Private LoRaWAN Network Deployment in Kuopio, Finland: A Case Study on AI-Based Water-Level Monitoring and Urban Flood Prediction

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***Abstract*—This paper addresses the overarching research problem: How can an Artificial Intelligence(AI)-based water-level monitoring service be implemented and deployed for effective flood prediction in an urban environment? To explore this, three research questions are posed: RQ1—What type of network architecture can be used in AI-based monitoring of water levels? RQ2—How can the AI-based water-level monitoring service be implemented regarding devices, components, and AI models? and RQ3—Which challenges are related to the implementation and deployment of the AI-based water-level monitoring service? A private LoRaWAN network was set up in Kuopio, Finland, integrating 16 Elsys ELT Ultrasonic sensors with Kerlink and RAK gateways to monitor stormwater wells despite structural obstacles. The study spanned from Fall 2023 to Spring 2025, employing iterative field tests, AI model comparisons (linear regression, decision trees, random forest), and Information Technology Infrastructure Library (ITIL)-based pattern matching. The findings demonstrate the feasibility and robustness of a tailored IoT network, highlighting best practices for sensor placement, gateway configuration, and predictive analytics. These insights provide a blueprint for other cities aiming to harness low-power technologies and AI for early flood warnings and data-driven urban water management.**

Keywords: LoRaWAN; IoT; Environmental Monitoring; Predictive Maintenance; Artificial Intelligence; Sensor Networks; Gateway Configuration; Field Testing; Kuopio; Random Forest; Implementation; ITIL 4; Pattern Matching

I. INTRODUCTION

The rapid evolution of the Internet of Things (IoT) has led to the emergence of wireless communication technologies designed for low-power, long-range applications. Among these, LoRa (Long Range) and its associated LoRaWAN protocol have attracted significant attention due to their extended coverage, minimal energy requirements, and cost effectiveness [1][2]. In many regions, including Kuopio, commercial networks may be either expensive, unavailable, or unsuitable for specific monitoring needs. In response, deploying a dedicated private LoRaWAN network becomes a viable alternative.

Climate change and urbanization are anticipated to cause more urban floods due to changing precipitation patterns. This necessitates a review of current design practices and the incorporation of climate change impacts into urban drainage systems [3]. In built-up areas where new design methods cannot be fully implemented, focus should shift to early warning and prediction systems based on IoT solutions. IoT refers to systems in which devices automatically transmit data used for monitoring or control over the internet. Wireless communication is typically essential, often relying on Low-Power Wide-Area Networks (LPWAN) [4]. Some of these networks utilize 3GPP-based 5G standards enabling massive Machine Type Communications (mMTC) [5].

Now in the era of Artificial Intelligence (AI), data serve as the foundation for warning and prediction models. In particular, data aggregation and appropriate latency considerations—edge or cloud processing—are crucial to achieving reliable and timely predictions [15]. This paper introduces an AI-assisted IoT system for urban flood prediction built on a private LoRaWAN network in Kuopio, Finland. The system employs three RAK7289 V2 WisGate Edge Pro Gateways with Elsys ELT Ultrasonic Industrial Distance Sensors installed in stormwater wells. Additionally, the Loriot platform was incorporated for network management, and the Tulvia.ai application was developed to provide real-time visualization and alerting services for water-level changes. The paper is organized as follows. Section II describes the theoretical framework. Section III explains the methodology. Section IV discusses the results and analysis, and Section V includes further discussion. Finally, Section VI presents conclusions.

II. THEORETICAL FRAMEWORK

LoRaWAN has gained prominence within the broader ecosystem of low-power wide-area networks (LPWAN) due to its capacity for energy-efficient, long-range data communications in Internet of Things (IoT) applications [1],

[2]. Competing LPWAN architectures (e.g., NB-IoT, Sigfox) also prioritize low power consumption and extended coverage, but LoRaWAN's unique attributes—including license-free frequency operation, adaptable spreading factors, and a star-of-stars topology—make it a compelling choice in challenging urban environments. Finland, for instance, experiences frequent snowfall and sub-zero temperatures that accelerate battery depletion, so the network design must ensure both robust signal propagation and reliable sensor operation. LoRaWAN's ability to support different Classes (A, B, and C) of end devices further enhances flexibility, enabling developers to balance factors, such as latency, power consumption, and communication patterns in varied use cases.

