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Towards Low-Cost IoT and LPWAN-Based Flood Forecast and Monitoring System

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Abstract

The recent floods have shown that the classic monitoring systems for watercourses are no longer adapted because other phenomena such as the insufficient capacity and/or obstruction of drainage networks, the modification of cultivation practices and rotations, the increase in the size of plots linked to the reparcelling, the urbanization of floodable areas, etc. The combination of all these causes, plus the modification of the water regime, implies an increase in the risk of flooding and an adapted monitoring that is no longer limited to watercourses in order to give early warning of the risk of flooding by runoff. The Internet of Things (IoT) and the availability of microcontrollers and sensors with low data rates and long ranges, as well as low-power wide area networks (LPWANs), allow for much more advanced monitoring systems.

Keywords: *Monitoring System, Warning System, Flood, Runoff, Moody Flood, Flash Flood, Runoff Flooding, Sewer, IoT, LPWAN, LoRaWan, NB-IoT*

1. Introduction

Flooding is the most common natural hazard affecting many parts of the world; nearly half of the world's natural hazards are not limited to overtopping of riverbanks inundating neighboring areas [1,2] but floods can also be caused by surface runoff or other local-scale runoff problems. Indeed, in temperate regions, more local phenomena such as mudslides at the bottom of agricultural plots, drainage backups due to insufficient capacity, obstruction or lack of maintenance, which can also be damaging to property and people, are never monitored. In semi-arid regions, flash floods pose a significant threat to human life and cause considerable damage. The cost of damage is estimated at more than 500 billion in Europe between 1980 and 2015 [3]. They therefore deserve our full attention and particularly close monitoring.

The causes of flooding are usually a combination of various environmental and man-made factors. Environmental factors are things we cannot control, such as the amount and intensity of rainfall, frozen or waterlogged soils, snowmelt, watershed topography and soil types, and slope exposure. Anthropogenic factors include all actions that impact runoff such as cropping practices and rotations, significant changes in land use, lack of maintenance of stormwater retention structures and/or the sewer system, infilling of agricultural land, deforestation, and urbanization. In addition to surface runoff flooding, some areas may also be subject to landslides. The monitoring of this type of risk is subject to a specific monitoring described in the previous article [4]. Two common approaches are used to monitor flooding. The first one is based on computer vision and image processing techniques, while the second one is based on wireless sensor networks (WSNs) and computer models such as artificial neural networks (ANNs) [2].

Today, most IoT WSN-based flood monitoring systems are limited to measuring water height at bridges or along riverbanks; they measure flows in monsoon drains in residential areas [1]. With the increasing complexity of watersheds due to human activities, climate change, social and economic aspects, traditional watershed management tools have become obsolete. Smart management provides a solution to facilitate complex watershed management by providing an integrated view of all aspects [5].

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Table 1. Sensors & Actuators implemented in flood monitoring / warning systems

Model	Manufacture	Measured	Precision	Interface	Voltage	Conso.	Ref.
LM35	Texas Instruments	Temp.	±0.5°C	Analog	4-30V	114µA	[1]
BME280	Bosch Sensortec	Temp., Hum., Pres.	±1∘C/±1%/±1ha	I^2C / SPI	1.2-3.6V	3.6µA	[1]
BMP180	Bosch Sensortec	Pressure	0.03hPa	I^2C / SPI	1.8-3.6V	5µA	[1]
LA16M-40	Eicos	Water Level	-	Digital	5V	0.5A	[14]
FDC1004	Texas Instrument	Water Level	-	I^2C	3-3.6V	750µA	[1]
HC-SR04	Adafruit	Water Level	±0.6cm	Digital	5V	15mA	[1, 14]
MB7066	MaxBotix	Water Level	±1cm	Analog	3-5V	100mA	[1]
SEN113104	Seeed Studio	Water Level	-	Analog	5V	20mA	[1]
JSN-SR04T-2.0	Miscellaneous	Water Level	±1cm	Digital	3.3-5.5V	30mA	[15]
YF-S201	Miscellaneous	Flow	±10%	Digital	5-24V	15mA	[1]
DHT11	Adafruit	Temp., Hum.	±2°C/±5%	Digital	3-5V	2.5mA	[1]
DS3231	Maxim Integrated	RTC	-	I^2C	2.3-5.5V	300µA	[15]
SIM800L	Miscellaneous	GSM module	N/A	TTL	3.5-4.2V	2A	[15]
Neo6m	u-blox	GPS	2.5 m	UART	2.7-3.6V	100mA	[14]
K30	Winsen Electronics	CO_2 rate	±30ppm±3%	Ana. /Dig	5.5-14V	40mA	[13]
YL-83	Vaisala	Rain	-	Analog	3.3-5V	100mA	[14]

