Towards smart agriculture in the Thiès region

Abstract:
The digital transition represents a major challenge for Senegalese agriculture, which is facing resource scarcity, the impacts of climate change, and the growing need to optimize production systems. In this context, our research aims to propose an integrated technological architecture, based on the Internet of Things (IoT), long-range communication (LoRa/LoRaWAN/4G), and artificial intelligence (AI), to digitize and modernize the five strategic areas of the agronomy cluster at Iba Der Thiam University in Thiès: arboriculture, market gardening, fish farming, dairy production, and poultry farming.

The platform to be developed will rely on the use of sensors adapted to each sector. In the **fruit** and **vegetable sectors**, the "7-in-1" NPK sensor provides essential measurements of soil fertility (nitrogen, phosphorus, potassium), pH, conductivity, and moisture, enabling the development of predictive models for water stress, phytosanitary risks, and nutrient requirements. In **fish farming**, an electrical conductivity (EC) sensor is deployed to continuously monitor the physicochemical quality of the water, anticipate eutrophication risks, and stabilize fish production. The **dairy** and **poultry sectors**, for their part, rely on DHT22 (temperature/humidity) sensors to monitor the microclimate, assess heat stress in cows or poultry, and improve animal welfare.

The data from these IoT devices will be transmitted via Heltec Wi-fi LoRa 32 modules to storage and processing platforms, thus constituting a reliable and adaptable multi-layered monitoring system.

The methodological approach combines a diagnostic phase of the agricultural site, a modular design of the IoT architecture, the development of artificial intelligence models (prediction of water and nutrient needs, early disease detection, yield estimation), and experimental validation on test plots. The first expected results concern the quality of LoRa transmission in the rural environment of Thiès, as well as the reliability of data from the NPK sensors and the electrical conductivity (EC) sensor.

Keywords: IoT, LoRa, smart agriculture, AI, digital transition, NPK,LoRaWAN, EC, Electronics, Networks.

1. Introduction

Senegalese agriculture is at a crossroads, facing climate variability, declining soil fertility, and pressure on water resources **(1,2)** . This context underscores the urgent need for an overhaul of production systems to ensure the country's food security. According to the FAO (**3**) , agricultural productivity in sub-Saharan Africa could decline if appropriate technologies are not combined with traditional farming practices. To meet future food demand, agricultural production must increase by 60 to 100 percent by 2050 **(4**) . Artificial intelligence and machine learning offer promising solutions for improving agricultural productivity and sustainability (**5**).(**6**) .
Senegal is facing an alarming climate reality that threatens the survival of its agricultural sector, a pillar of the national economy. Rising temperatures and variable rainfall have direct impacts on the productivity of agricultural land. The increasingly frequent severe droughts and intermittent floods of recent years have highlighted the vulnerability of traditional farming systems to climate change. According to the National Agency for Statistics and Demography, approximately 70% of the rural population depends on agriculture for their livelihoods, underscoring the crucial importance of this sector for the country's socio-economic

development **(7**) . Furthermore, 45% of Senegal's land is at risk of degradation, exacerbating the challenges faced by farmers. In this context, the urgency of action is undeniable to ensure food security and the well-being of rural communities (**8**) . On the other hand, cattle farming can greatly contribute to meeting this demand, as it allows the production of foods such as meat and dairy products, essential to meet the nutritional needs of this expanding population **(9**) .

In this context, IoT, LoRa/LoRaWAN/4G networks, and artificial intelligence (AI) are key tools for improving environmental monitoring, optimizing irrigation, minimizing losses, predicting diseases, and enhancing agronomic decision-making **(10**) . These technologies enable continuous and reliable data collection, making affordable precision agriculture possible, even in rural areas with low connectivity (**11**).(**12**) . AI applied to agriculture and livestock farming now makes it possible to:

- ✓ detecting soil nutritional deficiencies via supervised models (**13**) ,
- ✓ optimize irrigation using predictive algorithms based on humidity, NPK and conductivity (**14**) ,
- ✓ detect early anomalies in fish ponds (dissolved oxygen, conductivity) via neural networks **(9,15**) .
- ✓ preventing heat-related diseases or stress in cattle using AI thermal models (**16**) ,
- ✓ anticipating avian diseases and microclimate anomalies in poultry houses(**17**) .

The agronomy center at Iba Der Thiam University in Thiès is a prime experimental site, structured around five strategic areas: arboriculture, market gardening, fish farming, dairy production, and poultry farming. These sectors, emblematic of Senegal's agricultural value chains, constitute a relevant testing ground for the integration and evaluation of contextualized IoT and AI solutions. However, despite the growing interest in the digitalization of agricultural practices, few studies propose a unified architecture capable of serving multiple value chains within the same agricultural ecosystem.

In this work, we present a unified, modular, and scalable technological architecture for the digitalization of the Thiès agronomic hub. It relies on environmental sensors (NPK, EC, DHT22), LoRa modules, an 8-channel LoRa gateway, LoRaWAN monitoring platforms, advanced analysis tools, and drone mapping. The goal is to demonstrate the feasibility of a unified system for collecting, transmitting, analyzing, and utilizing data from various agroecological domains to improve the technical management and sustainability of farms.

This introduction has therefore established the framework of our scientific approach, which consists of combining new technologies and local agricultural know-how to build a reproducible, sustainable model adapted to the Senegalese context.

2. ExperimentalMaterials and Methods

The work carried out so far relies on a set of electronic devices and sensors for collecting agronomic and environmental data in the various areas of the cluster. The first tests were performed in the laboratory and successfully validated the complete LoRa transmission from the sensors in the field to the test laboratory.

2.1. LoRa communication modules (Heltec Wifi LoRa 32)

In recent years, the Internet of Things (IoT) has established itself as a benchmark, reaching unprecedented heights. A true future of communication, it has transformed real-world objects into intelligent devices. The goal of the IoT is to unify all the world's objects so that humans can control them via the internet. Furthermore, these objects regularly provide status updates to the end user (**18**) . The agricultural IoT network based on LoRa technology represents a significant advancement in modern technologies, specifically designed for the vast expanses of smart farms. Its architectural design prioritizes efficient, long-range communication, aiming to conserve energy while facilitating the transmission of critical data between the various components of the farm **(19**) .

Each sensor (NPK, EC and DHT22) was connected to a Heltec Wi-fi LoRa 32 V3 module(Figure 1) . This is a compact IoT development board, integrating a dual-core ESP32-S3 microcontroller and an SX1262 LoRa transceiver, enabling it to combine Wi-Fi, Bluetooth 5, and long-range LoRa radio connectivity (20) . It is used as a transceiver node. These modules, integrating an ESP32 microcontroller and a long-range compatible LoRa interface, have enabled:

- Reliable reading of sensor data,
- The encapsulation of measurements into LoRa frames,
- Sending data to a Heltec module configured as a receiver.

A second **Heltec LoRa 32 module** was configured as a receiver node, allowing direct data retrieval in the laboratory for analysis and display.

The LoRa communication tests carried out were conclusive, demonstrating the system's ability to transmit data from the agricultural field to the laboratory without critical loss, thus confirming the robustness of the LoRa protocol in a rural context.

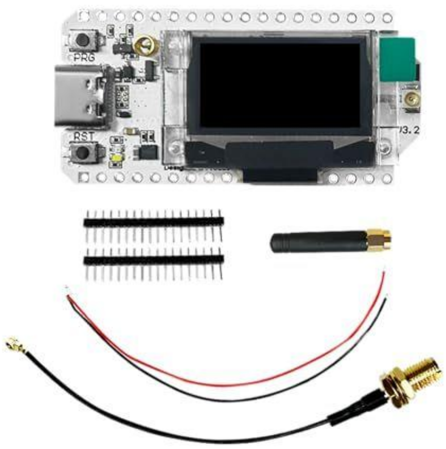

Figure 1: Heltec Wi-Fi LoRa 32

2.2. Sensors used in the experiments by axis:

The agronomy center at Iba Der Thiam University in Thiès comprises five distinct agroecological areas – arboriculture, market gardening, fish farming, dairy production, and poultry farming – which together form a complete ecosystem representative of Senegal's agricultural sectors. The methodological approach adopted in this study consists of selecting, for each area, a priority sensor corresponding to a critical performance or vulnerability indicator, thus enabling the development of an initial functional and scientifically relevant IoT architecture. The initial trials focused on three essential sensors, specifically chosen to meet the needs of the five areas within the agronomy center:

A. Arboriculture and market gardening: NPK sensor (7 in one)

The fruit and vegetable sectors are particularly sensitive to soil fertility and nutrient availability. The "7-in-1" NPK sensor (Figure 2) was therefore chosen as the primary sensor for these two areas. It allows for the simultaneous measurement of:

- Essential macronutrients (N, P, K),
- Soil pH,
- Electrical conductivity,
- Soil humidity and temperature.

