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"SMART WETLAND" – WHERE TRADITIONAL MANAGEMENT MEETS INNOVATION & TECHNOLOGY

Technical Report on Internet of Things (IoT) Application for Wetland Conservation in Mai Po Nature Reserve

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Abbreviations

AFCD	Agriculture, Fisheries and Conservation Department
AWS	Amazon Web Services
BMZ	Biodiversity Management Zone
CCFS	Country Conservation Funding Scheme
CCO	Countryside Conservation Office
CEPA	Community Engagement, Participation, and Awareness
CMS	Central Management System
DTM	Digital Terrain Model
DO	Dissolved Oxygen
EC	Education Centre
EEB	Environment and Ecology Bureau
EMSD	Electrical and Mechanical Services Department
GPS	Global Positioning System
GW	*gei wai*
GWIN	Government-Wide IoT Network
IoT	Internet of Things
LiDAR	Light Detection and Ranging
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
MPNR	Mai Po Nature Reserve
NH	Northern Hide (i.e. Floating Hide #1)
PSFSC	Peter Scott Field Studies Centre
RSSI	Received Signal Strength Indicator
SNR	Signal-to-Noise Ratio
WWF	World Wide Fund for Nature

Report citation

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Executive summary

This technical report documents the implementation and evaluation of an IoT (Internet of Things) system deployed to enhance habitat monitoring and management in Mai Po Nature Reserve. The project, undertaken by the World Wide Fund for Nature Hong Kong, aimed to leverage advanced sensor technologies and data analytics to improve decision-making and optimise resource allocation for wetland conservation efforts.

The IoT system comprised a network of environmental sensors strategically placed across the wetland, capturing near real-time data on water level, water quality, and buffalo movement. The collected data was integrated with a centralised cloud platform, enabling wetland managers to access comprehensive insights and make more informed decisions. The field performance of the IoT system was successful. The evaluation of the IoT system's performance demonstrated its effectiveness in improving data-driven decision-making, enhancing early threat detection, and optimising field operations. Additionally, the novel data collected through the IoT deployment has the potential to contribute to research and knowledge-sharing in the field of wetland conservation.

The findings and lessons learnt from this project have significant implications for wetland managers, aquaculture operators, and other conservation stakeholders interested in leveraging IoT technologies to improve habitat monitoring and management practices. The report provides recommendations for future IoT deployments in similar wetland environments, highlighting the scalability and replicability of this approach.

1. Introduction

Wetlands play a vital role in maintaining ecological balance, providing essential habitats for diverse flora and fauna, and supporting the livelihoods of local communities. However, these fragile ecosystems face numerous threats, including habitat degradation, pollution, and the impacts of climate change. Effective management and proactive conservation of wetlands have become increasingly crucial to ensuring the long-term sustainability of these valuable natural resources.

For over 40 years, the World Wide Fund for Nature Hong Kong (WWF-Hong Kong) has been at the forefront of wetland conservation efforts, working closely with local stakeholders to develop and implement strategies that address the complex challenges faced by these environments. In December 2022, WWF-Hong Kong launched the "Smart Wetlands" initiative, exploring I&T solutions for efficient wetland management. Under the initiative, a two-year project namely "Smart Wetland – Where Traditional Management Meets Innovation and Technology" has started and is funded through the Countryside Conservation Funding Scheme (CCFS), managed by the Countryside Conservation Office (CCO) under the Environment and Ecology Bureau (EEB). WWF-Hong Kong has undertaken this project to explore the potential of Internet of Things (IoT) technologies in enhancing habitat monitoring and management practices within a targeted wetland site.

The IoT represents a cutting-edge technology in which everyday items are equipped with miniature computers, wireless communication components and sophisticated networking protocols, enabling seamless machine-to-machine dialogue while simultaneously integrating human users as integral parts of the Internet. It has revolutionised the modern world by spanning different aspects, such as smart cities, healthcare and agriculture (Hammi et al., 2018; Shahab, 2024). It has transformed how users interact with applications, offering advanced networking and interfaces. Long Range (LoRa) technology is a physical layer of communication stack, with Long Range Wide Area Network (LoRaWAN) defining its higher-level functions. The energy efficiency of the technology, coupled with wide coverage, positions it as a leading contender for IoT applications.

Our project began with identifying the shortcomings of current habitat management practices. We also consulted wetland stakeholders and the innovation & technology sector, followed by designing the IoT system architecture and layout and selecting the hardware and software necessary for building the system prototype. The design and implementation of the IoT system, leveraging LoRa technology, were executed, including the establishment and testing of connections between various sensors, and the LoRa system components such as the gateway, power supply, and IoT cloud. After the installation of the hardware, software development and central management system (CMS) design were carried out to facilitate management tasks. Subsequently, the design was reviewed to ensure the system's functionality and identify potential issues. If any problems arose, the project would revert to the earlier phase for enhancement and optimisation. The IoT system development stage was considered complete once it exhibited robust performance. Finally, practical implementation and system performance evaluation were conducted to validate its effectiveness in improving habitat management. The timeline and key milestones are shown in Appendix A.

Three IoT applications are studied in this project, including water level monitoring, water quality monitoring and buffalo tracking. Water level control is essential for maintaining suitable habitats for waterbirds, as they prefer areas with shallow water mixed with bare mud or sand. Different shorebird species have varying preferences for water depth based on their leg length. IoT water level monitoring can optimise conditions for these birds by synchronising water levels with migratory and wintering seasons. By matching water level data from IoT applications with bird data at Mai Po Nature Reserve (MPNR), managers can quickly adjust any suboptimal levels, ensuring the ponds remain suitable for waterbirds. Additionally, water quality is vital for wetland productivity, especially in shrimp-farming *gei wai* (Ghosh, 2019) and IoT can help monitor water quality remotely. Data collected over time enable managers to make informed decisions about water exchanges. Furthermore, IoT tracking of buffalo provides insights into their grazing patterns and impacts on vegetation (Kaszta et al., 2016). This data could assist in evaluating the grazing effort of buffalo needed to maintain open wetland landscapes and shed light on how buffalo management can be applied to other wetland sites beyond Mai Po Nature Reserve. Through a real-time, remote IoT monitoring system, we aim to achieve better resource management and allocate manpower more effectively to managerial tasks.

This technical report presents the findings and insights from the trial IoT system deployed in MPNR. The primary objectives of this project are to:

1. Develop and integrate an IoT-based monitoring system to gather near real-time data on various environmental parameters and habitat conditions.
2. Assess the performance and effectiveness of the IoT system in supporting wetland managers' decision-making processes and conservation efforts.
3. Evaluate the potential for scalability and replication of the IoT approach in other wetland sites, providing recommendations for future deployments.

The target audience of this report includes researchers and experts in IoT and environmental monitoring, as well as wetland managers, aquaculture operators, and other conservation stakeholders interested in leveraging emerging technologies to improve their habitat management practices.

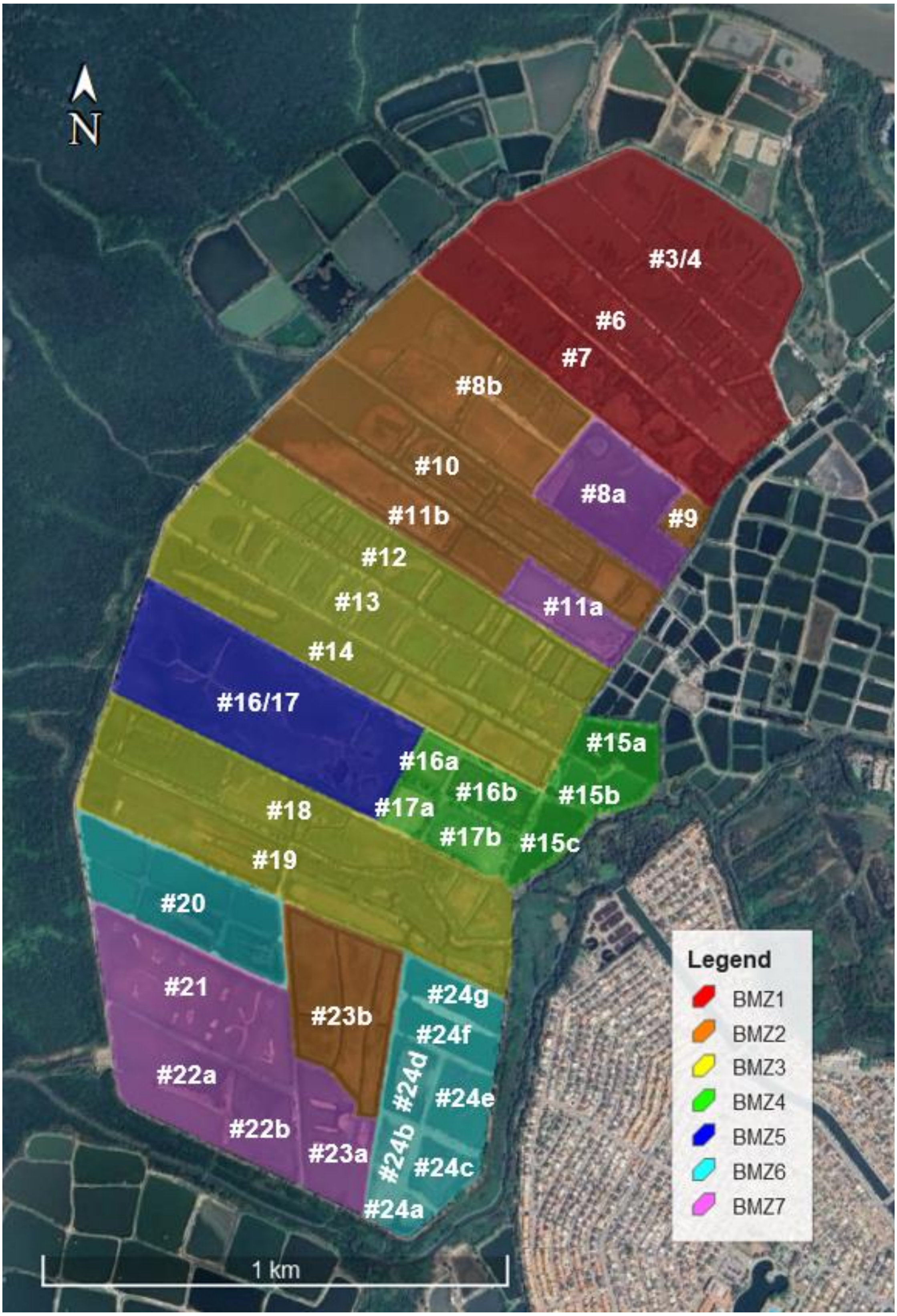
2. Site description

The MPNR is part of the Mai Po Inner Deep Bay Ramsar Site, located in the Northwest New Territories of the Hong Kong Special Administrative Region, along the southern bank of the Pearl River estuary. The MPNR comprises the *gei wai* that form the Biodiversity Management Zones (BMZs) (Figure 1; WWF-Hong Kong, 2024). The seven BMZs are managed primarily as shallow and deep open water areas, reedbed-dominated ponds, rain-fed ponds, and traditionally managed *gei wai* to provide a range of habitats for waterbirds and wetland-dependent species and their conservation. The functions of BMZs are described in Table 1.

Table 1. The function of the seven BMZs in MPNR (WWF-Hong Kong, 2024)

BMZ	Functions
BMZ1: GW #3, GW #4, GW #6, GW #7	Maintained as an open water area to benefit overwintering populations of black-faced spoonbills and ducks.
BMZ2: GW #8b, GW #9, GW #10, GW #11b, Pond #23b	Maintained as a reedbed habitat, with a range of water depths, for reedbed-associated passerine, bitterns, and herons.
BMZ3: GW #12, GW #13, GW #14, GW #18, GW #19	Maintained as traditionally operated brackish water *gei wai* for the benefit of black-faced spoonbills, egrets and herons, providing winter feeding habitats.
BMZ4: Pond #15a-c, Pond #16a-b, Pond #17a-b	Maintained as a series of rain-fed ponds to facilitate the implementation of education programmes.
BMZ5: GW #16/17	Maintained as shallow water high-tide roosting areas with islands for the benefit of passage and wintering shorebirds and other waterbirds, particularly roosting black-faced spoonbills and ducks.
BMZ6: Pond # 20, Pond #24a-g	Maintained as open rain-fed marshes or ponds with contouring and variable water depths, and/or for buffalo grazing.
BMZ7: GW #8a, GW #11a, GW #21, GW #22, GW #23a	Maintained as a shallow water high-tide roosting area as an alternative to BMZ5.

Figure 1. Biodiversity Management Zones in MPNR following Mai Po Nature Reserve Management Plan: 2019-2024



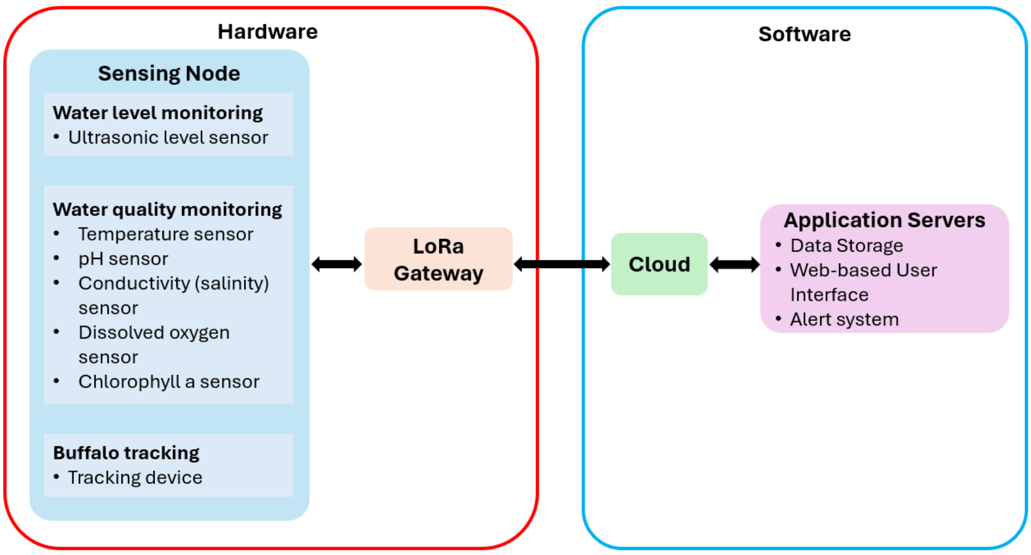
3. IoT system architecture

The IoT system architecture can be divided into hardware and software. The hardware components include tracking devices, ultrasonic level sensors, and all-in-one sensing units encompassing temperature sensors, pH sensors, conductivity (salinity) sensors, dissolved oxygen sensors and chlorophyll a sensors, 923 MHz LoRa gateway (Figure 2). Both solar panels and battery-powered mechanisms are involved in the system, subject to the type of applications. LoRa gateways are installed and maintained by the Electrical and Mechanical Services Department (EMSD) of Hong Kong.

Figure 2. Hardware - water level sensor, water quality sensors, buffalo tracker and LoRa gateway

The software components include application servers and data storage. The overall IoT system architecture is illustrated in Figure 3.

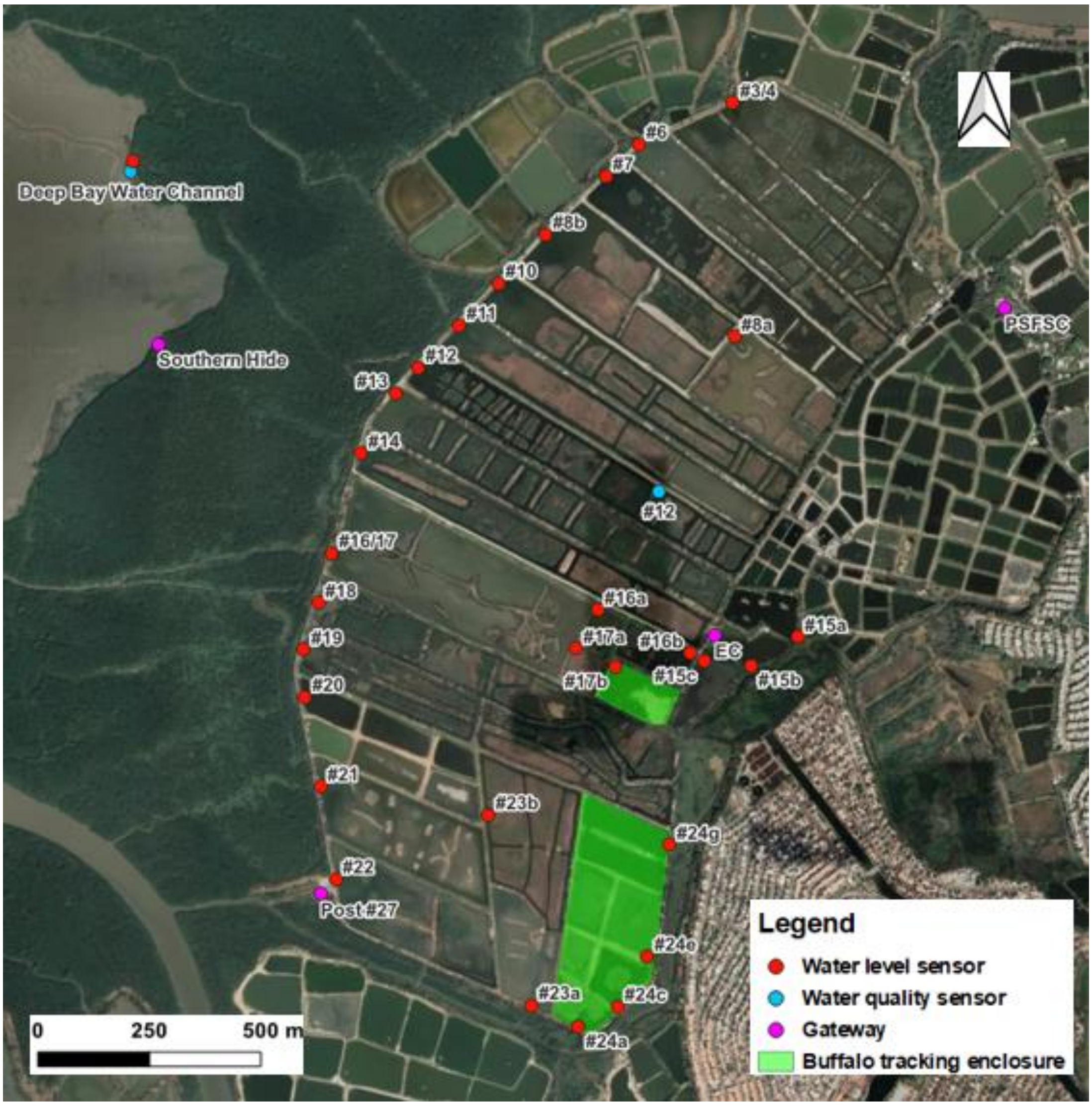
Figure 3. Overall IoT System Architecture



3.1. Hardware

The hardware system comprises 4 LoRa gateways, 30 water level sensors, 2 sets of water quality sensors, and 2 buffalo tracking devices. The ultrasonic water level sensor monitored the water level of *gei wai* and ponds. The water quality sensors monitored water temperature, pH, salinity, dissolved oxygen and chlorophyll a of *gei wai* and Deep Bay water channel. The buffalo trackers monitored the buffaloes' location within MPNR. Sensors, LoRa gateway and supporting infrastructure were installed in designated sites in MPNR shown in Figure 4.