Hydrological modeling is particularly important for estimating and forecasting flood flows in rivers and streams, as well as the volume of runoff at various critical points in the watershed. To be effective, modeling must be performed using accurate data acquired at short time intervals and distributed in space. The Internet of Things allows the massive acquisition of meteorological data (temperature, relative humidity, precipitation), on soil moisture, water level, flow rates, flow velocities that allow the validation and improvement of predictive models.

In this paper, we present a comprehensive monitoring system integrating both overflowing streams and surface runoff. In Section 2, we summarize contributions from the literature to select the elements needed to build our monitoring system. In Section 3, we describe the conceptualization of our architecture, and we continue with its implementation and evaluation in Section 4. Finally, we conclude, and outline our future work in Section 5.

2. Related Work

This section is composed of three parts: The first part summarizes major contributions from the literature while the second part focuses on architectural components and communication protocols. Building a flood monitoring system for runoff and overflow requires selecting sensors, transmitting the data, storing the data, and then analyzing the data and alerting authorities and stakeholders if necessary. In the third part, we present the necessary elements for the development of an overflow and runoff flood monitoring system.

2.1. Previous works

In our previous work, we worked on a landslide early warning system and evolved our monitoring system successively in [4,6,7]. The basis of our wireless sensor network was described in [6], the gateway in [7], and the landslide early warning system in [4] with the integration of fog-level federated learning. In this work, we extend our work to flood monitoring. For example, excessive runoff during periods of intense rainfall, which can otherwise lead to flooding, is also a common trigger for landslides. In addition, we developed an outlying A2IoT architecture in [8,9] and implemented in [10,11]. The fog gateway was developed and tested in [12].

2.2. Variables to monitor

The most monitored variable in the literature is the water level in the riverbed or under bridges. Arshad et al discussed the sensors to be implemented to estimate the water level to monitor flooding. The **pressure transducer** can measure the water level with an accuracy of 1 mm but requires calibration and is very sensitive to any vertical displacement of the installation point and may require air pressure control to correct the output of the pressure transducer. The **ultrasonic rangefinder** is a popular sensor that calculates the time between transition and reception of signals reflected from the water to determine the water level [2]. Flash floods are particularly destructive and forecasting them is crucial. Khan et al. developed a new approach based on correlating flash flood prediction with the increase in **soil moisture** and **carbon dioxide** with a K30 transducer at the seashore during wave rise. While a multilayer perceptron (MLP) reduces the number of false alarms [13]. Da Silva Júnior et al described IOTFlood, a modular and scalable low-cost platform to monitor floods in real time and send automatic messages [14]. Abdelal et al developed a hydrological monitoring platform called HydroMon3, which links different types of sensors. They proved that conventional hydrological data acquisition is not representative enough of the event and that high temporal resolution data obtained from connected sensors give a better representation of these events [15]. Table 1 provides a summary of sensors and actuators used in the literature.

2.3. Communication protocols

The main protocols implemented in LPWA applications are LoRaWAN, SigFox, LTEM and NB-IoT [17]. LoRaWan is organized in a star topology, where multiple end devices transmit data to a gateway in a single hop. Cotrim et al examined multi-hop communication using the LoRaWAN protocol and showed that they can extend battery life by decreasing transmission power. They classify the strategies into 6 approaches: (1) Device-relay; (2) Relay-gateway; (3) combination of the previous two approaches; (4) Device-router; (5) Router-gateway; (6) combination of the previous two approaches; (7) hybrid [18]. While Lestari et al presented the results of implementing LoRa in a mesh network topology used to transmit river water quality data from multiple sensors over a long distance [19]. If LoRaWan is not available, we can use NB-IoT (3GPP), but this is not free as it is deployed by telephone companies.