In the context of water-level monitoring, LoRaWAN devices, often placed underground in stormwater wells or obstructed by metal covers, must maintain connectivity despite physical barriers. Chirp Spread Spectrum (CSS) modulation underpins LoRaWAN's robustness, allowing signals to remain intelligible across relatively long distances and through moderate interference [7][16]. Moreover, Adaptive Data Rate (ADR) can automatically adjust a node's spreading factor, power settings, and bandwidth to optimize transmission based on real-world conditions. This adaptability helps preserve device battery life, an essential concern when sensors cannot be easily retrieved for replacement or recharging. Alongside these connectivity advantages, LoRaWAN employs a network server for packet handling, encryption, and device authentication. When environmental monitoring expands to dozens or hundreds of sensors, centralized management enables administrators to handle large volumes of traffic with relative ease.

Despite the importance of reliable data transmission, mere connectivity is not enough in applications where timely interventions, such as flood warnings are critical. Integrating Artificial Intelligence (AI) into environmental monitoring frameworks addresses this gap. Linear regression models, for example, are straightforward to implement but assume direct proportionality between input features (rainfall or temperature) and output (water levels). While suitable for quick or basic predictions, such models can be inadequate when water-level fluctuations exhibit non-linear patterns. Decision trees capture these complexities more effectively, yet they risk overfitting unless carefully tuned. Random forest ensembles, by contrast, aggregate multiple decision trees to produce more robust, accurate forecasts in noisy, real-world data settings [6]. Given the variability of precipitation, runoff, and well infrastructure across city districts, ensemble methods often offer superior performance for short-term water-level prediction.

In line with recent urban flood management studies, such as Kostopoulos et al. [11] and Keung et al. [12], effective solutions often hinge on combining IoT-based sensing networks with sophisticated data analytics pipelines. Recent applications include AI-driven flood depth sensors and real-time dashboards for urban drainage monitoring [12][13][14]. Moreover, Chang and Chang [15] underscore how advanced machine-learning methods and time-series modeling can further refine water-level forecasting, enabling targeted warnings that mitigate flood-related impacts. Together, these studies reinforce the importance of integrated approaches—merging hardware resilience with algorithmic intelligence—to address the multifaceted challenges of urban flooding.

Effective AI-based water-level monitoring also hinges on an appropriate balance between edge and cloud analytics. In many LoRaWAN setups, gateways forward sensor data to network and application servers located in the cloud, leveraging extensive computing and storage capacities for model training and large-scale analytics [4][5]. This configuration is generally sufficient for daily or hourly forecasts, but certain mission-critical scenarios—such as sudden flood events—may demand edge analytics to mitigate latency or manage intermittent connectivity. Whether fully cloud-based or employing a hybrid approach, the final design must consider the computational cost of AI models, sensor data volume, and reliability of internet backhaul.

An additional layer of complexity emerges from the human and organizational factors surrounding IoT deployments. Technical execution alone does not guarantee long-term success. The ITIL 4 framework emphasizes the interplay of multiple dimensions—Information and Technology, People and Processes, Value Streams and Processes, and Partners and Suppliers—to guide service management [8]. For water-level monitoring, "Information and Technology" challenges might include selecting gateways robust enough for harsh conditions. "People and Processes" could manifest in training requirements for field technicians who manage sensor installation and for data scientists who refine AI models. "Value Streams and Processes" directs focus to how data flows from sensor to predictive model, ensuring that insights are delivered to relevant stakeholders in time to prevent or mitigate flooding events. Finally, "Partners and Suppliers" become critical when firmware updates, hardware end-of-life, or differing service-level agreements can undermine a well-designed system. A practical strategy for coping with these variables is the pattern matching technique [9], where observed challenges such as a high sensor failure rate are systematically compared to theoretical predictions from existing literature or known constraints, confirming or refuting underlying assumptions.

By synthesizing the technical benefits of LoRaWAN with AI-driven analytics and structured service management, water-level monitoring systems can transcend basic data collection to achieve near real-time environmental intelligence and situational awareness. LoRaWAN's extended coverage, battery-friendly design, and flexible MAC-layer controls facilitate data acquisition in obstructed urban environments, while AI models transform these data into actionable alerts and forecasts. Simultaneously, frameworks like ITIL 4 ensure that human factors, partner dynamics, and operational workflows receive due attention, creating a holistic service that is both technologically sound and sustainably managed. This integrated view encompassing resilient low-power communication, adaptive AI analytics, and a multidimensional approach to service orchestration—underpins the feasibility of deploying robust, AI-enhanced water-level monitoring solutions in Kuopio's city area.