Figure 4. Location of the gateways and 34 sensors



LoRa gateways

The LoRa gateways facilitate data transmission from the sensing nodes to the Cloud. Due to the size of MPNR and limited internet access coverage, LoRa has been adopted for data transmission. The data is transmitted from the sensor units through the gateways to an IoT cloud platform for secure data storage and management.

The technology offers several benefits that make it well-suited for wireless data transmission in IoT applications. Its long-range capabilities allow data to be transmitted over a distance, making it ideal for vast rural areas. Furthermore, LoRa's efficient power consumption extends the battery life of battery-powered devices. LoRa data transmission also ensures the confidentiality and integrity of the data through secure protocols. This technology uses multi-symbol data formats and chirp spread spectrum (CSS) modulation for reliable data encoding and transmission. Depending on the region, LoRa may utilise different frequency bands.

With support from the Electrical and Mechanical Services Department (EMSD), four Government-Wide IoT Network (GWIN) LoRa gateways were installed in four sites within MPNR: Mai Po Marshes Wildlife Education Centre (EC), Southern Hide (as known as Floating Hide #1), Peter Scott Field Studies Centre (PSFSC) and at the top of the tower at post #27, which can provide high elevation points with minimum blockage (Figure 5). The sensors installed at MPNR are connected to gateways via the low-power and private LoRa network and eventually connected back to the GWIN backend via the 5G network. Besides the four installed ones, other GWIN gateways near MPNR can further secure data transmission.

Figure 5. On-site deployment of LoRa gateway

Water level sensors

The monitoring nodes of water level sensors sent packets constituting water level, battery voltage, Received Signal Strength Indicator (RSSI) and Signal-to-Noise Ratio (SNR). The specifications of water level sensors are summarised in Table 2. To seek a balance between the requirement of more frequent data retrieval from those water level-sensitive *gei wai*/ponds and the resources needed for sensor battery replacement, three different measurement intervals were set for the ultrasonic level sensors (Table 2). 30 water level sensors were deployed at various locations to cover all monitoring targets (i.e. *gei wai*, ponds and Deep Bay mudflat). Supporting infrastructure was also installed when needed. For instance, the extension of frames was installed so that the water level sensors could operate directly above the water (Figure 6).

Table 2. Details of water level sensor

Model	**Power source**	**Specification**	**Measurement intervals***
Decentlab DL-MBX-001	Battery	Measurement range: 0.5 – 10m Resolution: 1mm Accuracy: 1% Expected battery life: ~3.5 years (10-minute interval)	10 minutes: GW #7, GW #8a, GW #11, GW #16/17, GW #21, GW #22, GW #23a and water channel near NH 20 minutes: GW #3/4, GW #6, GW #8b, GW #10, GW #12, GW #13, GW #14, GW #18 and GW #19 30 minutes: Pond #15a, Pond #15b, Pond #15c, Pond #16a, Pond #16b, Pond #17a, Pond #17b, Pond #20, Pond #23b, Pond #24c, Pond #24e and Pond #24g

*During the initial deployment stage, a 10-minute measurement was applied for all sensors for testing. Also, measurement intervals of Pond #16a and Pond #17a were changed from 30 minutes to 10 minutes due to the paddy field trial.

Figure 6. On-site deployment of water level sensor

Water quality sensors

The monitoring nodes of water quality sensors sent packets containing temperature, pH, salinity, dissolved oxygen concentration, chlorophyll a, and battery voltage. RSSI and SNR were not included due to the limited space in the packets. The specifications of water quality sensors are summarised in Table 3. A measurement interval of 60 minutes was set for both sensors installed at GW #12 and the water channel near NH. Infrastructures were set to ensure that the sensors could submerge under water and that sufficient solar energy could be received (Figure 7).

Table 3. Details of water quality sensors

Model	**Power source**	**Specification**
In-Situ Aqua TROLL 500	Solar power	Temperature sensor Measurement range: -5 - 50 °C Resolution: 0.01 °C Accuracy: ± 0.1 °C Expected battery life: N.A. *pH sensor* Measurement range: 0 - 14 pH Resolution: 0.01 pH Accuracy: ± 0.1 pH Expected battery life: N.A. *Conductivity sensor* Measurement range: 0 - 50 ppt Resolution: 0.1 ppt Accuracy: ± 0.5 % Expected battery life: N.A.

Model	Power source	Specification
		Dissolved oxygen sensor Measurement range: 0 - 20 mg/L Resolution: 0.01 mg/L Accuracy: ± 0.1 mg/L Expected battery life: N.A. *Chlorophyll a sensor* Measurement range: 0 - 1000 µg/L Resolution: 0.001 RFU Accuracy: N.A. Expected battery life: N.A.

Figure 7. On-site deployment of water quality sensor

Buffalo trackers

The trackers' monitoring nodes sent packets constituting latitude, longitude, RSSI, SNR, and battery voltage. Details of the buffalo trackers can be found in Table 4. Both trackers were designed to be attached to the collar and deployed on buffalo at Pond #17b and Pond #24 (Figure 8), with a measurement interval of 20 minutes. In addition, geofencing was applied to pinpoint the buffalo's location within the enclosures.

Table 4. Details of buffalo trackers

Model	Power source	Specification
Digital Matter Oyster3 LoRaWAN	Battery	Accuracy: ~1m 2D RMS Expected battery life: ~2 years (60-minute interval)

Figure 8. On-site deployment of buffalo tracker

3.2. Software

The Central Management System (CMS) is a network appliance that provides real-time centralised management information. Together with the database, it is hosted in a cloud operated by Amazon Web Services (AWS). The primary database is backed up to the secondary database every 2 minutes and data is kept for at least 7 years.

The CMS was developed based on management requirements (Table 5). The platform would facilitate end users, mostly the wetland managers and field technicians, to effectively monitor the status of target applications and remotely control the settings of the sensors (Figure 9). Export of data is also feasible for data analysis. An action response plan was also developed to define the actions required to respond to alerts triggered. For alerts concerning the water level, threshold levels were determined based on previous observation and experience. Different threshold ranges (i.e. 2.5 cm or 5 cm) were applied, subject to the nature of the *gei wai* or pond. For instance, *gei wai* serving as a high-tide roost for shorebirds would have a narrower threshold range. For alerts concerning the water quality, threshold levels were determined using the 10-year 90th percentile of the parameter. For alerts concerning buffalo tracking, a geofence was established according to the location of the enclosure and alerts were triggered when the tracker was out of the geofence.

There are 6 major elements in CMS and user types can be broadly divided into privileged users and view-only users with different user rights. The functions of each element are listed in Table 6.

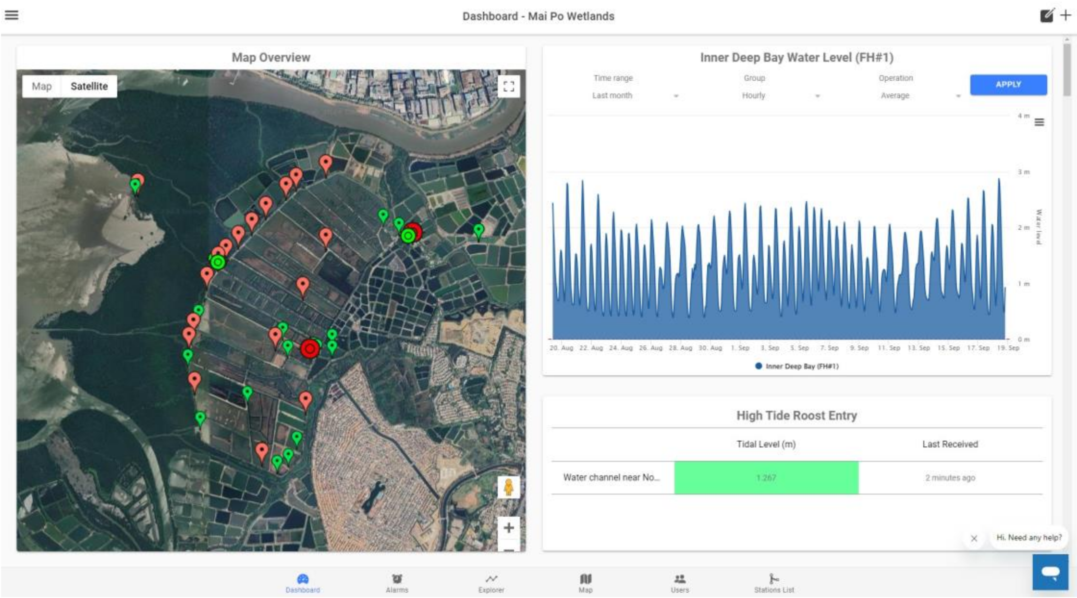
Table 5. Management requirements for the CMS

Requirement	Description
Visualisation	• Overview of parameters of different types of sensor in numeral format • Graphical display of the parameters • Latest battery reading of all sensors • Map of MPNR. Allow selection of devices being displayed • Notice board of alert and notification • Data refresh capability • Display in both traditional Chinese and English
Functionality	• Create user hierarchy with different user rights • Data review with filter and facet function • Data export in excel format • Admin user to rename each sensor
Alert and Notification	• Customizable alert settings for all sensors based on the aim of each application • Selection of media to receive alert, e.g. SMS or email notification

Table 6. Major elements of CMS and their functions

Elements	Function
Dashboard	Privileged users can create and modify the dashboard with different panels, e.g. Chart, Digital board and real-time table. View-only users can view the dashboard created by the privileged user.
Alarms	Privileged users can create and modify alerts with specified rules and selected preferred notification methods. View-only users can view the alert status of sensors.
Explorer	All users can retrieve a selected range of historical data and view it in a chart or export it to a spreadsheet for further manipulation.
Map	All users can check the location of each installed sensor through a map.
Users	Privileged users can create a user hierarchy and modify permission levels for any user.
Stations List	Privileged users can modify the information of each sensor. View-only users can check the information of each sensor.

Figure 9. Visualisation of the CMS



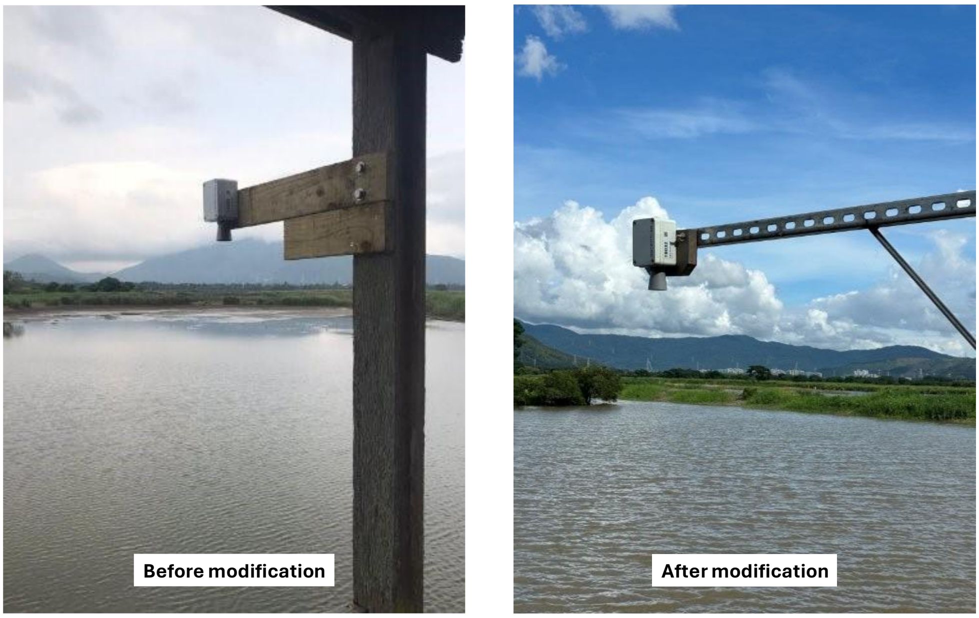
4. Field challenge and lesson learnt from sensor deployment

<u>Deployment phase</u>

Water level monitoring

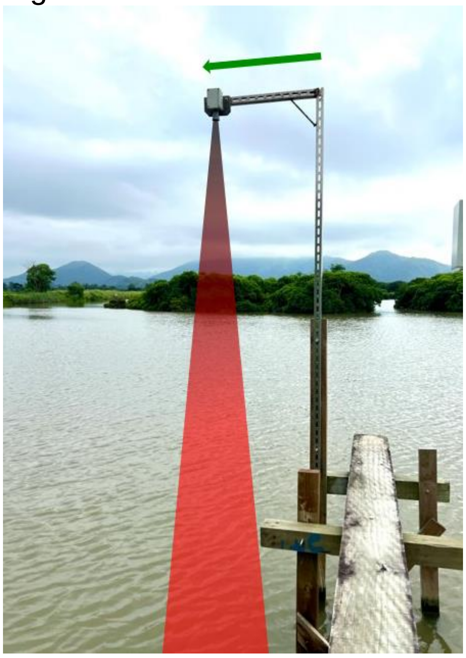
Initially, the water level sensor installation incorporated wood as the design material for the horizontal supports. However, after installing the first batch of sensors, we noted that wood is prone to thermal expansion and cold contraction, which can compromise measurement stability. Consequently, we replaced the wood with stainless steel for the horizontal supports (Figure 10).

Figure 10. Water level sensor and its supporting infrastructure before and after replacing supporting materials



In the original design, the length of the horizontal supports for many sensors was insufficient, leading to occasional inaccurate water level readings. Some measurements reflected obstacles along the sensor's projection path rather than the water surface. To tackle this issue, we extended some horizontal supports, considering the umbrella-shaped signal projection from the sensors (Figure 11).

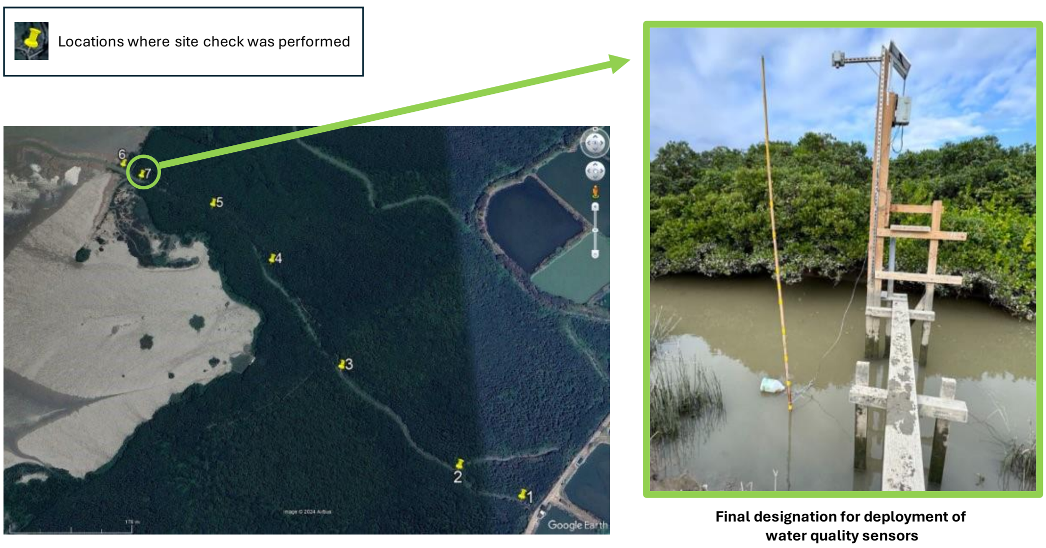
Figure 11. Extension of horizontal support



Water quality monitoring

The tidal movement would significantly affect the water quality sensors in the water channel near the NH. To ensure consistent data collection, a thorough site assessment was conducted during low tide (Figure 12). Seven locations were observed to identify optimal deployment locations where the sensors would remain submerged even at the lowest water levels. The careful selection of these sites is crucial for maintaining continuous monitoring capabilities throughout tidal cycles.

