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Development of a Platform for Monitoring the Levels of Dispersed Oxygen in River Components of a Water Supply Micro Basin Using Programmable Microcontrollers

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Abstract: The Internet of Things (IoT) has become widespread. Widely used worldwide, it already penetrates all spheres of life, and its symbiosis with the environment has become increasingly important and necessary. IoT in life sciences has gained much importance because it minimizes the costs associated with field research, shipments, and transportation of the sensors needed for physical and chemical measurements. This study proposes an IoT water monitoring system in real time that allows the measurement of dissolved oxygen levels in water at several monitoring points in a difficult-to-access location, the Pirapo River, in southern Brazil, responsible for supplying water to large urban centers in the region. The proposed method can be used in urban and rural areas for consumption and quality monitoring or extended to a modern water infrastructure that allows water providers and decision makers to supervise and make optimal decisions in difficult times. The experimental results prove that the system has excellent perspectives and can be used practically for environmental monitoring, providing interested parties with experiences acquired during the system implementation process and timely relevant information for safe decision making.

Keywords: IoT; water quality monitoring; wireless sensor network; oxygen dissolved

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1. Introduction

Water is considered one of the most essential natural resources on our planet. It is fundamental to all living beings [1–10]. Depending on the quality of the water, it can be a source of life and good health or a source of disease and death. In recent years, increasing environmental degradation resulting from urban development, population growth, and climate change has increased the need for researchers to observe the negative environmental impacts, especially on water sources, and their implications. In addition, the increase in water pollution in rivers, lakes, and oceans across the planet has necessitated more advanced monitoring systems, particularly in regards to water quality. Furthermore, developing countries such as Brazil often rely primarily on conventional water sampling and analysis methods. These are usually conducted through conventional procedures or by using portable testers, but they are expensive and laborious. More resources are needed for real-time data acquisition, analysis, and the rapid dissemination of collected information, which are crucial and essential for reasonable water quality monitoring efforts [1–10].

The Internet of Things (IoT) [11–17] is a concept that is being established both at a scientific and social level. IoT can transform various industries, including agriculture, healthcare, and transportation, as well as many other different fields. It encompasses an ecosystem of services hosted in the cloud, interacting with intelligent objects through the performance of computer programs connected through communication networks. The availability of a wide variety of resources in the cloud (cloud services) offers many possibilities for implementing chemical analysis monitoring systems, notably increasing their versatility and performance without dramatically increasing the cost or complexity of the resulting system [1,2]. With this constant technological evolution, multiple ecosystems have emerged for integrating hardware devices, embedded software, communication networks, and cloud processing, usually called IoT platforms. These modular IoT platforms can incorporate new modules as new technologies emerge. On the other hand, IoT encounters challenges from the point of view of interoperability and heterogeneity, with several compatibility challenges. In addition, different raw data types and formats make establishing a standardized communication interface complex [18].

Over the past decade, water resources have encountered challenges, including pollution, drought, etc. Thus, monitoring this vital resource is essential. In recent years, the Internet of Things (IoT) has seen a considerable evolution and has been adopted in various fields to improve human life [19].

Countless problems have been caused by the excessive emission of polluting gases, such as carbon dioxide (CO_2), into the atmosphere. Therefore, more effective monitoring of CO_2 is essential, especially in central or industrial regions [20,21].

In the literature, we found that most of the prototypes, despite not being directly focused on chemical species analysis, have tried to evaluate some physicochemical parameters (pH, turbidity, DO, TDS, temperature, flow rate, EC, ORP, etc.) in natural environments, such as rivers and lakes [22].

Electronic equipment is available for measuring several parameters considered important indicators of water quality, such as dissolved oxygen, pH, conductivity, and turbidity, where the measurement is carried out immediately through a sensor [22].

The growing increase in waste (industrial and residential) discarded in river beds and the resulting air pollution in large urban centers make it essential to monitor the environment by measuring the level of oxygen concentration in water from river beds as well as the level of CO_2 in the air [21].

Online (real-time) and in loco (onsite) monitoring of organic pollutants in water and air systems is a process that is essential not only for the protection of human health but also for the protection of the ecosystem. [20].

For onsite monitoring, several pieces of equipment available on the market for measuring the main parameters used in assessing water quality require the displacement of personnel to the place of interest to carry out the measurements.

Online monitoring has become a viable activity with the increasing development of wireless sensor network technology. However, the costs of equipment used in this modality are still relatively high when it comes to its application in developing countries [22].

Thus, the Arduino platform [11,12,14,23–29], an open-source platform, will be used as a basis for building this platform and the modules with ZigBee technology [30–34] for building the wireless sensor network.

The remote monitoring system operating Zigbee technology lowers expenses and maximizes adaptability. This system provides water-related data to the user. In addition, a system that employs temperature and pH sensors to check water quality is presented for the autonomous observation of artificial lake water [31].

One study conducted a real-time experiment of river water monitoring using Zigbee technology and three parameters: pH, turbidity, and TDS, to determine the classification of water quality. Observing their characteristics makes it possible to adjust the timing of data retrieval and the deployment of sensor nodes to reduce the number of sensors deployed and power consumption [32].

A real-time assessment of water quality parameters in distribution systems was carried out employing Raspberry Pi and Arduino development boards. The parameters were chosen based on the different categories identified by the Central Pollution and Control Board of India. An Arduino development board was used at the sensing node for water quality sensor interfacing, data acquisition, and transmission to the wireless sensor network via Zigbee [33].

Of the possible parameters to perform direct measurements through sensors, dissolved oxygen is an important indicator of aquatic environments [30,35,36], as is the water quality index developed by the "National Sanitation Foundation" and adopted by bodies such as the National Water Agency [37], the Environmental Company of the State of São Paulo, Brazil [38], and the Parana Secretariat for the Environment and Water Resources. Therefore, monitoring the dissolved oxygen index in water can provide a good indication of the quality of the analyzed water.

Although there are no standardized procedures for the frequency of measurements of these parameters, there is a high logistics cost for dispensing personnel and equipment to the collection points. The importance of water quality monitoring has led to the search for autonomous, low-cost, reliable, and flexible solutions [11–17,22–29], such as using a wireless sensor network to carry out water quality monitoring in different areas. One point of interest concerning this network is its ability to communicate with an information processing center to make this information available to bodies responsible for environmental monitoring, whether public or not, and citizens in general.

First, we give an overview of the development and technology of applications for continuous water monitoring, starting with a straightforward approach to the importance of water and the IoT concept. The rest of the paper is organized as follows: Section 2 demonstrates the architecture of the electronics, the system algorithm, and the electronic devices connected to the probes: dissolved oxygen and water temperature. Section 3 describes the results and discussion, the experiments, and the difficulties. Finally, the article concludes in Section 4.

2. Material and Methods

2.1. Study Area

The Pirapo watershed has a total area of 5098.10 km^2. The Pirapó River rises in the municipality of Apucarana and runs 168 km to the mouth of the Paranapanema River. The study was conducted in the Sanepar watershed on the Pirapo River in the state of Paraná in southern Brazil (Figure 1).

After visiting some probable locations for the installation of sensor nodes, the following locations were chosen: Point 1 (P1), Point 2 (P2), and Point 3 (P3).

For P1, the exact location was chosen where Sanepar collects water from the Pirapó River, before the confluence of the Sarandi stream. This is referred to as EEB-00. The location of P2, called EEB-01, where the lifting pumps for the treatment plant are installed, was chosen by Sanepar and is situated at the confluence of the Sarandi stream. Finally, P3 is located on the left bank of the Sarandi stream, as suggested by the Sanepar technician.

For choosing the location of the central node, called CE, an indispensable condition would be the possibility of connecting to a cell phone network. Therefore, the central node's location would be close to an existing tower in the EEB-01 to install the antenna that allows access to a cell phone network.

Figure 2 illustrates the points where the sensor nodes (P1, P2, and P3) and the central node (CE) were installed and the measured distances between the sensor nodes and the central node.

