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River and Rainfall Monitoring using the Internet of Things

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of the requirements for the degree of
Master (Computer Science)

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Summary

This dissertation seeks to explore if the Internet of Things is sufficiently accurate and reliable to be employed in a real-time rainfall and river monitoring system. To investigate this, three IoT datasets are analysed and compared with each other. The first dataset was from Pervasive Nation, who have created Ireland's IoT testbed and have active 12 rainfall sensors placed around the city. The second dataset comes from VT, who have river level sensors placed around Dublin streams and rivers. Lastly, Dublin City Council have both rainfall and river level sensors placed around city.

The rainfall and river level values that each dataset reported were analysed against publicly available Met Eireann and Office of Public Works data. These values were used as the control, therefore, each sensor was compared against these values in order to evaluate how accurate the IoT data was. The networks that the IoT sensors used were also analysed by establishing how often missing data and outliers occurred. Analysis was also carried to investigate whether rainfall had any impact on river levels in order to investigate what environmental variables are needed to accurately monitor and forecast river levels.

The results of this dissertation were promising, with many sensors achieving high correlations to both the official river and rainfall values and against each other. However, some sensors performed poorly suggesting that these IoT sensors are not ready yet to be used in a real-time river and rainfall monitoring system. This dissertation has also established that more sensors and other types of weather sensors are needed in order to create an effective IoT river and rainfall monitoring system.

Abstract

River and Rainfall Monitoring Using the Internet of Things
Laura Young
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We are all witnesses to the continued growth of Dublin's population and development of the city's infrastructure. With this in mind, and together with the impact of climate change, it has become ever more important to devise a system to measure and assess the risks of flooding. Whilst governmental bodies such as Met Eireann are currently examining flooding and its potential effects, the existing system is far from perfect, particularly in respect of predicting imminent risks. This is because a reliable, real-time rainfall and river level monitoring system only partially exists. Currently, flood damage costs the city €8m per annum and given that flooding events are likely to become more common with the impact of climate change, the installation of additional sensors to gather more data has the potential to allow the city take effective measures. This dissertation will analyse rainfall and river level data which has been collected by an Internet of Things system. The results of this will indicate how reliable and accurate an IoT infrastructure is.

Currently, the majority of Met Eireann's rainfall stations require a network of volunteers to collect the readings. At the end of each month, these readings are then sent to Met Eireann HQ. Met Eireann receives real-time data through the twenty automatic stations and by using radar. Though radar is accurate, it requires experts to decipher the images. The Internet of Things can report real-time data from many locations throughout the city by using multiple sensors. These readings are simple for non-experts to understand and which is a distinct advantage over radar. Currently, Office of Public Works have only one publicly available river level sensor in Dublin city. If an IoT river level system were installed, one significant advantage would be that the sensors utilised are much cheaper than their industrial counterparts. This means more sensors can be bought and therefore more information about the river can be collected. The Internet of Things is also a much easier way of collecting and storing the necessary data. Dublin relies heavily on hydrological models to predict floods. These models are complicated and rely on analysis by trained personnel. The primary reason that hydrological models are used instead of statistical models is that not enough information of previous floods are available. A well developed, expansive IoT system would be able to record rainfall and river variables during a flood. This means that the recorded data can be used to establish the events which happened leading up to a flood and can then be used to develop a statistical model to predict flood warnings.

This dissertation will investigate whether IoT sensors are accurate and reliable at reporting real-time rainfall and river data. Three IoT datasets are analysed and compared to one another.

The first set is from CONNECT's Pervasive Nation (PN), who has created Ireland's IoT testbed and has numerous rainfall sensors embedded in locations around Dublin. The second is from a project by Vizor Technology (VT), who have installed river level sensors throughout rivers and streams across Dublin. Lastly, Dublin City Council have both rainfall and river level sensors placed around the city. Not only will these datasets be compared with one another but will also be compared to the publicly available Met Eireann and OPW datasets. This will determine if these sensors are reporting accurate data by comparing each sensor with the nearest Met Eireann / OPW sensors. Pervasive Nation uses the LoRa network, VT uses the Sigfox network and DCC uses M2M SIM for their sensors, so it will also be established which network has the highest reliability.

It was discovered that half of Pervasive Nation's sensors had high correlations to Met Eireann sensors. The DCC sensors had high correlations to both the rain sensors and VT river level sensors. It is also noted that the VT sensors consistently reported data, while the PN sensors often had days go by where no data was reported by individual sensors. This means that it could be argued that the network used by VT was more reliable than the PN network. Because of the data loss from the PN sensors, it was difficult to assess how accurate the sensors truly were at reporting data. As it stands, the PN IoT infrastructure can not be used reliably at reporting accurate real-time data. The VT and DCC sensors could be relied upon to report real-time data, however, and due to the lack of nearby sensors of each of the analysed sensors, it cannot be said for sure how accurate they were.

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Nomenclature

Pluvial	Flooding causes by rivers
Fluvial	Flooding caused by rainfall

1 Introduction

The Internet of Things (IoT) aims to create a world where all objects in an environment are connected to a device allowing the exchange and collection of data to and from the object through a network. Since the 1990's, the concept has been continually growing in momentum and now an estimated 127 new devices are connecting to the internet every second (1). IoT has been integrated into a multitude of applications including buildings (2), cities (3) and healthcare (4).

Technological progress in flood monitoring, along with IoT sensors becoming more cost-efficient, is allowing a new stream of environmental data to be obtained (5). When it comes to natural disasters such as flooding, the only course of action in which to minimize damage is to give the public as much warning as possible in order to allow them take the necessary protective measures. With flood damage already costing Dublin €8m per annum, and floods being more likely in the future due to climate change and rising sea levels (6), the installation of additional sensors and gathering more data will help the city take more effective measures (7). Furthermore, the data can also be used for a multitude of purposes, such as creating statistical models to predict floods and to use in infrastructure by determining if certain areas are more flood-prone than others.

However, IoT is a relatively new concept and there are few cities around the world that have IoT projects that are not in the testing stages. Therefore, it is important to trial run a small IoT project and evaluate the results received from the sensors. The evaluation would involve testing the sensors quality of data. The data that is sent by the sensor could be interrupted by network errors or the value could be scrambled during transmission, meaning the wrong value could be stored in the database. In this dissertation I collaborated with two projects which have deployed IoT sensors that are currently in the prototype stages. In addition to these, one other more established IoT system has also been analysed. This dissertation carries out work which can be viewed as the initial evaluation stages to a project that will eventually become a flood monitoring and prediction system.

1.1 Motivation

The first motivation for this dissertation is the fact that climate change is a very real threat to our ecosystem and, in turn, our lives. With the rise of sea levels, heavier & more localised flash floods and storm runoff becoming more frequent (8) it is becoming ever more important to measure weather variables if we are to take any kind of correctional action in regard to the matter. If the Internet of Things proved to be an accurate and reliable system, then it would be a much cheaper and therefore more viable alternative than using industrial approved sensors to monitor more areas. The more sensors that there are means more data is being gathered and, therefore, a more in depth analysis to weather processes can be achieved.

The next motivation is that Ireland continues to use primitive methods of measuring weather variables. For example, the majority of Met Eireann's rainfall gauges do not report data in real-time. Met Eireann relies on a network of volunteers to travel to the site of rain gauges, who manually record the readings in special rainfall cards which are then sent by post to Met Eireann at month's end. The Internet of Things would be an ideal method of modernising Met Eireann's rainfall gathering methods. Due to the fact that flash floods are increasingly becoming more localised, it is becoming more important to be able to visualize real-time information from rainfall gauges in order to make some response to the heavy rainfall. An effective IoT system would not only deliver rainfall data in realtime but would also eliminate the process of relying on volunteers each month.

The final motivation was that there is virtually no historic flooding data in Dublin. If one were to try and build a predictive flooding model, it would be impossible without using a complicated hydrological model. In terms of previous river data, there is only one publicly available river level sensor in Dublin city. Therefore, it would be impossible for a person to analyse river processes in a flood. Office of Public Works claims to have a flood map website for Ireland, detailing past floods, but the information is scant for Dublin. It only details when a flood had happened and does not record any of the river or rainfall processes leading up to the flood. If a well established IoT system had been in place, all of this data would already be collected and ready to be used to build a flood prediction model for each area in Dublin.

1.2 Research Aim

The dissertation will delve into whether the Internet of Things is appropriate for use in river and rainfall monitoring. This will be achieved by analysing three IoT datasets and comparing them to official, publicly available datasets like Met Eireann and Office of Public Works. The results of this analysis will determine if IoT is effective or not.

1.3 Project Overview

In Chapter 2, the background of this dissertation will be discussed in order to explain the datasets as well as getting familiar with IoT networks. The State of the Art makes up Chapter 3, where current methods of rainfall and river monitoring is discussed as well as methods of predicting floods. Chapter 4 describes the Methodology and the work that was carried out to prepare the data for analysis. Chapter 5 evaluates each of the datasets, while Chapter 6 discusses the conclusion.