2.4. Rainfall spatialization

Ly et al compared the performance of deterministic and geostatistical methods to calculate spatial interpolation of rainfall data. The deterministic methods tested were multi-station averaging, Thiessen polygon (THI) also called nearest neighbor (NN), Inverse Distance Weighting (IDW) and its variants including elevation: Inverse Distance and Elevation Weighting (IDEW), Polynomial Interpolation (PI), Spline Interpolation (SI), Moving Window Regression (MWR). In addition, three geostatistical kriging interpolation methods were evaluated: Simple Kriging (SK), Ordinary Kriging (ORK), Universal Kriging (UNK). Multivariate geostatistical methods in combination with elevation with elevation data. They concluded that for daily precipitation interpolation, geostatistical and IDW methods have comparable accuracy while for annual and monthly precipitation interpolation, geostatistical and IDW methods give the best accuracy. Finally, they report that radar data used as a secondary variable in geostatistical methods improves the accuracy of hourly precipitation interpolation [19].

2.5. Hydrological modeling

The Soil Conservation Service Curve Number (SCS-CN) is a simple, well-recognized method widely used by hydrologists, engineers, and watershed managers to estimate the direct runoff from a storm rainfall event [20]. The general form of the SCS-CN equation is given below.

$$Q = \frac{(P-Ia)^2}{(P-Ia)+S} \tag{1}$$

Where *P* is rainfall expressed in mm, *Q* is runoff expressed in mm and *Ia* is the initial rainfall interception.
With the assumption of $Ia = 0.2S$, equation (1) becomes:

$$Q = \frac{(P-0.2S)^2}{P+0.8S} \tag{2}$$

Q, the runoff expressed in mm is calculated with equation (2), when $P > 0.2S$ and otherwise $Q = 0$.

$$S = \frac{25400}{CN} - 254 \tag{3}$$

Where *S* is a maximum potential retention after the onset of runoff expressed in mm and the curve number (CN) is a descriptive parameter of the runoff potential of the watershed reflecting soil and cover conditions. The SCS defines 3 antecedent moisture conditions: 1-dry (wilting point) in other words the lowest value the curve number can take under dry conditions, 2-average moisture, 3-moisture (field capacity). The number of curves in situation II is calculated for a slope of 5% but these values must be adjusted for the actual value of the slope expressed in %. Equation (2) is used to calculate the values of *CN2α*.

$$CN2\alpha = \frac{1}{3}(CN3 - CN2)(1 - 2e^{-13.86\alpha}) + CN2 \tag{4}$$

Where *CN2α* is the fitted value of CN2 and α is the soil slope in m/m. The curve numbers for the 1-dry and 3-wet conditions are calculated with the equations.

$$CN1\alpha = CN2\alpha - \frac{20(100-CN2\alpha)}{100-CN2\alpha+exp[2.533-0.0636(100-CN2\alpha)]} \tag{5}$$

$$CN3\alpha = CN2\alpha.exp[0.00673(100 - CN2\alpha)] \tag{6}$$

Where *CN1α* is the curve number of moisture condition I, *CN2α* is the curve number of moisture condition II (average condition: 12-28 mm in the dormant season and 35-53 mm in the growing season), and *CN3α* is the curve number of moisture condition III (near saturation: >28 mm in the dormant season and >53 mm in the growing season).

3. Our architectural proposition

In this section, we formulate our architectural proposal combining the smart watershed and smart home scales to achieve a monitoring system capable of monitoring stream overflow flooding and/or runoff for territorial authorities on a large scale and on a local scale for residents.

3.1. Conceptualization

Each watershed is different in its morphology as well as in the distribution of human and economic issues. This is why the detection nodes must be able to integrate different sensors depending on what needs to be monitored (water height, pressure in the pipes, flow rates, volume of water runoff, water flow speed, etc.). It is also easy to understand that for the same quantity, the sensors must be adapted according to the scale at which the quantity must be measured. The nodes will therefore have to support "plug and play", to be able to detect the type of sensor and their model without having to modify the source code. The sensor system must be optimized to be deployed in remote locations, be reliable, withstand harsh conditions, enable long-range communication, and accommodate different types of sensors [21]. In addition, they must be lightweight, small in size, inexpensive, low power, and powerful [22].
Monitoring the amount of rainfall, its intensity and temporal distribution is an important factor in the occurrence of floods. Temperature also plays an important role in soil permeability. Indeed, a frozen soil will not be able to infiltrate the rain and will allow a complete runoff of the precipitations. While a prolonged period of drought will have an impact on the infiltration capacity of the soil and will lead to a more important runoff. Similarly, rapid snowmelt results in a significant amount of runoff. Soil moisture at different depths has a direct impact on its ability to infiltrate precipitation and runoff. It is easy to understand that the water saturation rate of the soil has a direct impact on its infiltration capacity.
Low-power wide area networks (LPWANs) have become popular with the Internet of Things, such as LoRaWAN, SigFox, Ingenu, NB-IoT, which operate on unlicensed ISM frequencies and allow building a large wireless communication network at low cost [23]. Among them, LoRaWan allows to be deployed in a mesh network topology and supports multi-hop communication [17].