These parameters directly influence plant growth, nutrient assimilation, and overall productivity.

Nitrogen (N) and phosphorus (P) are key indicators of soil nutrient content in agriculture. Precise management of these nutrients is essential to ensure food security **(21**) . For example, nitrogen contributes to protein synthesis and carbon sequestration, phosphorus is essential for root development and energy transfer in plants, and potassium regulates key physiological processes and overall plant health, contributing significantly to drought tolerance and disease resistance (**22**) **.** Applying machine learning, through the analysis of this IoT data, to the agricultural sector will increase both the quantity and quality of agricultural production to meet growing food demand (**23**) .

During laboratory experiments, this sensor provided stable measurements, and these were successfully transmitted via LoRa to the receiving laboratory, demonstrating the feasibility of continuous monitoring on agricultural sites.

Figure 2: NPK SENSOR 7 IN ONE

Figure 3: Arboriculture sector (Papaya)

Figure 4: Market Gardening Sector (Chili Peppers)

B. Fish farming:EC sensor (Electrical conductivity of water)

The world's population is projected to reach approximately 9 billion by 2050. The growing demand for protein-rich foods makes aquaculture one of the fastest-growing agri-food sectors globally. Challenges to fish production include outdated aquaculture techniques, overexploitation of marine species, and inadequate water quality control (**24**) . Water quality parameters such as temperature, dissolved oxygen, pH, and turbidity play a crucial role in controlling the health and productivity of aquaculture systems.(25) . Therefore, continuous monitoring and control of these parameters are essential to improve fish health and growth, as well as the overall sustainability of aquaculture systems (26) .

Tilapia is valued for its tolerance to diverse environments, rapid growth, and strong market demand. However, water quality remains a major constraint affecting survival and growth. Seasonal and climatic fluctuations can reduce dissolved oxygen (DO), particularly during rainy or cloudy periods; sometimes, DO falls below critical thresholds, causing stress, hypoxia, and even fish mortality through surfacing ("air ingestion") (**27**) .

Deployed for **fish farming** (Figure 6), the sensor allows for the assessment of the physicochemical quality of the water (mineralization, salinity) (Figure 5). Water quality is a determining factor for fish farming. The EC sensor was chosen to measure the electrical conductivity of the water, a highly correlated variable:

- During mineralization,
- To salinity,
- Regarding the overall condition of the basin,
- And to the possible appearance of physico-chemical imbalances.

Initial experiments showed good sensor accuracy and real-time transmission to the LoRa receiver.

Figure 5: EC Sensor

Beyond the EC sensor currently used for water quality monitoring, future experiments will integrate dissolved oxygen (DO), pH, and temperature sensors to obtain a more comprehensive view of the physicochemical state of fish ponds. DO is considered the most sensitive critical parameter in aquaculture systems, as a rapid decrease leads to immediate stress, growth losses, and even mass mortality. Integrating DO sensors into the LoRa network will enable the implementation of real-time alert mechanisms, as well as artificial intelligence models for predicting hypoxia episodes, detecting anomalies in fish behavior, and optimizing aeration.(28) .

Figure 6: Fish farming ponds (Tilapia)

C. Dairy production: DHT22 sensor

In cattle enclosures, the microclimate plays a crucial role in cow welfare and can directly affect milk production. The DHT22 sensor (Figure 7) was selected to measure temperature and humidity in the shelters. Tests conducted showed:

- A rapid response from the sensor to ambient variations,
- A stable transmission via LoRa.
- A perfect consistency between the local measurement and the data received at the laboratory.

Climate change poses a global problem that profoundly affects livestock farming, with heat stress becoming a major concern in dairy production. Dairy cows are particularly sensitive to variations in ambient temperature due to their high metabolism and low capacity to dissipate heat (29) . As global warming progresses and the magnitude of temperature extremes increases, heat stress affecting livestock is expected to become a major economic concern. The growing demand for livestock products in the context of climate change presents an urgent challenge. Exceeding temperature thresholds induced by climate change leads to a decline in productivity (30) **.**The DHT22 sensor was used to measure temperature and humidity within the enclosure. The results showed a rapid response from the sensor to microclimatic variations and consistent transmission via LoRa.

The era of climate-smart livestock farming (Figure 8) is entering a new phase with the advent of digital technology. Numerous studies are currently being conducted on sensors, data collection and processing, modeling tools and algorithms, artificial neural networks, deep learning (DL), machine learning (ML), and other technologies to address issues related to animal identification, behavioral detection, disease monitoring, environmental control, and other challenges in livestock production systems. Artificial neural networks (ANNs), convolutional neural networks (CNNs), deep learning, adaptive neuro-fuzzyinference systems (ANFIS), machine learning, and pattern recognition (PR) are among the artificial intelligence (AI) models commonly used for modeling, predicting, and managing livestock farms (31) **.**

This first phase confirms the possibility of later installing a continuous thermal monitoring system, in particular with the integration of RNA, RNC, ANFIS and RP to predict periods of heat stress and the management of livestock (cows and poultry).

Figure 7: DHT22 Sensor

Figure 8: Bovine fattening

D. Poultry farming (chicken coop) :

The poultry industry contributes to food security by providing high-quality protein to meet growing global demand. With the constant increase in global production and consumption of poultry products, the development of new agricultural technologies is essential for the sector's progress **(32)** . Artificial intelligence (AI) plays a transformative role in livestock farming, particularly in complex decision-making processes **(33)** . In poultry farming, the integration of machine learning (ML) offers considerable advantages. Faced with the need to meet growing global demand while minimizing environmental impacts, the sector relies on ML to analyze complex datasets and extract actionable insights **(34)** .

Although initial testing has not yet been carried out in the poultry house (Figure 9), which is currently under construction, the same approach will be applied to this area, particularly through the use of the DHT22 sensor for monitoring the internal microclimate. This area will directly benefit from the architecture validated during previous tests.

Figure 9: Chicken Coop Under Construction

2.3. LoRa Gateway: Current limitations and prospects

Initial tests were conducted using a Dragino LG02 gateway (2 channels) available in the lab. While functional, this gateway is no longer compatible with modern LoRaWAN platforms such as The Things Network (TTN), which now require a minimum of 8-channel gateways like the Dragino LPS8. Dragino's open-source LPS8v2 LoRaWAN gateway integrates a local TTN and Node-RED server. It allows a LoRa wireless network to be connected to an IP network via Wi-Fi or Ethernet. Thanks to LoRa wireless technology, we will be able to transmit data over very long distances to ensure:

- Improved LoRa traffic management,
- A capacity to accommodate several sensors simultaneously,
- A reduction in packet collisions,
- Compliance with the global LoRaWAN standard.

Thus, our current architecture is validated in point-to-point mode (figure 10).The next strategic step is to acquire an 8-channel LoRaWAN gateway, essential for moving to the next level:

- ✓ Integration with TTN,
- ✓ Field deployment,
- ✓ Automated history tracking,
- ✓ Remote alerts and monitoring,
- ✓ Interconnection with Node-RED or other AI platforms.

This development will be the subject of the next article, where more advanced results (scalability, multi-axis analysis, predictive AI) will be presented.