2 Background

In this section, the sources of the data that are used in the dissertation are discussed. This includes Pervasive Nation, Vizor Technology, Dublin City Council, Met Eireann and Office of Public Works. For this dissertation, Pervasive Nation, Vizor Technology and Dublin City Council were individually contacted and each had agreed to provide the relevant datasets for this research. Pervasive Nation supplied data from their rain gauges by allowing access to their dashboard. Vizor Technology supplied river level data by also allowing access to their dashboard. Dublin City Council provided rain gauge and river level data by supplying each of the sensor's history through csv files. This means that both Pervasive Nation and Vizor Technology sensors could be accessed in real-time but Dublin City Council sensors could not. Met Eireann and OPW have publicly available data of each of their sensors which can be accessed through their respective websites. Met Eireann sensors cannot be viewed in real-time, however OPW's river levels and flows can be accessed in real-time.

2.1 Datasets

2.1.1 Pervasive Nation

Pervasive Nation's (PN) objective is to build an Internet of Things infrastructure and testbed which can then be used as a resource for industry, government and academia and to act as a leading example for IoT research and innovation. They are operated by CONNECT, who are the Science Foundation Ireland Research Centre for Future Networks and are headquartered at Trinity College Dublin. They use the latest Low Power Wide-Area Networks (LPWAN) technologies, software-defined radio and Application Enablement Platform.

Pervasive Nation currently has 12 active, low-cost rainfall sensors scattered around Dublin city, a map of which can be seen in Figure 2.1. There are two types of sensors that are currently deployed. One is manufactured by Casella, which sends a signal each time when 0.2mm of rainfall occurs. The other is a lower-cost unit which is capable of measuring 0.3mm of rainfall at a time. Each of the sensors are integrated with LoRa radio chipsets to allow data to be transmitted over the Pervasive Nation network. The data is reported in real-time and can be viewed through the Pervasive Nation dashboard. The maximum amount of data that can be retrieved by each of the devices is what was collected in the past year. Therefore, for this dissertation, only this data could be analysed as opposed to all of the data ever collected by each sensor. The history can be downloaded as a comma separated values file (csv) and the information that can be viewed from this file is the reported time of the reported data, the rainfall, battery level, tip-counter value, max RSSI and the gateway address.

Figure 2.1: Map of Pervasive Nation rainfall sensors. Red marks indicate where there are two sensors placed, green marks indicated where one sensor is placed.

2.1.2 Vizor Technology, DCC and TCD River Level Sensors Project

Vizor Technology (VT) and Dublin City Council, along with academic researchers from Trinity College Dublin, have deployed 11 river level sensors in Dublin streams and rivers, including the Rivers Liffey, Dodder and Tolka. A map of the sensors, as displayed on the dashboard, can be seen in Figure 2.2. Their end-goal is to develop a flood warning sensor network that will inform nearby inhabitants of these rivers of flood warnings which, in turn, will help minimise danger of lives and the damage properties.

This project employs Dunraven Apollo level sensors that send information through the Sigfox network. Figure 2.3 shows one of the sensors that has been installed in a river and it can be seen that the water is collected in a tube, or a 'tank'. Currently, the data can be viewed through a dashboard, where each device's current status can be displayed on a map. Each of the sensors report the litres (the amount in which the tank has filled up), the percentage of the tank that is full, the ullage percentage, the battery level of the sensor, and the date in which the report had been sent. Each of these sensor's full history can be downloaded as a csv file. Most of the sensors have been configured to send a message once every hour, while others send in intervals of every two hours. Only one of the sensors has run out of battery, with the last contact with the sensor being on the month of February in 2018. This can be viewed as a disappointing result, as Sigfox is known as being the most energy efficient form of connectivity on the market, with Sigfox enabled devices lasting 300 times longer than cellular modules. All of the devices were installed in November 2017.

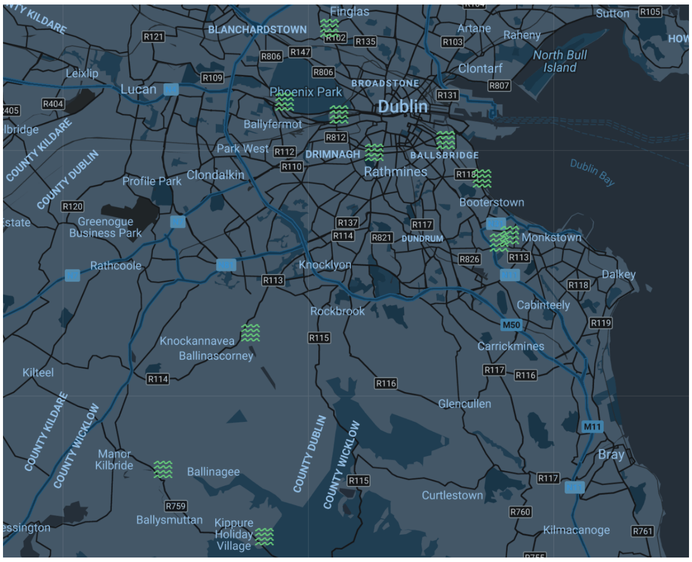

Figure 2.2: Map of VT river level sensors sensors. Green marks indicate where sensor is placed

Figure 2.3: River level sensor that was used.

2.1.3 Dublin City Council

DCC have a network of rain gauges and river monitors installed throughout Dublin city. Some of the locations have both a river level and rainfall gauge installed. Currently, these sensors are being monitored by personnel in Dublin City Council offices, as well has having a simple 'alarm' system when sensors reach defined thresholds.

Each of the sensors data history can be downloaded as a csv file, each defined by their data frequency. This includes intervals of 1 minute, 15 minute, 1 hour or 24 hour intervals. The csv files are also separated by date, each file containing about 6 months. Some of the sensors data goes as far back as 2012. Each of the files contain just the recorded rainfall / river level and the date that it was recorded. A map of the sensors can be seen in Figure 2.4.

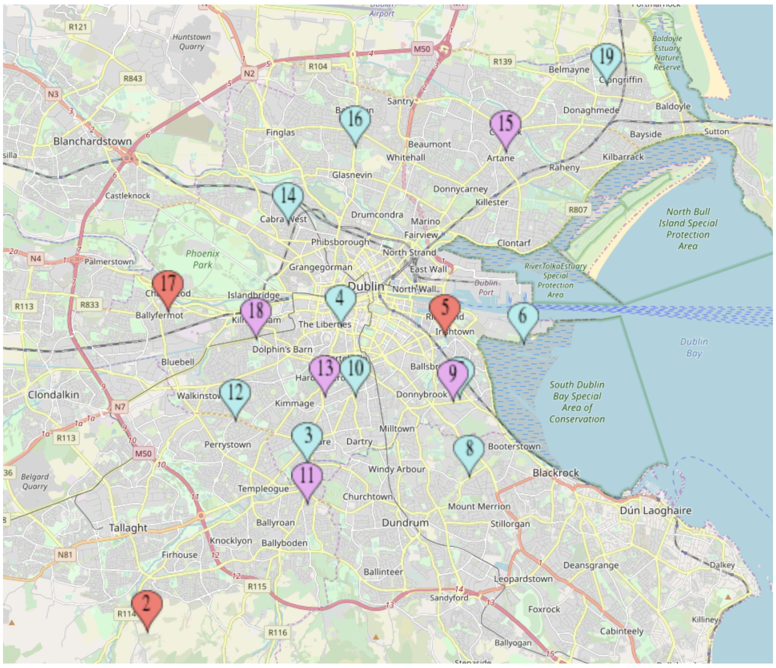

Figure 2.4: Map of DCC sensors. Blue inidcates a rainfall sensor, pink indicates a river level sensor and red represents both.

2.1.4 Met Eireann

Met Eireann (Irish Meteorological Service) has publicly available historical data of their stations. There are two weather stations located in Dublin, one at Dublin Airport and the other at Phoenix Park. The Dublin Airport weather station contains data dating back to 1939 whilst Phoenix Park contains data from 2006. Weather stations collect a range of weather variables including rain, temperature, soil temperature, dew point temperature, humidity and vapour pressure. In addition to this, Met Eireann has 14 rain stations throughout Dublin, a map of which can be seen in Figure 2.5. Each of the stations history can be downloaded as csv files.