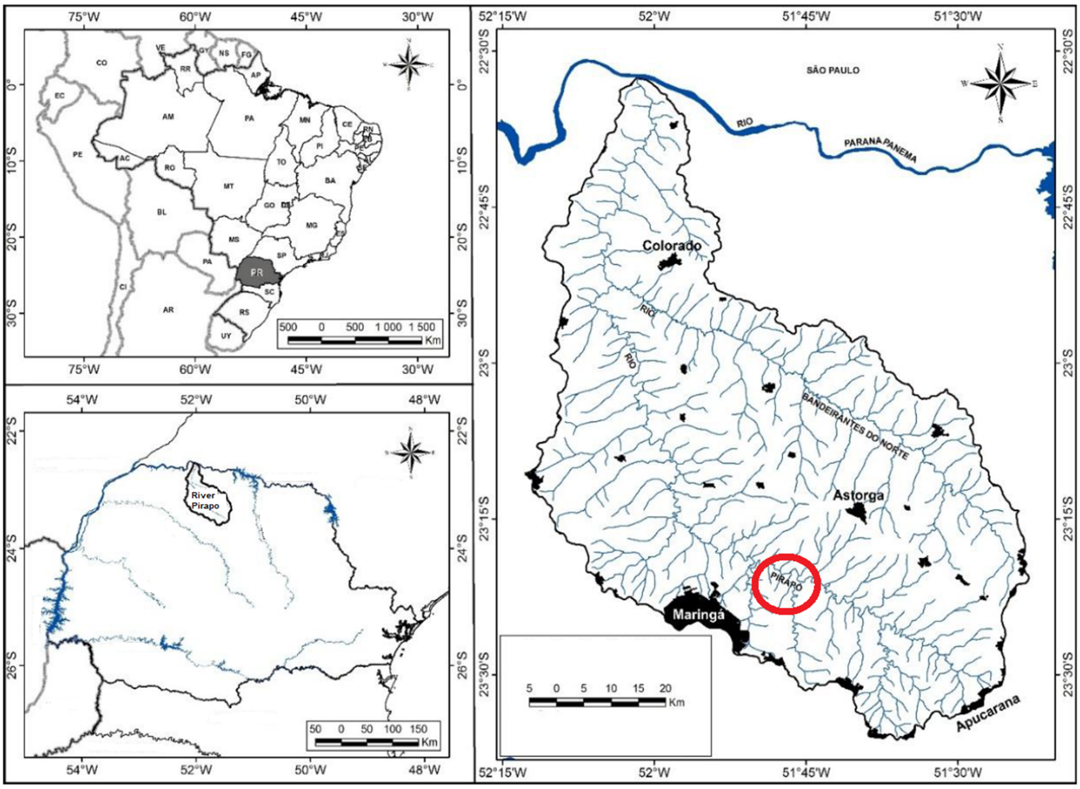

Figure 1. Highlighted in red: Location of the capture station—Sanepar Maringa, Brazil.

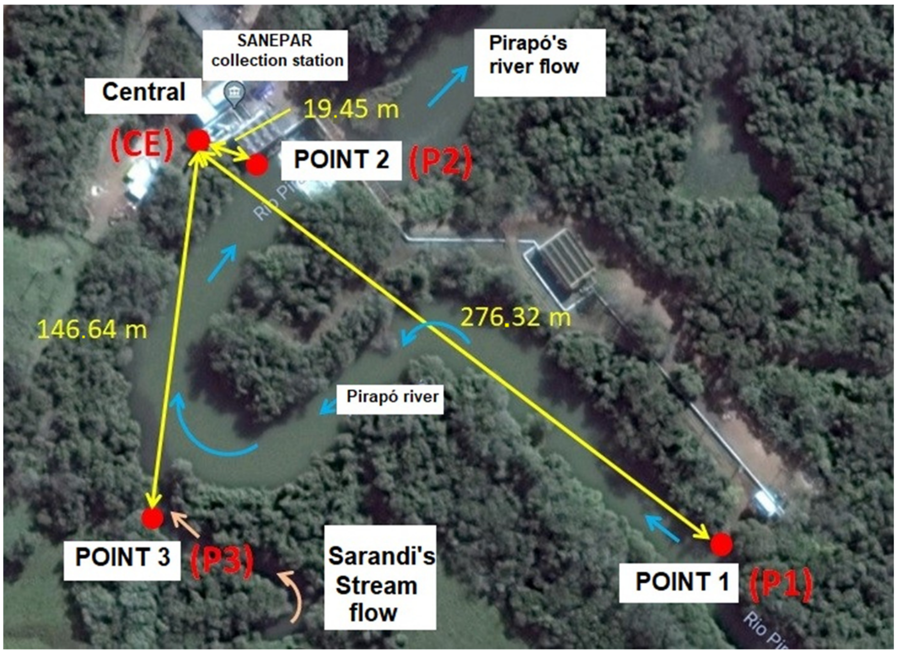

Figure 2. Positioning of sensor nodes and central node.

The sensor node installed at P1 started operating on 7 July 2018, along with the central node. The antenna for the XBee® (Lindon, UT, USA) module and the solar panel were installed on a bamboo pole that was attached to the existing structure, as shown in Figure 3. The height of the antenna was close to four meters and the solar panel was positioned with an orientation to the north and an incline of 30°. Due to the availability of accommodation at the location chosen to be Point 1, the circuit installed at that point did not need to use a cabinet for external installation, as illustrated in P1-BOX in Figure 3.

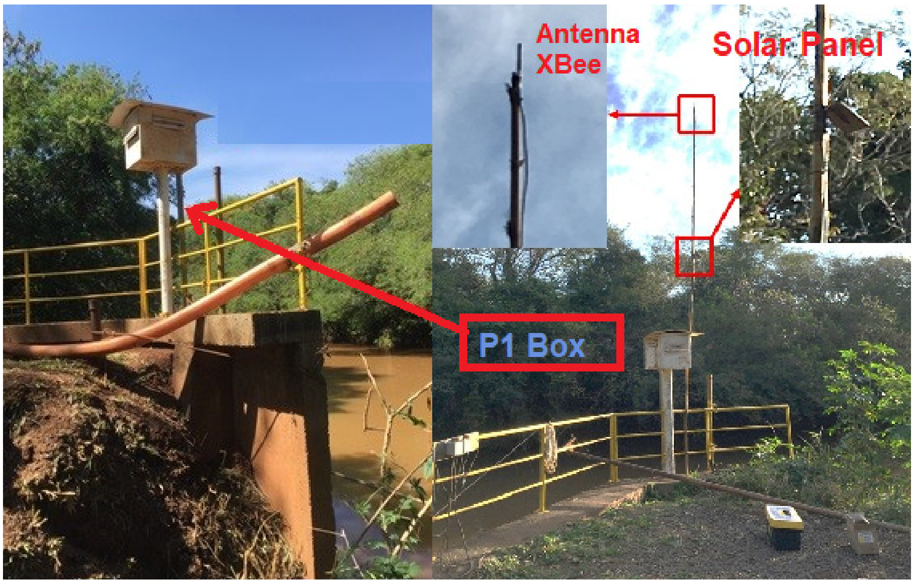

Figure 3. The sensor node installed at P1 started operating on 7 July 2018.

To install the sensor node at Point 2 (P2), a pipe dipped in water was necessary to store the temperature and dissolved oxygen sensors. We used an 11/4″ diameter galvanized steel tube with a wall of 1.2 mm and a length of six meters, fixed to the railing available on site, as shown in the Picture 4 on the left. The temperature and dissolved oxygen sensors were installed 45 cm from the water surface.

The sensor node circuit was also attached to the railing, and the solar panel was attached to a bamboo pole approximately three meters high, as shown in Figure 4 on the center and right. In this case, it was not necessary to lift the XBee® module antenna due to the proximity of this sensor node to the central node. The sensor node installed at P2 started operating on 10 July 2018.

Figure 4. The sensor node installed at P2 started operating on 10 July 2018.

The installation of the sensor node at P3 (Sarandi stream) was the most laborious, as there was no infrastructure for installing the equipment. Access to the site was also more difficult, as crossing a pasture area and entering the riparian forest was necessary, as shown in Figure 5. The sensors were immersed to a depth of thirty-five centimeters to the surface of the stream water. The sensor node installed at P3 started operating on 7 July 2018. The temperature and dissolved oxygen sensors were inserted inside a galvanized steel tube with an 11/4″ diameter, 1.2 mm wall, and six meters long, fixed in a tree on the bank of the Sarandi stream, as shown in the Figure 5 on the left. The sensors were immersed at a depth of thirty-five centimeters concerning the water surface of the stream.

Figure 5. The sensor node installed at P3 started operating on 7 July 2018.

The platform developed in this project measures the concentration of dissolved oxygen in waters of a watershed using a wireless sensor network composed of three sensor nodes and a central node. The sensor nodes measure the dissolved oxygen concentration at three locations in this watershed and send the measured values to the central node. The central node, in turn, receives the values sent by the sensor nodes, stores them in a non-volatile memory unit, and transmits these values to a data server using the cellular telephone network. The data stored on that server will be available for online queries.

In this platform, four XBee® Pro S3B modules were used [30–34]. One for each of the three sensor nodes and one for the central node. To meet the project's needs, some of the parameters of these modules were changed using the XCTU utility from Digi International, the manufacturer of XBee® modules.