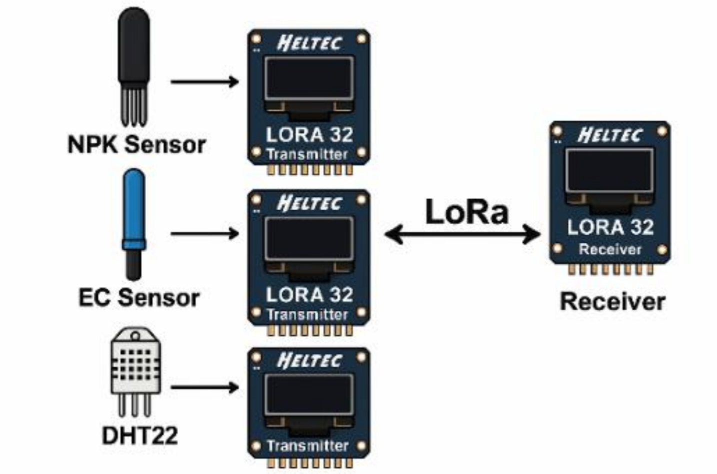

Figure 10: LoRa transmission

2.4 RS485 wired architecture and laboratory validation via the USR-M100 intelligent industrial gateway

Although the main experiments rely on LoRa communication, a complementary wired architecture was developed in the laboratory to validate the complete measurement, transmission, and data processing chain in a controlled environment(Figure 12). This configuration uses the USR-M100 industrial gateway (Figure 11), a multi-protocol device that natively integrates Ethernet, 4G, RS485/RS232, Modbus RTU/TCP, MQTT, and HTTP. The M100 thus plays a central role in the functional validation of the sensors before their deployment in the field.

Figure 11: USR-M100 Smart Industrial IoT Gateway

Figure 12: Overall system architecture

Several microcontrollers (ESP32, Arduino Uno, Heltec WIFI LoRa 32) were configured as Modbus RTU slave nodes via RS485, each exposing its measurements as registers (temperature, humidity, conductivity, NPK variables) (Figure 13). The RS485 bus, widely used in industrial and agricultural environments for its robustness to electromagnetic interference, allows here the simulation of a reliable and scalable multi-source wired network, capable of accommodating up to 32 nodes per port.

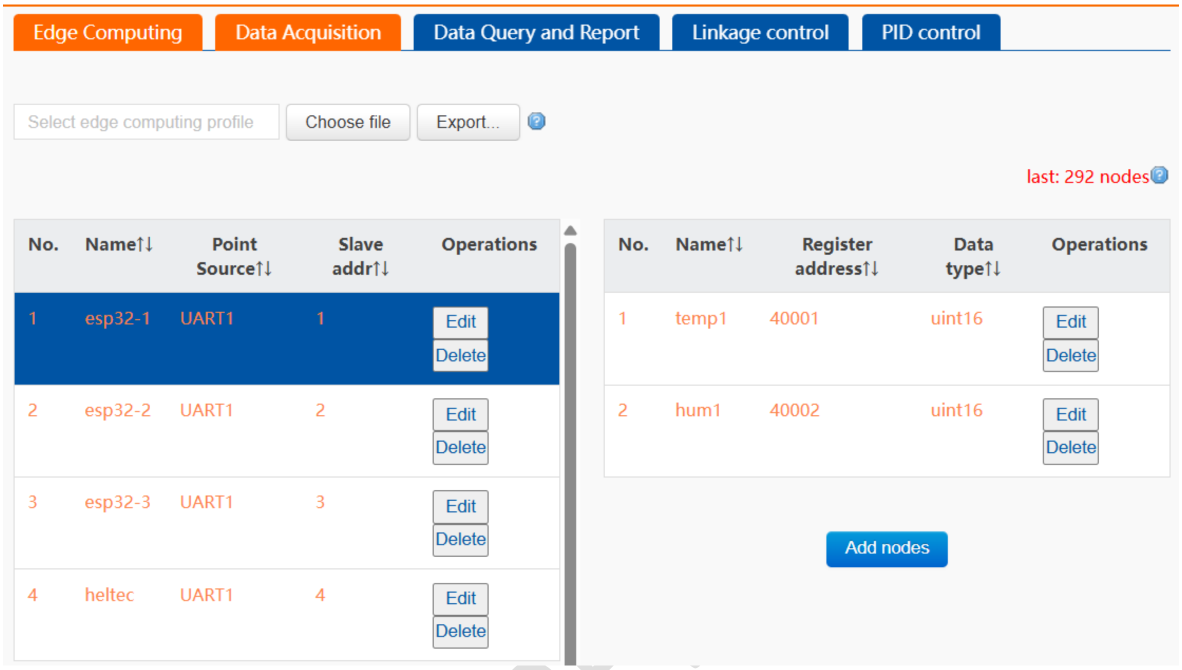

Figure 13: Addition of exclaves and registers

The USR-M100 gateway, acting as a Modbus master, cyclically polls the various sensors and aggregates the measurements. This data is then automatically converted into JSON parameters and published to an internal or external MQTT broker. Tests validated real-time publishing to a local MQTT server (mosquitto), visualized successively in MQTT Explorer (Figure 20), Node-RED (Figure 19), and in the Arduino IDE for monitoring. This step confirms the reliability of the communications, the consistency of the data, and the M100's ability to act as an intermediary between heterogeneous sensors and application services (Figure 21).

Beyond local validation, the M100 offers the ability to transmit data to cloud services such as AWS IoT Core, Azure IoT Hub, USR Cloud, or USR Cloud, thanks to its 4G and Ethernet interfaces. This opens the door to advanced distributed processing scenarios: local data preprocessing (edge computing), conditional transfer to the cloud, historical data logging, or even triggering artificial intelligence algorithms on predictive models (water stress, fish farming anomalies, poultry house microclimate, etc.) (Figure 14).

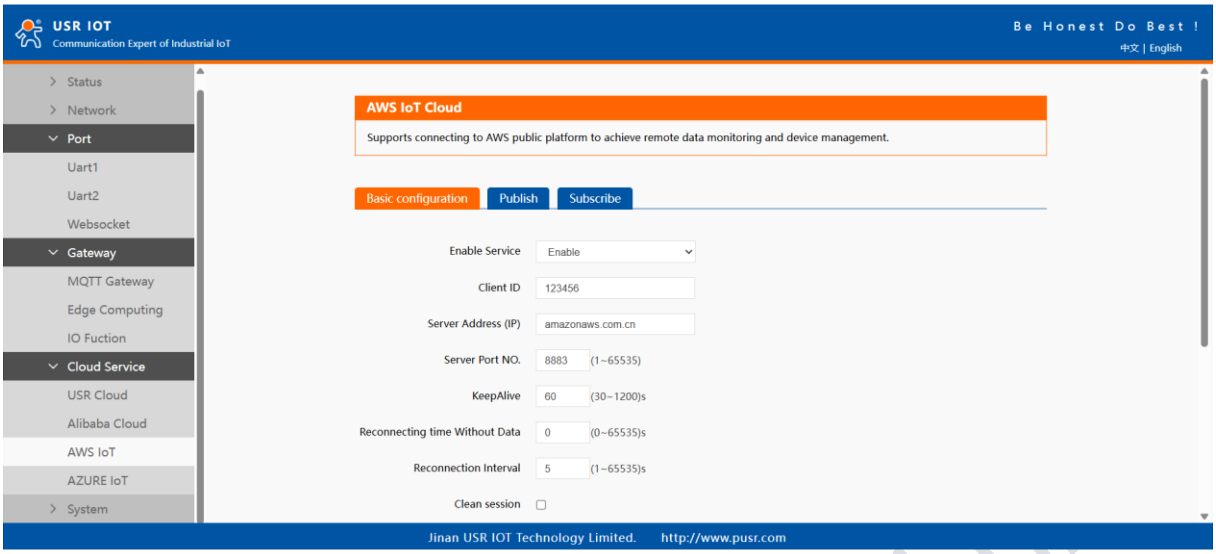

Figure 14: M100 Gateway Cloud Services

The RS485 wired architecture thus constitutes an essential intermediate step, enabling validation of sensor and microcontroller compatibility, evaluation of data flow stability, and preparation for the integration of future 8-channel LoRaWAN networks. The robustness demonstrated in the laboratory guarantees that the system can subsequently be deployed across the various axes of the agricultural hub, complementing long-range networks, while ensuring multi-gateway centralization via a simple Ethernet **switch (Figure 15).**