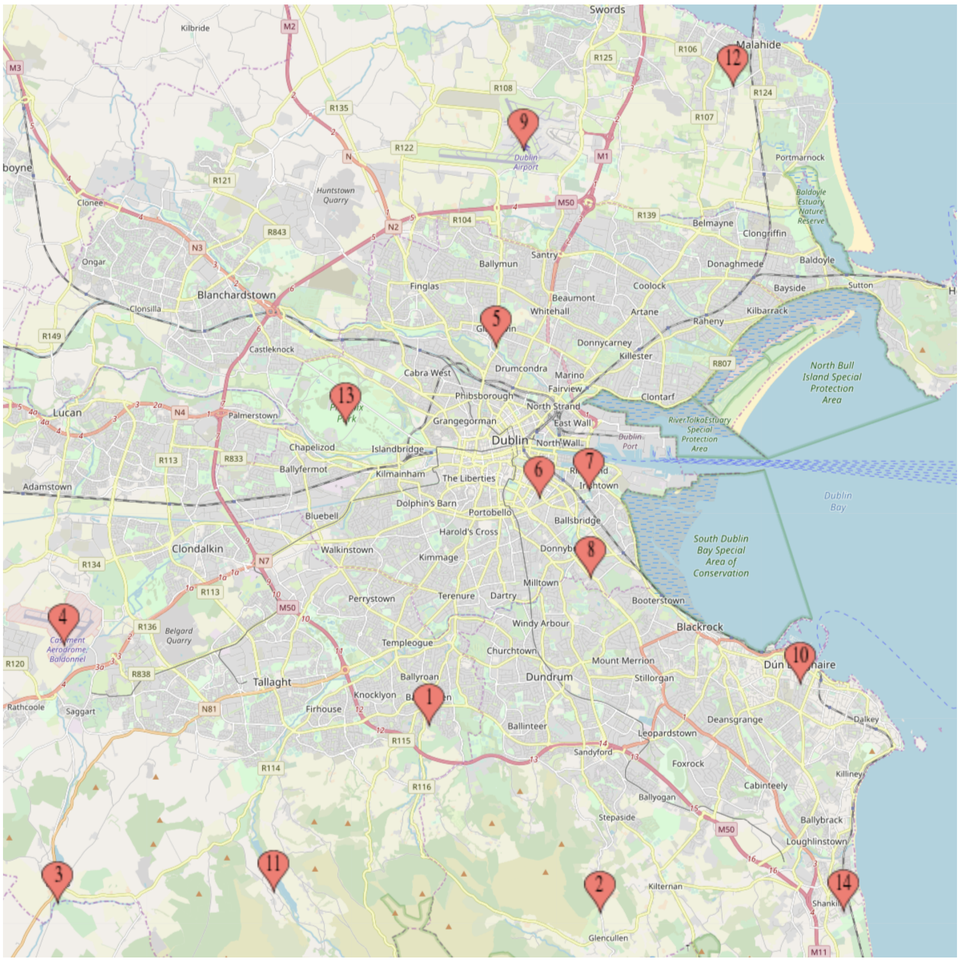

Figure 2.5: Map of Met Eireann sensors.

2.1.5 Office of Public Works

Office of Public Works hydrometric network provides a website that allows access to water level and flow readings of rivers and streams in real-time across Ireland. In addition to general station information, quality assessed level and flow reading are presented in commonly used formats, including daily mean of data, water level & flow duration curves and annual maxima water level & flow. Water level is collected using data loggers which digitally records the water level at set time intervals. Water level is measured by a pressure inducer immersed into the water body while water flow is measured by using acoustic doppler profiler devices (9). Although there are 380 active stations, only three are located in County Dublin, and only one is located close to the city.

2.2 IoT Networks

Pervasive Nation, VT and Dublin City Council all use different networks for transmitting data to and from the sensor. Pervasive Nation uses LoRaWAN, VT uses Sigfox and Dublin City Council uses SIM M2M. There is no specified network which must be used in an Internet of Things system as different types of devices would suit different network types. When choosing a network it should be noted that it directly affects the sensors hardware requirements and costs (10). A brief overview of an array of networks will be discussed in order to understand why different networks are employed.

2.2.1 Cellular Networks

One of the conventional cellular networks is 4G. 4G is a highly advanced radio system, that uses masts dotted around the landscape to broadcast signals necessary to allow 4G to achieve high speed download and upload rates (21Mb) (11). 3G works in much the same way as 4G, except that 4G can accommodate a much higher simultaneous capacity of users than 3G. For instance, a 3G tower may be able to give 100 users the best possible connection speeds, but a 4G tower would be able to deliver the same experience to 400 users. IoT devices are made to be simple and computationally light. Traditional cellular networks, like 4G and LTE, consume a lot of power and would not fit well in a system where a small amount of data is being transmitted infrequently (12). Another reason that cellular networks are not used in an IoT infrastructure is the fact that IoT networks alternatives are cheaper than cellular.

2.2.2 IoT Cellular Network

Cellular networks are different to IoT cellular networks. There are two types of IoT cellular networks, one being a narrowband IoT (NB-IoT) and category M1 (Cat-M1) IoT (12). Both have very long ranges, with NB-IoT theoretically having a range of up to 100 km. A cellular network has the advantage over low power networks such that a user does not have to set up their own private network. Therefore, they are piggybacking on the cellular infrastructure that is already present.

Machine to Machine Sim (M2M Sim) is one commonly used IoT cellular network. The difference between a M2M Sim and a normal Sim that you would find in a phone being that M2M Sim's are simpler, only being able to transmit a small amount of data rather than voice clips. Because they are simpler they are usually much cheaper than a standard SIM. The main benefit of choosing M2M over a low power network is that if a network goes down, an M2M sim will simply switch and transmit data through another network. Low Power Wide Area Networks depend on the Internet to report data and each of the sensors have only one network to transmit data on. M2M SIM is ideal for IoT systems where the data gathered must be sent without interruptions, so M2M SIM ensure the user will have a very small chance of all the networks being down.

2.2.3 Low Power Wide Area Networks - LoRa, Sigfox

Low Power Wide Area Networks (LPWAN) is a type of wireless network that offers connectivity to devices which require low power and transmits small packets of data at long intervals. The fact that it is low power makes it different to regular WAN, as WAN uses cellular technologies. Clearly, the issue of low power is very relevant in devices which use battery in circumstances where the sensors are located in areas which are difficult to access.

Both LoRa and Sigfox are companies which allow the configuration of devices to connect to LPWANs. The main difference between the two being that Sigfox itself is a network provider, while LoRa provides the technology to access a network. This means that some countries cannot use Sigfox as the coverage is not there but can use LoRa as they provide multiple service providers and all the user is required to do is set up the gateway. Both LoRa and Sigfox are low speed, low power and have long ranges (13). Because of this, they are appropriate networks to use in weather environment monitoring system, as the sensors can be placed in remote locations and that the fact data would only be sent 10 minutes or so.

3 State of the Art

This section will delve into projects and studies relating to an Internet of Things rainfall and river monitoring system. It will also discuss papers which have implemented a flood prediction model using IoT sensors, to highlight that one of the goals of such a system is to generate early flood warnings. Obviously, envisioning an appropriate system requires the data that it reports to be accurate and reliable. The setup and the upkeep of the monitoring system also needs to be cost-efficient and easy-to-learn. Current methods used by Met Eireann and Office of Public Works, as well as newer projects and papers that use the Internet of Things, will be discussed. Each will be evaluated in terms of their techniques, accuracy, cost, coverage, whether they require the involvement of expertise, the availability of real-time data, if data history is stored and, lastly, if a flood map is produced.

Dublin's weather and climate is monitored, analysed and predicted by Met Eireann, Ireland's official meteorological service. To assess rainfall, Met Eireann uses both rain gauges and radar. The rainfall gauge network relates to approx. 500 stations, located throughout Ireland. Out of the 500, only 20 of these station are automatic, sending minute-by-minute information through broadband or by a Public switched telephone network (PSTN). This means that the majority of gauges used my Met Eireann requires a large team of volunteers to gather the readings. Volunteers either visit the gauge daily or monthly, taking manual note of the collected rainfall on special 'rainfall cards'. At the end of each month, these cards are then sent to Met Eireann HQ, where they are assessed and stored in a database. Met Eireann allows access to this database, meaning thousands of rainfall entries from stations can be studied and analysed.

Met Eireann also uses radar to observe and forecast rainfall. Radar (Radio Detection and Ranging) was originally invented during WW2 to detect aircraft, and when it was discovered that precipitation frequently obstructed the signal. Radar consists of a transmitter and a receiver. When the transmitter emits pulses of microwaves, precipitation scatters the waves, sending energy back to the receiver. The intensity of the received signal indicates how intense the precipitation is. By measuring the time it takes for the radio wave to leave the radar and return determines how distant the storm is. Radar is generally accepted as being highly accurate, however, the images produced by radar require analysis by an expert.

Met Eireann, as Ireland's official meteorological service, can be seen as the gold standard for producing accurate and reliable rainfall monitoring data and rainfall forecasts. However, an Internet of Things system can score an advantage over the current Met Eireann rainfall monitoring method. Firstly, an IoT system can produce real-time results, as opposed to Met Eireann's method of receiving the data at the end of each month. Radar produces huge datasets that need to be analysed by an expert and which is also time-consuming (14). Although radar is quite accurate, it is not entirely reliable. An IoT system can deliver data that is simple to understand in that it reports the amount of rainfall at that moment and no further analysis is required to understand the data. Using real-time sensor data in combination with radar, and by comparing both sets of data, means that you are ensuring the received rainfall data is correct.

Unlike Met Eireann, Office of Public Works focus solely on river processes. OPW has produced Ireland's HyrdoNet system. The hydronet website provides users with a summary of surface water and hydrometric data that has been collected by hydrometric stations. The website allows access to over 380 real-time water level and flow sensors distributed throughout Ireland. However, the website only has one publicly available water level and flow sensor located in Dublin city. Office of Public Works also focuses heavily on floods. The OPW has responsibility for carrying out the implementation of the National Flood Risk Policy. For numerous areas across Ireland, OPW has assessed and mapped the flood extents and risks of both frequent, minor flood events up to (very rare) extreme events (15). These maps describe the characteristics of the predicted flood and includes information such as the flood depth and level, the flood extent, and the flow of the floodwater. Flood maps are created by surveying areas and creating a hydrological model that produces the details of a hypothetical flood. The results are measured against past floods to evaluate how accurate the model was. The flood map itself is a diagram of the results that the model had produced. An example of a flood map can be seen in Figure 3.1.

