was obtained per sensor for the slurry flume. Under these conditions, Decentlab recorded a measurement error of −0.71 mm, while Maxbotix recorded a measurement error of −3.14 mm (Table 3).

Under static water conditions, all three sensors exhibited low measurement variability; in the density tank, Decentlab demonstrated the lowest variability, while Maxbotix and Milesight showed similarly low but slightly higher variability.

Dynamic (moving water) performance

Dynamic performance was assessed in the slurry flume only, taking five sensor readings per reference water level. Sensor precision was lower under dynamic water conditions than under static conditions, with measurement variability increasing with pump frequency (Table 4). At a reference water level of 0.191 m and a pump frequency of 15 Hz, a standard deviation of 0.00 mm was recorded for Decentlab and 0.96 mm for Maxbotix. At a reference water level of 0.243 m and a pump frequency of 25 Hz, standard deviation increased to 1.30 mm for Decentlab and 2.17 mm for Maxbotix. At the same reference water level with pump frequency increased to 35 Hz, standard deviation was 1.38 mm for Decentlab and 3.74 mm for Maxbotix.

When both reference water level and pump frequency were changed from 0.191 m at 15 Hz to 0.243 m at 25 Hz, measurement error was −0.8 mm for Decentlab and −3.0 mm for Maxbotix (Table 5). At a constant water level of 0.243 m, changing pump frequency from 25 Hz to 35 Hz resulted in a measurement error of 0.3 mm for Decentlab and −2.8 mm for Maxbotix.

Under dynamic water conditions, both sensors exhibited increased variability and measurement error with increasing pump frequency, with Decentlab maintaining lower variability and smaller errors than Maxbotix across all tested conditions.

Table 2: Static water level sensor performance. Mean sensor-measured water level and associated standard deviation under static water conditions in two laboratory facilities. Sensor measurements were normalised using the known sensor mounting height and density tank or slurry flume geometry to remove differences due solely to installation height, enabling direct comparison of water-level measurements across sensors.

Test facility	Sensor	Reference water level (mm)	Sensor-measured mean water level (mm)	Standard deviation of sensor-measured water level (mm)
Density tank	Decentlab	2980	2981.8	0.58
Density tank	Maxbotix	2980	2979.9	0.58
Density tank	Milesight	2980	2982.6	0.82
Density tank	Decentlab	2880	2883.2	0.00
Density tank	Maxbotix	2880	2881.8	0.71
Density tank	Milesight	2880	2880.6	0.00
Density tank	Decentlab	2780	2780.2	0.00
Density tank	Maxbotix	2780	2781.3	0.00
Density tank	Milesight	2780	2779.6	0.00
Density tank	Decentlab	2680	2678.2	0.00
Density tank	Maxbotix	2680	2678.3	0.00
Density tank	Milesight	2680	2678.1	0.71
Density tank	Decentlab	2560	2557.2	0.00
Density tank	Maxbotix	2560	2559.3	0.00
Density tank	Milesight	2560	2557.6	0.00
Flume	Decentlab	241	240.60	1.11
Flume	Maxbotix	241	239.40	0.79
Flume	Decentlab	220	220.40	1.13
Flume	Maxbotix	220	221.60	0.79

Table 3: Static water level change detection performance. Differences in normalised sensor-derived water depth calculated from the mean values reported in Table 2. Reference water level differences represent known changes in density tank or slurry flume water depth. Measurement error is defined as the difference between sensor-derived water depth change and the corresponding reference water level change.

Test facility	Sensor	Reference water levels compared (mm)	Reference water level change (mm)	Sensor-measured mean water level change (mm)	Measurement error (mm)
Density tank	Decentlab	2980 -> 2880	100	98.7	-1.33
Density tank	Maxbotix	2980 -> 2880	100	98.2	-1.83
Density tank	Milesight	2980 -> 2880	100	102.0	2.00
Density tank	Decentlab	2880 -> 2780	100	103.0	3.00
Density tank	Maxbotix	2880 -> 2780	100	100.5	0.50
Density tank	Milesight	2880 -> 2780	100	101.0	1.00
Density tank	Decentlab	2780 -> 2680	100	102.0	2.00
Density tank	Maxbotix	2780 -> 2680	100	103.0	3.00
Density tank	Milesight	2780 -> 2680	100	101.5	1.50
Density tank	Decentlab	2680 -> 2560	120	121.0	1.00
Density tank	Maxbotix	2680 -> 2560	120	119.0	-1.00
Density tank	Milesight	2680 -> 2560	120	120.5	0.50
Flume	Decentlab	241 -> 220	21.0	20.3	-0.71
Flume	Maxbotix	241 -> 220	21.0	17.9	-3.14