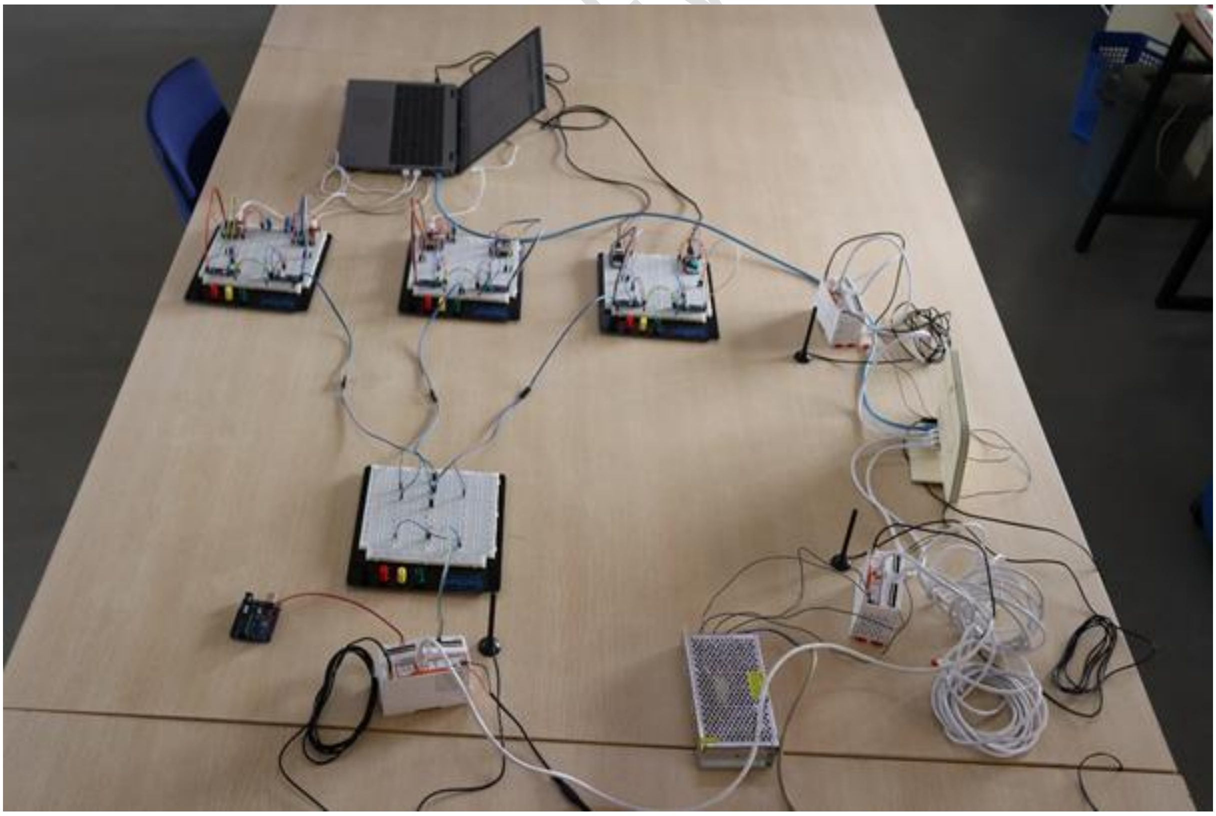

Figure 15: RS485 wired architecture with the MAX485 converter

3. Design of a private LoRa network to cover the agronomy center and the university campus

One of the major objectives of this project is the establishment of a **private LoRa network** to cover the entire agricultural area as well as the campus of Iba Der Thiam University in Thiès. The creation of such an infrastructure is a key step towards enabling the large-scale deployment of IoT sensors, the integration of LoRaWAN services, and the historical and advanced analysis of data through cloud platforms such as The Things Network (TTN).

The images taken by a drone (figures 16 and 17) respectively represent the agricultural area and the siteUniversity studies have allowed for the analysis of the spatial configuration of the two areas and the assessment of LoRa coverage needs. The agricultural area presents a relatively open zone with few obstacles, while the university campus has a more complex structure with several dense buildings that can generate signal loss.

This configuration justifies the deployment of a hybrid network comprising:

- A central gateway covering the agricultural sector,
- One or two additional gateways covering the different areas of the campus,
- And the ability to relay data between different gateways if necessary.

3.1. Spatial analysis of the agricultural domain

The orthophoto of the agricultural area (Figure 16) shows an open zone with a low density of infrastructure. This type of environment is favorable for LoRa propagation. With a range of several kilometers in open field conditions, a single 8-channel LoRaWAN gateway mounted high on a building or central mast would be sufficient to cover the entire agricultural area.

This gateway will serve as the main entry point for data from the NPK, EC and DHT22 sensors deployed along the different area of the hub.

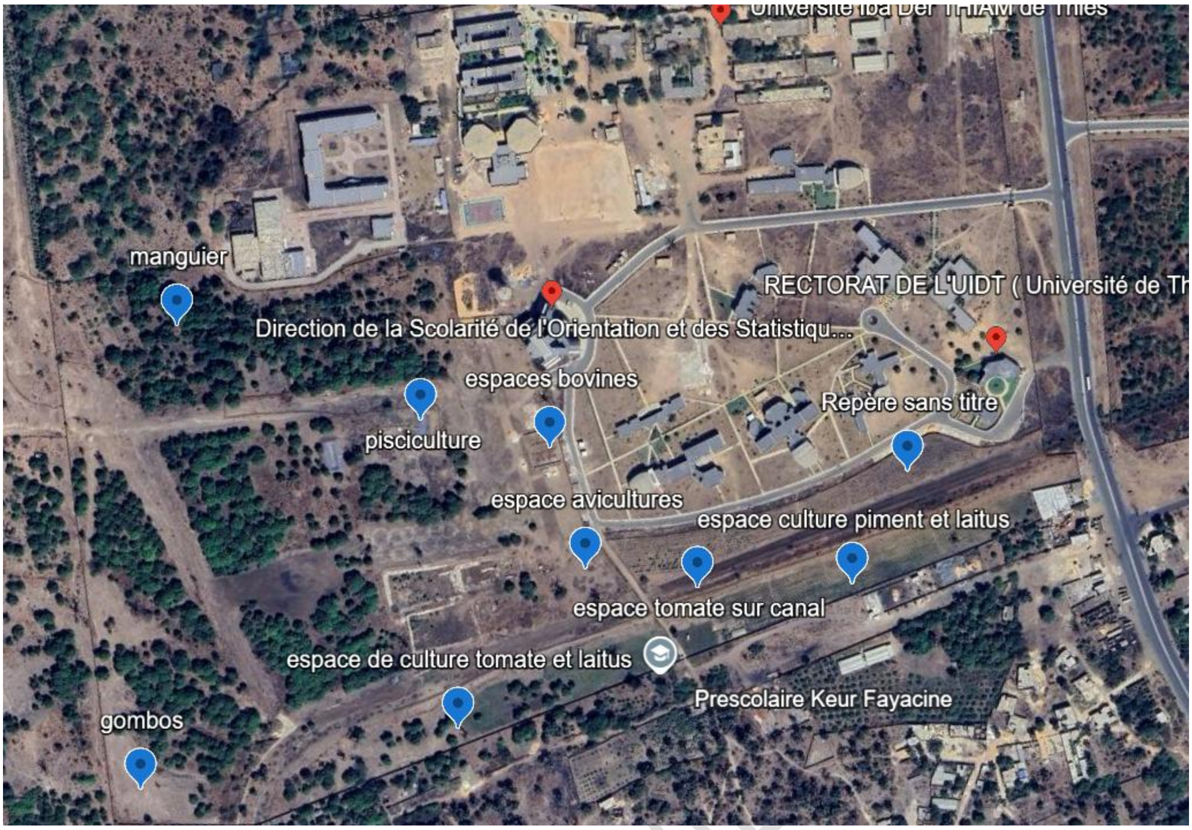

Figure 16: Spatial analysis of the agricultural area

3.2. Spatial analysis of the university campus

The image of the university campus (Figure 17) highlights a denser layout, with several permanent buildings that could weaken signal propagation. In such an environment, deploying a single gateway could lead to:

- areas of uncertainty,
- a reduction in the RSSI (Return on Security Income) rate,
- a potential increase in collisions in the event of a high density of sensors.

Therefore, two strategically positioned 8-channel gateways on campus would be recommended:

- one on a central building to cover the heart of the campus,
- the other towards peripheral areas or technical laboratories.

This deployment would guarantee redundancy, improved reception, and increased resilience.