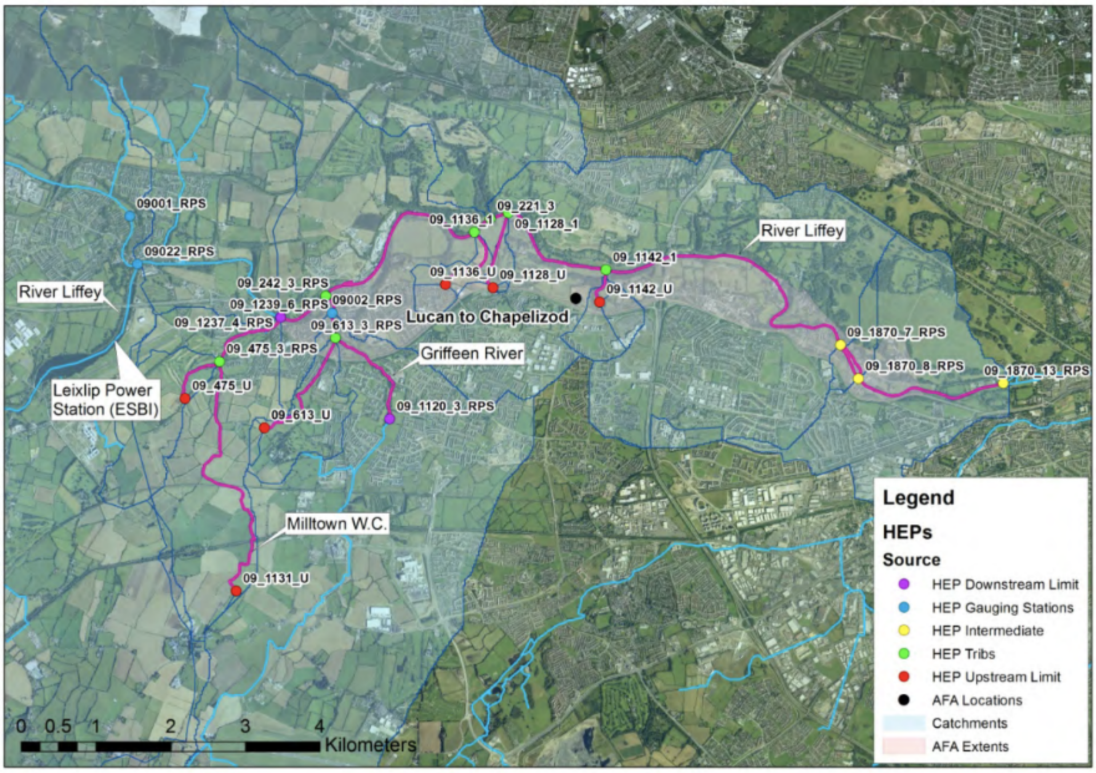

Figure 3.1: Flood Extent Map of Lucan

An Internet of Things river monitoring system can be used to improve the OPW's method of river modelling and flood forecasting. For example, the first issue is the lack of sensors present in Dublin city. If this were a cost issue, IoT enabled sensors are known to be cheaper than their industrial counterparts. In this project, the VT river level sensors that were used were 60% cheaper than then the previous, industrial-approved level sensors. In that particular case, three sensors could have been purchased for the price of one. This means that more sensors can be placed in more locations and, therefore, a much greater spread of data on river processes can be collected and analysed. The Office of Public Works also has another drawback being the lack of historical flood data available to them. On their Flood Info website, they show that they have the option of viewing past flood events which have occurred in Ireland. However, it records very few past minor floods and appears to focus nearly entirely on serious flooding events. For example, many news outlets reported several events of pluvial flooding in Dublin, however, there was no information of these in the Flood Maps website. Even with the flood events that are recorded there is no details of the river and weather processes that led up to the flooding. This means that an interested party is not provided with sufficient information to understand the thresholds or environmental factors which causes flooding. Consequently, this is why OPW relies on hydrological models, as previous flood details are not needed to implement them. An expansive IoT river level system will benefit the OPW because of the data that it will collect and store. In the future, this data can then be assessed when floods occur. The data can then be analysed to establish river thresholds and weather variables which can be used to trigger flood warnings. Using IoT historical rainfall and river data, along with OPW's flood maps, will give a better understanding of flood processes. This improved understanding will help Dublin evaluate risks and prepare for both minor or serious flooding events.

Dublin City Council is another body analysing weather variables and flood risks. DCC has river monitors, stream "trash screen" monitors, sewer depth monitors, tide gauges and weather stations placed around the city to monitor Dublin's water and weather processes. DCC is currently developing a flood defence plan involving the creation of multiple smaller schemes and tackling individual flooding problems. For example, they are working with Pervasive Nation to build an IoT rainfall monitoring system which will eventually be used issue early warnings of flooding. Until that system is in place, Dublin City Council monitors rainfall, using their rain gauges, and also use rainfall return periods in order to assess if there is reason to be concerned for a flood. 'Rainfall return periods' (RRP) are supplied by Met Eireann and are generated by a Depth Duration Frequency (DDF) model. They are often used by experts to develop criteria when constructing water management or drainage systems. The underlying concept is to seek to be economically efficient when developing these systems - instead of trying to cope with the heaviest rainfall the system is designed in order that it is "capable of accommodating a rainfall likely to be exceeded only once in a specified number of years" (16). An example of rainfall return periods can be seen in Figure 3.2.

Met Eireann
Return Period Rainfall Depths for sliding Durations
Irish Grid: Easting: 311528, Northing: 235450,

	Interval		Years								
DURATION	6months,	1year,	2,	3,	4,	5,	10,	20,	30,	50,	75,
5 mins	2.4,	3.5,	4.1,	5.1,	5.7,	6.2,	7.8,	9.7,	10.9,	12.7,	14.3,
10 mins	3.4,	4.9,	5.8,	7.0,	7.9,	8.6,	10.9,	13.5,	15.2,	17.7,	20.0,
15 mins	4.0,	5.8,	6.8,	8.3,	9.3,	10.1,	12.8,	15.9,	17.9,	20.9,	23.5,
30 mins	5.3,	7.6,	8.8,	10.7,	11.9,	12.9,	16.2,	20.0,	22.4,	26.0,	29.1,
1 hours	7.0,	9.9,	11.4,	13.7,	15.3,	16.5,	20.5,	25.1,	28.1,	32.3,	36.1,
2 hours	9.2,	12.9,	14.8,	17.7,	19.6,	21.1,	26.0,	31.6,	35.2,	40.3,	44.8,
3 hours	10.9,	15.0,	17.2,	20.5,	22.7,	24.4,	29.9,	36.1,	40.1,	45.8,	50.8,
4 hours	12.2,	16.8,	19.2,	22.8,	25.2,	27.0,	33.0,	39.7,	44.1,	50.2,	55.5,

Figure 3.2: Rainfall Return Periods for Phoenix Park

However, rainfall return periods were not made to predict potential flooding. Though they can be used as a general indication of what heavy rainfall is for a locality, it is not suitable for flash floods. Flash floods can happen in a matter of minutes, so having an alarm system using rainfall return periods as thresholds would not be effective. As matters stand, a pluvial flooding forecast system simply does not exist in Ireland. Again, RRPs are used because historical flood data does not exist in Dublin.

One notable project, 'StormSense' (17), is an award winning, coastal flood resilience initiative that is the forefront of using the Internet of Things in weather monitoring. This interactive system, which can be found on their website, is currently active in Virginia, U.S. This project involves bringing municipal governments together along with the Virginia Institute of Marine Science (VIMS) to "develop a regional resilience monitoring network, with the installation of 28 new publicly-broadcasting water level sensors". This had involved partnering with various flood-resilient communities by creating a standardised monitoring system by integrating disparate data sources. As a result of this, the data was used to improve VIMS' inundation forecasting efforts & models which uses variables like water levels, wind speeds and air pressure to predict which areas will be flooded in advance of up to 36 hours (18). The predictions are visualised as a map, meaning that emergency services, as well as resident close to the flooding locations, can take an appropriate response. The objective of StormSense is to enhance the preparedness and responsiveness of communities to floods in ways that are "replicable, scalable, measurable and make a comparable difference" (19).

The 28 newly deployed IoT water level sensors are a mix between ultrasonic and microwave radar sensors and were installed in three different areas (Newport News, Virginia Beach and Norfolk). These sensors are an addition to the previously installed, separately owned, water level sensors. The new StormSense IoT ultrasonic sensors transmit data either by cellular transmission protocols or using Long Range Wireless Area (LoRa) networks. Noted advantages of this dense, cost-effective network of water level sensors included archiving water level observations for flood reporting, automated advance flood alert messaging and producing valid inputs for hydrodynamic flood models. To evaluate the effectiveness and accuracy of the IoT sensors, three were installed adjacent to industry approved United State Geological Survey (USGS) radar sensors. This project is relatively new, therefore the comparison of the results between the two sensors is yet to be published. A cursory experiment noted that the ultrasonic sonar units were accurate in the lab to a RMSE of ± 5 mm and accurate in the field to an average of ± 18 mm. The radar sensors were accurate in the lab to ± 1 mm and accurate as deployed in the field to ± 9 mm. The cost of each of the ultrasonic sensors were $3,000, while the radar sensors were purchased at $4,400 each. A cheaper inundation sensor, costing $400 each, were also deployed and were accurate in the lab to approximately ± 15 mm and accurate in the field ± 45 mm.