III. METHODOLOGY

The methodology of this study was structured around an explorative single case study approach [9] spanning from Fall 2023 to Spring 2025 in Kuopio's city area. In alignment with Yin's definition of a single-case design, the case can be framed as the deployment project of a LoRaWAN-based urban flood prediction system in Kuopio. This approach allowed for an in-depth, context-rich examination of how the network architecture, AI models, and stakeholder processes interact within a real-world setting. Within-case analysis, as described by Eisenhardt [10], was adopted to deepen the understanding of the dynamics at play in this specific municipal context. During the first phase in Fall 2023, sixteen ultrasonic sensors were acquired (Elsys ELT Ultrasonic) and placed in designated stormwater wells. Preliminary site surveys identified each well's physical constraints, such as metal covers and limited space, guiding decisions on sensor mounting and gateway installation. A Kerlink Wirnet iFemtoCell LoRaWAN Gateway served as the core node. Trial runs were performed to verify sensor connectivity and data transmission intervals, after which battery drain studies commenced. Results indicated that sensors operating at high transmission frequency could deplete batteries in roughly 9 months under winter conditions, aligning with the local data logs. Figure 1 illustrates the daily fluctuations in link-quality indicators (RSSI, SNR) and gateway reach, highlighting why adaptive data-rate and multi-gateway diversity are essential for a resilient smart-city LoRaWAN network.

Figure 1. Understanding signal variability helps in designing more resilient networks for smart cities.

In Spring 2024, additional RAK7289 gateways were deployed in strategic locations across Kuopio, aiming to improve coverage in areas where high-rise buildings or underground infrastructure attenuated signals. Antenna orientations and power settings were systematically tested. Network management during this phase was facilitated by the Loriot platform, which provided real-time oversight of gateway status, packet routing, and sensor activations. The Tulvia.ai application was also conceptualized to eventually deliver front-end visualizations and alerts based on aggregated data. The Tulvia.ai application—conceptualised and developed within this project—offers an interactive dashboard for real-time situational awareness (see Figure 2) During these pilot tests, each sensor reported ultrasonic distance measurements at set intervals, enabling near real-time monitoring of water levels alongside signal quality indices like RSSI and SNR.

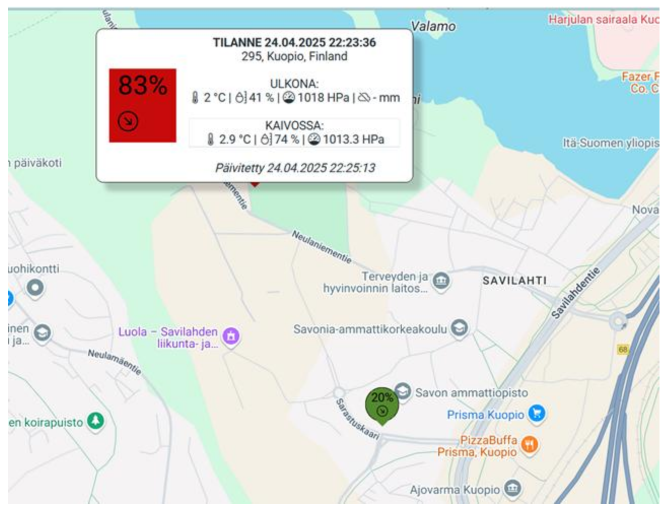

Figure 2. Screenshot of the Tulvia.ai web dashboard (site 295, Kuopio)

From Fall 2024 to Spring 2025, the project shifted toward optimization and AI model integration. Different antenna types, including 5.8 dBi fiberglass antennas and smaller 2 dBi SubG versions, were tested to identify the most effective configuration under Kuopio's urban conditions. Two AI models were then developed: an initial model trained on approximately 10,000 sensor readings, which compared linear regression, decision trees, and random forests for short-term water-level forecasting; and a subsequent model that integrated precipitation and temperature data. As illustrated in Figure 3, the random forest approach consistently demonstrated the highest predictive performance, particularly for the two-hour horizon. The internal structure of the Random-Forest ensemble is illustrated in Figure 4, where the Pythagorean-forest view depicts key splits across the 1 000 constituent trees, revealing heterogeneous yet complementary decision patterns. Maintenance staff feedback led to refined procedures for sensor inspections, especially under winter conditions when snow accumulation, ice, or wind could disturb gateway enclosures.