3.3. Importance of the LoRaWAN network in the future evolution of the system

Low-power wide area network (LPWAN) technologies offer competitive advantages, including broad connectivity for low-power, low-bandwidth devices, unlike traditional wireless technologies. LPWANs interconnect many simple and inexpensive devices and enable direct wireless interconnections between endpoints and gateways over geographic areas of up to tens of square kilometers **(35)** . Among LPWAN protocols, LoRaWAN stands out for its use of unlicensed spectrum, its support for asynchronous communication, and its minimal infrastructure requirements.**(36)** , which makes it ideal for agricultural areas. Previous research has focused on urban or mining environments, neglecting critical rural conditions: topographical variations, dense vegetation and average distances (1 to 5 km) with natural obstacles **(37)** .

Although the total area to be covered is relatively small, approximately 78 ha (58 ha for the social and educational campus and 20 ha for the agricultural area), or 0.78 km^2, the justification for deploying three LoRaWAN gateways is not based solely on the area, but rather on the need for robust and consistent communication between the university campus and the agricultural area. However, achieving better communication quality for nodes located at greater distances remains a challenge **(38)** .

A LoRa gateway can theoretically achieve a range of 10 to 15 km in open areas, but this maximum distance is rarely achievable in environments with numerous obstacles such as buildings, technical laboratories, metal structures, and dense vegetation. These factors significantly reduce radio sensitivity (RSSI, SNR) and increase the risk of packet collisions **(39).(40)** . **(41)** Yusuf et al. showed that three gateways are sufficient to cover a dense urban area within a radius of approximately 15 km. Moreover, a single gateway can support up to 10^5 terminals, each sending 50 bytes of data per hour with negligible packet loss.

In this context, the option of an architecture integrating three 8-channel LoRaWAN gateways (one dedicated to the agricultural sector and two for the various campus areas) ensures uniform and reliable coverage in order to:

- ➢ to optimize the reception quality of peripheral nodes,
- ➢ to ensure enhanced network resilience against physical disruptions
- ➢ and to plan for future expansion with an accumulated number of sensors and artificial intelligence services.

Furthermore, the pedagogical aspect is a crucial factor in the selection of this infrastructure. The creation of a private LoRaWAN network encompassing all university campuses facilitates the integration of IoT technologies into practical work in laboratories **(42)** . Students have the opportunity to manipulate a real network, analyze field data in the lab, test LoRa modulation, study propagation, measure RSSI/SNR, design dashboards or alerts, and develop prototypes with concrete use cases. This infrastructure thus becomes a powerful learning tool, supporting practical training, experimentation, and student innovation. Therefore, the three gateways represent both a technical requirement to ensure system reliability and a strategic investment in education, facilitating the emergence of a genuine IoT experimentation ecosystem within the university.

Based on the visual analysis of the two sites, we propose to install three LoRaWAN gateways (figure 17):

1. Gateway 1 (Agricultural Domain)
   - ✓ Placed on a high point (hangar, tank, technical room)
   - ✓ Ensures complete coverage of plots and basins
2. Gateway 2 (Educational Campus – Central Area)
   - ✓ Located on the main building of the IUT
   - ✓ Covers classrooms, offices, laboratories
3. Gateway 3 (Social Campus – peripheral area)
   - ✓ Located near technical laboratories or scientific departments
   - ✓ Covers dense areas and compensates for obstacles

This configuration offers:

- ✓ coverage between the university and the agricultural sector,
- ✓ a multipoint capability allowing for the integration of more sensors,
- ✓ a perfect adaptation to the constraints of LoRaWAN (8 channels, low collision).

The transition to a private LoRaWAN network is a natural progression following the results already obtained. While initial tests demonstrated the **feasibility of the point-to-point LoRa chain** , implementing a LoRaWAN network will enable:

- ✓ recording of sensor data on TTN
- ✓ centralized data history,
- ✓ the implementation of intelligent dashboards,
- ✓ sending SMS/Email alerts,
- ✓ the integration of automation scenarios via AI,
- ✓ the ability to connect dozens or even hundreds of sensors simultaneously.

Thus, the creation of a private LoRaWAN network represents an **essential pillar of the digitalization of the agronomic hub**, and will constitute a major step forward in the continuation of this thesis.

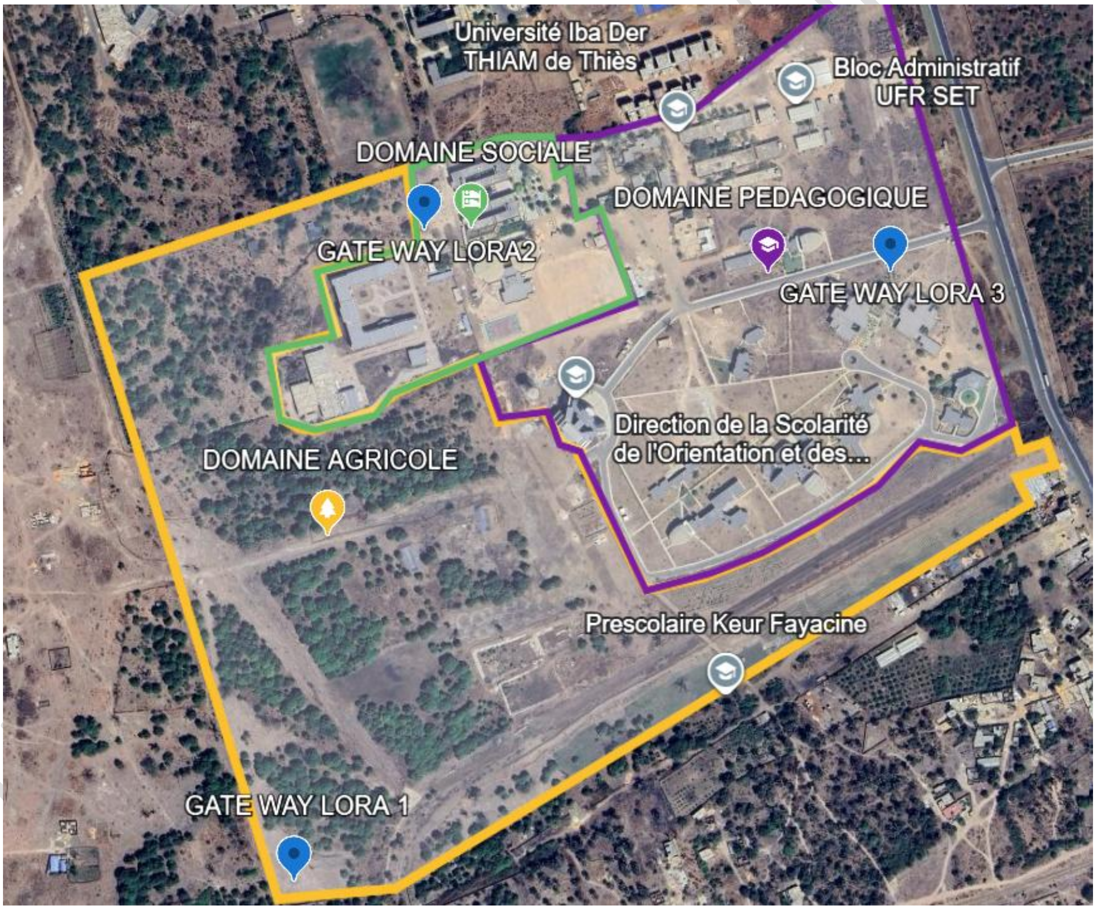

Figure 17: Positioning of gateways

4. Results

Laboratory experiments conducted with the USR-M100 gateway and ESP32/Heltec microcontrollers configured for Modbus RTU validated the technical feasibility of a distributed data collection architecture adapted to the context of the Thiès agronomic center. The main results obtained are organized below according to the complete data acquisition, transmission, and retrieval chain.

4.1. Multi-node Modbus RTU Acquisition

Three independent measurement nodes (ESP32) were configured as Modbus RTU slave devices, each exposing a set of registers (temperature, humidity) (Figure 18). The main points observed are:

- ✓ communication remained stable across all tests, with a zero-error rate on Modbus readings.
- ✓ The M100 gateway was able to query several consecutive slaves without addressing conflicts.
- ✓ The gradual addition of a fourth node (Heltec LoRa32 V3.2 in RS485 mode) did not alter the bus performance.
- ✓ The registers updated by the microcontrollers were read correctly by the gateway.

These results confirm that the Modbus RTU architecture is compatible with an installation comprising several agricultural workshops spread across the same site.