In respect of this dissertation, this project is a leading example of collaborating with different initiatives to get a better and more detailed description of weather events during storms and floods. Not only are the results of this being fed into a flood prediction model, but the data collected will help in future flood analysis. However, it does state that it has not integrated rainfall inputs into forecasted flood maps. Obviously, rainfall has a major role in flooding, with precipitation being the primary cause of flash floods (20). Another criticism of this project is that the sensors appear to be very expensive. One of the main advantages of the Internet of Things is that it is often cheaper than industry standard gauges. Although the sensor technology is fundamentally different, here a river level sensor cost more than $4,000 and, in comparison, this dissertation studied level sensors costing only €150 ($168) each.

La Emilia, a small village in Beunos Aires, Argentina, has developed an early flood detection and warning system using sensor technology. After several failed attempts to construct effective dikes to defend against floods, the local government implemented a river monitoring network to manage floods and prevent tragedies. The aim of this project was to produce risk alerts but to also record the behaviour of the Arroyo del Medio river.

A mix of wireless sensors were installed in four different locations along the river, including ultrasound sensors, temperature, relative humidity & air pressure sensors, pluviometers, wind speed sensors and wind direction sensors. The system used a double telecommunication technology base, using a LoRaWAN network as the principal communication protocol for where the telecommunication infrastructure was not stable enough and 4G as a redundant communication protocol. The data gathered by the sensors was visualised and analysed using a 'Sense2Cloud' dashboard. The dashboard allows users to check the status of the sensors every 30 minutes as well as receive warning alerts for when the river had exceeded set thresholds.

This project demonstrates that an Internet of Things river monitoring network is achievable. However, there were no reports if the monitoring system was actually successful or not. Also, it did not define how the thresholds were set. It does state that they employed experts to analyse the river before deciding where to place the sensors. To build an effective river monitoring system, it must involve prior analysis of the river to ensure the readings are truly reflective of the river's behaviour. That is, to avoid placing the sensors in areas which are merely convenient for the installers. A credible monitoring system would require an in-depth survey of the land to determine where sensors should be located.

In regard to the predictive side of flooding, 'Model-Based Monitoring for Early Warning Flood Detection' (21) is one paper that created a sensor network comprised of sensor nodes and computational nodes. The sensor nodes send the river and environmental variables to the computational nodes. The computational nodes then perform the distributed computation of the prediction. They used a small number of nodes to cover basins of 1000-10,000 km2 using a unique heterogeneous communication structure to provide real-time sensed data. They relied upon past river data and linear regressions to produce their flood prediction algorithm. To determine the viability of their 24hr predictions, they examined the autocorrelation of the dataset. The results showed that their predictions for floods 24hrs in advance had a correlation of 0.64 with the real river data. It reported that the algorithm produced 25 false positives and 9 false negatives.

This paper shows that there are algorithms that exist to produce flood warnings. The main priority of this study was to design a system that was very cost-efficient and low-energy. In doing this, they used fewer parameters in their flood prediction model (only flow, level and temperature). However, it should be noted that this paper dates to 2008. Surprisingly, not much research is available that concentrates on the predictive side of flooding in an IoT system. Nowadays, sensors and computational nodes are cheaper and more energy efficient. If the study had been less concerned with energy and cost they would, perhaps, have created a prediction algorithm which may have been more computational heavy but would have produced superior results.

'Flood forecasting using Internet of things and Artificial Neural Networks' (22) is another paper that uses an IoT system's data to predict floods. In this research, an Internet of Things and machine learning based embedded system is proposed to predict the probability of floods in a river basin. A modified mesh network transmitted data over a ZigBee network. This data was evaluated using an artificial neural network model. The results of the neural network showed improvement over the previous methods of flood forecasting. Using rainfall, humidity and water flow as the input parameters, it achieved a correlation of 0.9 between the simulated and predicted data. However, this study remains in the preliminary stages, with a real-world model yet to be implemented. Again, this paper, despite not producing substantial real-world results, does show that the possibility & practicalities of creating a real-time IoT flood forecasting system do exist.

This section has given an overview of current methods of flood forecasting. Practical lessons and techniques can be learned from each of the described methods/studies when building the ideal IoT rainfall and river monitoring system. A table below summarises the points made and discussed with the column names reflecting key features of the proposed IoT system.

Table 3.1: State of the Art Summary Table Part 1

Method	**Technique**	**Accuracy**	**Flood Map Available**
Met Eireann	Gauges and radar	Highly accurate	n/a
Office of Public Works	Experts to analyse areas	Accurate	Yes
Dublin City Council	Sensors	Not accurate	n/a
StormSense	IoT river level	Uncomfirmed	n/a
La Emilia	IoT weather sensors	Uncomfirmed	n/a
Model-Based Monitoring	IoT and NN's	Uncomfirmed	n/a
Flood forecasting	IoT and NN's	Uncomfirmed	n/a

Table 3.2: State of the Art Summary Part 2

Method	Expert?	Cost	Real-Time	History Available	Coverage
Met Eireann	Yes	Expensive	No	Yes	Poor
Office of Public Works	Yes	Expensive	No	No	Poor
Dublin City Council	No	No	Yes	Yes	Good
StormSense	Yes	Expensive	Yes	Yes	Good
La Emilia	No	Affordable	Yes	Yes	Good
Model-Based Monitoring	No	Affordable	Yes	Yes	Good
Flood forecasting	No	Affordable	Yes	Yes	Good

4 Methodology

In this section, the process of creating graphs of the datasets and the analysation techniques are discussed. This includes the process of collecting the data, how the data was organised and then how the analysation process carried through. This section will give a better understanding of how the graphs were made in the evaluation section of this dissertation.

4.1 Gathering Data

The first dataset retrieved for this dissertation was Pervasive Nation's rainfall data. Not much could be done with this dataset without having other disparate datasets to use and with which to compare. Pervasive Nation had previously been working with Dublin City Council and advised & encouraged me to contact DCC to enquire if they had other rainfall datasets to work with. After contacting DCC, they had set meetings up with two people, Alan Vickers and Conor Dowling. Alan Vickers is employed by DCC and manages the river level and rainfall sensors which were used in this dissertation. Conor Dowling is a TCD phd student, working with VT by installing Sigfox enabled river level sensors. Both agreed to allow the use of their datasets to be analysed in this dissertation.

Following a rigorous online search, only two publicly available datasets could be used in relation to this dissertation. The first was Met Eireann, who had a number of weather stations placed around Dublin that collected rainfall data. The second was OPW, who had river level and flow data available for one river location in Dublin. One impact of gathering real datasets is that the dissertation was delayed by virtue of the length of time it took to receive the data. For example, Pervasive Nation's data was accessible at the end of January while the DCC data was only received in mid-March. This meant that not as much analysis could be carried out.

4.2 Organisation

All of the gathered data had to be organised before commencing analysis. The first step was to figure out where exactly each of the sensors were placed. This was time consuming, as the rainfall sensors from both Pervasive Nation and DCC did not provide a precise location. For a number of sensors, there was more than one location that the allocated name could have been associated with. When the sites were identified they were mapped in order to define where the sensors were in location to one and other. The sensors were then grouped by location so that the sensors that were in the same area were compared to one another.

A Python program was implemented in order to generate a workable dataset of each of the sensors data for analysis. The first issue was organising the dates of the values reported, for example, some reported the date with the day first (i.e. dd/mm/yyyy) and others reported the date with the month first (i.e. mm/dd/yyyy). After each of the datasets were sorted, missing values had to be accounted for. If an hour or day date value was not reported by a dataset, then it meant that we did not know what the rain/river value was for that time. Therefore, that missing date was added to the dataset and was given a null rainfall/river value. For example, if Met Eireann's data for January had values for all of the days, but Pervasive Nation's had a missing value for the 1st of January, the 1st would be added to the dataset and then given a null rainfall value. The analysis later could decide how to approach the null values. This means that a date was present for each of the datasets, meaning that all the datasets could easily be compared to one another.

The next organisational task to be carried out was to normalise the time interval in which each of the sensors reported data. This time value was dependent on what type of sensor was located in each area. For example, Met Eireann's Phoenix Park station could report hourly information, as could DCC's Chapelizod sensor and because of which the values could be compared on an hour by hour basis. But most of Met Eireann's stations reported daily values, therefore most of the analysis had to be done on a day by day basis. Pervasive Nation's sensors, though often reported numerous times a day, did not report information on the hour. Therefore in the Chapelizod area, the analysis was carried out on the daily values collected by sensors.

After establishing what the time interval was, the data reported in that interval had to be computed. For the rainfall values, the sum of the rain was used. In the hourly intervals, sometimes rainfall was reported multiple times within the hour, so the sum of these values were used for the final value. If the reports related to daily intervals, the sum of all of the rainfall that day was used as the value. For river levels, the mean river level was used. Careful attention was applied when evaluating river levels, as an unusually high outlier could skew the mean that was reported.

The last organisational step was to establish when datasets were reporting information. This was required in order to only use the data from each dataset where the information was reported at the same time. Most of Pervasive Nations had data from 2018-2019, so the data from 2018-2019 from Met Eireann and DCC was used. The VT river level sensors have been reporting data since 2017, so data from 2017 from DCC and OPW was used.