Some parameters were changed in the XBee® modules of the central node and the sensor nodes. These reconfigurations were carried out to create a network identity (CM Channel Mask), configure the radio for maximum power (PL TX Power Level), configure the node type (CE Routing/Messaging Mode), and configure operation in API mode (AP API Enable). In addition, the configuration for operation in sleep mode (SM Sleep Mode) was made only for the sensor nodes since the central node does not go into sleep mode. The other parameters were not changed.

2.2. Sensor Node Project

The sensor node consists of a microcontroller Arduino [11,12,14,23–29], a temperature sensor (DS18B20), an Atlas Scientific [39] dissolved oxygen sensor, an XBee® module, an omnidirectional antenna, a DC-DC converter, a charge controller, a solar panel, and a battery, and is illustrated in Figure 6.

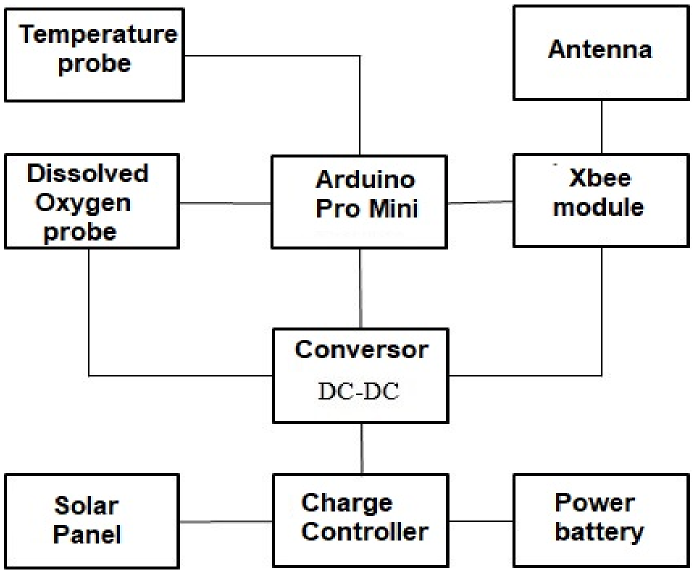

Figure 6. Sensor node block diagram.

The Arduino is a small computer capable of receiving and processing signals from sensors or other devices and then generating signals for actuators or other devices, according to the programming developed by the user. This type of system is called physical or embedded computing and is characterized by being able to interact with the environment through hardware and software [11,12,14,23,25].

The XBee module is a wireless transceiver that operates alongside the ZigBee protocol, providing the necessary resources to form a robust wireless sensor network (WSN). The ZigBee communication protocol is used in developing wireless sensor networks (WSN) due to its low cost, small size, security, reliability, open frequency operation, and low energy consumption modules [30,31,33,34].

This project evaluated the need to use a system to recharge the batteries that supplied the modules' energy. Therefore, the project had photovoltaic panels (Figure 7). The dimensioning of the solar panel for the central node must be such that it replaces the charge that the battery supplies to the circuit in periods when there is no sun. The charge controller is directly connected to the solar panel. It controls the charge of the batteries, preserving their useful life and protecting them from the effects of overload or sudden discharge.

The sensor node operates by taking measurements of temperature, dissolved oxygen, and supply voltage and sending them to the central node. In order to eliminate probable noise that may occur during measurements, an algorithm was created for reading temperature, dissolved oxygen, and supply voltage. The algorithm performs twelve measurements in sequence and eliminates the highest and lowest measured value. Finally, the arithmetic average is taken from the ten remaining measurements, thus obtaining the quantity. The execution time of this algorithm is twenty-six seconds for the three parameters (supply voltage, water temperature, and dissolved oxygen level in the water) measured.

The difference between the current and previous measurements of dissolved oxygen level is that if it is greater than 2 mg/L, the subsequent measurement is performed in 15 min. If the difference is greater than 1 mg/L and less than 2 mg/L, the subsequent measurement is performed in 30 min. Furthermore, if the difference is less than or equal to 1 mg/L, the subsequent measurement is performed in 60 min.

Figure 7. Solar panel—central node.

2.3. Central Node Project

The central node receives the information from the sensor nodes, stores it in non-volatile local memory, and transmits it to a data server. The central node block diagram is illustrated in Figure 8.

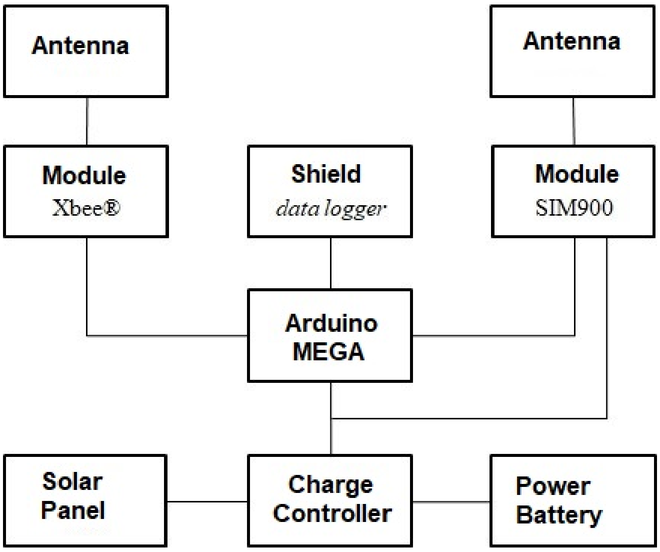

Figure 8. Central node block diagram.

Using a data logger shield and a shield for XBee® facilitated the connections of these modules with the Arduino Mega, as shown in Figure 9a. Figure 9b illustrates the connection of the SIM900 module with the Arduino Mega, made using cables.

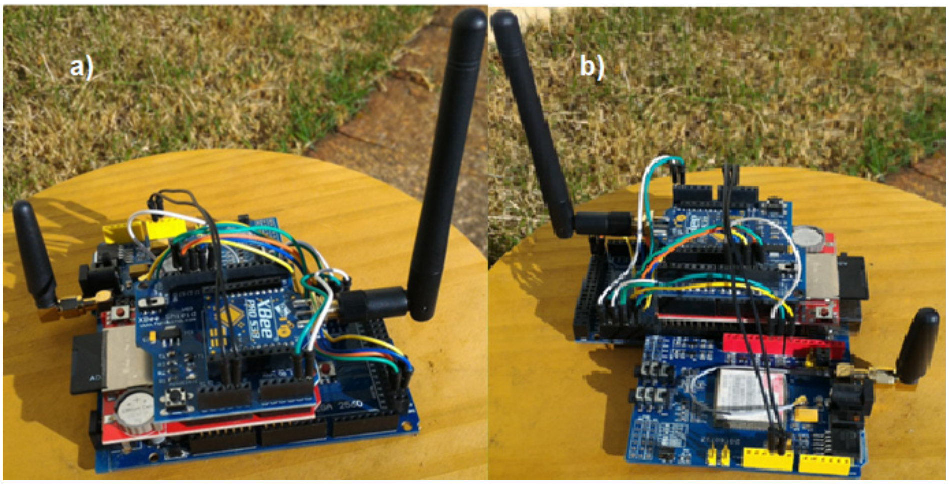

Figure 9. Shield details: (**a**) Assembling the shields with the Arduino Mega (**b**) Connections of the SIM900 module with the Arduino Mega.

The Arduino Mega used to control the platform's central node was developed for projects requiring a more significant number of input and output lines, more program memory (flash), and more data memory (RAM).

The GPRS shield is compatible with Arduino Mega and is based on the SIM900 module from SIMCom. This model is used in the central node of the platform to send the readings performed by the sensor nodes to a WEB server.

2.4. Data Server: Configuration/Visualization

This project created three channels, one for each sensor node, identified as P1, P2, and P3. For each of the channels, eight available fields used, including the water temperature, the dissolved oxygen concentration, the supply voltage of the sensor node, and the power supply voltage of the central node, and information was stored on the day, month, hour, and minute of the reading performed.

Thingspeak® (version 1.0.4) [40–42] is used to access the data read from the sensors in real time.

To visualize previous data, the user can insert parameters in the access link to visualize more records (up to 8000 are available) or establish the initial and final dates of the period of interest. In addition, Thingspeak® makes it possible to transfer stored channel data in a csv format.

3. Results and Discussion

The measurement period starts on 7 July 2018 and ends on 31 October 2018. In this period, a total of 8706 measurements were collected. From this total, 703 measurements considered invalid due to abnormal situations were removed, such as test measurements and measurements while performing maintenance, for which the dates and times of their execution were noted. Some measurements were also removed due to the dirty sensor and incorrect sensor installation, as identified by the null values of the oxygen concentration reading.

We used probes manufactured by Atlas Scientific. Atlas Scientific is an American company that has years of experience manufacturing high-performance water quality sensors, which are widely used in scientific projects [39,43,44]. The calibration of each Atlas Scientific sensor is mandatory before deployment [44]. The OD sensor is calibrated using a 9.00 mg/L reading in air and at atmospheric pressure. Before the DO probe reading, the algorithm reads the water temperature, then sets the DO probe in alignment with the actual water temperature.