Figure 12. Site check at water channel along the Frontier Closed Area during low tide



Final designation for deployment of water quality sensors

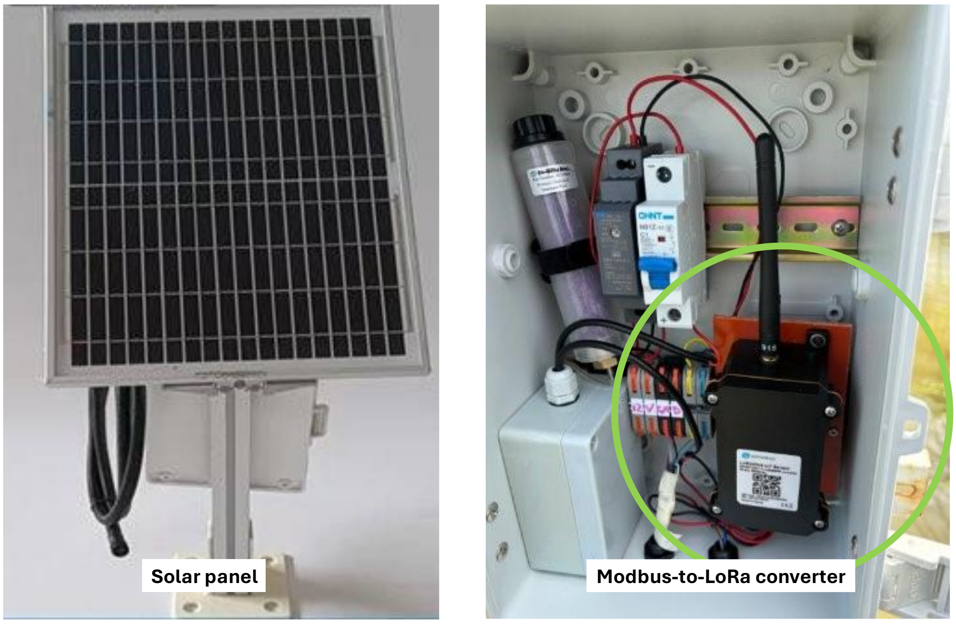
We customised a buoyage solution to address the dual challenges of submerging the sensors while preventing contact with the muddy bottom. This design involves attaching a floatation to the sensors (Figure 13). The buoyage system allows the sensor to stay underwater for accurate readings while avoiding interference from bottom sediments. This approach enhances data reliability and protects the sensitive sensors from potential damage from being exposed.

Figure 13. Design of buoyant set-up

Given the absence of conventional power infrastructure in the *gei wai* and mudflat areas, we've adopted a sustainable energy approach. Solar panels have been installed to generate electricity for our monitoring equipment (Figure 14). This renewable energy solution provides a reliable power source (Jabbar et al., 2024). The solar setup is designed to ensure continuous operation of the sensors and Modbus-to-LoRa converter, even in these remote locations, while minimising our ecological footprint.

The water quality sensors utilize Modbus RS-485 protocol, which is not compatible with LoRa technology, for data communication. To integrate these sensors into our LoRa-based network, we implemented a Modbus-to-LoRa converter (Figure 14). This crucial piece of hardware acts as a bridge between the two communication protocols, enabling seamless data transfer from the sensors to our long-range, low-power network infrastructure.

Figure 14. Solar panel and Modbus-to-LoRa converter for the water quality monitoring system



Buffalo tracking

During the initial phase of deploying the buffalo tracker, we faced significant challenges in attaching the device to the collar and securely fastening it to the buffalo. Several attachment methods did not succeed, and each attempt required close coordination and assistance from the AFCD cattle team. Ultimately, we developed a custom plastic platform that effectively secures the tracker to the buffalo (Figure 15).

Figure 15. Trials of collar and tracker housing method

First trial
(Result: unsuccessful)

Second trial
(Result: unsuccessful)

Third trial
(Result: successful)

Data collection phase

Water level monitoring

A recurring challenge was the sensor's transmission head obstructed by insect netting. This interference compromised data accuracy, as the netting impeded the sensor's ability to take clear readings. Hence, we implemented inspections once the abnormal reading was received. When insect netting was found, sensor heads would be cleaned to maintain the transmission pathway unobstructed.

The vegetation emergence at the water surface detectable by our sensors can lead to inaccurate water level readings by physically obstructing the sensor's measurement mechanism. Hence, we implemented inspections once the abnormal reading was received. When blockage by vegetation was found, maintenance would be conducted.

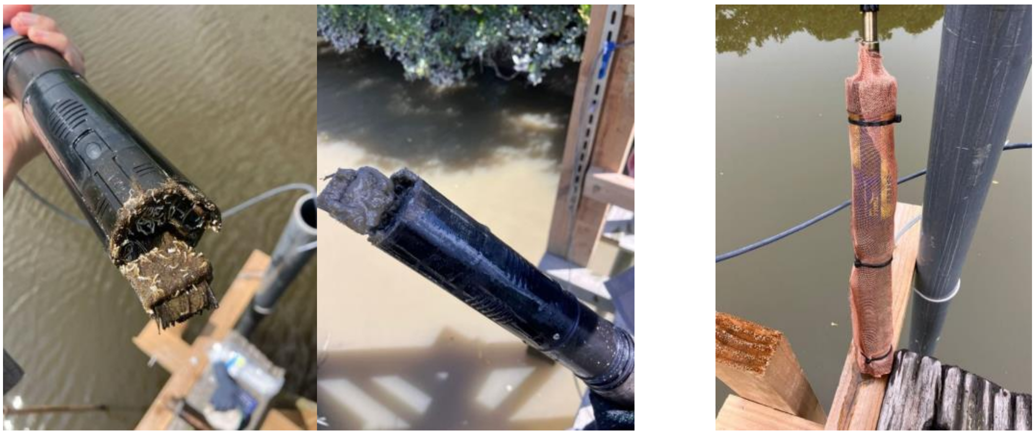
Water quality monitoring

The waterproof box containing the equipment for the water quality sensor was discovered to be damaged a few months post-deployment. It is believed that high pressure inside the box during hot weather may have caused the failure. Modifications were implemented to the waterproof box where an exhaust hole was made to alleviate internal pressure (Figure 16).

Figure 16. Waterproof box with exhaust hole

Biofouling on the sensor can severely compromise measurement accuracy and even sensor conditions. To mitigate this issue, we encased the sensors in copper mesh. Copper's natural anti-fouling properties help deter the growth of organisms on the sensor surface (Figure 17).

Figure 17. Water quality sensors before and after maintenance



Before maintenance **After maintenance**

The sensors installed in the water channel near NH would become exposed to air during extreme low tides. This exposure compromises data collection and potentially affects sensor integrity. We extended the sensor cable and allowed for deeper placement in the channel, maximising submersion time. Despite these efforts, the entire avoidance of air exposure during certain low-tide events remained unachievable. This limitation highlights the complex nature of estuarine monitoring and underscores the need to review deployment locations to ensure continuous data collection in highly dynamic tidal environments.

Buffalo tracking

Data was found absent when the buffalo were mostly submerged in water. This occurred more often during the summer months. The LoRa technology exhibited limited penetration power in these conditions. There is no applicable solution at this moment. It may be worthwhile to explore alternative tracking devices such as those attached to the buffalo’s ear or horn.

5. Evaluation of IoT system performance

Evaluation criteria can be broadly defined as (1) field performance of the IoT system, (2) facilitation for management and (3) novelty of data. Details of each are elaborated as follows.

5.1. Evaluation criteria

<u>Field performance of the IoT system</u>

- Data Accuracy

  An accuracy test was conducted before deployment.

  - ❖ Water level monitoring: sensors were calibrated using a Global Navigation Satellite System (GNSS) device. Data from the water level sensor would be cross-referenced with readings from another brand of sensor installed at the same site during standard and drained levels. The mean ± standard deviation of the differences would indicate the sensor's accuracy.

  - ❖ Water quality monitoring: Data from the water quality sensor would be compared to readings from a different sensor brand simultaneously deployed in the field. The difference between the two would serve as a reference for accuracy. Regular calibration of the sensors would occur according to the manufacturer's recommendations before and after deployment to ensure ongoing accuracy.

  - ❖ Buffalo tracking: A stationary test of the tracking device was conducted in an open area and under the buffalo shelter, with the accuracy determined by calculating the mean ± standard deviation of the location error from the actual location.

- Battery Life

  The actual battery life observed would be documented and compared against the manufacturer's claimed lifespan by recording any battery replacements during the project.

- Data Reliability

  The number of data points received during the data collection period would be compared to the predetermined frequency. Fix success rate is calculated by dividing the number of successful fixes without duplicates by the expected number of data collected during the sensor deployment period. False data that does not reflect the actual status, such as spikes, was further filtered out to calculate the accuracy rate. Duplicates refer to consecutive data entries that overlap with the preceding entry within a brief time frame and contain identical readings. Spikes indicate an unusual surge in sensor readings. The frequency of data was also calculated as the mean of actual frequency to check if the data was sent according to the set frequency.

- Alerts Accuracy

Alerts would be reviewed to assess the IoT system's ability to inform wetland managers. The number of alerts generated by the IoT monitoring system and those discovered through manual checks would be recorded and categorised as follows:

- ❖ Basic Alert: The IoT system triggers alerts correctly.
- ❖ False Alert: The IoT system triggers alerts incorrectly.
- ❖ Missed Alert by Smart System: An alert is raised only by manual checking.
- ❖ Missed Alert by Manual Check: An alert is raised only by the smart system.
- ❖ Lagged Alert by Smart System: Both raise alerts, but the smart system has a time delay, which will be recorded.
- ❖ Lagged Alert by Manual Check: Both raise alerts, but manual checking has a delay, which will be noted.
- ❖ Early Detection of Abnormality: This will be reported as a percentage of early detections by the IoT system compared to all recorded abnormalities.

Manual checks include any discovery method by staff, with regular water level checking conducted by field personnel on non-water exchange days. Monthly water quality monitoring follows the Mai Po Management Plan 2019-2024, and visual inspections of the water buffalo occur at least twice a week. Alerts would be further scrutinised by filtering out false alerts such as sensor malfunction to access true alerts.

<u>Facilitation for management</u>

- Data frequency

Any increase in data collection frequency would be reported as a percentage increase by comparing manual checks with IoT data collection.

- Man-day

The inferred number of man-days that can be saved from regular patrol/monitoring assuming that the sensors are functioning properly was calculated.

- Data Usefulness

Data was further analysed to assess information useful for habitat management.

Water level monitoring

- ❖ Continual water level data allowed evaluation of the performance of water level management and effectively helped ensure the tasks were implemented as planned. Data collected by the IoT system was matched with planned tasks to ensure tasks were fulfilled.

- ❖ Night-time data was available to aid night-time water level management work. Any assistance made in this aspect was noted.

- ❖ Quantitative data allowed the study of habitat suitability to our conservation targets and evaluation of water level management effectiveness. Data was related to actual wildlife usage of the *gei wai*/ponds, particularly waterbirds given their sensitivity to water level and help explain changes in waterbird numbers.

- ❖ Instead of using qualitative terms, such as higher or lower water level, real-time quantitative data also helped to develop effective communication and review between external researchers, managers and field staff in managing the water level to deliver the most optimal level for research activity, particularly bird ringing which often occurred in early morning or late evening that is outside office hours. The suitable water level was explored with the ringing group leader regarding their observation.

Water quality monitoring

- ❖ Continual water quality data allowed evaluation of the performance of water quality. Also, instead of assuming water exchange was helpful, the effectiveness of water exchange in maintaining water quality would be assessed quantitatively for the first time by reviewing the change in water quality over time and before and after water exchange.

Buffalo tracking

- ❖ Area use pattern of the buffalo would be assessed to identify areas that may need additional habitat management work.

- Alert Usefulness

Alerts generated by the smart system would be evaluated for their usefulness concerning the intended goals. Following an alert, staff might decide on the necessity of a field check and any subsequent actions taken would be logged as part of management facilitation. An action response plan was developed to define a set of actions in response to alerts (Appendix C - E).

Novelty of data

- Comparison with Manual Monitoring Methods

  New information gathered from the IoT system compared to existing monitoring approaches would be considered new data.

  Water level monitoring

  ❖ Without the smart system, measurements were manually recorded on paper. The new insights generated through the smart system would be documented.

  Water quality monitoring

  ❖ Comparisons would be made with existing monthly monitoring data, highlighting any new findings.

  Buffalo tracking

  ❖ As buffalo locations were not previously monitored without the smart system, all tracking data gathered would be considered new.

- Exploration of Potential Research Avenues

  Potential future research implications based on the data collected were noted to expand application opportunities.

5.2. Evaluation result

Field performance of the IoT system

- Data Accuracy

Water level sensors and water quality sensors of different brands were used to validate the sensor accuracy under outdoor conditions. The comparison showed that the readings of the six parameters were within the acceptable range (Table 7).

Table 7. Accuracy analysis of water level, temperature, pH, salinity, dissolved oxygen and chlorophyll a value from the IoT system validating with different sensor brands

Parameters	Mean of difference ± SD	Min	Max
Water level (cm)	1.53 ± 3.66	0.00	6.10
Temperature (°C)	0.37 ± 0.06	0.31	0.41
pH	0.40 ± 0.25	0.25	0.68
Salinity (ppt)	0.09 ± 0.04	0.06	0.14
Dissolved oxygen (mg/L)	0.55 ± 0.04	0.53	0.59
Chlorophyll a (µg/L)*	4.26 ± NA	NA	NA

*For comparison of chlorophyll a, only the mean of the control sample was obtained from the laboratory.

Location error for all stationary tests (n = 2683) of buffalo tracker was 12.74 m ± 17.22 with 95% of errors ≤ 13.39 m. Errors were similar in sheltered and open conditions as shown in Table 8. All of them possessed a high fixed success rate (i.e. >80%).

Table 8. Result of stationary test of buffalo tracker recorded at fixed positions under sheltered condition (Shelter) and open condition (Open) in Pond #17b and Pond #24.

Location	Location error ± SD (m)	Actual data frequency	Expected data frequency	Fixed success rate (%)
Pond #17b -Shelter	13.83 ± 12.99	697	720	96.81
Pond #17b -Open	13.01 ± 24.38	692	720	96.11
Pond #24 -Shelter	11.10 ± 14.12	696	720	96.67
Pond #24 - Open	13.05 ± 14.50	598	720	83.06

- Battery Life

Water level monitoring

Over the 17-month data collection period, the battery levels of all 30 sensors did not drop below the cut-off voltage (2.6V) except the one from GW #14. The cut-off voltage was used to trigger low battery alerts to inform managers as an early warning. Yet, no battery replacement was required until they were drained out. The estimated battery life of water level sensors based on the actual power consumption for 10-min, 20-min and 30-min measurement intervals were 2.57 ± 0.18, 2.85 ± 0.67 and 3.34 ± 0.23 years respectively. All estimations were lower than the battery life claimed by the manufacturer, which is 3.5 years with a 10-minute interval using the longest signal range (i.e. Spreading Factor 12). Considering that no battery change was needed during the project period and the predicted battery life was over two years, the battery consumption was satisfactory.

Water quality monitoring

Over the 17-month data collection period, the batteries of the two deployed nodes did not drop below 11.6 V due to the solar top-up system, implying that the IoT water quality monitoring system could self-sustain in terms of power consumption (Figure 18 and Figure 19). On the other hand, a decline in voltage was observed in the set-up of the water channel near NH from 6th July 2023 to 17th August 2023, indicating a solar disconnection. The set-up was retrieved for troubleshooting. Possible reasons for the disconnection were solar panel malfunction and open solar circuit. The problem was resolved and the set-up resumed operation on 21st November 2024. Since then, the voltage showed no decline.

Figure 18. Battery voltage of water quality monitoring set-up at GW #12 across the data collection period

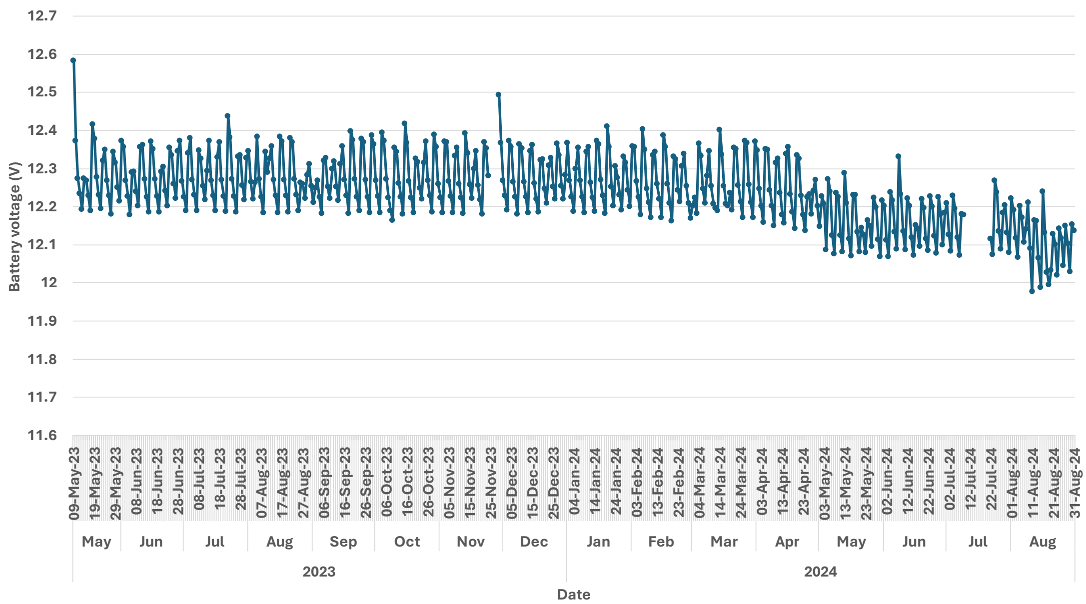
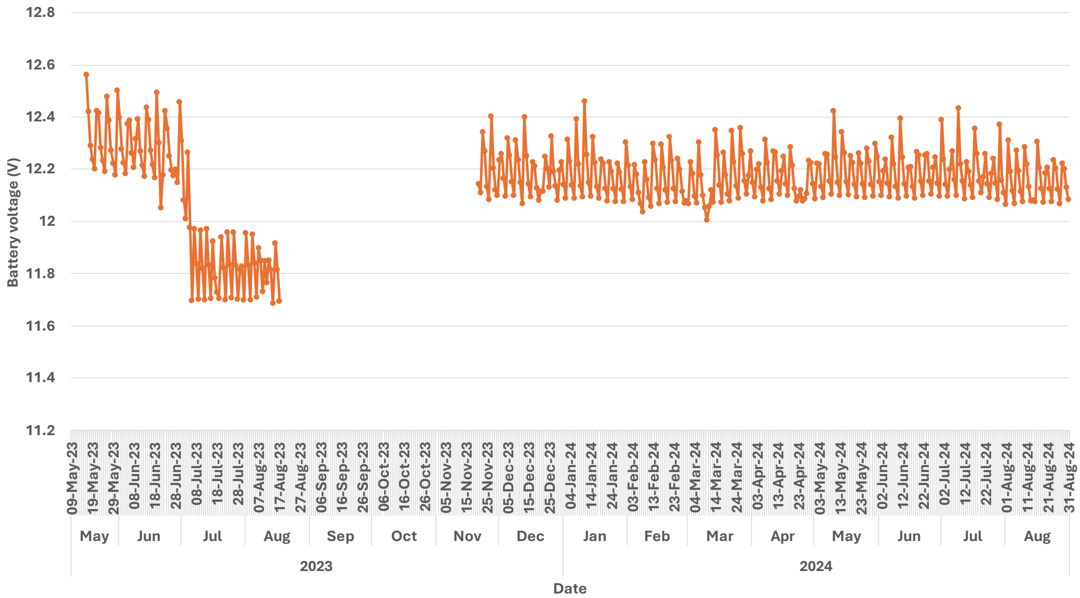


Figure 19. Battery voltage of water quality monitoring set-up at Deep Bay water channel across the data collection period



Buffalo tracking

For the tracker deployed in Pond #17b enclosure, the performance was satisfactory, with no significant decline observed in battery voltage (Figure 20). However, the tracker installed in Pond #24 enclosure started experiencing a voltage decline since its initial deployment and eventually stopped transmitting data in less than 3 months (Figure 21). The tracker was retrieved, and the manufacturer recommended using a different type of battery. As a result, the voltage profile for the second deployment of the tracker in Pond #24 differed from the first deployment, changing from ~11V to ~5.5V of initial battery voltage.