Table 4: Dynamic water level sensor performance as a function of pump frequency. Mean sensor-derived water depth and associated standard deviation under dynamic water conditions in the hydraulic flume. Sensor-derived measurements were converted to water depth using the fixed sensor mounting height and flume geometry prior to calculation of summary statistics. Measurements are summarised by sensor, reference water level, and pump frequency (Hz), illustrating the effect of surface motion on measurement variability.

Test facility	Sensor	Reference water level (mm)	Pump frequency (Hz)	Sensor-measured mean water level (mm)	Standard deviation of sensor-measured water level (mm)
Flume	Decentlab	191	15	191.5	0.00
Flume	Maxbotix	191	15	194.3	0.96
Flume	Decentlab	243	25	242.7	1.30
Flume	Decentlab	243	35	243.3	1.38
Flume	Maxbotix	243	25	243.0	2.17
Flume	Maxbotix	243	35	240.5	3.74

Table 5: Dynamic water level change detection performance as a function of pump frequency. Dynamic water level change detection performance under dynamic conditions in the hydraulic flume. Differences in normalised sensor-derived water depth were calculated between known reference water levels for each pump frequency using the mean sensor-derived water depths reported in Table 4. Measurement error is defined as the difference between sensor-derived water level change and the corresponding reference water level change.

Test facility	Sensor	Reference water levels compared (mm)	Pump frequency (Hz)	Reference water level change (mm)	Sensor-measured mean water level change (mm)	Measurement error (mm)
Flume	Decentlab	191 -> 243	15 -> 25	52.0	51.2	-0.8
Flume	Maxbotix	191 -> 243	15 -> 25	52.0	49.1	-3.0
Flume	Decentlab	243 -> 243	25 -> 35	0.00	0.3	0.3
Flume	Maxbotix	243 -> 243	25 -> 35	0.00	-2.8	-2.8

Discussion

All three of the commercially available LoRaWAN water level sensors demonstrated high precision under controlled laboratory conditions.

Static water level performance

Under static water conditions, sub-millimetre standard deviations were observed across multiple water levels and test facilities. Among the sensors tested, the Decentlab sensor consistently exhibited the lowest measurement variability under static conditions, followed by the Maxbotix and Milesight sensors. All sensors recorded minimum standard deviations of 0.00 mm, which was also the most frequently observed value across static measurements.

Relative to reference water levels, all sensors demonstrated small measurement errors under static conditions. Mean measurement error was highest for the Milesight sensor (1.25 mm), followed by the Decentlab (1.17 mm), with the Maxbotix sensor exhibiting the lowest mean error (0.17 mm). While both the Decentlab and Maxbotix sensors exhibited instances of under- and over-estimation of water level, the Milesight sensor consistently over-estimated water level, indicating a systematic positive bias.

It should be noted that these results describe relative sensor performance under controlled laboratory conditions; the measurements do not constitute an absolute calibration or certification of sensor accuracy against a formal reference standard.

Dynamic water level performance

Only two sensors (Decentlab and Maxbotix) could be evaluated under dynamic (moving) water conditions. For both sensors, measurement precision decreased under dynamic conditions compared to static conditions, with variability increasing as pump frequency increased. Across all tested pump frequencies and water depths, the Decentlab sensor consistently exhibited higher precision and smaller measurement errors than the Maxbotix sensor.

Implications for deployment

These results indicate that LoRaWAN-based water-level sensors can provide highly precise measurements under stable conditions, but performance degrades in the presence of surface motion. Although measurements were obtained under laboratory-controlled conditions, the sensors demonstrated distinct relative strengths with respect to precision and measurement error.

In field environments, water bodies are routinely subject to dynamic conditions resulting from wind, rainfall, vegetation movement, animals, and debris. Both wave action and changing water levels may therefore simultaneously influence sensor performance. Consequently, sensor selection for field deployment should consider both measurement precision and measurement error.