3.1. Weather Parameters

For the period of sensor readings studied in this work, collected through the floating IoT monitoring station, the following parameters were observed: solar radiation had a maximum of 4089 KJ/m^2 and a minimum of 0 when it was night; precipitation only occurred for a few days over almost four months of observation of data collections, characterizing this period as a dry period, with a maximum total precipitation of 42 mm; atmospheric pressure oscillated between 963 and 953 hPa; the wind speed had a maximum of 7.6 m/s and a minimum of 0 m/s; the maximum relative humidity was 99% and the minimum was 17%. Figure 10 shows the data from the Main Climatological Station of Maringá (ECPM).

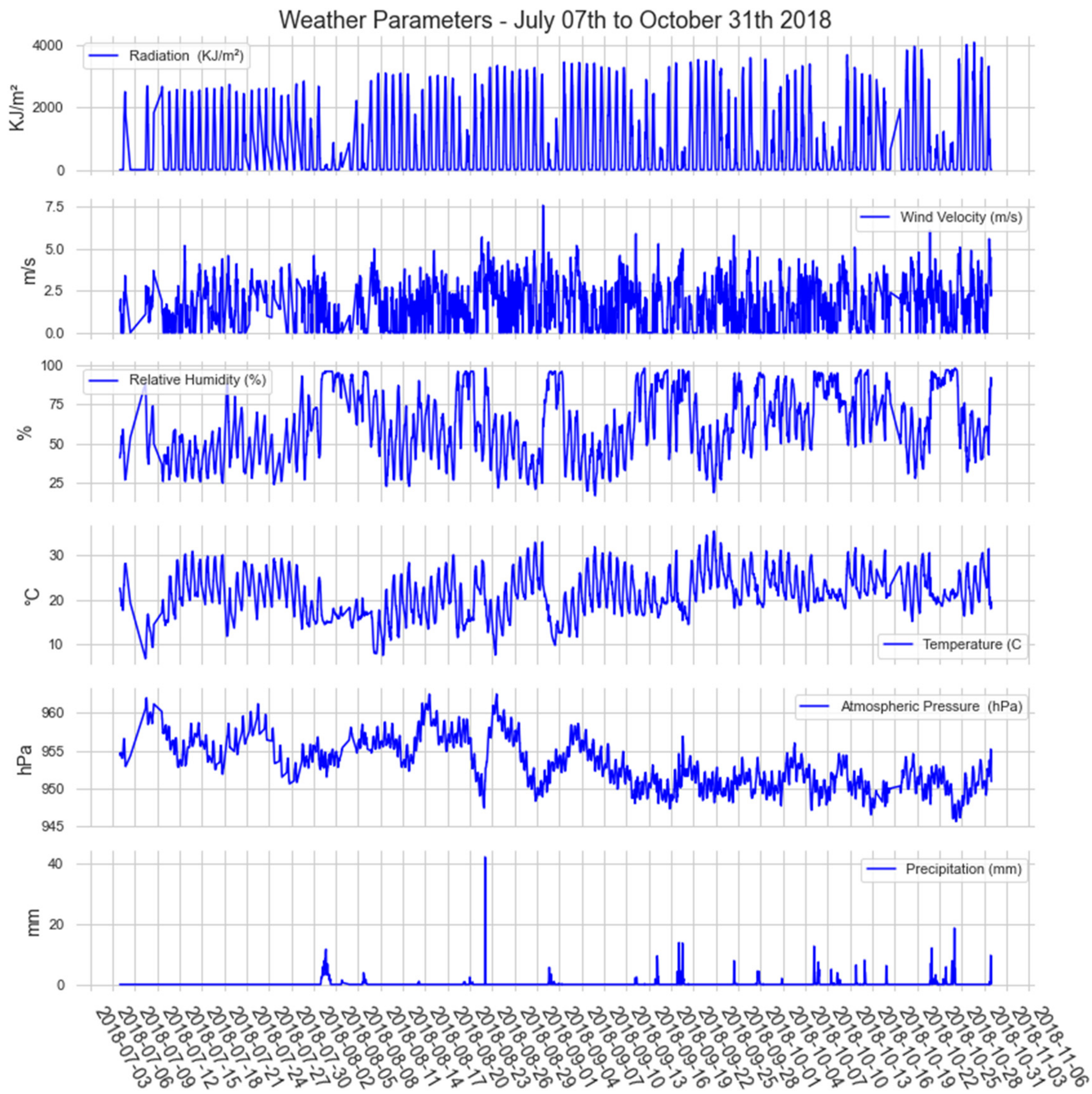

Figure 10. Data from the Main Climatological Station of Maringá (ECPM).

3.2. Dissolved Oxygen Concentration during the Measurement Period

Figure 11 illustrates the dissolved oxygen levels, in mg/L, of the three points during the measurement period.

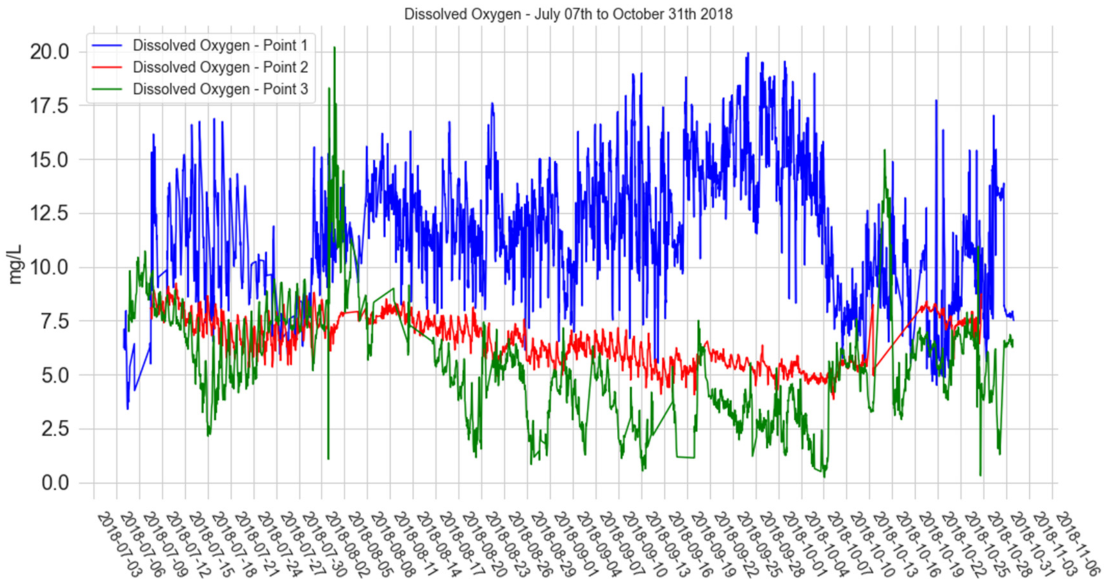

Figure 11. Dissolved Oxygen levels throughout the measurement period at Point 1–3.

We observed that the dissolved oxygen sensor installed at P1 showed large oscillations during the measurement period. As Sanepar performed the backwashing on the pumps for capture and de-sanding in the water inlet area, these operations were initially attributed to the fluctuations in the measurements. Later, at the end of the measurement period, it was discovered that the oscillations were caused by the sensor itself. We verified that the readings of the DO probe in P1 were always much higher than the expected value, with readings that sometimes exceeded 10 mg/L, where the average water temperature is above 20 °C. This can be justified due to the movement of the sensor in the water. The sudden movement caused by water turbulence due to the installation location in P1 favored readings above expectations. This fact is due to the change in the partial pressure of oxygen [45–47] in the galvanic electrode equipment's membrane, which considerably increased its readings. Therefore, its reading throughout the time series was accentuated, according to Figure 12.

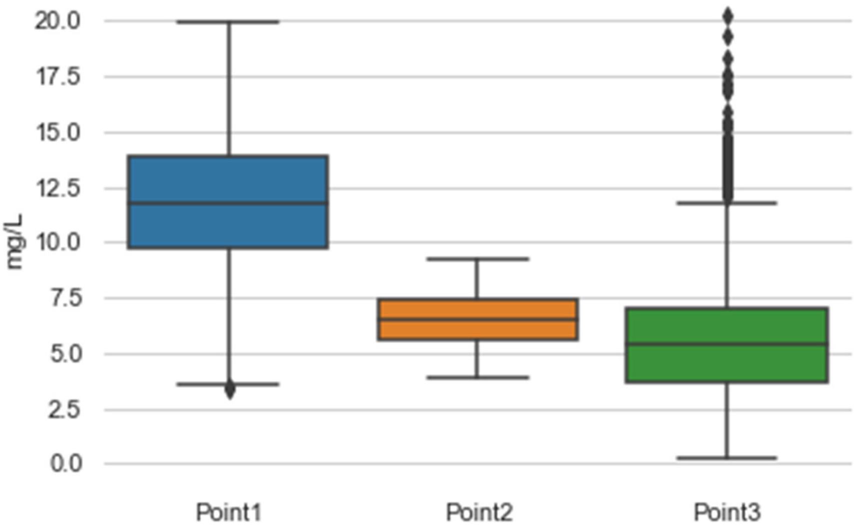

Figure 12. Dissolved oxygen boxplot of P1, P2 and P3 throughout the measurement period.