The revised tracker in Pond #24 continued transmitting data, exhibiting a more gradual decline in voltage over the six months. Such longer duration demonstrated an improvement in power consumption compared to the first deployment.

Figure 20. Battery voltage of Pond #17b tracking device across the data collection period

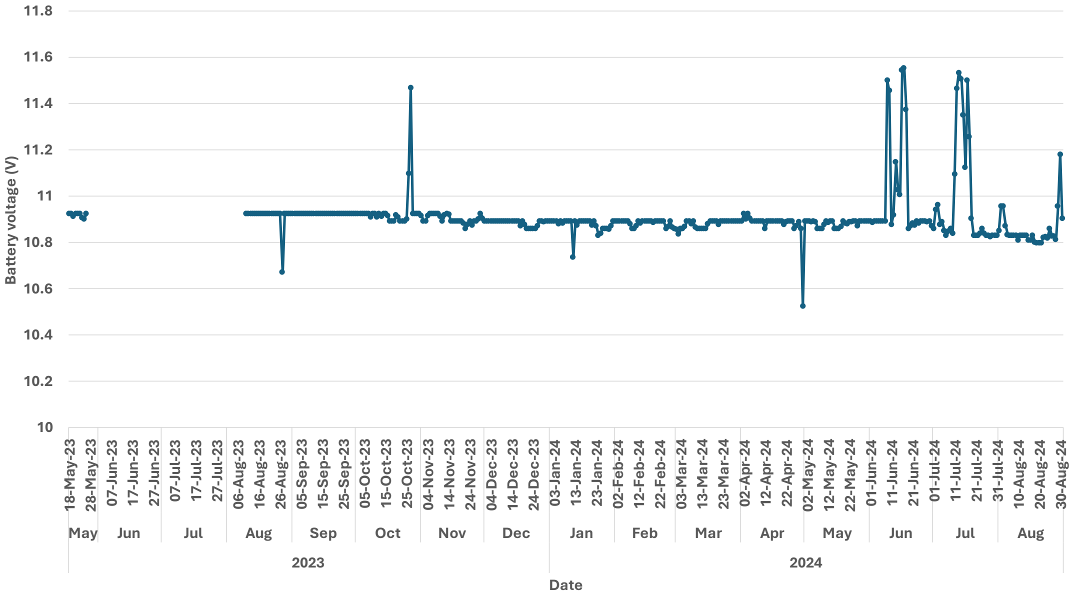
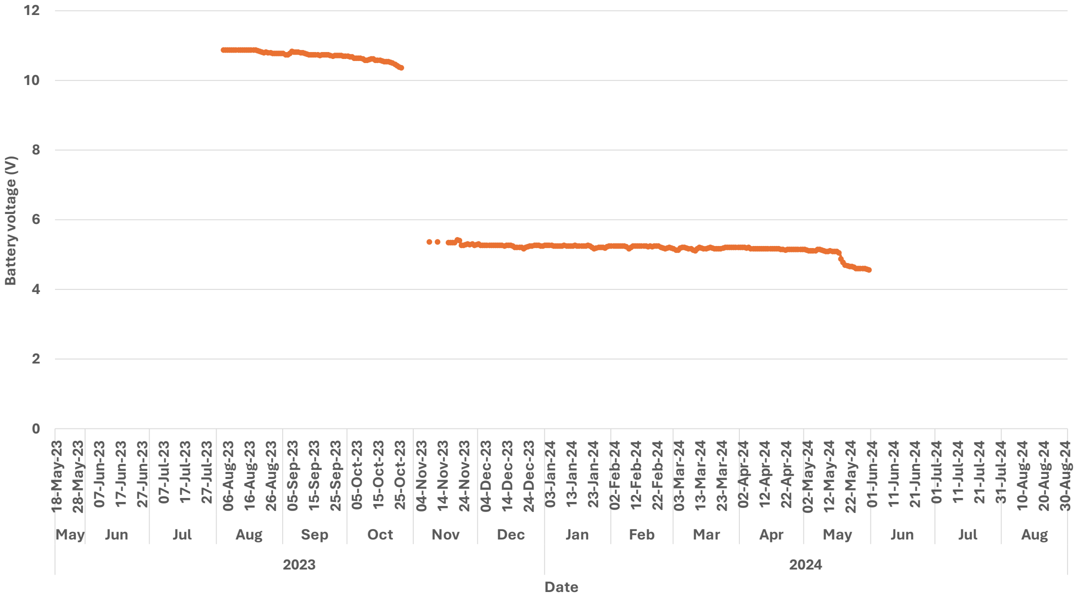


Figure 21. Battery voltage of Pond #24 tracking device across the data collection period



- Data Reliability

Water level monitoring

The 30 water level sensors generated 1,399,845 pieces of data during the data collection period. Duplicate data occurred intermittently throughout the project, with an average fix success rate of 90.81% ± 3.89% (Table 9). Data were further scrutinised by filtering out false data such as spikes and interference. The mean accuracy rate was determined to be 86.11% ± 7.49%. All sensors were transmitting data with the set measurement interval.

Table 9. Details of data collected from water level sensors

Measurement interval (min)	Location	Deployment date	Number of data collected	Fix success rate (%)	Accuracy rate (%)	Frequency of data ± SD (mm:ss)
10	GW #7	03-Apr-23	81,418	99.07	89.19	10:06 ± 02:51
	GW #8a	09-Nov-23	48,109	99.99	88.54	10:01 ± 02:26
	GW #11	03-Apr-23	86,115	100.05	85.79	10:00 ± 02:46
	GW #16/17	03-Apr-23	83,758	99.57	88.15	10:03 ± 02:54
	GW #21	03-Apr-23	86,797	99.93	82.73	10:01 ± 03:01
	GW #22	03-Apr-23	87,714	100.17	84.84	09:59 ± 02:54
	GW #23a	03-Apr-23	84,803	99.51	86.14	10:03 ± 03:35
	Water Channel near NH	04-May-23	71,119	99.46	96.50	10:42 ± 19:03
20	GW #3/4	03-Apr-23	39,355	99.20	99.23	20:10 ± 04:07
	GW #6	06-Apr-23	38,935	99.22	94.63	20:12 ± 04:08
	GW #8b	03-Apr-23	44,622	98.69	85.38	20:18 ± 05:12
	GW #10	03-Apr-23	44,838	106.40	82.51	20:05 ± 04:30
	GW #12	03-Apr-23	44,406	99.46	88.85	20:08 ± 11:01
	GW #13	03-Apr-23	44,650	100.04	81.87	20:00 ± 04:30
	GW #14	06-Apr-23	42,726	99.26	86.38	20:14 ± 04:52
	GW #18	03-Apr-23	44,671	99.60	76.54	20:09 ± 03:54
	GW #19	09-Nov-23	23,656	99.49	89.63	20:06 ± 04:34
	Pond #24a	03-Apr-23	41,111	97.42	94.01	20:34 ± 05:32
30	GW #20	03-Apr-23	29,987	96.62	88.03	31:16 ± 33:38
	Pond #15a	03-Apr-23	29,803	98.90	85.45	30:23 ± 07:44
	Pond #15b	03-Apr-23	30,464	98.41	90.85	30:35 ± 07:12
	Pond #15c	03-Apr-23	29,630	96.88	91.30	31:11 ± 11:30
	Pond #16a	03-Apr-23	33,955	95.88	82.65	31:57 ± 25:27
	Pond #16b	03-Apr-23	29,871	99.07	86.60	30:20 ± 06:01
	Pond #17a	03-Apr-23	31,027	92.90	89.43	33:21 ± 15:00
	Pond #17b	03-Apr-23	29,681	97.19	62.35	31:02 ± 11:09
	Pond #23b	26-Apr-23	29,475	107.60	84.27	30:02 ± 05:59
	Pond #24c	03-Apr-23	28,166	94.41	94.02	31:27 ± 11:53
	Pond #24e	03-Apr-23	29,789	98.42	92.42	30:33 ± 06:55
	Pond #24g	03-Apr-23	29,194	97.28	83.90	31:38 ± 12:00

Water quality monitoring

The 10 water quality sensors generated 101,697 pieces of data during the project period. Loss of water level data occurred intermittently throughout the project, with an average fix success rate of 96.03% ± 3.07% (Table 10). Data were further scrutinised by filtering out false data such as duplicates, spikes and interference. The accuracy rate was determined to be 86.59% ± 7.36%. All sensors were transmitting data with the set measurement interval.

Table 10. Details of data collected from water quality sensors

Location	Sensor	Deployment date	Number of data collected	Fix success rate (%)	Accuracy rate (%)	Frequency of data ± SD (hh:mm:ss)
GW #12	Temperature	9-May-23	11,710	98.53	93.27	1:00:58 ± 00:13:02
	pH	9-May-23	11,789	98.88	67.19	1:00:44 ± 00:12:39
	Salinity	9-May-23	11,756	98.47	90.99	1:00:59 ± 00:13:23
	DO	9-May-23	11,761	98.82	86.06	1:00:46 ± 00:13:16
	Chlorophyll a	9-May-23	11,715	98.53	92.48	1:00:57 ± 00:12:53
Water Channel near NH	Temperature	16-May-23	8,610	94.10	85.02	1:03:50 ± 00:34:59
	pH	16-May-23	8,569	93.89	87.40	1:03:58 ± 00:47:17
	Salinity	16-May-23	8,592	93.89	86.29	1:03:58 ± 00:49:15
	DO	16-May-23	8,599	93.85	87.87	1:03:59 ± 00:38:38
	Chlorophyll a	16-May-23	8,596	94.08	89.32	1:03:51 ± 00:44:09

Buffalo tracking

The 2 trackers generated 29,080 pieces of data during the project period. Collars were lost from the buffalo during the initial stage or found to malfunction. The average fix success rate was calculated to be 95.83% ± 0.59% (Table 11). The data was further scrutinised by filtering out false entries, such as duplicates, out-of-zone readings, and interference. The accuracy rate after this data cleansing process was 72.55% ± 4.84%. Additionally, intermittent loss of GPS data packets was observed throughout the project, resulting in all sensors transmitting data at a slightly lower frequency than the set measurement interval.

Table 11. Details of data collected from buffalo trackers

Deployment date	**Deployment date**	**Number of data collected**	**Fix success rate (%)**	**Accuracy rate (%)**	**Frequency of data ± SD (hh:mm:ss)**
Pond #17b enclosure	18-May-23	18,419	61.64	69.22	0:32:22 ± 0:48:44
Pond #24 enclosure	4-Aug-23	10,661	50.36	76.07	0:32:46 ± 0:32:17

- Alerts Accuracy

In total, 353 alerts were triggered. 243 alerts were generated from water level sensors, 58 from water quality sensors, and 52 from buffalo trackers. Among these 353 alerts, 248 were basic and all early alerts compared to manual checks. The remaining 105 alerts were falsely triggered (Table 12). Potential causes of false alerts include environmental factors, such as emerging vegetation obstructing the water surface detected by water level sensors and technical issues, like inaccurate GPS location readings from trackers. No alerts were missed or lagged by the IoT monitoring system.

Table 12. Alerts triggered by the IoT monitoring system during the data collection period

Application	Type	TRUE	FALSE
Water level monitoring	GW#10 HIGH WATER LEVEL ALERT (SUMMER)	11	0
	GW#10 HIGH WATER LEVEL ALERT (WINTER)	10	0
	GW#11 HIGH WATER LEVEL ALERT (SUMMER)	3	0
	GW#11 HIGH WATER LEVEL ALERT (WINTER)	24	0
	GW#12 HIGH WATER LEVEL ALERT (YEAR ROUND)	15	0
	GW#13 HIGH WATER LEVEL ALERT (YEAR ROUND)	10	0
	GW#14 HIGH WATER LEVEL ALERT (YEAR ROUND)	19	0
	GW#16_17 HIGH WATER LEVEL ALERT (WINTER)	15	0
	GW#18 HIGH WATER LEVEL ALERT (YEAR ROUND)	10	0
	GW#19 HIGH WATER LEVEL ALERT (YEAR ROUND)	9	0
	GW#21 HIGH WATER LEVEL ALERT (SUMMER)	13	0
	GW#21 HIGH WATER LEVEL ALERT (WINTER)	5	0
	GW#23A HIGH WATER LEVEL ALERT (SUMMER)	10	0
	GW#23A HIGH WATER LEVEL ALERT (WINTER)	12	0
	GW#3_4 HIGH WATER LEVEL ALERT (WINTER)	8	0
	GW#3_4 HIGH WATER LEVEL ALERT(SUMMER)	9	0
	GW#6 HIGH WATER LEVEL ALERT (SUMMER)	10	0
	GW#6 HIGH WATER LEVEL ALERT (WINTER)	12	0
	GW#7 HIGH WATER LEVEL ALERT (SUMMER)	5	0
	GW#7 HIGH WATER LEVEL ALERT (WINTER)	9	0
	GW#8A HIGH WATER LEVEL ALERT (SUMMER)	6	0
	GW#8B HIGH WATER LEVEL ALERT (YEAR ROUND)	8	0
	POND#17A FLOODING ALERT	1	3
	POND#24E FLOODING ALERT	1	0
	POND#16A FLOODING ALERT	0	2
	POND#24G FLOODING ALERT	0	2
	WL-#14 BATTERY LOW ALERT	1	0

Application	Type	TRUE	FALSE
Water quality monitoring	DEEP BAY CHANNEL HIGH PH ALERT	1	1
	DEEP BAY CHANNEL LOW DISSOLVED OXYGEN ALERT	1	15
	DEEP BAY CHANNEL LOW PH ALERT	0	3
	DEEP BAY CHANNEL LOW TEMPERATURE ALERT	0	7
	GW#12 HIGH PH ALERT	1	6
	GW#12 HIGH TEMPERATURE ALERT	3	0
	GW#12 LOW DISSOLVED OXYGEN ALERT	2	10
	GW#12 LOW PH ALERT	0	2
	GW#12 LOW TEMPERATURE ALERT	4	2
Buffalo tracking	BL-#17B(AH BO) GEOFENCING ALERT	0	43
	BL-#24 BATTERY LOW ALERT	0	1
	BL-#24(CLT) GEOFENCING ALERT	0	8
Total		248	105

<u>Facilitation for management</u>

- Data frequency

The IoT monitoring approach resulted in significant increases in data frequency across the three applications (Table 13):

❖ Water level monitoring experienced an average 26,612.87% ± 11,672.32% (SD) increase in data frequency compared to manual methods.

❖ Water quality monitoring experienced an average 51,637.06% ± 9,484.05% (SD) increase in data frequency.

❖ Buffalo tracking data frequency increased by an average of 3,154.89% ± 962.08% (SD).

Such increases in data availability could significantly enhance the depth of insights and decision-making capabilities for wetland management.