The processing architecture must be salvageable to be scalable to many nodes and allow for real-time data processing as well as provide the ability to post-process time series of data to estimate trends in their evolution. The data management plan must provide for permanent storage of raw data and processed data for research purposes.

3.2. Implementation

Our proposed monitoring system consists of a weather station to monitor precipitation and environmental parameters, sensor nodes to acquire data such as water height, flow rate, pressure, an architecture to store and process the data.
The common element of the weather station and sensing nodes is Pycom microcontrollers (GPy, LoPy 4, and FiPy) based on Espressif's ESP32 Soc to which chips have been added to enable the implementation of several communication protocols. Table 2 shows a comparison of the communication protocols supported by the three selected PyCom microcontroller models. All three microcontrollers support Bluetooth Low Energy and conventional, as well as Wi-Fi. GPy will be preferred when only NB-IoT is available while LoPy4 will be implemented when LoRaWan or SigFox is available. Finally, FiPy is the most successful with support for NB-IoT, LoRaWan and SigFox allowing for example to use LoRaWan and NB-IoT as a backup when both networks are available. We chose Pycom microcontrollers is powered by 2 processors with 4MB of RAM, 8MB of external flash, floating point hardware acceleration. The main processor is fully free to run the user application while an additional ULP processor that can monitor the 22 or 24 GPIOs, ADC channels and control most of the internal peripherals in deep sleep mode consuming only 25µA. It is equipped with Wi-Fi, BLE, RTC, 2 UART, 2 SPI, I2C, I2S, micro-SD card. In addition, it supports SHA, MD5, DES, AES encryption algorithms. In addition, it supports over-the-air (OTA) programming, which allows you to update the software remotely.

Table 2. Comparison of protocols between GiPy, LoPy4, and FiPy

Protocol	GPy	LoPy4	Fipy
Wi-Fi	yes	yes	yes
Bluetooth	yes	yes	yes
LTE M1/NB1	yes	no	yes
LoRaWan	no	yes	yes
SigFox	no	yes	yes

We chose the LoRaWan protocol, which is widely implemented in various use cases and has demonstrated its robustness in harsh environments [6, 24] because spread spectrum data transmission allows data to be sent under the noise level. Nevertheless, in harsh conditions, devices will require more energy to transmit and decrease the lifetime. Dense networks of devices can degrade the performance of the overall network (longer delay and low reliability) [16]. We deployed our object stack to build our private and secure end-to-end network and use the object network as a backup network.

The **Weather station** which aims to measure the volumes and intensities of precipitation but also the air and soil temperature, soil moisture. We used the Bosch Sensortec BME280, an air temperature and humidity sensor and a barometric sensor with respective accuracies of ±1°C / ±1% / ±1ha. While a SparkFun SEN-08942 Weather Measurement Kit containing a rain gauge, a wind vane and an anemometer that measure respectively the amount of rain, wind direction and wind speed. Soil moisture at 10cm and 25cm depth and soil temperature are respectively measured with the Irrometer 200SS and the Irrometer 200ST mounted with two 74HC4051 multiplexers as shown in Fig. 3 in the documentation proposed by Irrometer.

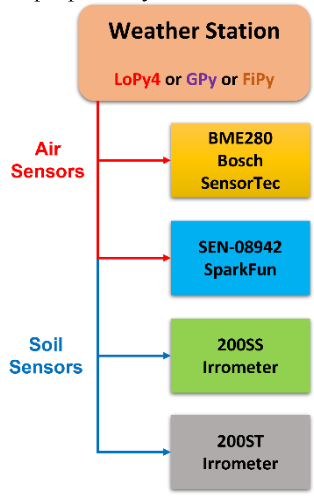

Fig. 1. Schema of the Weather Station

The **sensor node** can adopt different configurations depending on the target to be monitored. To measure the water level, we chose the ultrasonic distance sensor MB7389 HRXL-MaxSonar-WRMLT which is a sensor designed for outdoor use and meets the IP67 standard. It can be read in three modes: analog voltage, serial, pulse width. We use it in Pulse Width mode with the PyCom microcontroller. The monitoring of the flow in the sewers is realized with the Beluga Flow-Tronic for nominal diameters from 150 to 2500 mm connected in Modbus.