After the data was organised, the datasets used in the analysis stage was then ready to use. For each area, each of the sensors data had the same date range and same time intervals.

4.3 Analysis

To analyse the data, graphs were generated for each of the datasets in order to interpret the relationships that existed between the different datasets. Pearson's method of computing the correlation coefficient r between the variables was used to define the relationship.

The first analysis carried out on the Pervasive Nation sensors was to inspect the average rainfall that each of the sensors reported. The results of this would then give an indication of the general accuracy of the data. The longest distance between two sensors was 11km which related to Ballymun and Terenure. Inspecting the monthly rainfall data that each sensor reported provided an indication which sensor was under or over reporting.

Each of Pervasive Nation's sensors were then analysed against the nearest Met Eireann sensor. Each graph contained both of the reports from Met Eireann and Pervasive Nation. Date was the x-axis value while the rainfall amount was the y-axis value. Each graph demonstrates when the sensors reported the same values and when they did not. Null values were ignored in the graphs, so it can also be seen when no rainfall values were reported at a time. The correlation of each of the graphs was then computed, indicating how accurate the Pervasive Nation's sensors were. Analysis was also carried out on LoRaWAN, the network the sensors were enabled with. This included investigating how much data each of the sensors were reporting and if the sensors were dropping packets at the same times.

The next analysis was carried out on the VT river level sensors and the DCC sensors. This included plotting the levels of each of the VT river level sensors to examine if there were any outliers and to investigate if data was not reported at a particular time. A graph was also made to indicate how many reports each sensor submitted. The VT sensors were then compared with the closest DCC sensors on the same river/stream to establish if there was a relationship between them. The OPW data was then compared with the closest DCC and VT river level sensor.

The rainfall and river level data was then analysed to determine if a relationship existed.

The purpose of this was to explore what impact different weather variables had on one another. The Met Eireann data, which included a number of weather variables such as rainfall, humidity and temperature were compared with river levels. Analysis was also carried out to see if the rainfall had any impact on the river levels. This was conducted because if a flood warning system was to be developed, it is vital to establish which variables are required in order to predict flooding. By finding some sort of a relationship between different variables meant that a predictive flood model could be built.

4.4 Technologies

Python was chosen as the main programming language to carry out the analysis of the data. I did so because Python was a familiar language to me and it also offered great libraries for plotting and working with csv files. To import and work with the data, the Pandas library was used. Pandas makes it much more straightforward to work with different data sources by importing each csv file as a DataFrame. DataFrames has a number of functions which can assist in organising the data and, for instance, can recognise the date as the index and can sort by the date in one line of code. The plotting libraries that were chosen were matplotlib and seaborn. Matplotlib has a MATLAB style module that simplifies plotting line charts. Seaborn is excellent for creating correlation graphs with many different variables as the input.

5 Evaluation

In this section, the Pervasive Nation, Vizor Technology and Dublin City Centre IoT sensors are analysed. Graphs are used in this section as a visual aid in the explanation of the evaluations. Each of the graphs will indicate the differences and similarities reported by the sensors. The evaluation will be discussed by using the following methods:

- The correlation of the sensors under comparison.
  - Discretion will be applied in respect of rainfall sensors as they are not located on the same site.
  - Low correlation will indicate if there is an issue with the IoT sensor.
- Graphs will visualise the correlation
  - River levels are not expected to be the same as the sensors are placed in different stages along the river. It is expected to reflect that if the river level increases at the early stage then it will also increase at the later stage.
  - It is important to visualise the rainfall values as we are expecting the same values for each time steps.
  - Graphs will help visualise when the sensors reported different values at time steps.

5.1 Analysis of Pervasive Nation Sensors

In this section, the Pervasive Nation sensors will be analysed. It will be noted when studying the graphs that more sensors are present than in others. This is due to the fact that for some analysis, specific sensors were chosen to give the best overview of how the sensors were performing. For example, some sensors had fewer months to compare with other sensors i.e. the sensors ‘Bannow 1’ stopped reporting data in December 2018 but the majority of the sensors continued reporting data for March 2019.

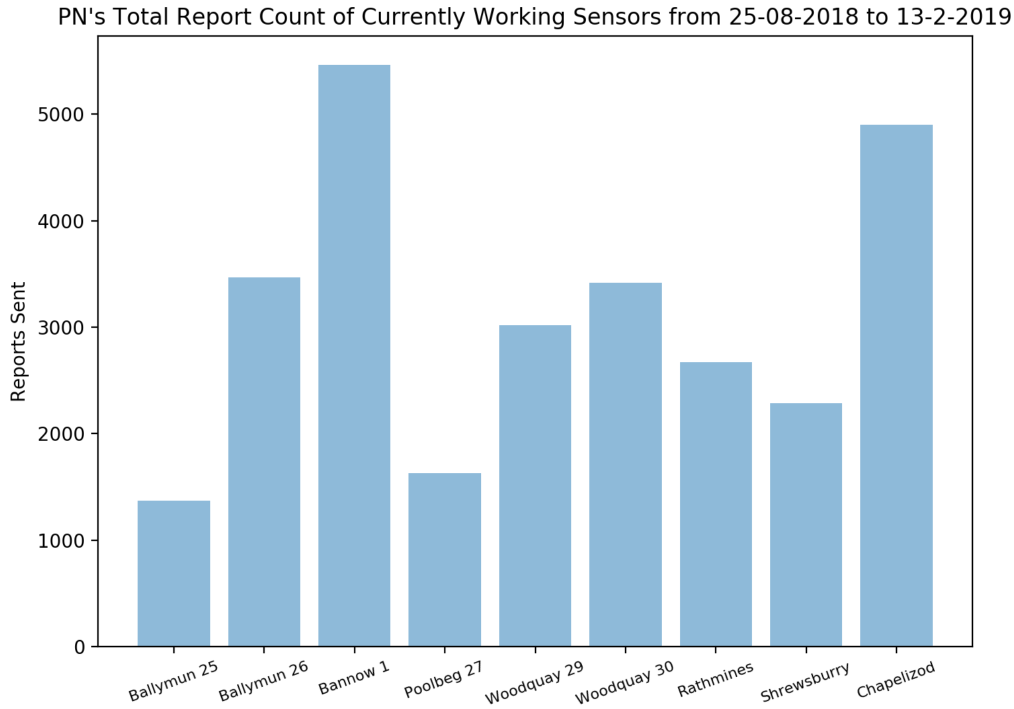

Figure 5.1: This graph depicts the total amount of reported data from each of the currently active sensors from August 2018 to February 2019

Figure 5.1 depicts the total amount of reports sent by each of the Pervasive Nation sensors from August to February. Each of the sensors are configured to send reports back every two hours to indicate that they are still 'alive'. The sensors also send data when the rain tipper has 'tipped', that is every time 0.2mm or 0.3mm of rainfall is collected. The purpose of this graph was to visualise if there are any sensors reporting back much fewer or much more data than other sensors in order to get a sense of which sensors, if any, were acting abnormally. It would be expected to see slight changes in the reports as some sensors will report a little more rainfall in one area then another. The graph depicts that sensor 'Ballymun 25' has the lowest reports sent, with nearly 1,500 reports between August and February. There are 172 days in between the 25th of August 2018 and 13th of February 2019 and if a 'status' report is sent every two hours then each sensor should at least have 2,064 reports sent in that space of time. This means that the sensor 'Poolbeg 27' also did not manage to report this amount. From initial observation, it seems that 'Chapelizod' and 'Bannow 1' are appearing high, with each reporting under 5000 and over 5000 respectively.