Table 13. Comparison of data collection frequency between manual monitoring and IoT monitoring

Application	Sensors	Manual frequency	IoT frequency	Percentage increase (%)
Water level monitoring	GW #3/4	213	38,983	18,201.88
	GW #6	230	36,824	15,910.43
	GW #7	173	72,614	41,873.41
	GW #8a	-	42,447	-
	GW #8b	230	37,529	16,216.96
	GW #10	230	36,975	15,976.09
	GW #11	230	73,853	32,010.00
	GW #12	223	39,455	17,592.83
	GW #13	135	36,557	26,979.26
	GW #14	205	36,907	17,903.41
	GW #16/17	201	73,824	36,628.36
	GW #18	156	34,191	21,817.31
	GW #19	136	21,203	15,490.44
	GW #20	-	26,397	-
	GW #21	212	71,579	33,663.68
	GW #22	140	74,411	53,050.71
	GW #23a	203	73,036	35,878.33
	Pond #15a	-	25,468	-
	Pond #15b	-	27,677	-
	Pond #15c	-	27,052	-
	Pond #16a	-	28,065	-
	Pond #16b	-	25,869	-
	Pond #17a	-	27,746	-
	Pond #17b	-	18,505	-
	Pond #23b	-	24,839	-
	Pond #24a	-	27,726	-
	Pond #24c	-	26,481	-
	Pond #24e	-	27,531	-
	Pond #24g	-	24,493	-
	Water Channel near NH	-	68,629	-
Water quality monitoring	GW #12: Temperature	17	10,922	64,147.06
	GW #12: pH	17	7,921	46,494.12
	GW #12: Salinity	17	10,697	62,823.53
	GW #12: Dissolved oxygen	17	10,122	59,441.18
	GW #12: Chlorophyll a	17	10,834	63,629.41
	Water Channel near NH: Temperature	17	7,320	42,958.82
	Water Channel near NH: pH	17	7,489	43,952.94

Application	Sensors	Manual frequency	IoT frequency	Percentage increase (%)
	Water Channel near NH: Salinity	17	7,414	43,511.76
	Water Channel near NH: Dissolved oxygen	17	7,556	44,347.06
	Water Channel near NH: Chlorophyll a	17	7,678	45,064.71
Buffalo tracking	Pond #17b enclosure	324	12,750	3,835.19
	Pond #24 enclosure	315	8,110	2,474.60

- Man-day

Significant increases in data frequency across the three applications compared to manual monitoring could be translated to significant numbers of man-days saved. Water quality has the highest percentage saved (Table 14) due to the lower man-day used for manual monitoring, where the monitoring frequency was once per month.

Table 14. Man-days saved across the three applications during the data collection period

Applications	Total man-day used for manual monitoring	Inferred man-day used for IoT monitoring	Man-day saved	Percentage saved (%)
Water level monitoring	23	4653	4630	20,130
Water quality monitoring	4	2868	2864	71,600
Buffalo tracking	37.5	960	922.5	2,460

- Data Usefulness

Water level monitoring

❖ Assessing the performance of water level management and fulfilment of tasks

Water levels across different *gei wai* are categorised into three ranges: optimal range, below optimal range and above optimal range. The percentage of time for each category is presented in Table 15. The highest time percentage of optimal water levels is observed in GW #6, followed by GW #16/17 and GW #3/4, indicating effective water level control in these *gei wai*. GW #23a shows an alarming 77.15% of the time where the water level fell below the optimal range. Other *gei wai* such as GW #8b and GW #13 also exhibit high time percentages of below-optimal levels, suggesting potential water leakage or evaporation. Prolonged low water levels may facilitate the growth of undesirable vegetation, reducing the availability of open water areas for waterbirds. The highest percentages of periods when the water level exceeds the optimal threshold are reported in GW #12 and GW #21, suggesting that the bird islands of these *gei wai* might not be beneficial to waterbirds.

The data collected from IoT sensors provides a comprehensive assessment of water level management across different *gei wai*, allowing for a detailed evaluation of the effectiveness of current practices. By analysing the percentages of periods where water levels fall in each category (i.e. optimal, below optimal, and above optimal), we can gain insights into the performance of MPNR as roosting sites for waterbirds.

This information is crucial for identifying specific *gei wai* that require immediate attention or intervention. For instance, the significant time percentage of above-optimal water levels in GW #21 was due to serious surface runoff adjacent to the sluice gate. Technician field staff intended to import more water from Deep Bay during water exchange to compromise the leakage caused by the runoff. The poor condition of the sluice gate indicates a pressing need for repair to improve water level control.

Table 15. Review of water level performance of *gei wai* during the data collection period excluding water exchange dates

Gei wai	**% of time that water level fell within optimal range**	**% of time that water level exceeded optimal range**	**% of time that water level fell below optimal range**
GW #3/4	60.55	12.87	26.58
GW #6	66.41	20.41	13.18
GW #7	22.51	26.67	50.82
GW #8b	34.49	10.25	55.26
GW #10	49.96	13.04	37.00
GW #11	53.10	15.34	31.56
GW #12	26.19	55.47	18.33
GW #13	32.06	10.82	57.12
GW #14	58.95	4.66	36.38
GW #16/17	61.41	17.41	21.19
GW #18	31.35	29.28	39.36
GW #19	40.76	41.21	18.03
GW #21	23.19	57.37	19.44
GW #22	14.14	44.96	40.90
GW #23a	13.38	9.47	77.15

Regarding the fulfilment of tasks, managers were able to verify all intended management actions, including 34 water exchanges, 23 drain-downs and 2 flooding events, through the CMS. In addition, the CMS provided snapshots of unscheduled hydrological changes such as the drop in water level by evaporation and/or leakage. This helped inform management action to refill water to maintain optimal water levels.

- ❖ Aiding night-time water level management work

The digital visualisation of water level data via mobile devices facilitated field operation and elevated occupation safety, especially during night water exchange shifts, where the wooden scale that placed in the *gei wai* was difficult to observe under dim conditions.

- ❖ Assessing wildlife usage

Water level data was used to correlate shorebird data among high-tide roosts. Through bird monitoring, we were able to confirm the performance of major and alternative high-tide roosts (i.e. *gei wai* in BMZ5 and BMZ 7) as shorebird usage was recorded with suitable water levels. Also, shorebirds were recorded in non-high-tide roosts, serving as a basis for optimal water level evaluation for shorebird usage of each *gei wai/pond*

- ❖ Facilitating communication with quantitative data

With the precise water level data, it has been determined that the optimal water level for shorebird ringing at GW #16/17 would be 1.57m after consulting with Hong Kong Waterbird Ringing Group's leader.

- ❖ Response to extreme weather

The IoT monitoring system enhanced our response to extreme weather events by enabling real-time monitoring and data-driven decision-making. For instance, in the case of the brackish rice paddy trial at Pond #16a in the year 2022, manual monitoring methods faced delays in response to heavy rainfalls, resulting in imprecise water control and hence crop failures. After the IoT water level sensors were deployed in 2023, we were able to continuously and remotely track water levels, allowing for earlier detection of changes in water levels. In addition, we were able to respond to the unusual low precipitation in June 2023 by tracking the loss of water in the paddy field with a water level sensor. Re-filling water from the adjacent pond was conducted when the water level of the paddy field was too low. This approach not only mitigated the impacts of extreme weather but also facilitated the recreation of favorable habitats for target wildlife.

Water quality monitoring

- ❖ Water quality performance

The water quality of both sampling sites over the data collection period was assessed (Table 16). Parameters, except dissolved oxygen, in both sampling sites showed strong alignment to optimal range (ie. >90% of time within optimal range). Notably, dissolved oxygen levels were below the optimal range for relatively significant periods at both locations (27.41% at GW #12 and 36.83% at the water channel near NH).

Table 16. Review of water quality performance during the data collection period

Location	Parameter	% of time that water level fell within optimal range	% of time that water level exceeded optimal range	% of time that water level fell below optimal range
GW #12	Temperature	92.89	6.91	0.20
	pH	98.47	1.50	0.03
	Salinity	100.00	0.00	0.00
	DO	72.59	0.00	27.41
	Chlorophyll a	100.00	0.00	0.00
Water Channel near Northern Hide	Temperature	96.83	2.86	0.31
	pH	99.97	0.03	0.00
	Salinity	99.99	0.01	0.00
	DO	63.17	0.00	36.83
	Chlorophyll a	100.00	0.00	0.00

❖ Evaluate water exchange frequency

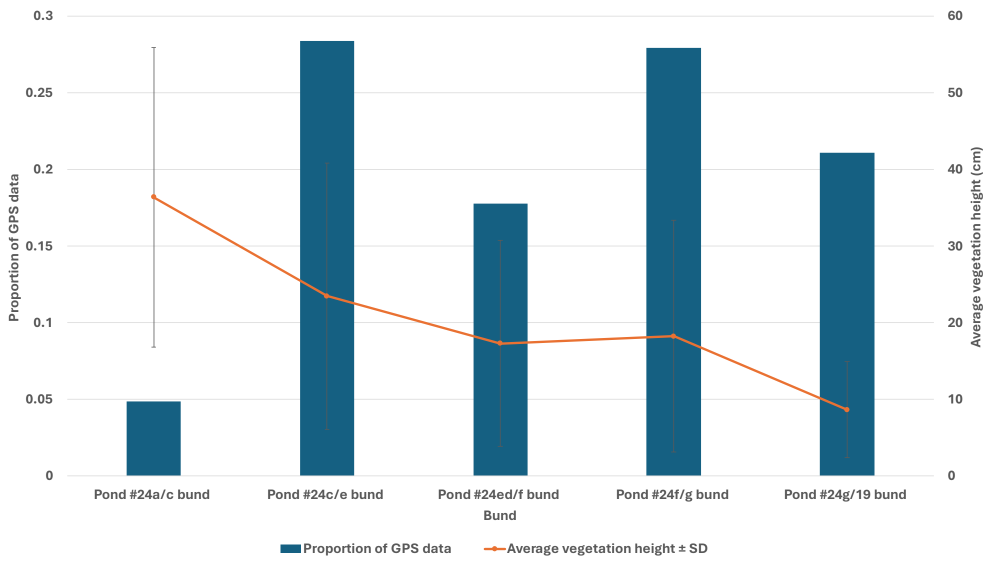
A statistical test was performed to evaluate the water exchange frequency. Results showed no significant differences in water quality before and after water exchange. ($p > 0.05$ for all parameters; Temperature: $p = 0.214$; pH: $p = 0.641$; salinity: $p = 0.789$; dissolved oxygen: $p = 0.066$; chlorophyll a: $p = 0.800$). With no deterioration in water quality, the existing frequency (i.e. twice per month) appears to maintain water quality.

Buffalo tracking

❖ Area use of the buffalo

By correlating field measurement of vegetation height in different sub-bunds within Pond#24 and the buffalo GPS data at each bund, it was shown that areas with higher buffalo activity corresponded to lower vegetation heights (Figure 22), implying that the presence and movement of buffaloes in these areas may have contributed to vegetation control. The buffaloes' grazing and trampling behaviour have likely shaped the heterogeneous vegetation structure at Pond #24. Since the vegetation was kept at an acceptable height, it was concluded that no further habitat management efforts were required during the study period.

Figure 22. Relationship between GPS data and vegetation height



- Alert Usefulness

Water level monitoring

High water level alerts were primarily triggered by scheduled water exchanges, temporary fluctuations from natural factors, and precipitation. Management actions were according to the action response plan (Appendix B-D). All alerts triggered by the scheduled water exchange practices were acknowledged as cross-checking of fieldwork during the project period. For freshwater ponds, when visual inspections confirmed water levels were out of range, excess water was removed through an underground pipe. During the project, 14 water level adjustments were made for the freshwater ponds.

Water quality monitoring

Water quality alerts were primarily triggered by temporary fluctuations. Following the action response plan, field checks were performed once alerts were triggered. For confirmed true alerts, no water exchange was carried out since the values returned to acceptable thresholds before the water exchange could be implemented. Importantly, water exchange is not always a direct response to true alerts due to the dynamic nature of wetlands, where values can quickly normalize. In this context, the IoT monitoring system is essential for capturing data on these extreme values.

Buffalo tracking

All were false alarms and hence no management action was required.

Novelty of data

- Comparison with Manual Monitoring Methods

Water level monitoring

Water levels obtained from manual observations showed a significant discrepancy from IoT monitoring data (Figure 23). The IoT water level sensors proved more accurate than manual observations, which often had errors due to the observer's distance from the wooden scale for manual check (Figure 24). Additionally, the wooden scale used for manual checks had a limited range of 0 to 95 cm. Readings below this range were recorded as “0 cm,” while those above 95 cm were unmeasured. IoT data were available in these cases with a possible range up to 1,000 cm.

Figure 23. Comparison of water level data between manual monitoring and IoT monitoring

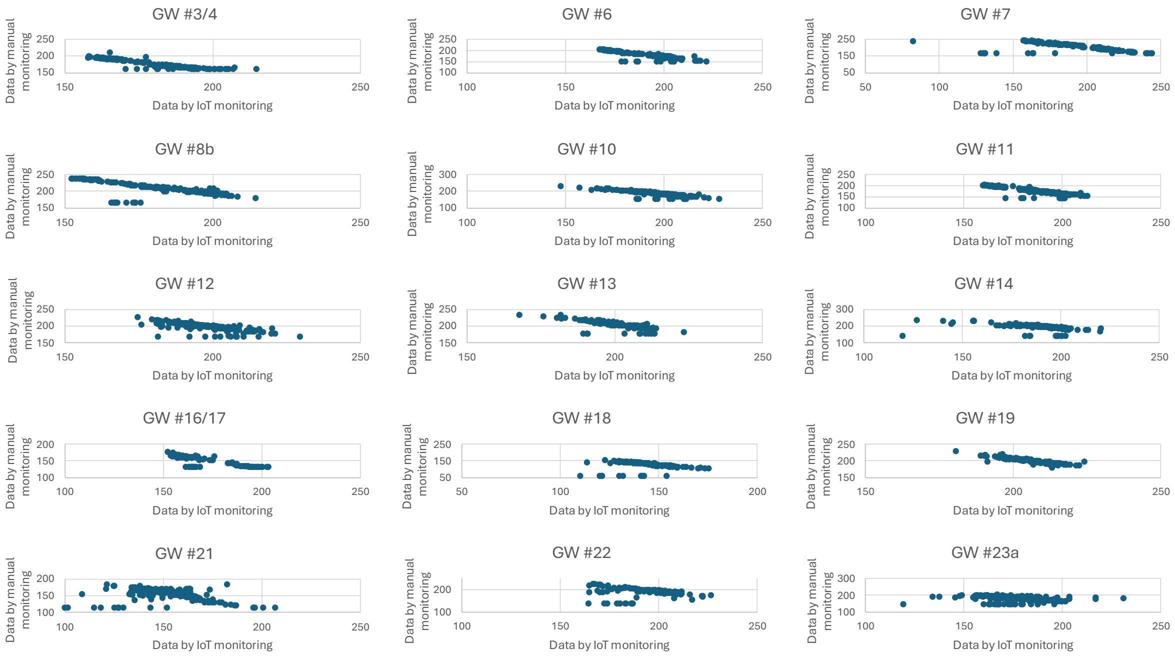


Figure 24. Wooden scale for manual observation

Water quality monitoring

Discrepancies between the manual and IoT sensor data for temperature, pH, salinity and chlorophyll a were found to be acceptable (Temperature: $p = 0.45$, $R^2 = 0.97$; pH: $p = 0.83$, $R^2 = 0.83$; salinity: $p = 0.52$, $R^2 = 0.89$; and chlorophyll a: $p = 0.55$, $R^2 = 0.57$) (Figure *25*; Figure *26*; Figure *27*; and Figure *29*). However, a significant difference was observed for dissolved oxygen ($p = 0.05$, $R^2 = 0.11$, Figure 28) The potential reason for these differences could be the occurrence of siltation, which may have affected the sensor readings.

Figure 25. Comparison of temperature between manual monitoring and IoT monitoring