Model	MSE	RMSE	MAE	MAPE	R2
Linear Regression	142112.666	376.978	115.150	0.050	0.901
Random Forest	9676.905	98.371	20.762	0.007	0.993
Tree	22580.684	150.269	23.685	0.008	0.984

Figure 3. Comparative performance of the AI models

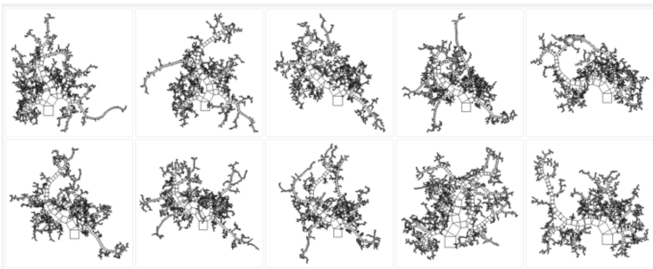

Figure 4. Pythagorean Forest Visualization of Random Forest Models in Orange Data Mining Software

Throughout these phases, both quantitative and qualitative data were collected, reflecting Yin's emphasis on multiple sources of evidence [9] to build a comprehensive case study database. Sensors continuously logged water-level readings, while gateway telemetry captured battery performance, signal strength, and firmware health. Supplementary stakeholder interviews with maintenance technicians, data scientists, and city officials offered perspectives on device calibration, mag-mount reliability, and the complexities of scheduling on-site inspections. Participant observation further enriched the dataset, as researchers took part in the physical tasks of installing gateways, opening wells, and retrieving sensors. Physical artifacts (e.g., sensor mounting hardware, gateway enclosures) also provided tangible evidence for understanding real-world constraints.

The within-case analysis approach advocated by Eisenhardt [10] allowed researchers to delve deeply into the specific operational, technical, and organizational factors shaping the project's outcomes. Data were triangulated across different sources—sensor logs, interviews, field notes, and artifacts—to identify emerging themes and refine implementation practices. A pattern matching analysis [9] systematically compared observed challenges—such as disruptions from metal well covers or sensor detachments—to establish theoretical constraints, confirming the importance of organizational readiness and robust hardware selection for stable LoRaWAN-based monitoring. By incorporating iterative feedback loops, the methodology ensured that insights from each phase informed subsequent optimization, culminating in a data-driven framework for AI-based flood prediction in Kuopio's urban environment.

IV. RESULTS AND ANALYSIS

A. Research Question 1 (RQ1): Network Architecture

RQ1 asks: What type of network architecture can be used in AI-based monitoring of water levels? In Kuopio's city context, the LoRaWAN-based architecture proved effective due to its low power needs, modular design, and adaptability to various obstructions. Table I summarizes key findings regarding coverage improvement, antenna orientation, power optimization, and the importance of gateway placement near tall buildings.

TABLE I. FINDINGS RELATED TO NETWORK ARCHITECTURE

Finding	***Data Source***
Multiple gateways improved coverage and reliability.	Field tests, coverage logs
Proper antenna orientation reduced signal degradation in urban areas.	Pilot test measurements
Adjusting transmit power optimized energy consumption	Battery discharge records
Gateway placement was critical for line-of-sight near tall buildings.	GPS-based signal mapping
Well covers and sensor magnetic mounts can impede signal transmission, especially below ground.	Field notes, pilot test results
Strong above-ground signal coverage does not guarantee adequate underground coverage (LoRaWAN signals attenuate quickly); NB-IoT could be tested as an alternative.	Winter field observations
Routers (gateways) and their antennas should be placed as high as possible, ideally with clear line-of-sight, to maximize coverage.	Implementation logs
Changing sensor antenna orientation (vertical vs. horizontal) can modestly improve transmission quality.	Pilot test measurements
Different antenna types feature varying coverage patterns; certain models "hear" better from all directions but with a smaller range, which can be advantageous for underground reception.	Lab and field testing
Building a private LoRaWAN network can be an effective solution in areas with many sensors or lacking a commercial network.	Stakeholder interviews

Through iterative testing, positioning gateways at elevated points and experimenting with different antennas proved beneficial in mitigating coverage blind spots in Kuopio's dense city environment.