As the main objective of this study was to observe and test the efficiency of the IoT sensor network and not to make an in-depth analysis of the values read by the probes, this sensor was kept for carrying out the measurements. For better visualization and to assist in interpreting the information, we used the boxplot graph for these same values, as shown in Figure 12. The oxygen levels at Point 1 showed higher values, followed by P2 and P3. Point 2 presented minor variations in the level of dissolved oxygen over the period.

Analyzing the boxplot above, we observe the possible influence of the Sarandi stream (P3), which may contain domestic sewage [48,49]. The oxygen concentration at Point 3, where it receives the Sarandi stream, has the lowest readings, many below 4 mg/L. Another important observation is that the point where the probe has more cloudy and muddy water contributes to the obstruction and impregnation of clay in the probe, especially the membrane, making it impossible for the equipment to function optimally.

Point 3, installed in the Sarandi stream, had a significant number of possible invalid measurements. The excess residues in this stream caused the sensor membrane to block contact with the water, thus measuring values close to zero or even zero. Figure 13 illustrates the state of the dissolved oxygen sensor in this condition.

Figure 13. Physical condition of the oxygen probe at Point P3.

Observing the readings in P3, with values below the other points, we believe that it is due to a place where the water is muddier, justified by the state of the probe seen in Figure 13. Therefore, a place where the water is cloudy and muddy in low light considerably lowers photosynthesis and water oxygenation at that point, in addition to soiling and making it impossible for the dissolved oxygen probe membrane to perform more accurate readings. During the measurement period, the dissolved oxygen sensor was cleaned on 10 August, 31 August, 7 October, and 13 October. The sensor installed at P3 was replaced on October 13th for measurements with significant variations and interruptions in operation.

Figure 14 shows significantly increased readings after cleaning the dissolved oxygen probe in P3. In Figure 14, we observe four cleaning procedures. In all procedures, the same fact observed above occurred. With this, we conclude that the values of the dissolved oxygen readings in P3 were low, possibly due to the dirty membrane present in the probe, and there may also be other factors parallel to this, contributing to these low values for OD readings in P3.

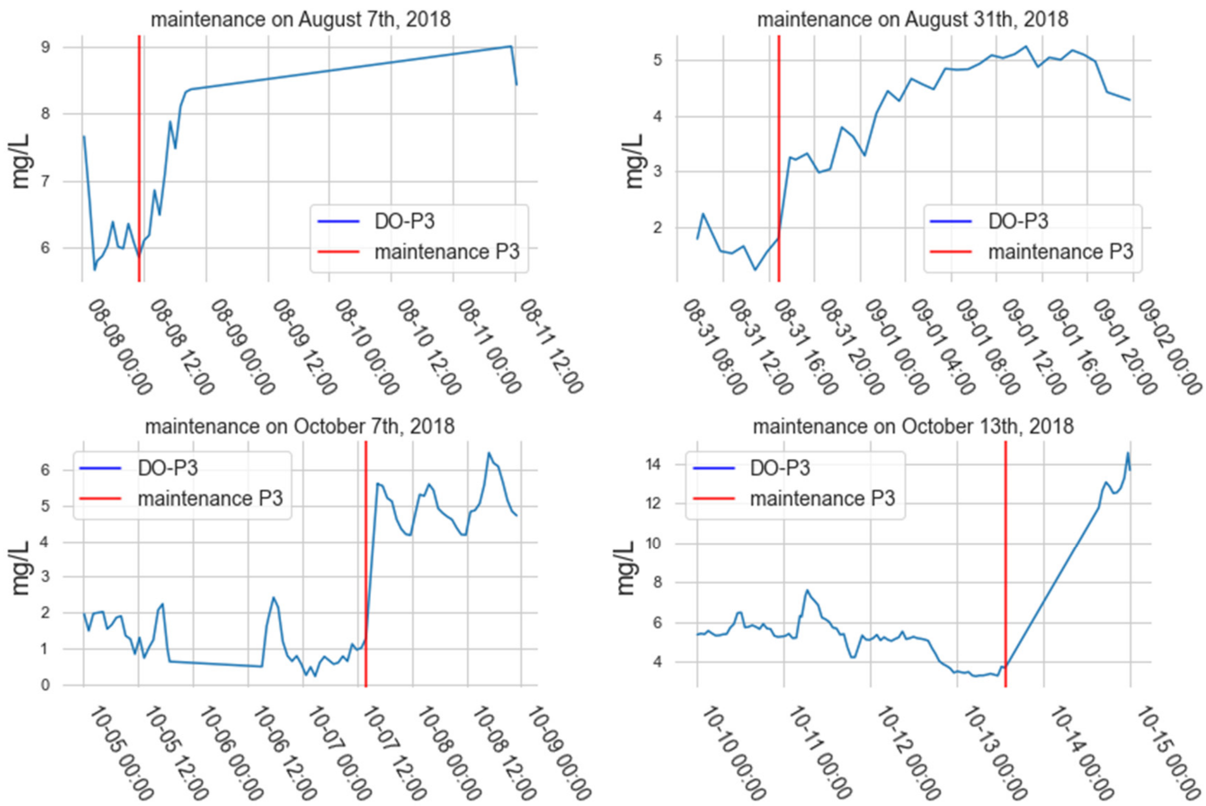

Figure 14. Days Maintenance DO Probe in Point 3.

3.3. Dissolved Oxygen Level in Relation to Water Temperature

Pearson Correlation of Physicochemical Parameters Pearson's correlation is a test statistic that measures the statistical relationship or association between two continuous variables. It is known to measure the association between variables of interest because it is based on the method of covariance [49]. Thus, the correlations between physicochemical parameters support and explain the relationships between them. For the correlation matrix between parameters, the results are given in Figure 15. An R value that is greater than ± 0.5 to near ± 1 indicates a strong correlation, while one that is below ± 0.5 is considered a weak correlation.

Figure 15 illustrates the measured water temperature and dissolved oxygen values at Points 1–3 during the measurement period. In Points 1–3, we observed a decrease in the average level of dissolved oxygen with the average increase in water temperature, which agrees with [45–47], who found that the level of dissolved oxygen in water decreases with the increase in water temperature.

Figure 15 on the right shows a correlation pair from the data, including DO-WT, demonstrating a negative correlation [45–47]. The Pearson correlation matrix was calculated among the parameters.