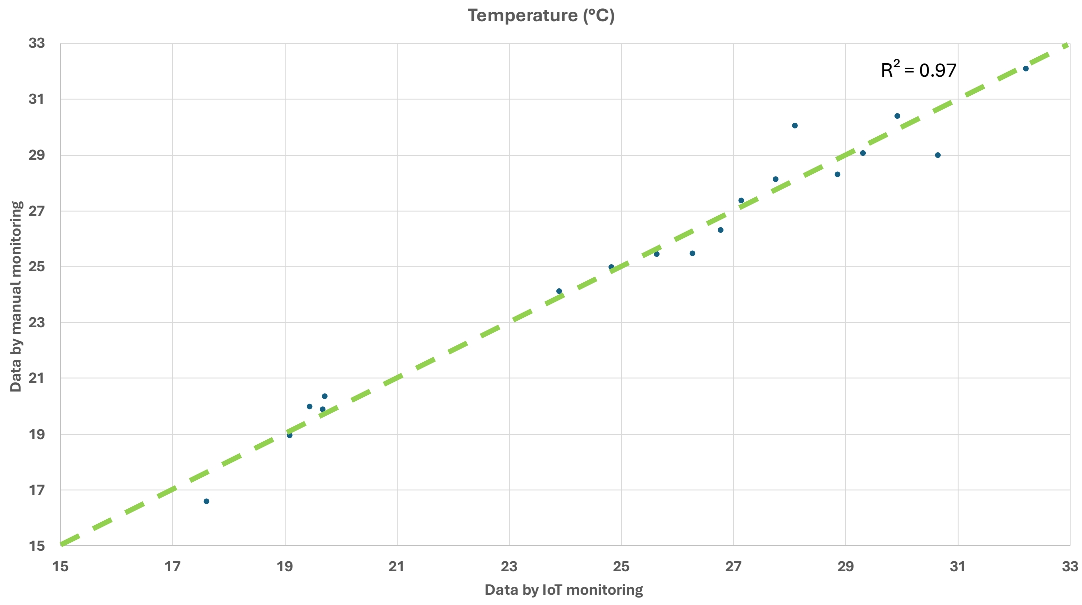


Figure 26. Comparison of pH between manual monitoring and IoT monitoring

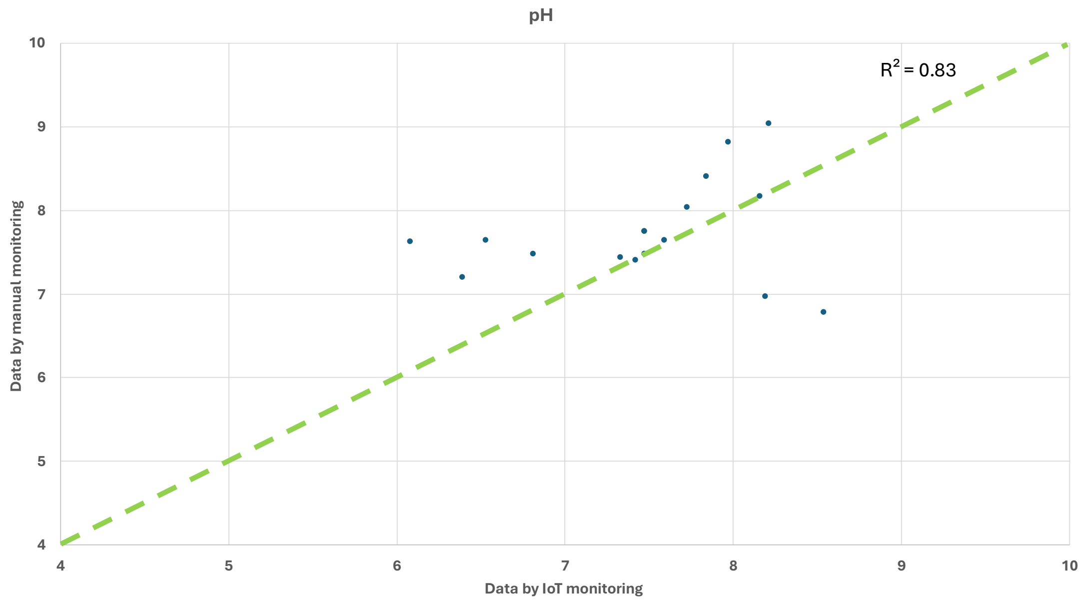


Figure 27. Comparison of salinity between manual monitoring and IoT monitoring

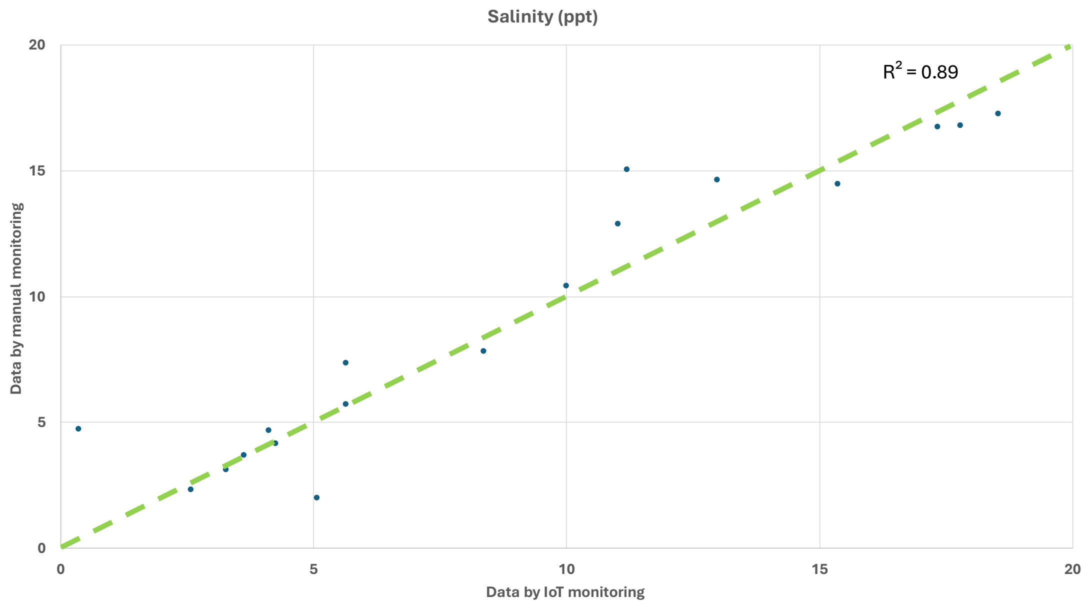


Figure 28. Comparison of dissolved oxygen between manual monitoring and IoT monitoring

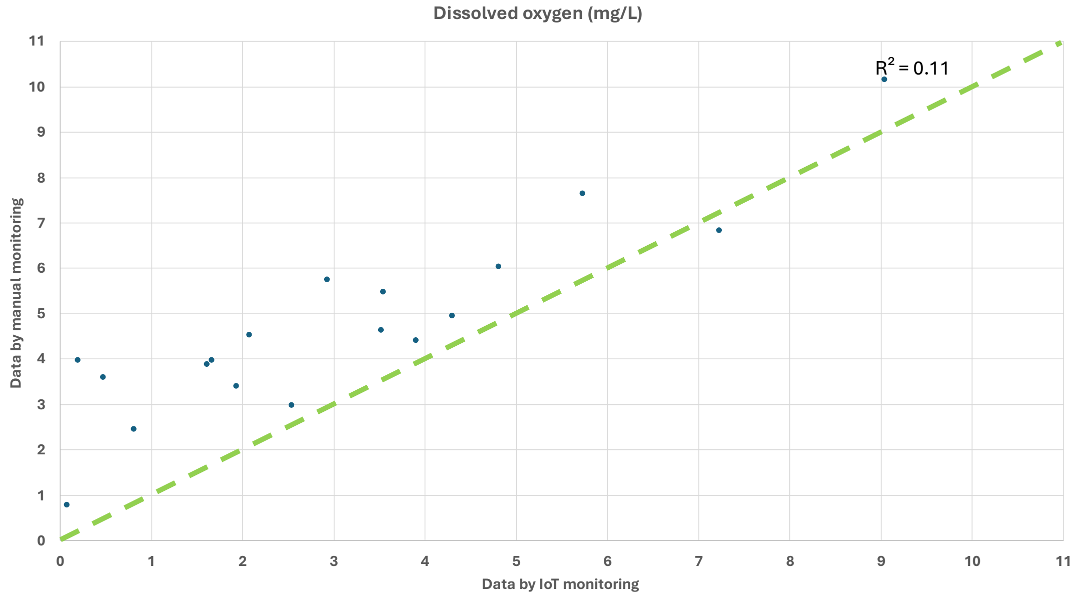
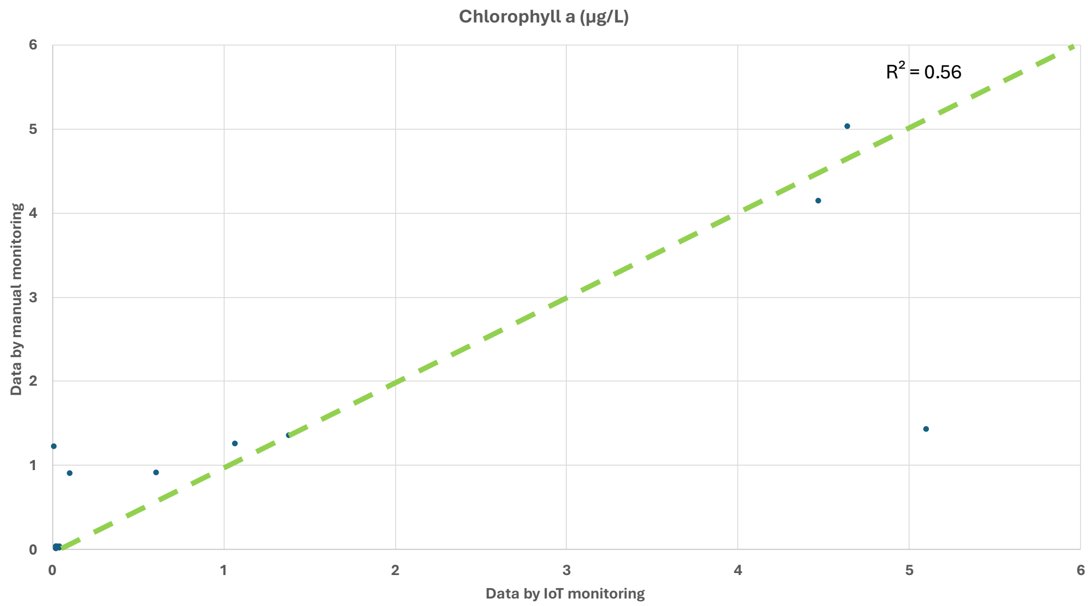


Figure 29. Comparison of chlorophyll a between manual monitoring and IoT monitoring



Buffalo tracking

The trackers captured 24-hour buffalo's location so that day-night differences in distribution could be assessed. For Pond #17b, area usage was implied by the similar diurnal and nocturnal presence in the middle and eastern areas. A higher preference for staying at the edge of the enclosure at night was also noted (Figure 30 and Figure 31). For Pond #24, there was a considerable difference in day and nocturnal area usage (Figure 32 and Figure 33). The herd prefer staying in the centre part of Pond #24 (i.e. sub-Pond#24b-e) in daytime while staying along the bund between sub-Pond #24f and sub-Pond #24g at night. By analyzing the correlation between GPS data and vegetation height across various sub-bunds within Pond #24, we found that areas with higher buffalo activity were associated with lower vegetation heights (Figure 22). This suggests that the presence and movement of buffaloes may have played a role in controlling vegetation. The grazing and trampling behaviors of the buffaloes likely influenced the vegetation structure of the pond. Given that the buffalo area usage covered most of the land within the enclosure and that the vegetation was maintained at an acceptable height (equal or less than 20 cm), we concluded that no additional habitat management efforts were necessary during the study period.

Figure 30. Heatmap of buffalo's location fixes at Pond #17b in daytime

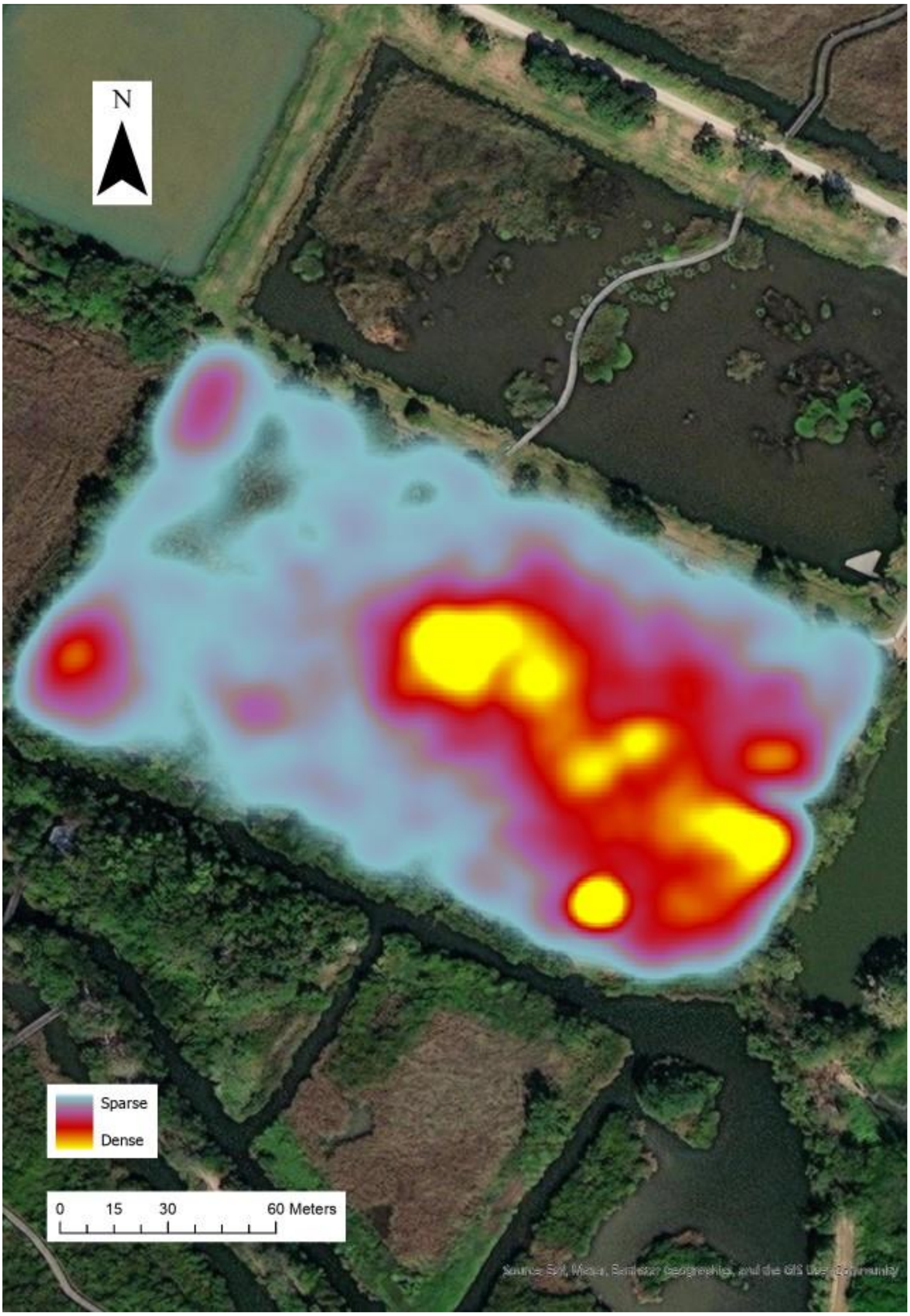


Figure 31. Heatmap of buffalo's location fixes at Pond #17b at night

Figure 32. Heatmap of buffalo's location fixes at Pond #24 in daytime

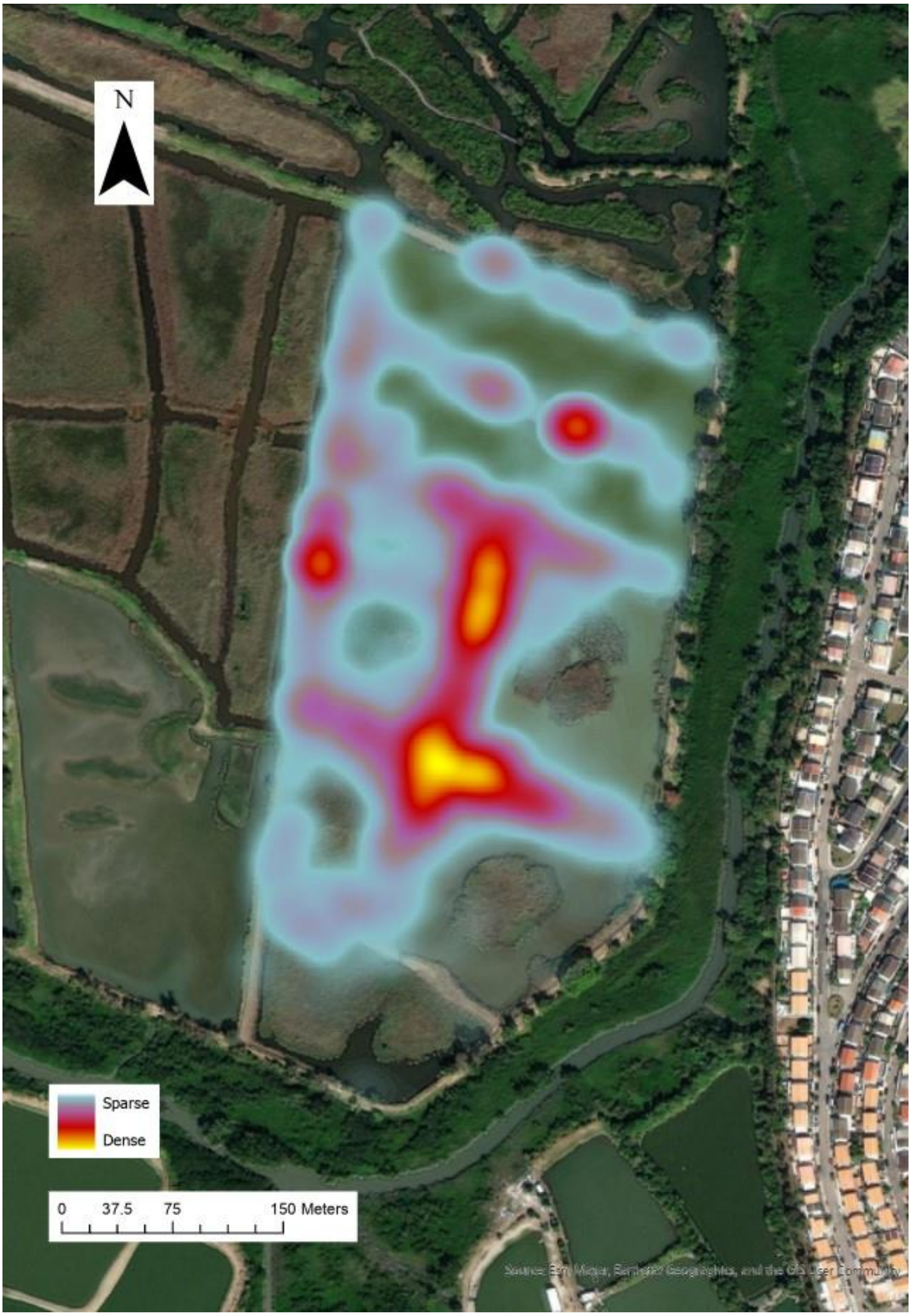
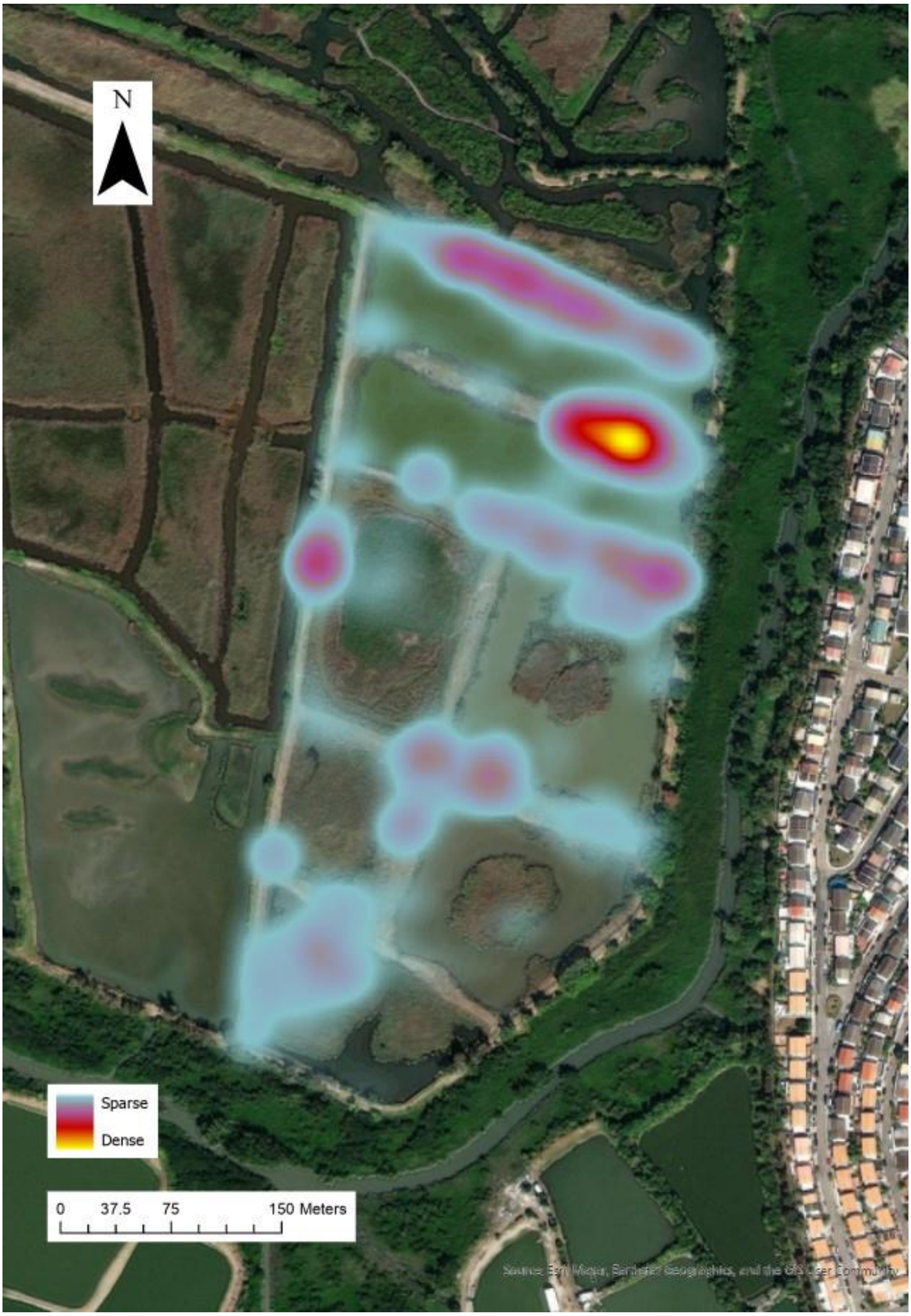