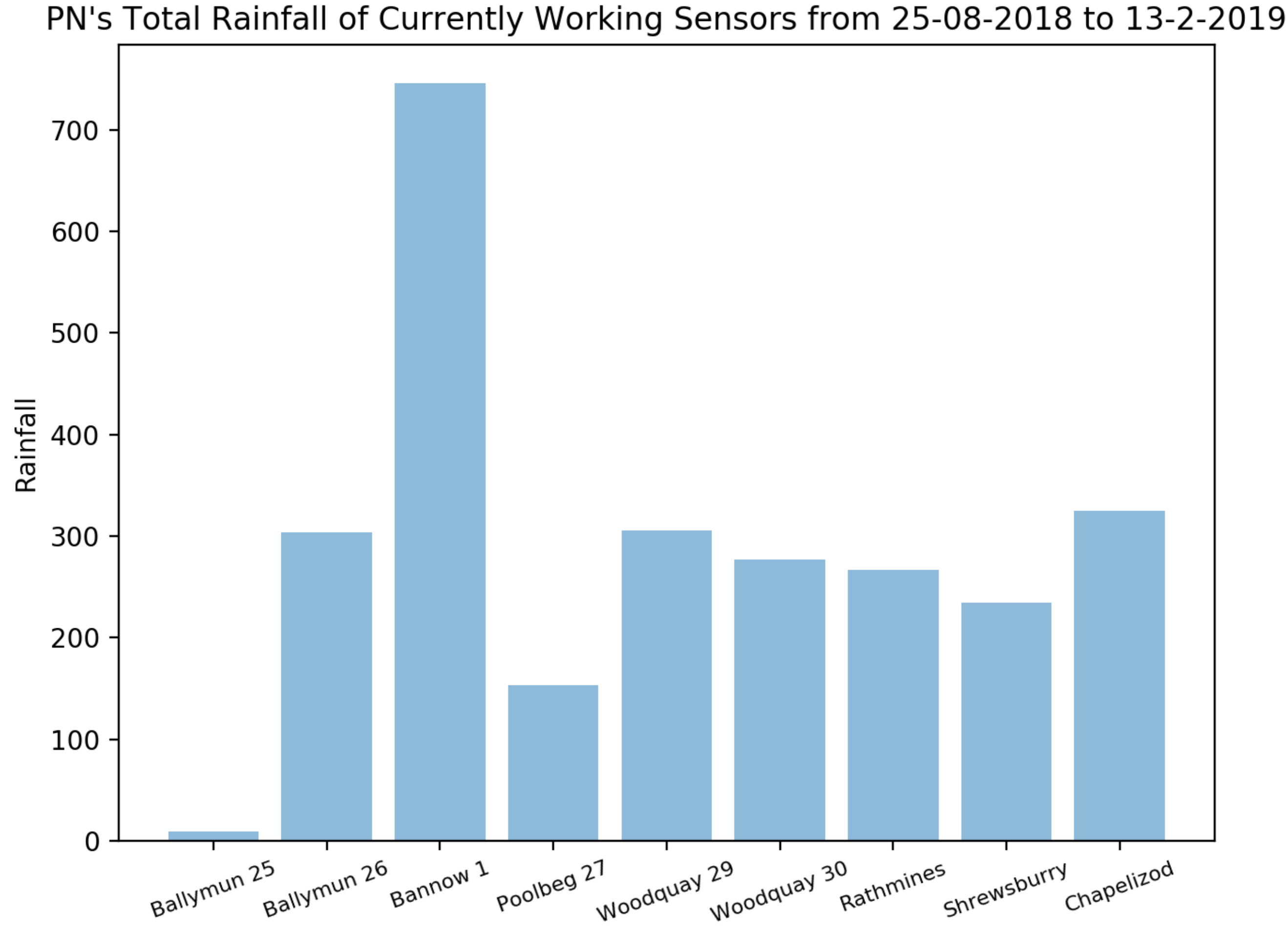

Figure 5.2: This graph depicts the total amount of rainfall collected from each of the currently active sensors from August 2018 to February 2019

Figure 5.2 expands on the true meaning of the evaluation of Figure 5.1. This figure shows the total amount of rainfall which was collected by each sensor from August to February. The sensor 'Bannow 1' is reporting far higher rainfall amounts than the rest of the sensors. The next highest amount of rainfall reported came from 'Chapelizod', but 'Bannow 1' reported approx. 400ml more than 'Chapelizod'. The sensor 'Ballymun 25' reported the lowest amount of total rainfall, with around 10ml being reported for the 6 month period. The sensors 'Poolbeg 27' reported the second lowest total rainfall, with around 140ml being recorded. The rest of the sensors seem to be reporting around the same levels of rainfall. It is also interesting to note that although 'Chapelizod' transmitted more data than the other sensors (Figure 5.1), the total amount of rainfall was comparable to them. Most of the sensors reported values that fell between 250ml and 300ml.

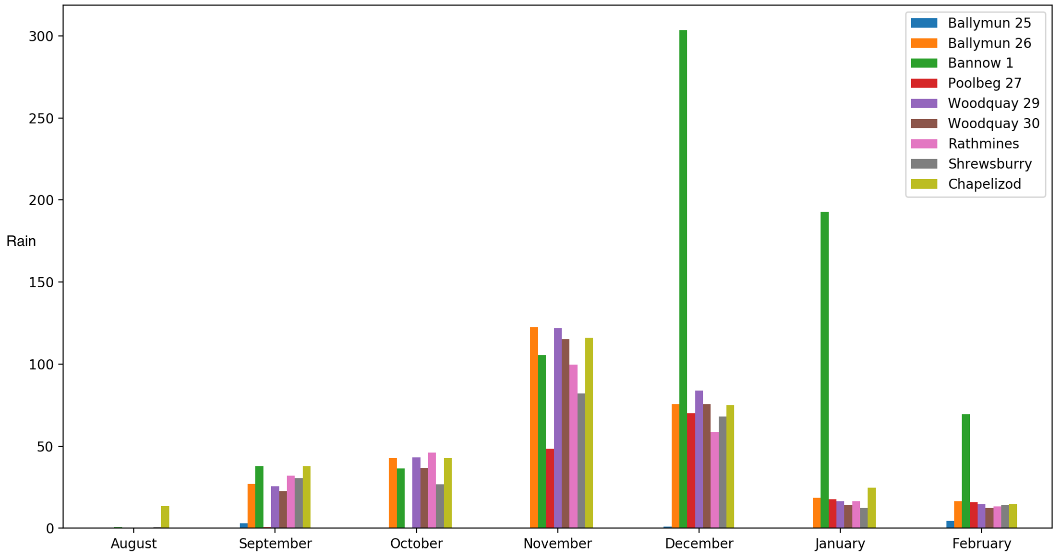

Figure 5.3: This graph depicts the total amount of rainfall of each month from each of the currently active sensors from August 2018 to February 2019

Figure 5.3 takes a more in-depth view of the rainfall amounts that each sensor reported. Again, the sensor 'Bannow 1' is the most distinct value. From the months August to November, it is observed that 'Bannow 1' reported rainfall values that were similar to the other sensors. However, from December onwards, 'Bannow 1' started to report rainfall values which were significantly higher than the other sensors. It is relevant that 'Bannow 1' is located less than 3 km from both 'Woodquay 29' and 'Woodquay 30' and, therefore, it is reasonable to assume that the values reported do not reflect the true amount of rainfall that fell in that area. Why 'Bannow 1' is reporting more rainfall could be caused by a number of factors, such as the infrastructure surrounding the sensor changing (channelling additional water into the sensor). Another interesting point reflected in this graph is that 'Ballymun 25' shows very few reports of rainfall data. In September, December and February, it can be seen that some rainfall is reported indicating that it has not entirely ceased collecting rainfall. This means that when compared to Figure 5.2, it is not that rainfall had stopped reporting after a while to explain the low results, as it had reported rainfall again in February. For each month, it would appear that the rest of the sensors seem to be consistent with one another when reporting rainfall data.

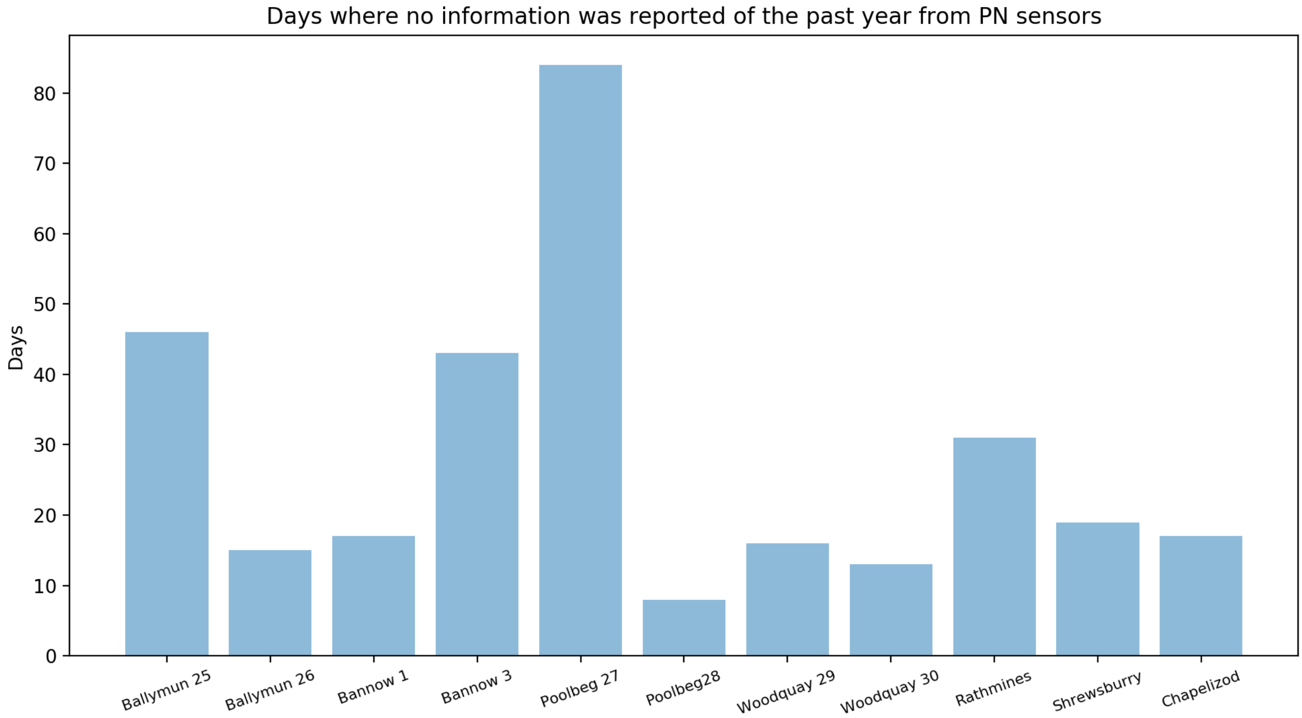

Figure 5.4: This graph depicts the total amount of days where no information was collected.