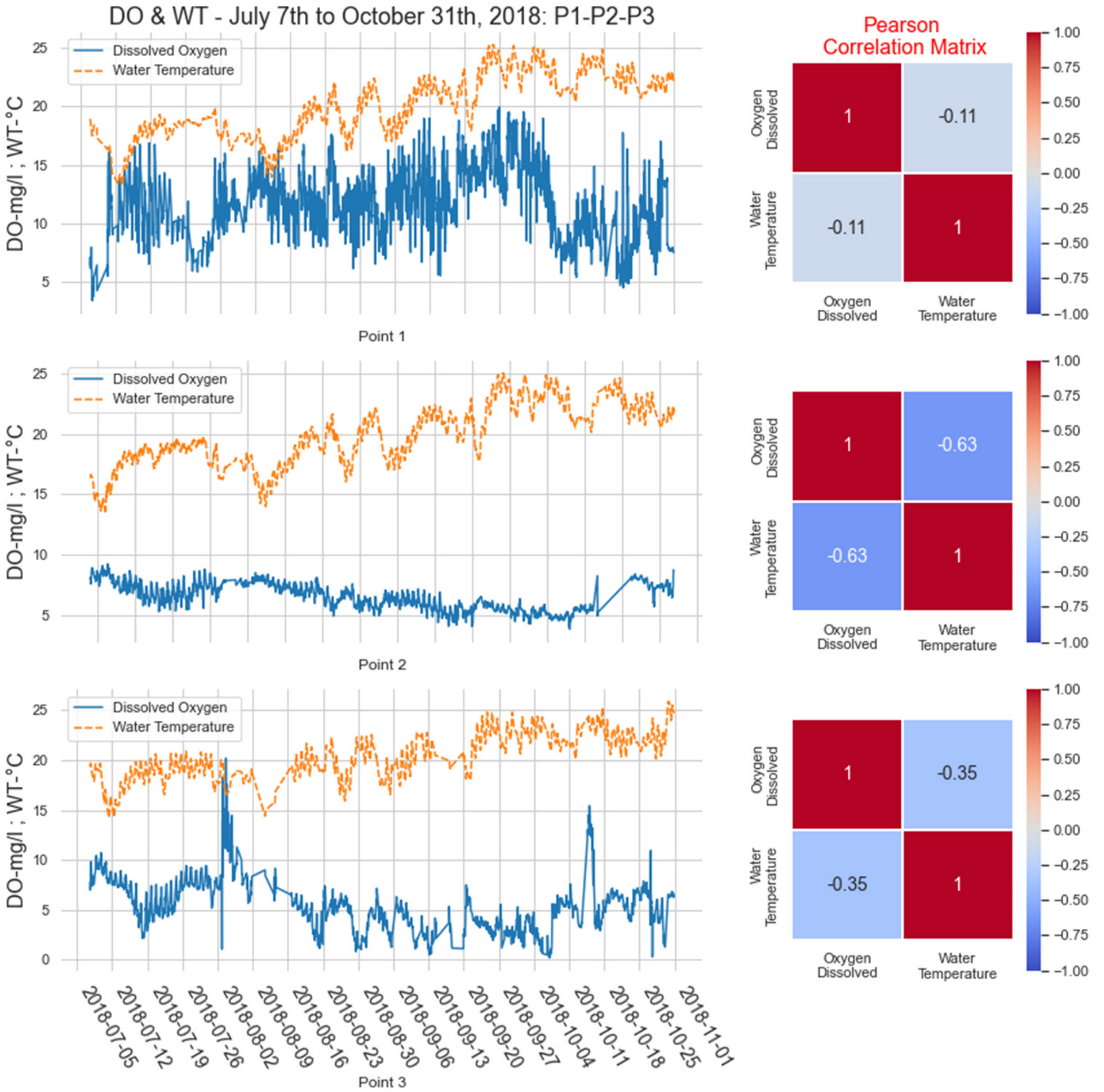

Figure 15. Dissolved oxygen level in relation to water temperature in P1, P2 and P3 and correlation at period.

Concerning daily temperature variations, this does not occur, and as shown in Figure 16 obtained from the day of the measurement on August 17th, we observed that an increase in temperature does not imply a decrease in the level of dissolved oxygen in the water. Therefore, variations in the level of oxygen in the water occur for reasons other than temperature variations, such as solar radiation [35,45–47]. Figure 16 on the right shows a correlation pair from the data, including DO-WT, demonstrating a positive correlation [45–47]. The Pearson correlation matrix was calculated among the parameters on a single day: 17 August 2018.

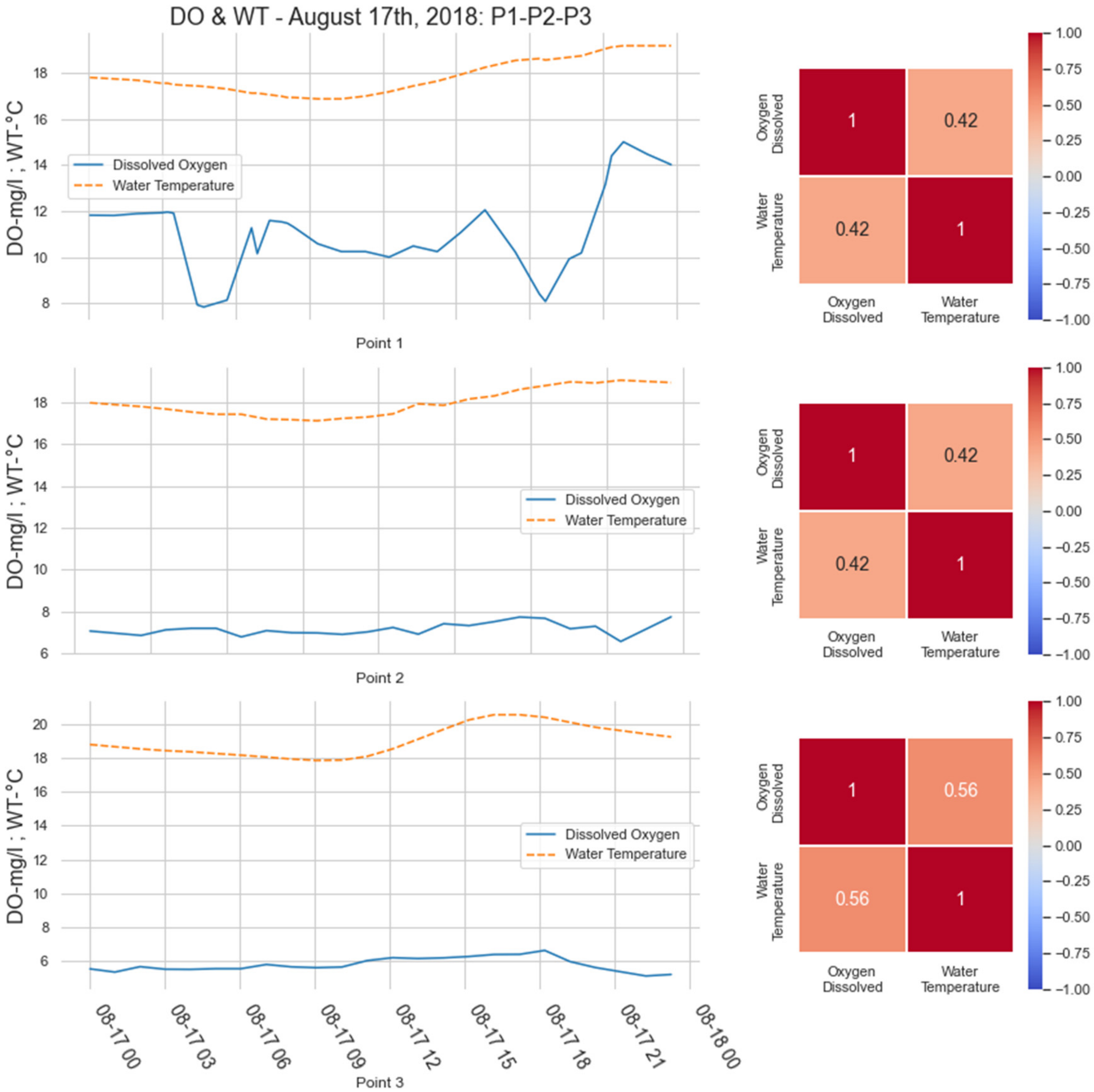

Figure 16. Dissolved oxygen Level correlation Water Temperature by day 17 August 2018.

3.4. The Influence of Rainfall on Dissolved Oxygen Concentration

During the same period in which the measurements of water temperature and dissolved oxygen concentration were carried out, meteorological data were also obtained from the Climatological Station of Maringá, located at the State University of Maringa, for the parameters of ambient temperature, rainfall index, and index of solar radiation.

Due to its location, we observed that the rain recorded at the Climatological Station of Maringá significantly influenced the dissolved oxygen in the Sarandi Stream (Point 3), as shown in Figure 17.