Figure 33. Heatmap of buffalo's location fixes at Pond #24 at night



- Exploration of Research Opportunities
  - ❖ Topography of high-tide roost

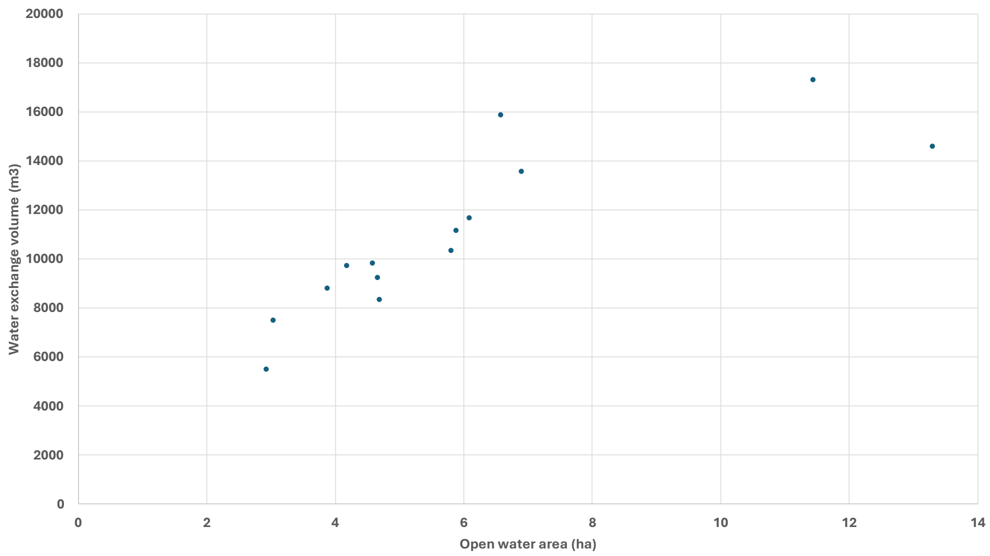
Waterbirds, especially small waders, are sensitive to water levels. Generally, lower water level favours small waders but vegetation growth in the roost would increase. To find out the suitable water level for management, the topography of the major high-tide roost (i.e. GW #16/17) was studied as a separate project using a LiDAR drone and a digital terrain model (DTM) was generated. Its relationship to the water level adopted by the IoT system was analysed. Inundation and exposed areas at different water levels were calculated based on the water depth profile generated (Figure 34, adopted from WWF-Hong Kong's unpublished report). The result provides quantitative spatial data for studying the relationship between topography, water level, and waterbird usage.

Figure 34. Digital terrain model referencing IoT water level monitoring system (adopted from WWF-Hong Kong's unpublished report)

❖ Water exchange

Studying the volume of water exchange enables wetland managers to evaluate water exchange efficiency. The volume of water exchange refers to the maximum change in water volume of a *gei wai* based on its open water area and the difference between the maximum and minimum water levels during water exchange period. Water exchange efficiency refers to the amount of water being exchanged within the *gei wai* during water exchange period. It's important for understanding water balance, managing aquatic ecosystems, and optimizing agricultural practices. Great variation in water exchange volumes across different *gei wai* was observed (Table 17). *Gei wai* with larger open water areas, such as GW #3/4 and GW #16/17, tend to show higher average water exchange volumes (Figure 35). In contrast, *gei wai* with smaller open water areas, such as GW #14 and GW #23a, exhibit lower exchange volumes, suggesting limitations in water exchange capabilities.

Figure 35. Relationship between open water area and water exchange volume



An exceptional case was observed at GW #22, of which the open water area is not large, yet it possesses a high water exchange volume. This could be attributed to the special management that the *gei wai* allows free water exchange from November to March, resulting in experience in the entire intertidal change with higher water volume exchanged.

Table 17. Water exchange volumes across *gei wai* during the data collection period

Gei wai	**Open water area* (ha)**	**Range of water exchange volume (m^3)**	**Average water exchange volume ± SD (m^3)**
GW #3/4	11.44	2173.17 - 85668.84	17275.16 ± 13614.37
GW #6	5.80	870.46 - 24082.79	10199.13 ± 5569.33
GW #7	6.09	1278.72 - 54376.18	11408.35 ± 9595.43
GW #10	4.59	917.13 - 24900.18	9495.76 ± 5414.92
GW #11	4.69	891.17 - 24577.62	8230.95 ± 5097.73
GW #12	4.66	931.83 - 29073.13	9268.01 ± 5055.96
GW #13	3.88	542.90 - 22065.11	8359.80 ± 6282.91
GW #14	2.93	292.58 - 16267.38	5370.57 ± 3622.48
GW #16/17	13.30	2526.25 - 95332.65	13755.63 ± 12980.81
GW #18	4.18	962.25 - 40958.28	9990.71 ± 7903.78
GW #19	5.89	941.98 - 63406.92	10850.64 ± 13351.88
GW #21	6.90	1518.80 - 81117.98	13174.14 ± 12945.62

GW #22	6.58	1381.45 - 36444.00	15080.13 ± 8599.04
GW #23a	3.03	636.99 - 32182.92	7740.54 ± 5917.60

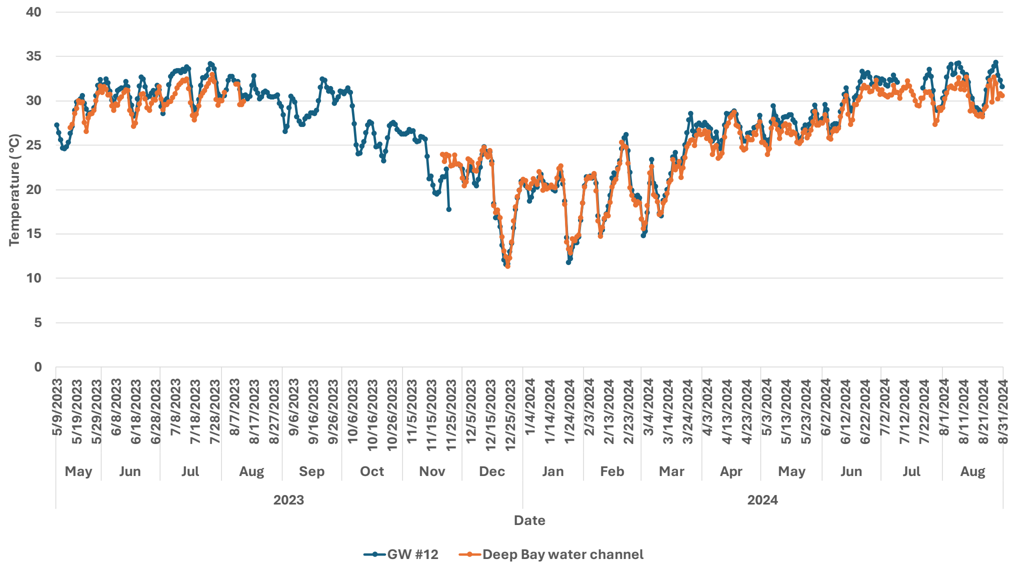
*Open water area is as of the year 2023.

❖ Comparison between the water channel near NH and GW #12

Water quality data collected at NH and GW #12 were compared for the first time to understand the characteristics of water quality in two different habitats, one as *gei wai* and the other represented tidal water in Deep Bay. Periods of sensor malfunction, calibration issues, and low tide exposure were filtered out to focus on the optimal functionality of the sensors, providing clearer insights into water quality dynamics.

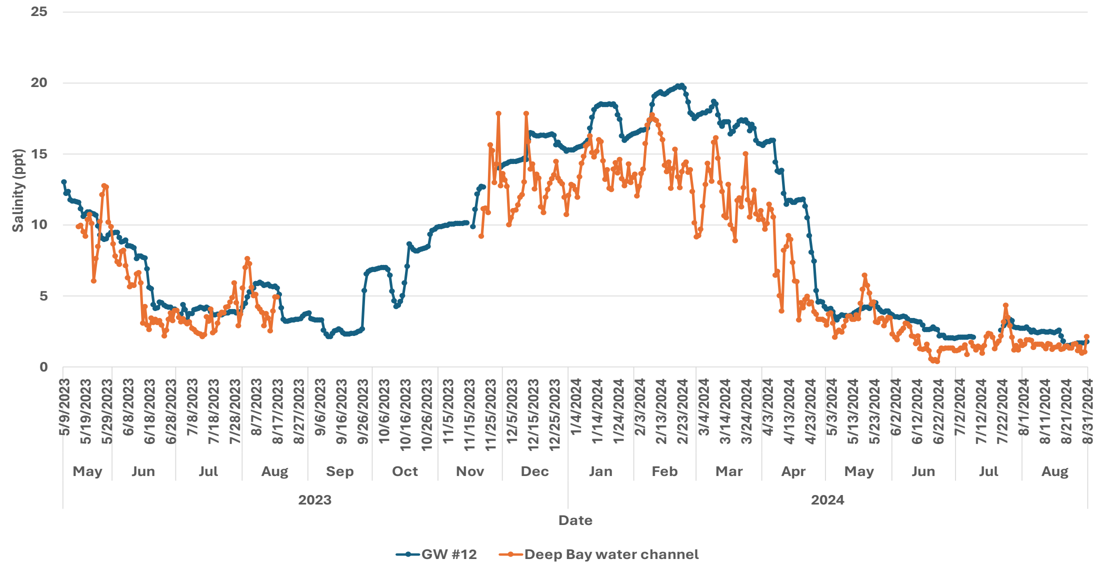
Temperature: Both sites exhibited similar temperature trends (Figure 36). Seasonal fluctuations were evident, with summer temperature exceeding 32 °C, potentially stressing aquatic organisms in the *gei wai*, such as shrimp and fish (Wyban et al., 1995; Ghosh, 2019).

Figure 36. Daily average water temperature in GW #12 and Deep Bay water channel from 1st May 2023 to 31st August 2023



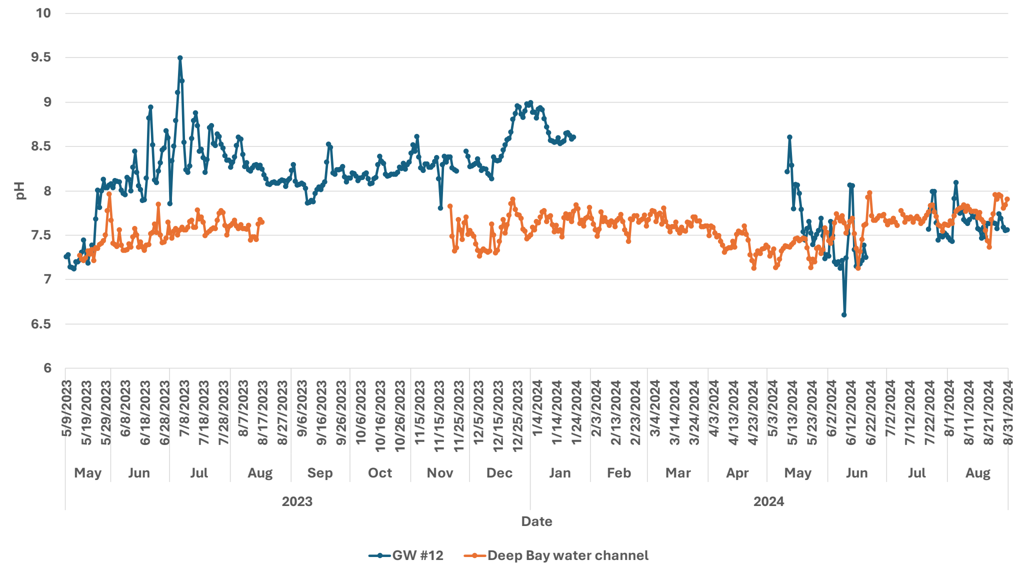
Salinity: GW #12 maintained relatively stable levels, while the Deep Bay water channel experienced significant fluctuations (Figure 37). The readings allowed wetland managers to estimate the shrimp production in peak shrimp harvest seasons such as April to May, as low salinity could inhibit shrimp growth (Chen et al., 1995).

Figure 37. Daily average salinity of GW #12 and Deep Bay water channel from 1st May 2023 to 31st August 2023



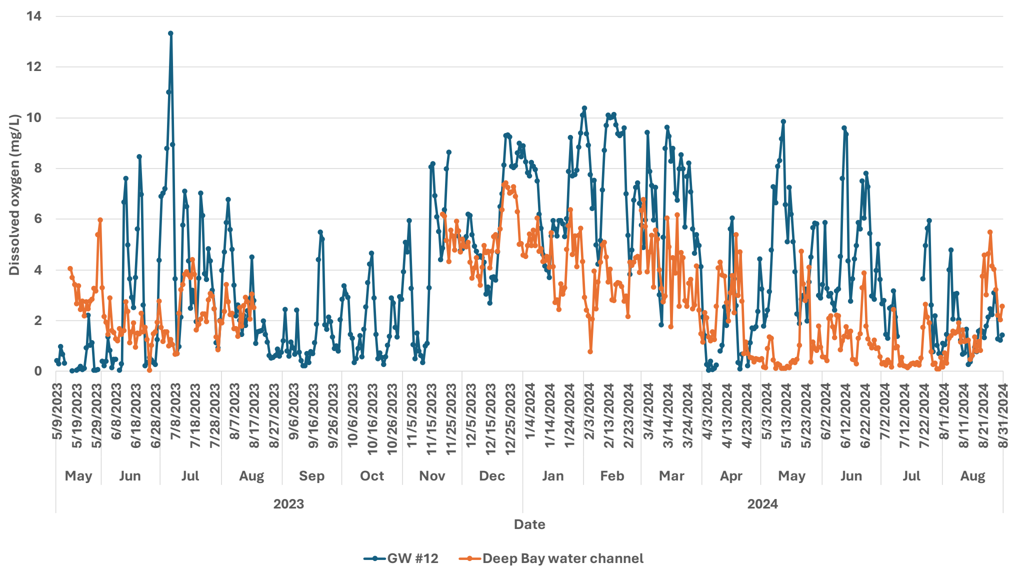
pH: GW #12 consistently had a higher pH than the Deep Bay water channel (Figure 38). A gradual increase in pH levels in GW #12 was noted.