In the context of flood management, measurement error — defined here as the difference between sensor-derived and true water level — is particularly important, as operational decisions such as road closures or pump activation are typically based on water depth thresholds. Sub-millimetre accuracy may therefore be less critical than reliable detection of water-level changes and sufficiently frequent measurement to capture the rate of change. Given that all sensors demonstrated dynamic precision of up to < 3.75 mm and measurement error < 3.00 mm under the tested pump frequencies (≤ 35 Hz), practical considerations such as sensor cost, ease of installation, maintenance requirements, communications reliability, and battery life may ultimately drive sensor choice (see Table 1). In real-world use, how frequently updated water-level data are available depends not only on sensor accuracy but also on how often sensors measure and transmit data via LoRaWAN, which was not evaluated in this laboratory study but may influence how quickly rising water levels are detected.

Differences were observed between the slurry flume and the T-tank under static conditions, with higher sensor precision recorded in the wider T-tank (Tables 2 & 3). This is likely attributable to edge effects associated with the width of the experimental equipment and the acoustic cone angle of the sensors, which determines the effective measurement footprint. Notably, the Milesight sensor could not be deployed in the narrow slurry flume due to its wide 60° cone angle.

In field deployments, the width of the zone of interest (e.g. rivers, roadways, storage basins) is likely to exceed the 0.3 m width of the slurry flume and may be wider or narrower than the 1.6 m T-tank. Sensor choice should therefore account for the spatial extent of the measurement area. For example, wide tanks, lakes, or ponds may be better suited to sensors with wider cone angles. Measurements may also be affected by field-based edge effects such as seasonal vegetation growth, debris transported during storm events, static infrastructure (e.g. road signs), or temporary moving objects (e.g. vehicles or pedestrians). These factors may result in falsely elevated readings or suppressed sensitivity to true water-level changes, such as when a sensor measures an obstructing object instead of the water surface.

Evidence gaps and scope limits

The results presented here are based on a limited set of static water depths and pump frequencies. Further evaluation under more complex flow regimes is recommended, alongside field-based deployments to assess performance under realistic operational conditions. Key factors warranting further investigation include battery efficiency over time, performance under varying weather and seasonal conditions, and application-specific contexts such as fluvial versus pluvial flood environments.

The Milesight sensor could not be evaluated under dynamic conditions within the laboratory set-up; consequently, no conclusions can be drawn regarding its dynamic performance. Additionally, sensor behaviour under partially obstructed measurement fields (e.g. asymmetric vegetation growth within the acoustic footprint) remains uncertain. Manufacturer guidance suggests that ultrasonic sensors should not be assumed to average all objects within the acoustic footprint. Instead, readings are influenced by how each sensor identifies a valid acoustic return. The MaxBotix sensor reports the largest acoustic return and gives preference to the closest target where reflections are similar, while Decentlab variants may detect either the first or largest detectable target. The Milesight sensor guidance confirms that reflections or obstructions within its wide 60° detection range may affect measurement, although its target-selection behaviour is not specified. As such, further testing is needed to determine how each sensor responds to vegetation, debris, channel edges or other partial obstructions under field conditions.

Environmental factors such as humidity and temperature may also influence measurement accuracy temporally and seasonally. While all sensors are designed to meet IP67 waterproofing standards and to operate under a range of environmental conditions (Table 1), their long-term performance under diverse field conditions remains an important area for future evaluation.

Conclusion

This study demonstrates that commercially available LoRaWAN-based ultrasonic water-level sensors can achieve sub-millimetre precision and small measurement errors under controlled static laboratory conditions once differences in sensor mounting height are accounted for. Sensor performance degraded under dynamic conditions, with increased measurement variability in the presence of surface motion. Of the two sensors tested under dynamic conditions, the Decentlab sensor consistently exhibited lower variability and smaller errors than the Maxbotix sensor across tested conditions. These findings provide a laboratory-based, relative performance baseline to inform sensor selection for surface-water flood monitoring, while recognising that real-world performance will also depend on site geometry, environmental complexity, and operational configuration. Further work is required to evaluate sensor performance under field conditions.

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