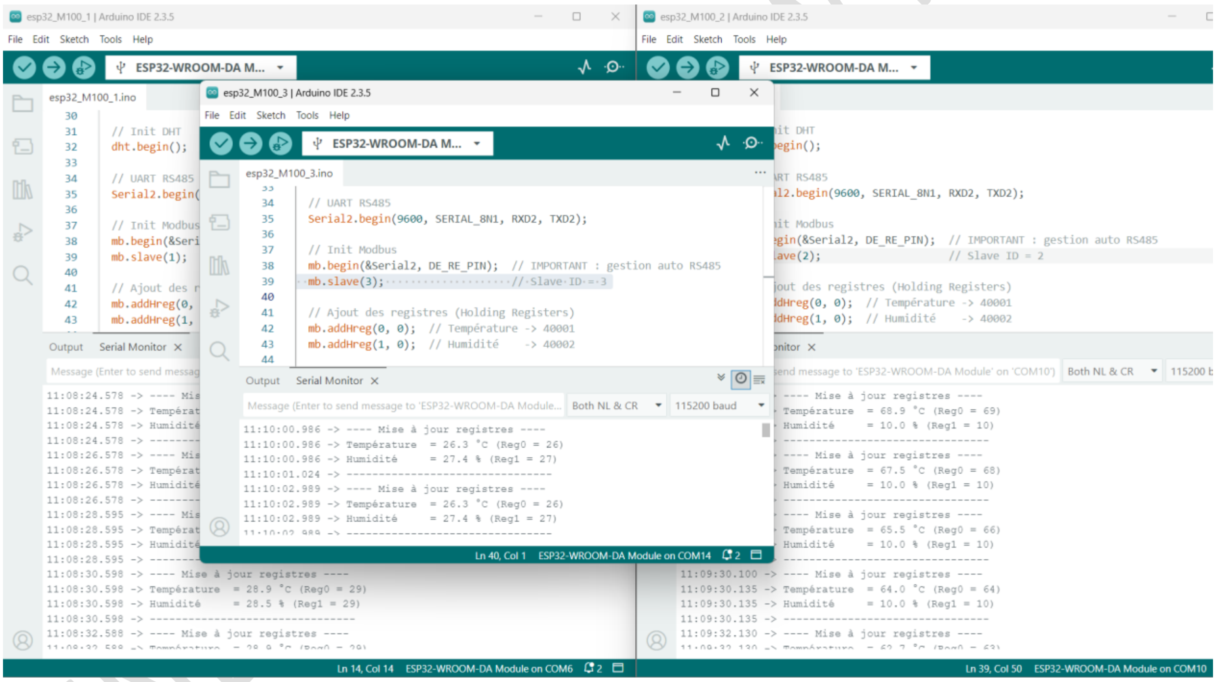

Figure 18: Data sent by microcontrollers using Modbus RS485

4.2. Automatic Conversion and Generation of JSON Frames

The USR-M100 gateway ensured the automatic conversion of data collected on the RS485 bus into structured JSON frames, confirming the system's ability to aggregate multiple Modbus nodes simultaneously. Each microcontroller (ESP32-1, ESP32-2, ESP32-3, Arduino, Heltec in wired mode) was correctly identified in the published messages, and the converted values corresponded exactly to the measurements observed on the serial monitors (Figure 20). The M100's JSON template engine enabled the integration of multiple nodes into a single message, without addressing collisions or format degradation, thus guaranteeing direct interoperability with monitoring and processing platforms.

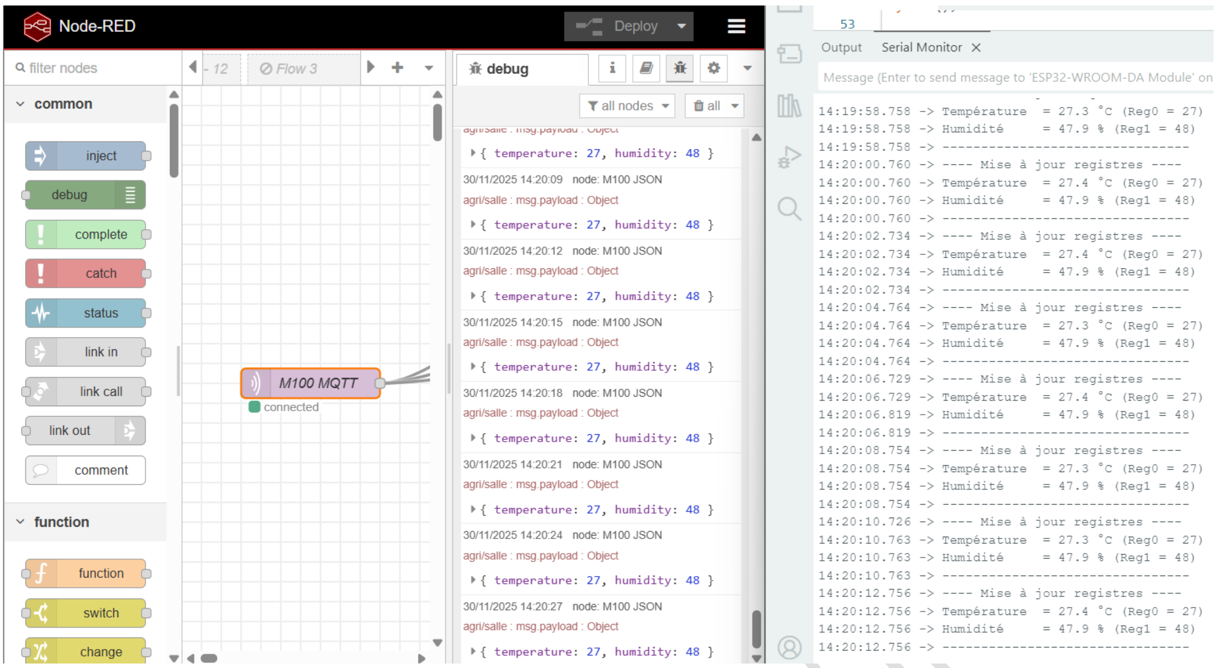

Figure 19: Comparison of data sent to the gateway (serial monitor) and data transmitted by it (node-RED reception)

Once converted, the JSON frames were published via MQTT, using the gateway's Ethernet and 4G interfaces alternately. Transmissions via Ethernet proved perfectly stable, with no message loss, while 4G showed a slight increase in latency but complete continuity of the MQTT stream. The messages were received in real time by Node-RED for graphical display, by the MQTT Explorer (Figure 20) for detailed inspection, and by internal dashboards for functional monitoring. No major reconfiguration was required when switching from Ethernet to 4G, demonstrating the gateway's flexibility for remote agricultural environments or those lacking network infrastructure.

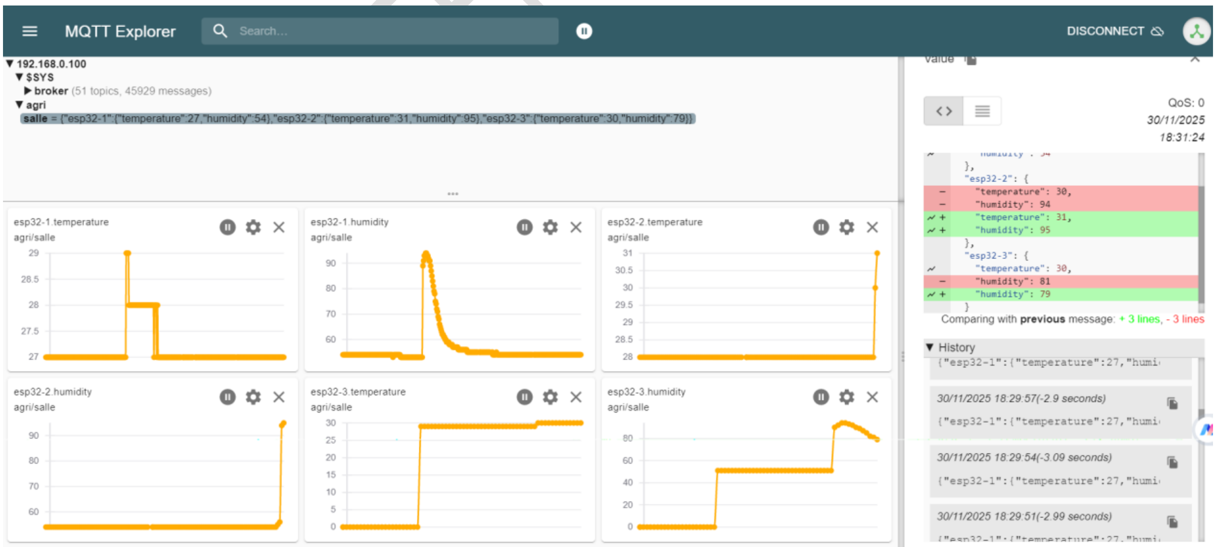

Figure 20: Data visualization using the MQTT Explorer client

The data published via MQTT was then visualized on a Node-RED dashboard, allowing simultaneous display of values from multiple nodes, monitoring of the Modbus bus status, observation of temporal variations in measurements (every 3 seconds), and comparison of these values with the source data displayed in the serial monitors. The results (Figure 21) show perfect consistency between the measured values, those converted to JSON, and those displayed in the monitoring interface, thus validating the reliability of the entire acquisition, conversion, and display chain.