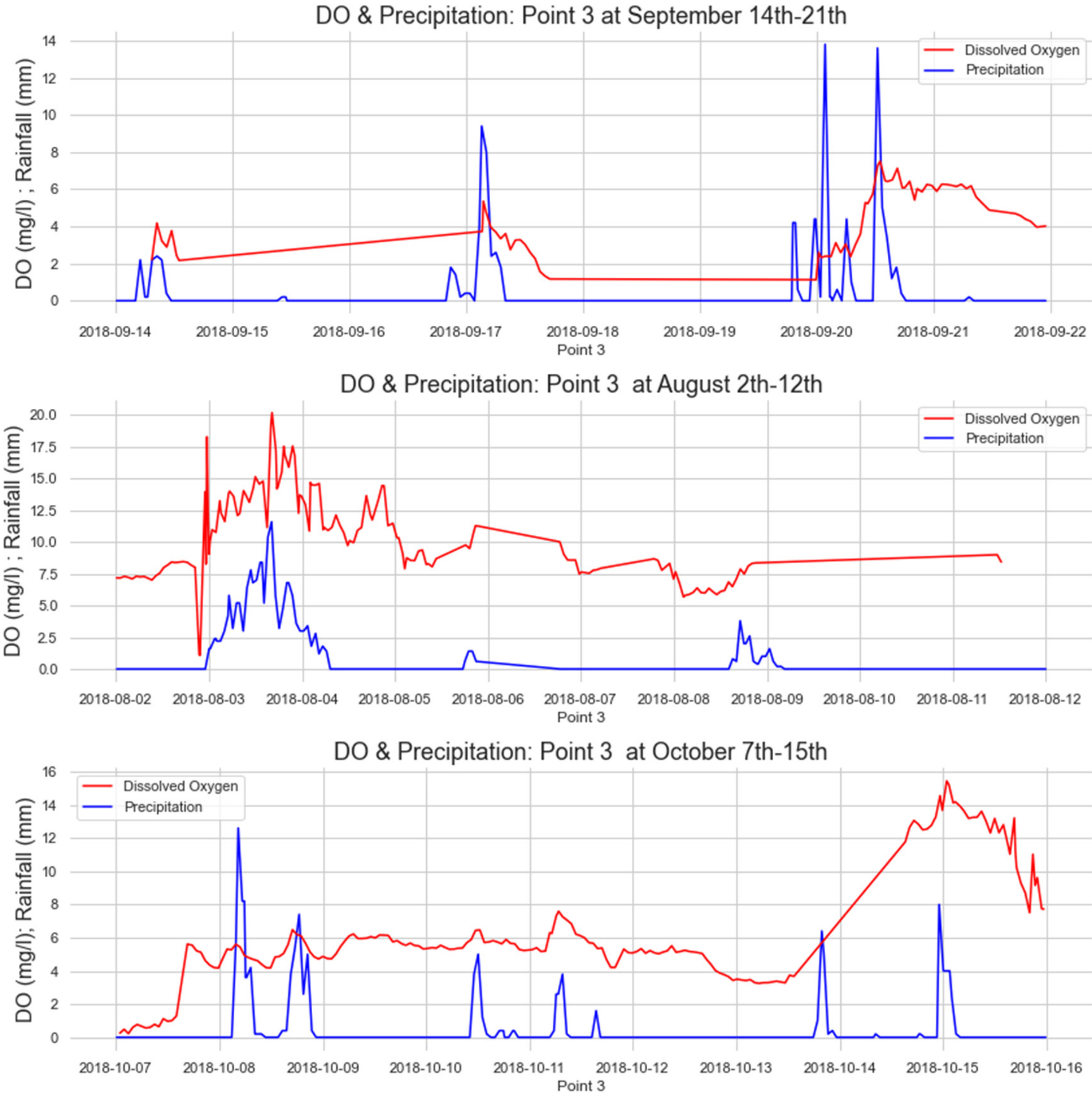

Figure 17. Dissolved oxygen Level and precipitation at P3.

At Point 2, installed in the EEB-01, we observed a slight influence of rain on the level of dissolved oxygen due to variations in dissolved oxygen in the Sarandi Stream, as shown in Figure 18.

At P1, rain did not have a significant influence on dissolved oxygen, as illustrated in Figure 18. For a better analysis of the influence of rain on the waters of the Pirapó River, climatological data must be acquired. The region is composed of the Pirapó river basin.

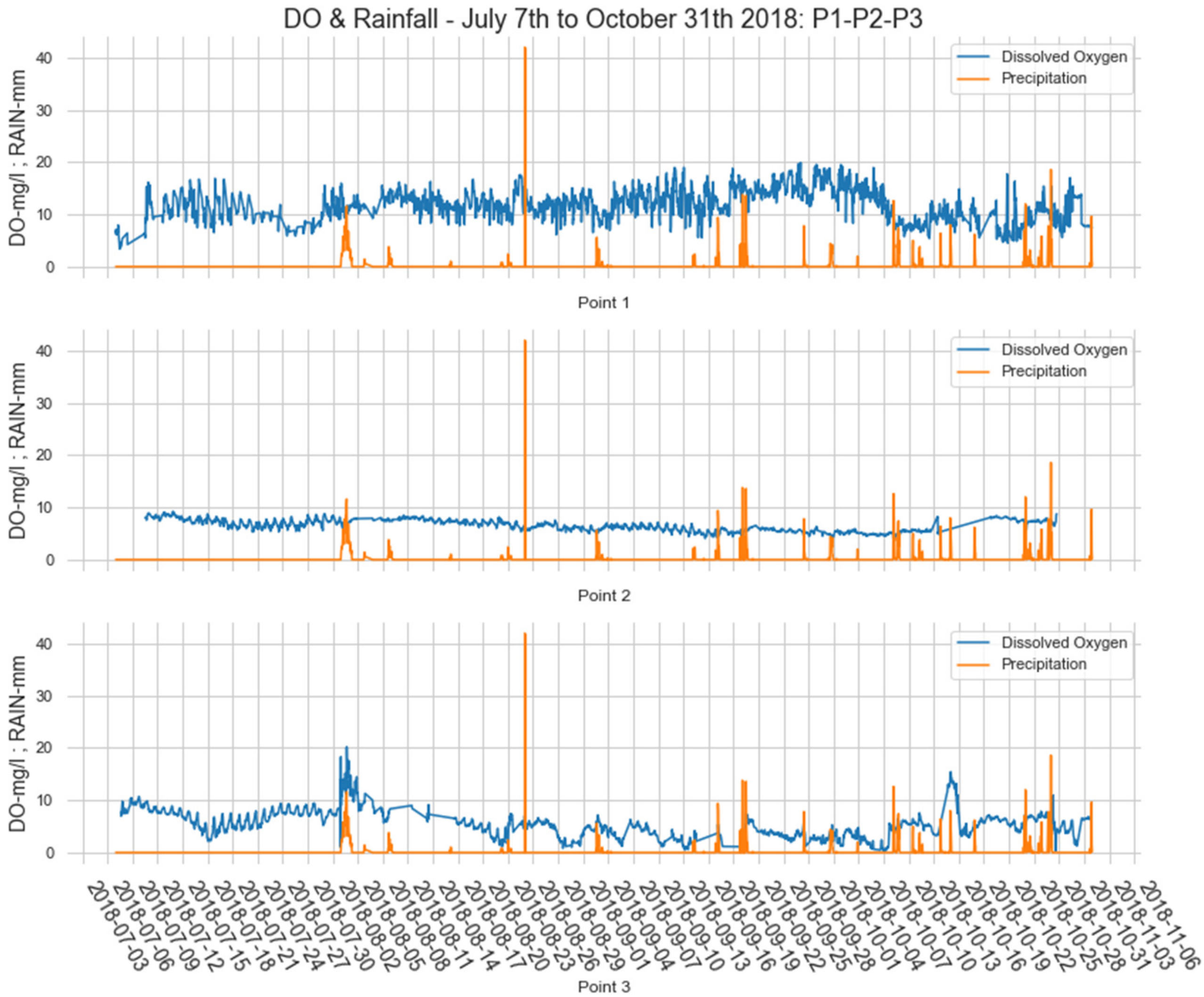

Figure 18. Influence of rain on oxygen dissolved: P1–P3.

3.5. The Influence of Solar Radiation on Dissolved Oxygen Concentration

We can see in Figure 19 that the level of dissolved oxygen at Points 1–3 increases with increasing solar radiation and decreases often at night after 21:00.

The variations in dissolved oxygen levels in the water with the influence of solar radiation were analyzed, and the measured values of the water temperature at each measurement point were added. With the inclusion of water temperature in the graphs, we observed that increases in water temperature accompanied increases in dissolved oxygen levels in the water [35,45–47].

According to Figure 20, we have a daily behavior of probes from points 1–3. We verified that the behavior of the DO variable is in line with the literature [35,45–47]. Therefore, with the presence of solar radiation, positively correlated readings were observed. This correlation is a behavior observed in the three probes: after the period of solar radiation, the process of decline in the values read in OD begins, probably due to the respiration of the ecosystem and the lack of photosynthesis, a behavior observed until the beginning of solar radiation of the following day.