B. Research Question 2 (RQ2): Implementation of the AI-based Service

RQ2 asks: How can the AI-based water level monitoring service be implemented regarding devices, components, and AI models? A combination of hardware and software components was employed, including resilient LoRaWAN sensors, multiple gateways, the Loriot network server for device authentication and packet forwarding, and an application server that hosted AI-based analytics and the

Tulvia.ai interface. Table II highlights the main implementation aspects, findings, and data sources.

TABLE II. IMPLEMENTATION ASPECTS, FINDINGS, AND DATA SOURCES

Implementation Aspect	*Finding*	*Data Source*
Data Network	5.8 dBi antennas provided adequate coverage in open areas	Interviews, physical artifacts
Sensor Deployment	Magnetic mounts interfered with signal in certain wells.	Field notes, pilot test results
AI Model	Random forest outperformed linear regression & decision trees for short-term forecasting.	Model training logs, local dataset
Maintenance Scheduling	Battery drain rate required adjustments in transmission intervals (~9 months when sending data every two minutes).	Testing data, system logs
Well Access	Stormwater well covers may be buried and not opened for a long time; GPS data can be inaccurate, so extra tools (e.g., shovels, manual searches) are needed to locate and expose the well.	Field notes, additional observations
Mount Reliability	Magnetic sensor mounts do not always hold under winter conditions; two sensors fell into the well, yet one continued to transmit despite immersion.	Winter pilot test results
Weather Conditions	Strong winds, freezing temperatures, and snow accumulation can complicate outdoor gateway installation and affect sensor placement feasibility.	Implementation logs
Private Network Feasibility	Setting up a self-managed LoRaWAN network can be advantageous if there is no commercial LoRaWAN or if a large number of sensors are concentrated in one location.	Stakeholder interviews
Network Management	Platforms like Loriot, WisGate support remote gateway updates, device authentication, and encryption key management, but require technical expertise and adherence to frequency/duty cycle regulations.	Network server logs, vendor docs
AI Model Complexity	If large volumes of sensor data are collected, training AI models (e.g., random forests) can become resource-intensive; cloud computing resources may be required.	Model training logs, interviews
Algorithm Comparison	Lighter models (e.g., linear regression) may be faster to run, while more complex models (e.g., random forest) offer higher accuracy, so balancing speed vs. accuracy is crucial.	Model evaluations

By combining robust network hardware with advanced AI models, the solution ensures both continuous data capture and accurate water-level forecasting, enabling effective early urban flood warning mechanisms. The Tulvia.ai application leverages this data to display real-time water levels, issue alerts, and provide predictive insights to municipal authorities.

C. Research Question 3 (RQ3): Challenges and Pattern Matching

RQ3 asks: Which challenges are related to the implementation and deployment of the AI-based water level monitoring service? Numerous challenges arose, ranging from physical obstructions like metal well covers to organizational factors, such as firmware updates and staff training. These were categorized using a pattern matching technique [9] aligned with ITIL 4 service management dimensions [8]. Table III illustrates the primary findings.

TABLE III. CHALLENGES BY ITIL 4 SERVICE MANAGEMENT DIMENSIONS

Dimension	*Finding*	*Data Source*
Information and Technology	Metal well covers and magnetic mounts disrupted signals; hardware selection proved critical.	Interviews, field notes
People and Processes	Technicians needed re-training on sensors and updated software tools.	Interviews, documentation
Value Streams and Processes	Delays in data flow due to suboptimal network routes impacted real-time analytics.	Network server logs
Partners and Suppliers	Third-party gateway firmware updates occasionally caused minor downtime for gateways. Also misscommunication caused minor delays for logistics (antennas delivery time).	Vendor communication
Information and Technology	Surface-level coverage does not guarantee underground connectivity; thorough on-site testing is required to mitigate well cover interference.	Field notes, pilot tests
People and Processes	Multiple stakeholders in the installation process can delay schedules; staff must coordinate to handle well openings, seasonal conditions, and sensor calibrations.	Maintenance logs, interviews
Value Streams and Processes	Strict duty cycle and frequency regulations must be followed to avoid network congestion and data loss, requiring updated processes for device configuration.	Vendor documentation, local regs
People and Processes	Maintaining a private network demands specialized knowledge of gateway configuration, encryption key management, and sensor troubleshooting.	Stakeholder interviews
Information and Technology	Winter weather can damage or dislodge gateways and sensors, necessitating adjustments to both hardware selection and maintenance schedules.	Field notes, pilot test results

By systematically aligning observed issues with theoretical patterns, the project team was able to implement targeted improvements. This approach confirmed that both technological and human factors must be addressed throughout the entire service lifecycle.