Figure 38. Daily average pH of GW #12 and Deep Bay water channel from 1st May 2023 to 31st August 2023



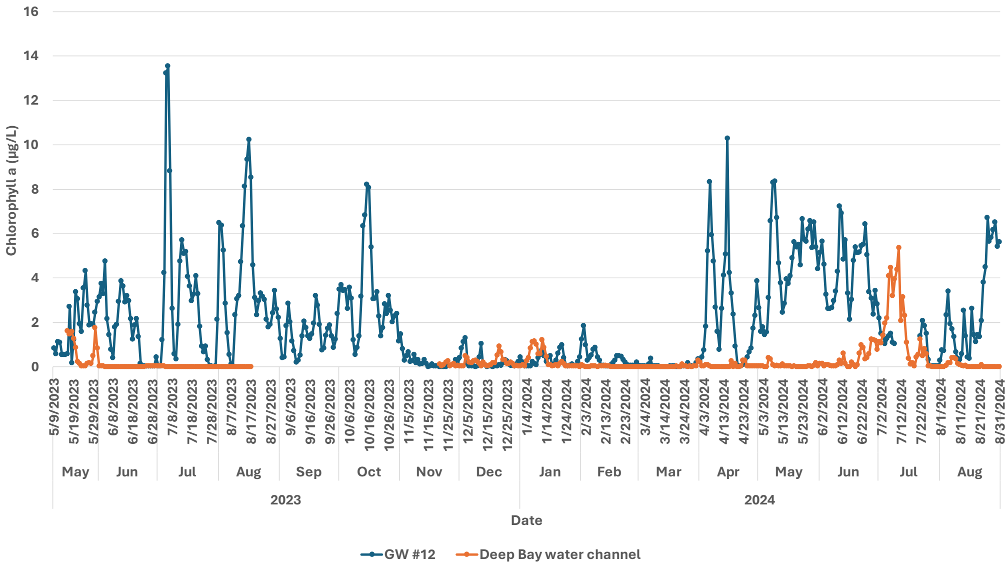
Dissolved oxygen: GW #12 consistently showed higher dissolved oxygen concentrations than the Deep Bay water channel (Figure 39). The lower levels in the channel may indicate reduced photosynthetic activity and higher organic matter decomposition. Both sites demonstrated seasonal trends, with increased DO levels during cooler months, such as January and February 2024. While both sites exhibit considerable fluctuations, GW #12 showed more pronounced variability. With the continuous monitoring of dissolved oxygen, we were able to check how recurrent management practices would affect the water quality and hence the aquatic organisms. Sudden changes in the aquatic environment such as declining water level for waterbird usage could lead to the death of large-size fish due to insufficient water. The decomposition caused by such an event did not affect the dissolved oxygen level as the reading showed no significant decline during and after the low-water-level period. Hence, no specific management action was needed.

Figure 39. Daily average dissolved oxygen of GW #12 and Deep Bay water channel from 1st May 2023 to 31st August 2023



Chlorophyll a: GW #12 displayed higher levels compared to the Deep Bay water channel throughout most of the data collection period, indicating periods of phytoplankton activity (Figure 40). In contrast, the Deep Bay water channel showed consistently lower chlorophyll a level, rarely exceeding 5 µg/L. This suggests less favourable conditions for phytoplankton growth or more effective grazing by zooplankton. While no algal boom was noted during the study period, such difference between *gei wai* and Deep Bay highlighted the need for wetland managers to proactively monitor potential issues related to rising chlorophyll a level, such as the risk of algal blooms in *gei wai*.

Figure 40. Daily average chlorophyll a of GW #12 and Deep Bay water channel from 1st May 2023 to 31st August 2023



6. Implication of wetland management

- Overall IoT monitoring system performance

The gateways at the MPNR successfully received data from sensors. The IoT monitoring system ran continuously with robust data collection. The results prove that our system is efficient, reliable and suitable for implementation in rural areas.

- Challenges, limitations and recommendations for MPNR

Water level sensor

Comprehensive coverage was achieved in this project by installing water level sensors in all *gei wai*/ponds managed by WWF-Hong Kong, alongside one at the water channel near NH.

Water quality sensor

Sensors at GW #12 and the Deep Bay water channel provided real-time data and supported hydrological management. Extending monitoring to cover all seven BMZs would capture spatial variations and offer managers a holistic view of MPNR conditions. However, based on the trial, it is suggested that the water quality sensors shall not be deployed at the water channel between mudflat and mangrove due to unconformity of the environmental setting and siltation, which likely affect the sensors' performance. Further location in the Deep Bay where the water depth is deeper is recommended.

Buffalo tracker

Daily and seasonal patterns of buffalo were captured and associated with vegetation growth. Yet, buffalo could be separated into groups even within the same enclosure. Thus, tracking devices can be deployed per herd to more accurately monitor their activities. Also, data was found to be absent when the buffalo were mostly submerged in water due to the limited penetration power of LoRa technology in underwater conditions. There is no applicable solution at this moment. It may be worthwhile to explore alternative tracking devices such as those attached to the buffalo's ear or horn.

CMS

Around 70% of alerts triggered during the project period were true. Among them, 75% were triggered due to regular management practices, such as water exchange leading to high water level alerts. To avoid false alerts being triggered due to management events, an actionable mode can be made to separate these alerts from true alerts. Wetland manager can input the management schedule to the CMS to activate this mode. When actionable mode is active during the occurrence of a management event, data exceeding the threshold value will be labelled or tagged. The CMS can then ignore the false alerts automatically. Around 30% of the alerts triggered during the project period were false alerts, with half of them being related to buffalo tracking. To reduce the number of false geofencing alerts triggered by buffalo trackers, software enhancement can be made only to issue alerts when 2 consecutive data received are found out of the pre-set geofence.

6.1. Potential applications for future management

In this project, sensors were used for monitoring purposes. Nevertheless, the capabilities of IoT can extend far beyond mere sensing. They encompass the potential to act as effectors that respond dynamically to detected stimuli. This transformative aspect of IoT can significantly enhance environmental management strategies. For example, consider a smart sluice gate equipped with automated controls. When water level sensors detect that levels have surpassed a predetermined threshold, the sluice gate can be programmed to open automatically, allowing excess water to flow out and prevent potential flooding. This not only mitigates risks associated with extreme weather conditions but also optimizes water resource management. By integrating such responsive systems, we can create a more proactive approach to environmental monitoring and management, allowing for real-time interventions that improve outcomes. The dual role of IoT as both a monitoring tool and an active effector can lead to more efficient and effective environmental stewardship, ultimately fostering a more resilient ecosystem.

In addition to the sensors used in this project, which primarily focus on habitat management and monitoring, IoT technology has the potential to enhance wetland management in several key areas (Bhardwaj et al. 2024; Montero et al., 2024; Zhang & Deng, 2024), including visitor management, Community Engagement, Participation, and Awareness (CEPA), and surveillance. The experience gained in developing and implementing IoT architecture in this project lays a solid foundation for the broader application of IoT technologies in wetland conservation.

7. Conclusion

This project focused on evaluating the IoT monitoring system's field performance and its facilitation in both hydrology and vegetation management in MPNR. The IoT application has ensured and supported on-site planned management tasks. With the data collected from the IoT system, we were able to evaluate the optimal water level for waterbirds, water exchange frequency as well as area use of buffalo. Both field workers and managers could benefit from the IoT application in management, research and monitoring aspects. As a proof of concept, the trial validated the system's functionality and laid the groundwork for future larger-scale deployments, providing a reference case for Wetland Conservation Parks under the Northern Metropolis Development Strategy. By harnessing the power of IoT, the resources of the countryside can be better monitored and conserved while fostering a management model for wetland conservation.

8. References

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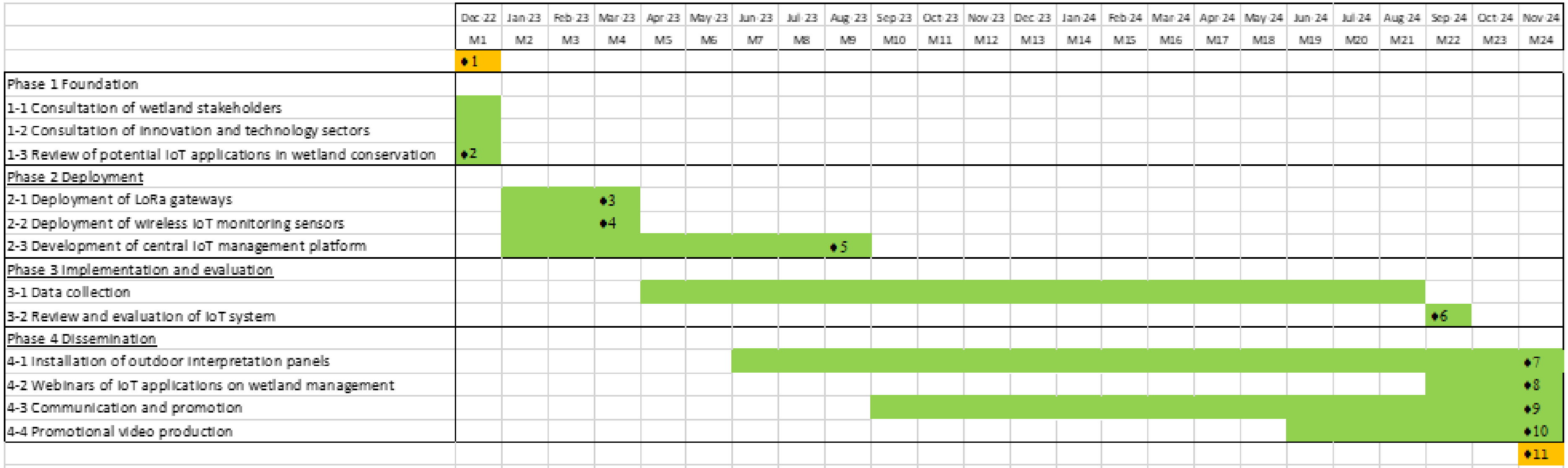
9. Appendices

Appendix A. Project timeline and key milestones



♦ - Milestone

♦1 - Project start on 1 Dec 2022

♦2 - 1 review summary of potential IoT application ready by 31 Dec 2023

♦3 - 3-4 LoRa gateways installed by 31 Mar 2023

♦4 - 34 IoT sensors installed by 31 Mar 2023

♦5 - Central IoT management platfom developed and ready by 31 Aug 2023

♦6 - 1 technical report on the review and evaluation of IoT system ready by 30 Sep 2024

♦7 - 3 outdoor interpretation panels installed by 30 Nov 2024

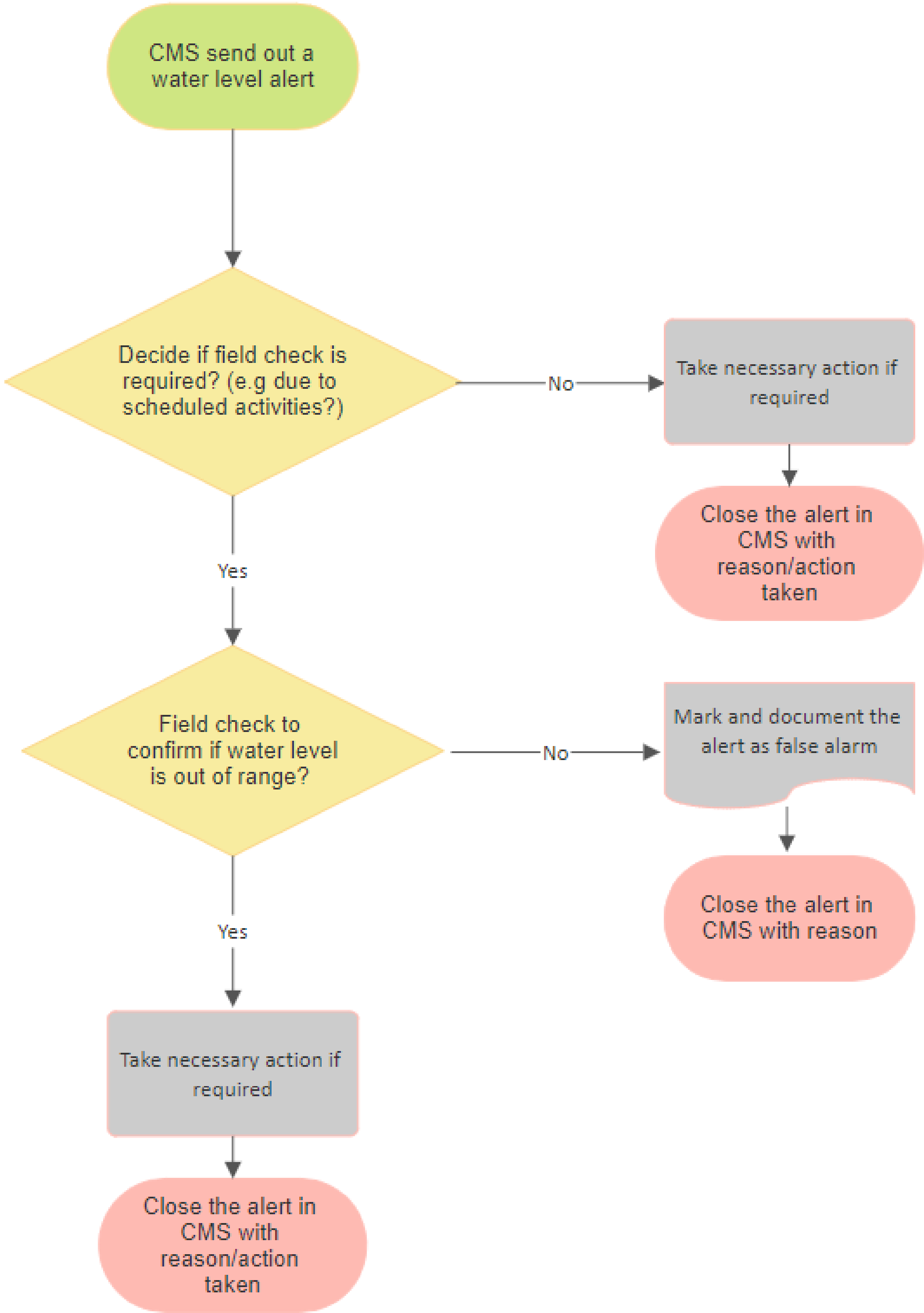
♦8 - 3 webinars of IoT applications on wetland management performed by 30 Nov 2024

♦9 - 1 media engagement and 6 social media posts completed by 30 Nov 2024

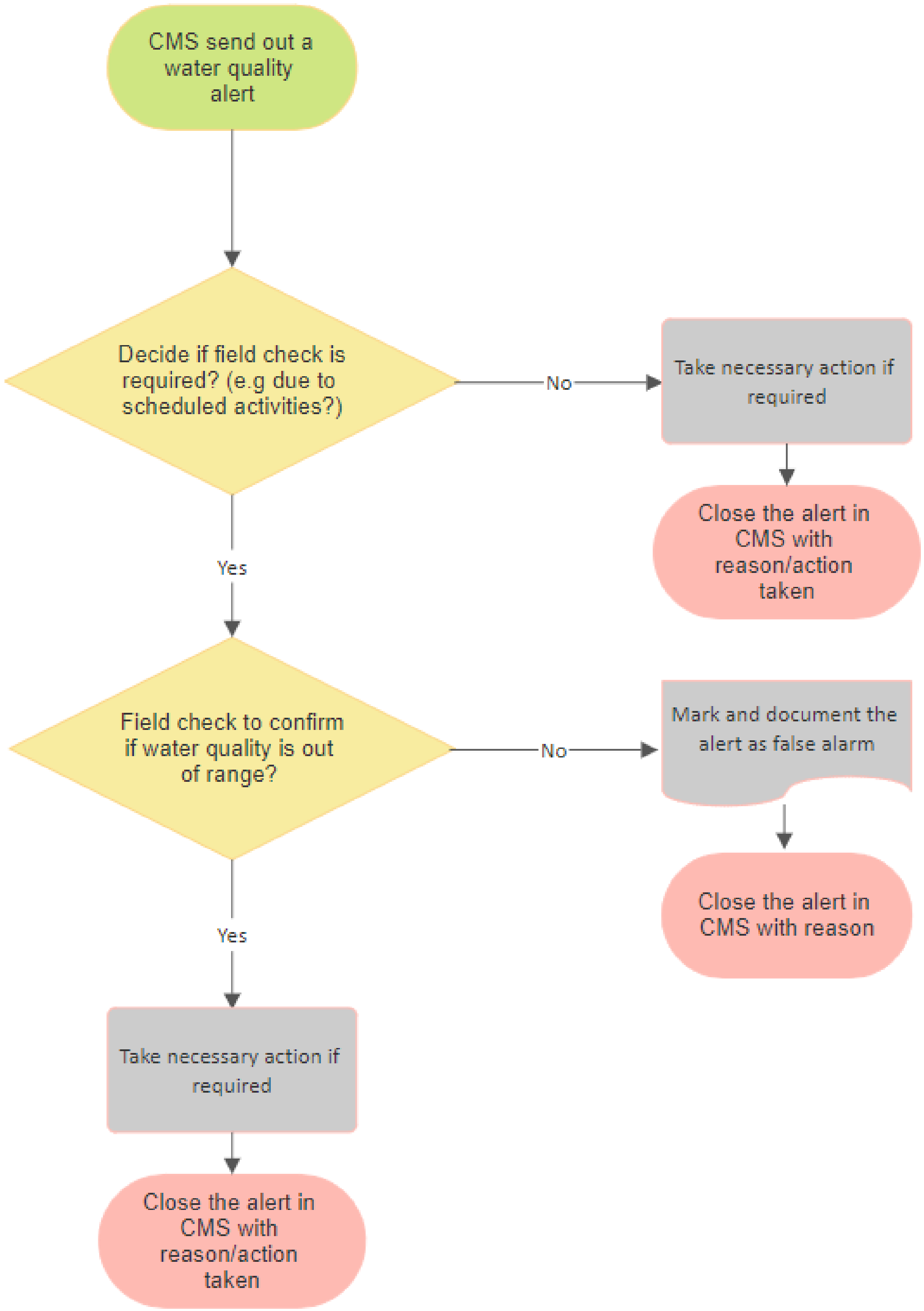
♦10 - 1 promotional video produced and published by 30 Nov 2024

♦11 - Project complete on 30 Nov 2024

Appendix B. Action Response Plan when receiving water level alert



Appendix C. Action Response Plan when receiving water quality alert



Appendix D. Action Response Plan when receiving buffalo out-of-fence alert