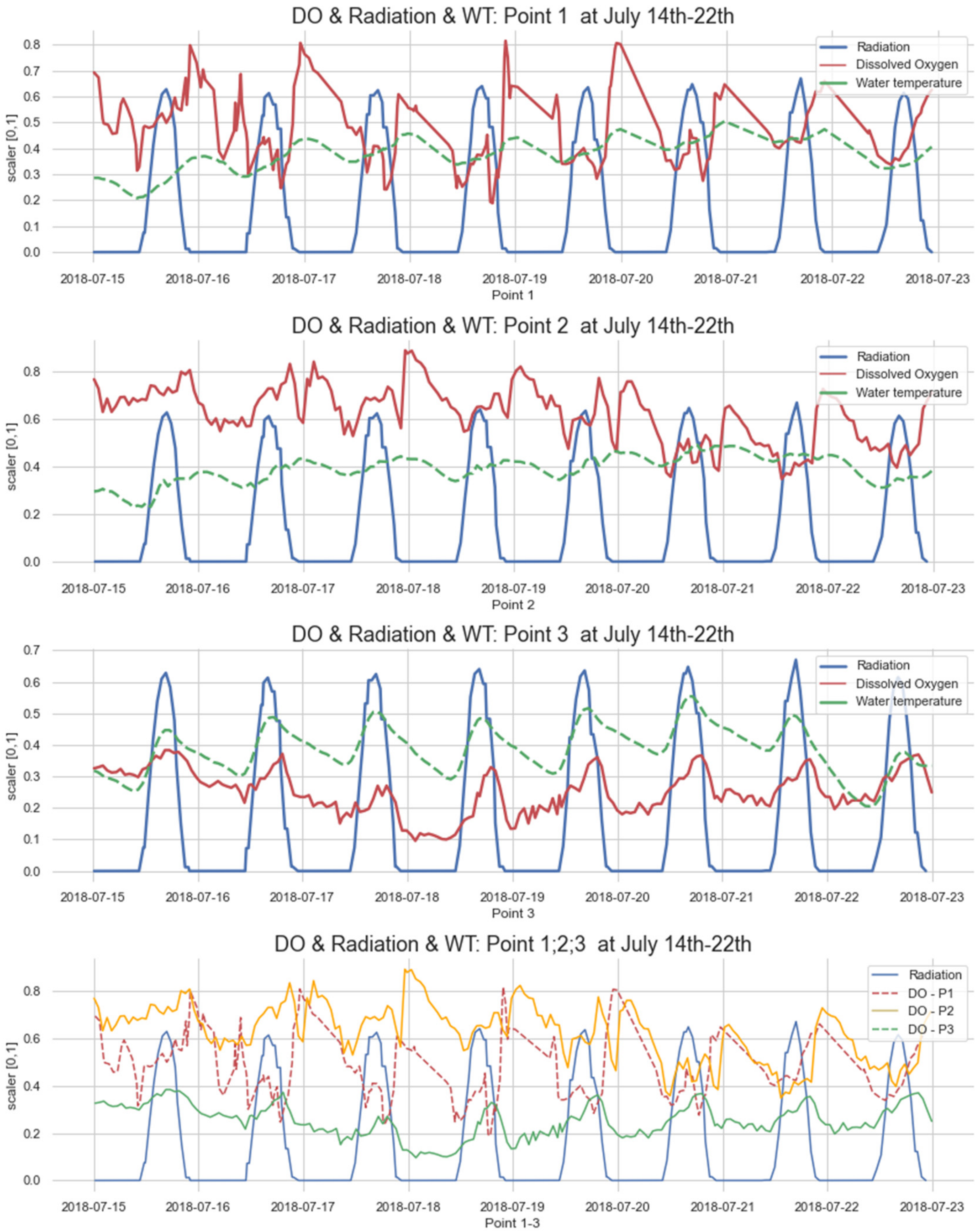

Figure 19. Influence of radiation on dissolved oxygen level in an interval.

Figure 20 shows the vertical line marking the period where the end of radiation occurs and, consequently, the decline in the rates of OD readings.

At the end of the measurement period, more precisely on 25 October 2018, Sanepar measured the dissolved oxygen level in P1 and P2 using Hach brand on-site measurement equipment, model HQ40D. According to Sanepar's readings, at P2, the reading was 7.7 mg/L, and in P1, it was 7.98 mg/L. During this project, the reading at P2 was 7.39 mg/L, and P1 was 11.86 mg/L.

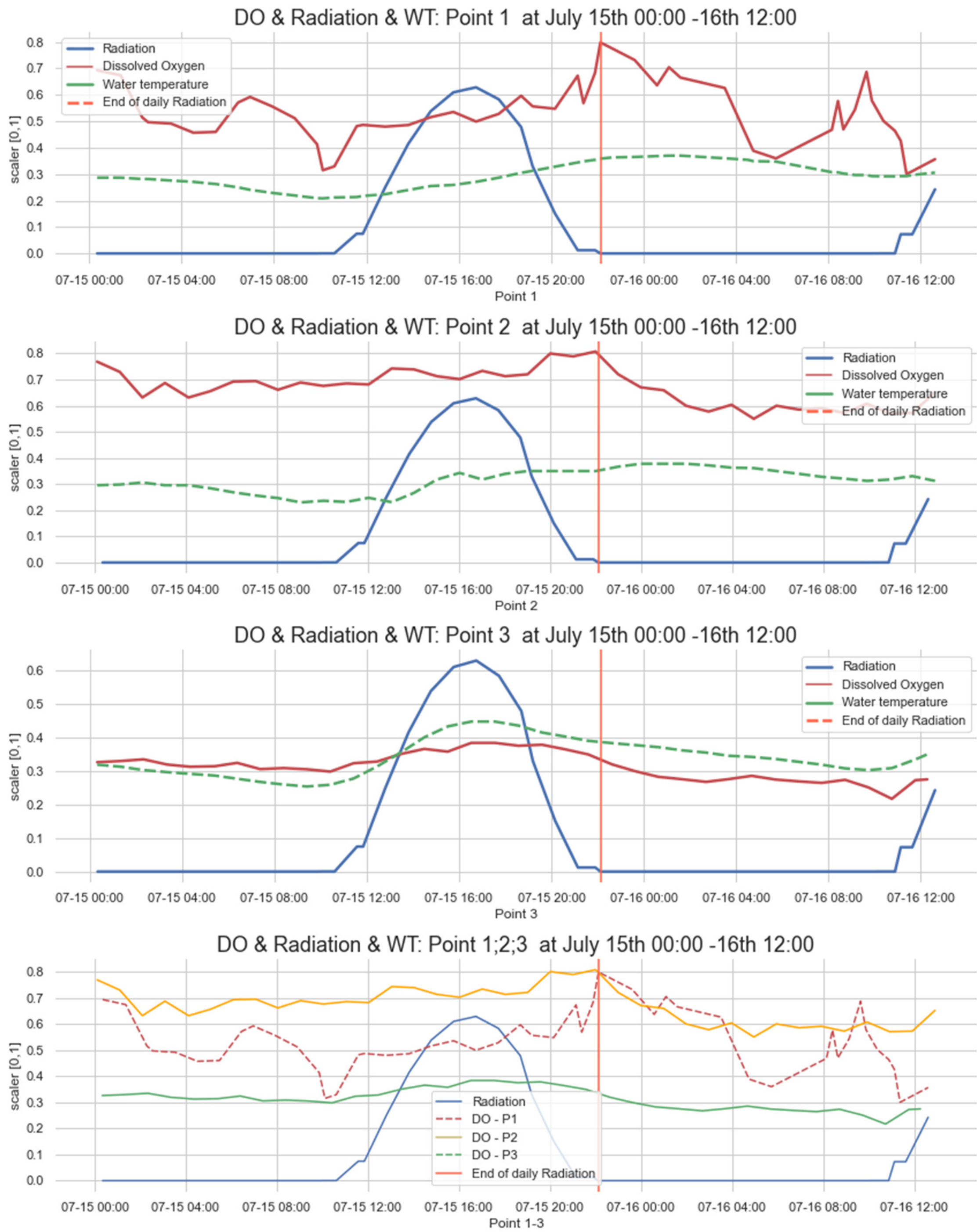

Figure 20. Oxygen levels by radiation from 19 July 2018 to 20 July 2018.

The difference between the P2 sensor and the measurement performed by Sanepar was only 0.31 mg/L. As for P1, this difference was 3.88 mg/L. As mentioned in Section 3.1, this point had significant fluctuations in its readings during the project, and the justification is the sensitivity of the galvanic probe that measures the partial pressure of oxygen in the water to be in turbulent motion, therefore justifying the reading above reported by Sanepar.

4. Conclusions

This article discusses how we can design and implement multiparametric sensors in an IoT environment in the context of a case study on a river for urban supply that is difficult to access. First, a guideline was provided on how researchers can build their own custom

IoT network to test and develop a platform with 24/7 monitoring options at three different points. Then, an analysis of the data collected by the project was presented, a brief analysis was made, and a correlation between them and climate variables was demonstrated.

During the research period, the system encountered many adverse situations since it is a project subject to the weather and direct contact with the local ecosystem. As a result, the conditions for the investigation were very different from those of a simulation in a laboratory, which would naturally not be subject to these observations. Finally, the proposed methodology was implemented and evaluated in a real-world environment, and experimental results confirmed the applicability of our approach. In future work, it would be worth investigating the use of new probes, such as pH, ORP, turbidity, TDS, electrical conductivity, and salinity, and applying machine learning and deep learning models to study the relationships between physical sensor metrics and replace most of them with virtual counterparts. The final vision of this future direction is to approach an intelligent environment, monitored 24/7, using a minimum of physical sensors that automatically make decisions and interact with the data presented in real time, making it possible to analyze future environmental imbalances and providing the possibility of anticipating some details of environmental disasters related to the lotic ecosystem, such as rivers of great importance used for urban supply.

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