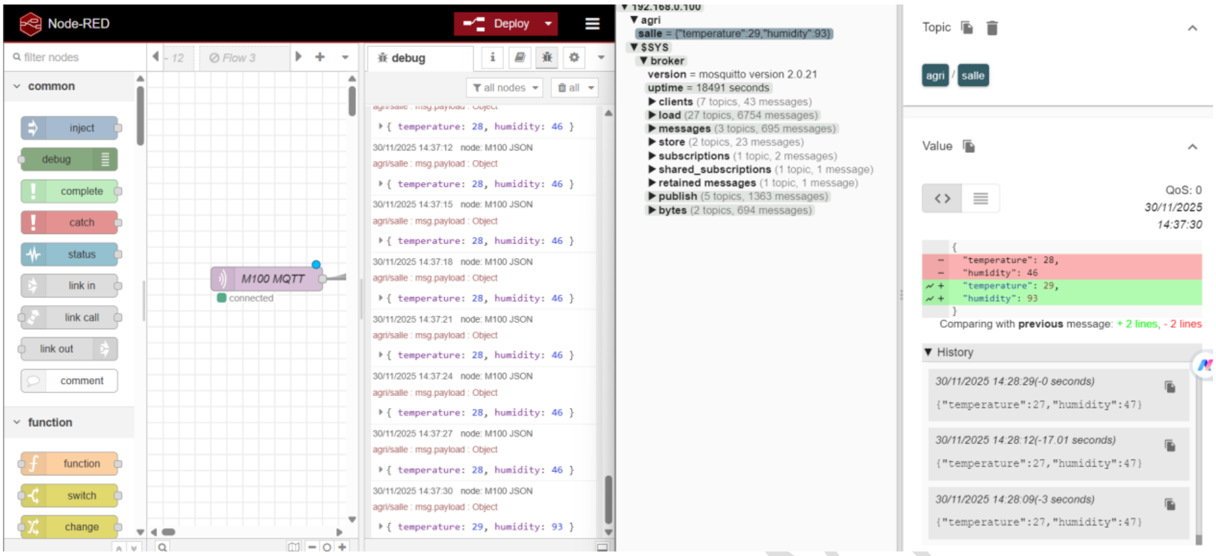

Figure 21: Visualization of data transmitted by M100: Node-RED vs MQTT Explorer

The experiments also highlighted the architecture's scalability potential. The RS485 bus supported the gradual addition of several Modbus slaves (4 ESP32s, 2 Heltec WiFi LoRa 32s) to a single uart2 (RS485) port without any degradation, and the M100 gateway maintained consistent and stable polling even with multiple devices present. This scalability also extends to complementary protocols such as RS232 for the Arduino microcontroller to increase the number of analog inputs, 4G for broadband (Figure 22), and the Heltec LoRa 32 modules used in wired connections to densify the sensor network. These results confirm that the tested architecture is perfectly suited to a multi-plot, multi-workshop environment like that of the Thiès agronomic center, where the diversity of sensors and geographical dispersion necessitate a heterogeneous, robust, and scalable data collection solution.

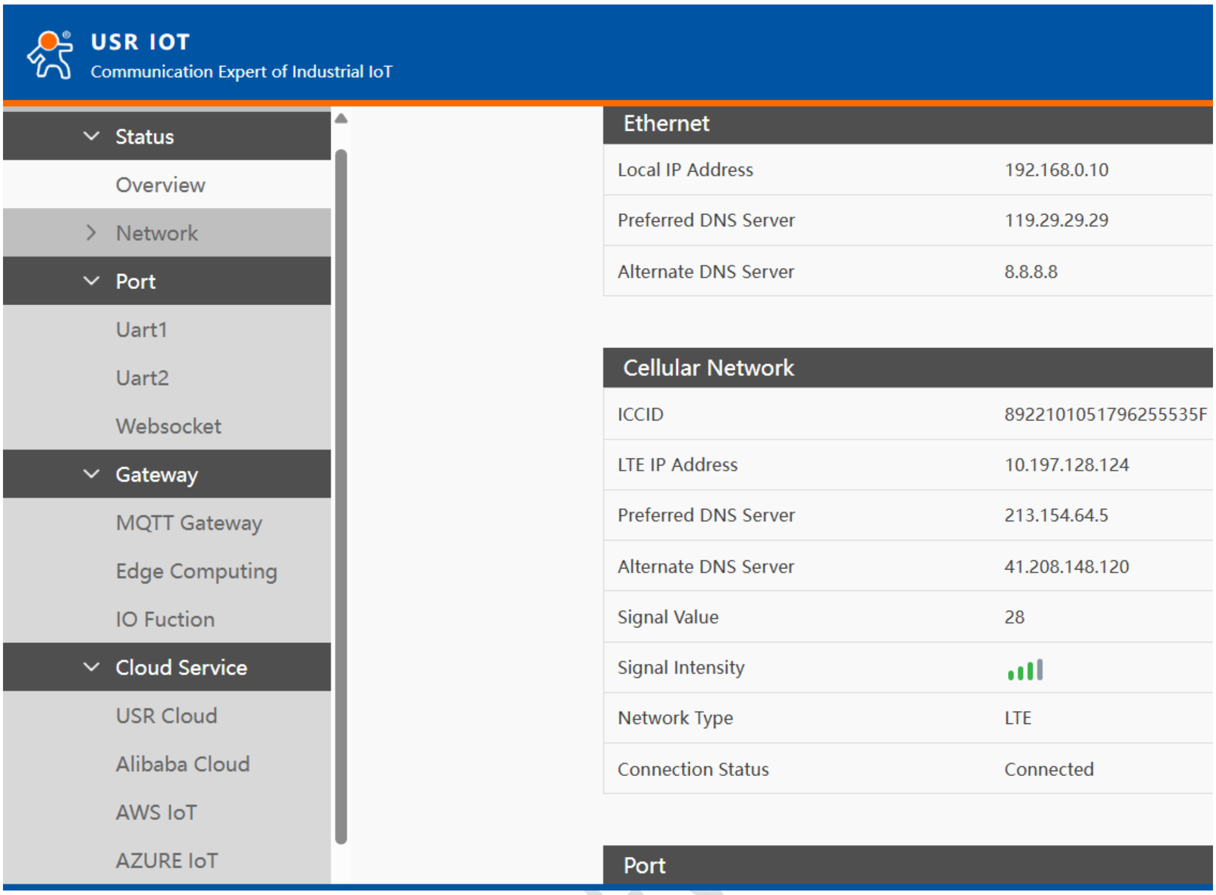

Figure 22: Establishment of the 4G cellular network

4.3 Long-range LoRa transmission

In addition to the RS485 tests, a separate experiment was conducted to evaluate the suitability of LoRa communication within the context of the Thiès agronomic hub. For this purpose, two Heltec Wi-Fi LoRa 32 V3 modules were used:

- ✓ one configured as a LoRa transmitter,
- ✓ the other as a LoRa receiver.

This architecture therefore did not involve the M100 gateway, which does not have Wi-Fi or LoRa connectivity, but aimed to validate the feasibility of a long-range node-to-node network.

The results show that:

- ✓ The LoRa frame transmitted from the agricultural area was successfully received by the module located in the laboratory.
- ✓ Communication remained stable despite physical obstacles (buildings, vegetation, variations in terrain),
- ✓ No significant packet loss was observed.
- ✓ The range obtained is consistent with the typical distances between agricultural plots in the region.
- ✓ The throughput, although low (because inherent to LoRa), remains perfectly sufficient for agro-environmental parameters (temperature, humidity, light, gas).