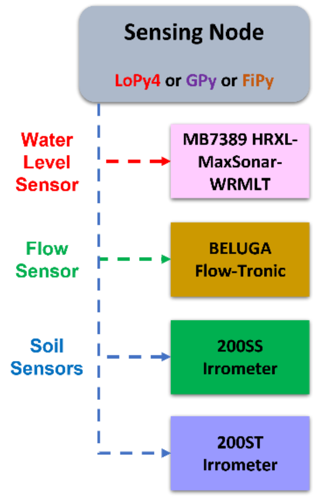

Fig. 2. Schema of the Sensing Node

Processing and storage architecture. Our architecture is built around a Lambda architecture (Fig. 3) using Apache Kafka, Apache Beam, Apache Samza, Hadoop and two databases: Apache Druid as the time series database and PostgreSQL with PostGIS as the geodatabase. The Lambda architecture is well suited for data processing when batch and stream processing are two different processes[25]. The Lambda architecture is inherently composed of 3 layers: (1) A velocity layer that processes real-time data produced by weather stations and sensing nodes; (2) A batch layer based on Apache Hadoop and the map reduce paradigm to produce maps from the data stored in Apache Druid; (3) The service layer allows querying the databases.

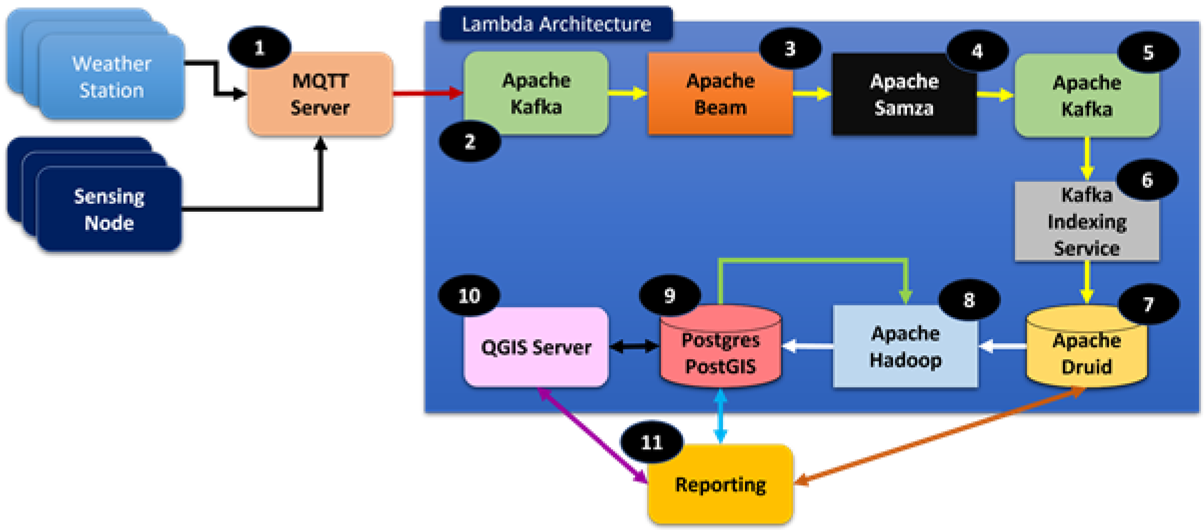

Fig. 3. Overview of the global architecture

The data is transmitted to the Lambda architecture using the MQTT publish-subscribe protocol to an MQTT server (1) which transmits the data to Apache Kafka (2). The latter temporarily stores the data before it is processed by a model developed with Apache Beam (3) and executed on Apache Samza (4). The results of the processing are stored in a new Apache Kafka topic (5) while a Kafka indexing service (6) ingests the data stored in the Kafka topics and inserts it into Apace Druid (7). Nkamla Penka et al have shown that the combination Apache Kafka, Apache Samza, and Apache Druid is particularly well optimized to process IoT data [26]. The real-time data stored in Apache Druid is post-processed in a batch process with Apache Hadoop (8) where the precipitation data is interpolated to create a precipitation map using Ordinary Cokriging (OCK) which considers the elevation of the weather stations. Anomaly detection is performed by cross-validation consisting of eliminating a station and calculating the interpolation and then comparing with the measured value. The results of the spatialization are stored in PostgreSQL/PostGIS (9). A QGIS server is used to allow visualization of the maps made from the data stored in the PostgreSQL database (10). The report integrates the map from the QGIS server, and the time series data to provide the calculated runoff rate and volume at different points in the watershed with the SCS method (11).