V. DISCUSSION

The findings validate the premise that integrating a private LoRaWAN network with AI-driven analytics can enhance water-level monitoring and urban flood prediction in Kuopio's city area. Early in the research, theoretical arguments emphasized LoRaWAN's adaptability and coverage potential, particularly if antennas and gateways were strategically positioned to overcome obstacles like metal stormwater covers and tall buildings. Empirical results backed these claims; field tests revealed that coverage reliability improved markedly when multiple gateways were installed at higher vantage points, and when antenna power settings were tuned based on real-world signal measurements.

On the AI front, experimental comparisons confirmed that random forests excel in handling non-linear and rapidly changing hydrological data. These findings underscore the value of ensemble methods, particularly when aided by contextual information, such as precipitation and temperature logs. The two-hour forecast window aligns well with the need for timely interventions, granting local authorities enough lead time to respond to imminent surges in well levels or potential flood events. By incorporating these predictive tools into the Tulvia.ai application, city personnel receive actionable updates capable of prompting proactive drainage checks or other preventative measures.

From an organizational standpoint, pattern matching revealed that sensor calibration, firmware updates, and staff training often dictated the project's day-to-day success as much as the underlying technology. Metal well covers, for instance, necessitated repeated on-site adjustments to ensure signals could penetrate effectively. Firmware updates from hardware vendors occasionally introduced compatibility issues, demanding swift responses from the technical team to maintain continuity. Coupled with winter conditions that tested battery performance and sensor stability, these factors reaffirmed the importance of an integrated service management framework (ITIL 4). Ensuring that all stakeholders—maintenance crews, data analysts, municipal decision-makers—operated with a coherent workflow helped preserve the system's overall reliability.

Lastly, the study's results hint at promising avenues for future exploration. Although LoRaWAN proved effective in Kuopio's urban environment, alternative LPWAN technologies, such as NB-IoT, may offer better underground penetration under certain conditions. On the AI side, advanced ensemble or deep-learning models could prove even more accurate given larger datasets that incorporate seasonality and extended climate patterns. Enhanced security measures, including advanced encryption methods and anomaly detection, are also increasingly relevant as IoT data sensitivity grows.

VI. CONCLUSIONS

This study demonstrated the feasibility of deploying a private LoRaWAN network, augmented by AI-based prediction models, to monitor and forecast water levels in Kuopio's city environment. Systematic refinement of network architecture—through gateway placement, antenna configuration, and iterative transmit power adjustments—addressed key challenges linked to metal well covers, tall buildings, and subzero temperatures. The project's phased approach, from sensor installation in Fall 2023 to comprehensive field tests and AI integration by Spring 2025, effectively resolved practical obstacles tied to hardware setup, coverage blind spots, and battery limitations.

Empirical comparisons of AI models indicated that ensemble learning methods, especially random forests, delivered robust short-term forecasts when coupled with local sensor data and environmental metrics. These predictive enhancements can significantly improve municipal responses to sudden well-level changes or urban flooding. At the same time, incorporating an ITIL 4-inspired pattern matching technique confirmed that human factors—ranging from technician retraining to vendor firmware compatibility—must be integrated into planning and operations for the system to remain durable.

Overall, the alignment of low-power IoT infrastructure with AI-driven analytics shows strong potential for proactively managing stormwater wells in Kuopio. In addition to improving local flood preparedness, the results illuminate how future studies might delve deeper into alternative LPWAN technologies, develop advanced machine learning architectures, and strengthen IoT security protocols. By balancing innovative technical solutions with consistent service management practices, this project provides a replicable model for cities seeking to harness IoT data in mitigating flood risks.

ACKNOWLEDGMENT

This work was partially supported by Advanced CoMputing Continuum Solutions for Boosting DigITalization acrOss EUropean RegionS, Grant Agreement: 101115116, funded by the European Union. The views and opinions expressed in this paper are solely those of the author(s) and do not necessarily reflect the official policies or positions of the European Union, the European Innovation Council, or the SMEs Executive Agency (EISMEA). Neither the European Union nor the granting authority can be held responsible for any use that may be made of the information contained herein.

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