This experiment thus validates the possibility of using LoRa as a long-range data collection layer, particularly for areas such as:

- ✓ distant,
- ✓ lacking mains power,
- ✓ or difficult to access for a wired deployment.

Summary conclusion of the results

The experiments confirm:

- ✓ the robustness of the RS485 bus for multi-node data collection,
- ✓ the USR-M100 gateway's ability to centralize, convert, and transmit data,
- ✓ the reliability of MQTT transport (Ethernet and 4G),
- ✓ the consistency of values across monitoring tools (Node-RED, MQTT Explorer),
- ✓ the possibility of extending this architecture to other sensors, protocols and cloud services.

2.4. Expansion Prospects

The results obtained pave the way for a broader deployment including:

- ✓ The addition of new sensors (water level, rainfall, light intensity, etc.),
- ✓ The integration of drones for NDVI mapping,
- ✓ The merging of spatial and IoT data,
- ✓ And the development of AI algorithms for agronomic prediction.

Once the 8-channel LoRaWAN gateway is operational, monitoring, alerting, and data logging services can be automated, enabling a transition to complete precision agriculture. This milestone will be the subject of future work and publications.

The system also integrates two essential components that extend the capabilities of the IoT architecture. The first is the **Kendryte K210** (Figure 23), a RISC-V microcontroller with a dedicated AI accelerator (KPU), capable of locally running CNN models for object detection and real-time visual analysis. It enables the implementation of embedded vision for foliar disease detection, fish behavioral analysis, cattle stress monitoring, and poultry house surveillance, while transmitting only metadata via LoRa, thus drastically reducing network load.

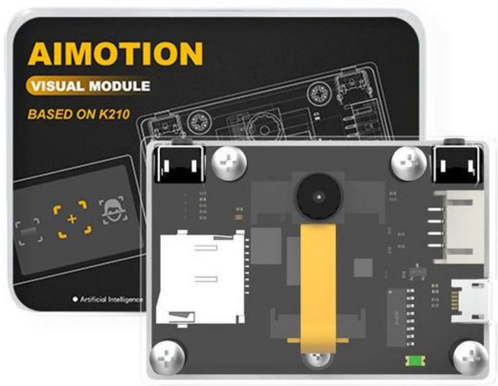

Figure 23: K210 Visual Recognition Module

a. Market gardening and arboriculture

AI cameras can:

- ✓ detect foliar diseases (spots, yellowing, necrosis),
- ✓ identify visible deficiencies (chlorosis, sunburn),
- ✓ assess the vegetation cover rate,
- ✓ monitor the growth of the plants,
- ✓ detect pests (e.g., caterpillars, insects).

Within the arboriculture focus area, a significant extension of the planned system involves the use of drones equipped with high-resolution cameras and onboard or remote artificial intelligence modules. This approach would complement ground-based measurements with a detailed aerial analysis of the phytosanitary status of mango trees (Figure 24). Mango trees affected by various diseases often exhibit distinctive foliar symptoms. Accurate and rapid diagnosis is crucial for mango cultivation. Deep learning algorithms offer a viable solution for the precise detection of mango foliar diseases (43) . Drones could thus perform periodic overflights to detect foliar diseases early, identify areas of water stress, detect pest infestations, and estimate yield potential based on observed floral density and leaf volume. The collected RGB or multispectral images would serve as the basis for segmentation, classification, and object detection algorithms, enabling automated diagnosis at the plot level. Integrating these aerial observations with data from ground sensors would be a major step towards establishing a comprehensive and intelligent monitoring system for the orchards of the agronomic hub, and would pave the way for more effective and sustainable predictive management.

The main benefit will be to complement the multi-parameter soil sensors that measure the soil, by providing a visual analysis of the plant itself.

Recent approaches using multispectral UAV images coupled with neural networks (CNN, ViT , YOLOv8) have shown a good ability to detect mango diseases and estimate yield (44,45)

Figure 24: Mango Tree Zone

b. Fish farming

AI cameras enable:

- ✓ the detection of abnormal fish behavior,
- ✓ monitoring fish health (color, mobility),
- ✓ the detection of early mortality,
- ✓ monitoring water levels,
- ✓ Intrusion detection (predatory birds).

This perfectly complements the EC sensor, which measures water quality but not the visual condition of fish (46,47) .

c. Dairy production (cattle)

For the beef industry, the AI vision enables:

- ✓ identification of cows (bovine facial recognition),
- ✓ Detection of heat stress through posture and behavior
- ✓ Body Condition Score estimation
- ✓ detection of lameness,
- ✓ monitoring of presence/absence in the enclosure (automated management).

Combined with DHT22, we obtain a bimodal system: microclimate + behavior.

d. Poultry farming (chicken coop)

AI vision is particularly useful for:

- ✓ monitor the density of poultry in the henhouse,
- ✓ detect abnormal behaviors (lethargy, aggression, grouping),
- ✓ identify visible diseases (plumage, posture),
- ✓ monitor growth through image analysis,
- ✓ detect nocturnal intrusions or predators.

This complements the DHT22, which monitors the environment, by adding behavioral and visual health monitoring.

Conclusion:

This article presented and validated a modular and scalable technological architecture for the digitalization of the Thiès agronomic hub. Using an experimental protocol conducted in the laboratory, we demonstrated the feasibility and robustness of a complete data acquisition and processing chain: sensors (NPK, EC, DHT22), microcontrollers (ESP32, Arduino, Heltec), RS485 bus (Modbus RTU), USR-M100 industrial gateway, Modbus to JSON conversion, MQTT publishing, and monitoring (Node-RED, MQTT Explorer). These results confirm the consistency of measurements, the stability of wired communications, and the ability of the data collection strategy to ensure a reliable database for advanced processing.

The experiments conducted also validated complementary solutions for areas without cabling: a point-to-point LoRa transmission between Heltec modules enabled data to be routed from the farm to the laboratory with negligible packet loss and a range compatible with the distances observed on site. Furthermore, the M100 gateway demonstrated its ability to continuously publish frames over Ethernet and 4G channels, thus confirming the flexibility required for deployments in rural environments. These elements provide the architecture with dual assurance: local reliability (RS485) and distributed coverage (LoRa/4G).

In terms of scalability, tests show that the approach supports the gradual addition of Modbus nodes and can be extended to a multi-gateway (8-channel) LoRaWAN network to cover the entire campus and agricultural area. The proposed infrastructure also lends itself to multi-gateway centralization via a simple Ethernet switch, facilitating the aggregation of data from heterogeneous subnets. This modular nature makes the solution suitable for the diverse activities of the cluster (market gardening, arboriculture, fish farming, poultry farming, dairy production) and their specific measurement requirements.

The main contribution of this work is twofold: firstly, the experimental validation of an operational chain for collecting and publishing agro-environmental data adapted to the constraints of the Senegalese context; secondly, the definition of an interoperable technical foundation enabling the future integration of analytical and AI services. In particular, the architecture provides the data quality and frequency necessary for predictive models (water stress, anomaly detection in fish farming, thermal monitoring in livestock) and for multimodal approaches including aerial imagery.

In the short and medium term, the next steps are operational: (i) deployment of an 8-channel LoRaWAN gateway and migration to a private LoRaWAN network for scaling; (ii) expansion of the sensor network (dry matter, pH, rainfall, radiometry) and widespread implementation of the RS485 bus in priority workshops; (iii) establishment of a cloud-based data logging chain (AWS/Azure/ThingsBoard) and a data tagging policy for training AI models; (iv) launch of a pilot phase on a plot (mango orchard) combining ground sensors and multispectral UAV acquisitions to create real-world, annotated datasets. These actions will allow for rapid iteration on the algorithms and evaluation of the agronomic impact of the model recommendations.

Finally, beyond the technical aspects, this work has educational and institutional implications: the proposed platform will offer a testing ground for students and researchers, fostering the adoption of IoT and AI technologies and contributing to the training of local stakeholders capable of leading the digital transition in agriculture. Through the combination of reproducible experiments, operational indicators, and impact objectives (productivity, sustainability, resilience), the proposed architecture represents a concrete and immediately applicable step forward for the modernization of the Thiès agronomic hub and, more broadly, for similar agricultural systems in tropical and semi-arid contexts.

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