4. Experimentation

To experiment our architectural proposal, we installed a weather station, a sensing node to measure the river level using an electromagnetic distance meter at the level of an opening and another sensing node to measure the water level sensor in the cellar of a house adjoining the river. The weather station, outdoor sensing node, indoor sensing node are respectively located at following coordinates expressed in latitude and longitude: (50.317055, 4.4382366), (50.3168558, 4.4385589), and (50.3170988, 4.4385435).

The system was tested during the floods of July 13 and 14, 2020 in the municipality of Ham-sur-Heure/Nalinnes, Walloon Region, Belgium. The measurements were carried out on the brook of the Mill at the level of the Lavalle street and of a joint house whose garage is located in the cellar below the Lavalle street. When the brook overflows, the water comes from the street and floods the cellar through the garage entrance.

The Fig. 4 presents measures each 15 minutes of water level achieved in the cellar during the flooding event. On the figure we can see the submersion of the cellar, the stagnant water level followed by the emptying by pumping.

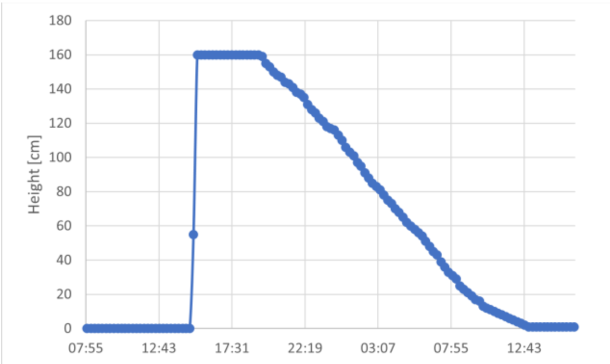

Fig. 4. Measure of water level in the cellar

The Fig. 5 presents measures of water level achieved at the bridge over the river. In this figure, we can see the base level of the creek increasing rapidly due to the inflow from the fields to reach the maximum admissible level in the sluice causing the overflow and the flooding of the cellar and then the period of recession.

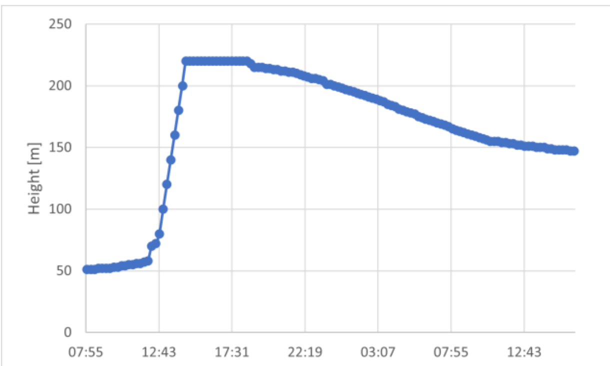

Fig. 5. Water Height measured over the bridge

At this stage, the operation has been demonstrated on a very small scale and further experiments on a larger scale are still needed to improve the system and validate it.

5. Conclusion and perspective

This research work is motivated by the observation that floods are generally monitored at the level of rivers, dams and wadis and rarely at the level of drainage networks and river tributaries, or at the level of watershed areas producing significant quantities of surface runoff. As the analysis of the literature has shown, two approaches coexist for the monitoring of floods through the use of sensors, or the analysis of images acquired by camera or drones. Our work has so far been limited to the exploration of the implementation of sensors. The use of images and their processing at the level of the cloud architecture is planned at a later stage.

Monitoring and alert systems are currently not designed to be used by citizens. However, the latter living in flood-prone areas generally have empirical benchmarks in terms of water level and /or runoff which allow them to assess the imminent risk of flooding for their property. We believe that allowing stakeholders to have access to official data and to be able to add data from their own sensors can, if these are standardized, allow a very local analysis of the flood risk. The possibility of deploying large-scale sensor networks is no longer to be demonstrated because they are widely used, particularly in smart cities and in smart farming. LoRaWan and NB-IoT or 5G communication protocols make it possible to cover large territorial areas.

In this work, we propose a weather station and sensing node in which sensors can be changed and detected automatically. Once the sensor(s) are detected, the configuration is sent to the cloud, or a script is automatically generated to retrieve the data. The code is then deployed via OTA.

The limitations of our work are the current limitation of nodes to LoRaWan / SigFox and NB-IoT protocols. 5G and Ingenu are currently not supported by sensor nodes and weather stations.

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