Figure 5.4 shows the total amount of days in a year that no information was reported by a sensor. This graph was required because if a real-time rainfall monitoring system was in place, it would be the expectation that rainfall is reported regularly. The sensor 'Poolbeg 27' visually stands out from the rest of the sensors given that in excess of 80 days were recorded during which no information from the sensor was reported. The second highest was 'Ballymun 25' which recorded nearly 50 days during which no information was received. After this, it was 'Bannow 1' with approx. 40 days and then 'Rathmines' with approx. 30 days. The majority of the sensors lay between the values of 15 and 20. The sensor that had the lowest amount of days where no information was reported was 'Poolbeg 28' at approx. 10 days. Regardless, this is not the best result as sensors are configured to report information every two hours meaning each sensor was programmed to send information 12 times a day. Therefore, this graph reflects that for all of the 12 opportunities that each sensor had to send a report, it had failed to send a report consecutively at least 12 times.

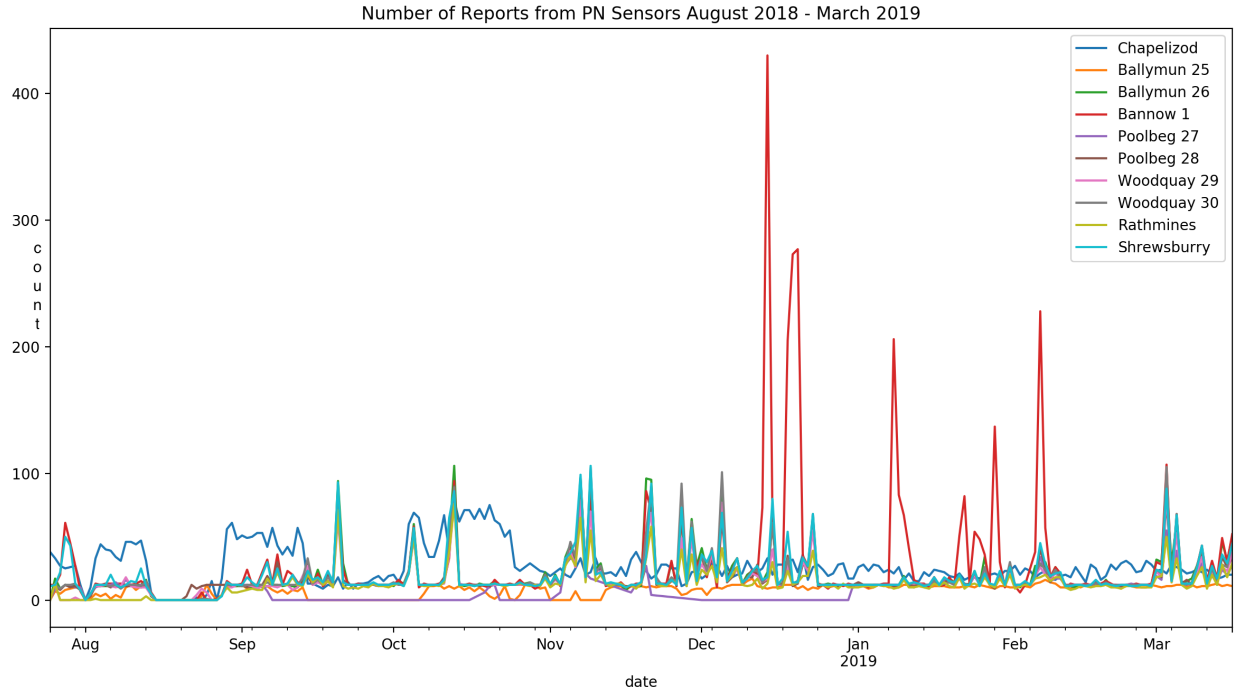

Figure 5.5: This graph depicts the total amount of reports sent by each sensor from August 2018 to March 2019

Figure 5.5, depicts each of the sensors reports from August 2018 to March 2019. The purpose of this graph was to try and visualise whether sensors were reporting the same amount of information simultaneously. In addition to this, it could display if there were network problems at certain times. For example, when inspecting this graph it is noticeable that at the end of August, all of the sensors did not report any data. Because this affected all of the sensors and given that all sensors relied on the same network it is reasonable to surmise that network problems could be the reason for no data transmission. When investigating further, we notice that 'Shrewsbury', 'Rathmines', 'Woodquay 29', 'Woodquay 30', 'Poolbeg 28' and 'Ballymun 26' are very consistent with each other when reporting data. This is visible in the month of December and also in March, where it appears that the reports are spiking at the same time. Other noticeable features of this graph is that 'Bannow 1' had a spike in reports at different times from December to February. As detailed, it was discovered that for a number of days at a time during these months 'Bannow 1' reported unusually high amounts of data. This shows that 'Bannow 1' does not consistently report higher amounts of data, as for the other days it is consistent with the rest of the sensors, as can bee seen at the end of December to the start of January. The sensor 'Chapelizod' regularly reports higher amounts of data compared to the rest of the sensors, whilst 'Poolbeg 27' and 'Ballymun 25' shows no reports were sent at days at a time.

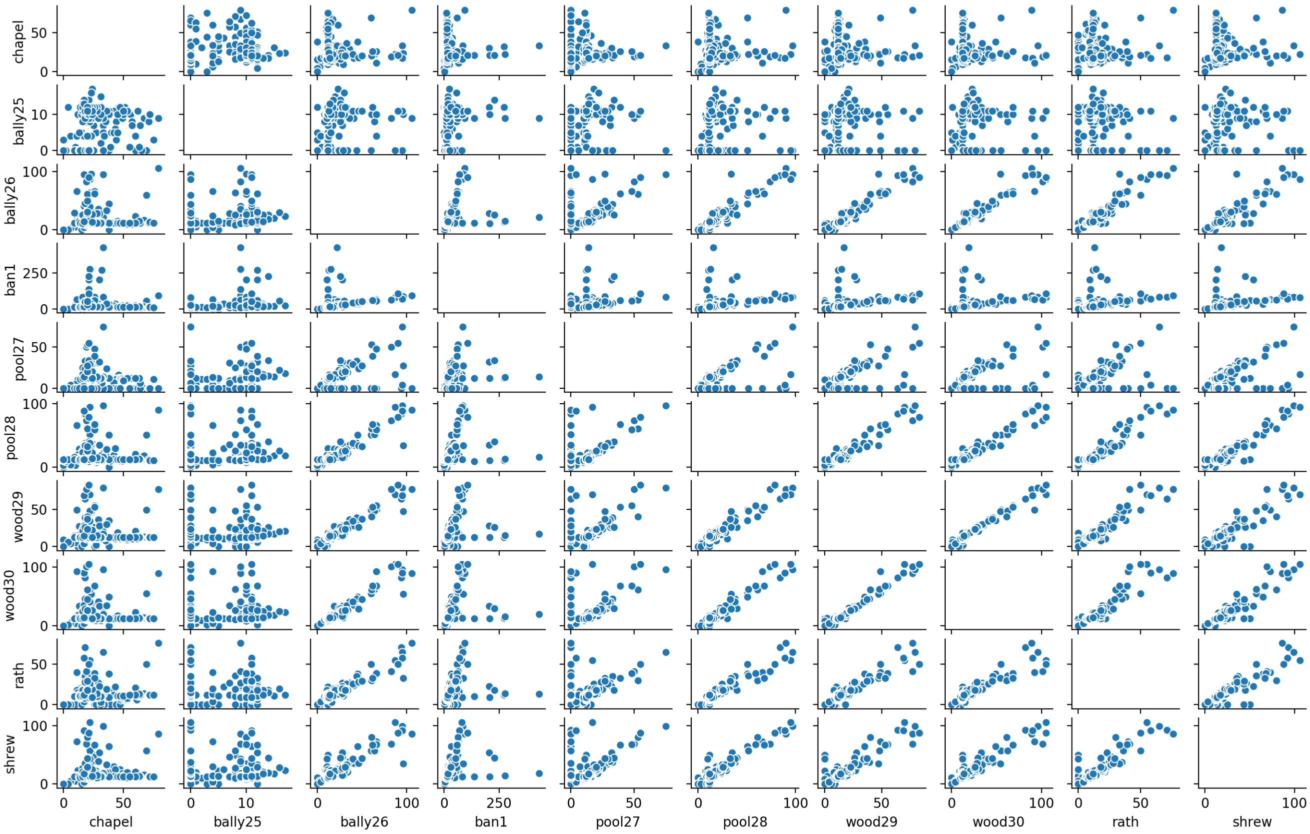

Figure 5.6: Relationship between different PN sensors reporting rate

Figure 5.6 shows the relationship of each of the sensors reporting rate. As can be seen, some sensors such as ‘bally26’ (Ballymun 26), ‘pool28’ (Poolbeg 28), ‘wood29’ (Woodquay 29’), ‘wood30’ (Woodquay 30), ‘rath’ (Rathmines) and ‘shrew’ (Shrewsbury) all have high correlations with each other. This supports the previous statement made in Figure 5.5 i.e. that they were consistent with one another. It also shows that ‘bally25’ (Ballymun 25) has no definable relationship with the rest of the sensors. This graph also shows more insight to the behaviour of ‘Bannow 1’ (‘ban1’) such that it does have some relationship with the rest of the sensors but quite a few outliers here and there.

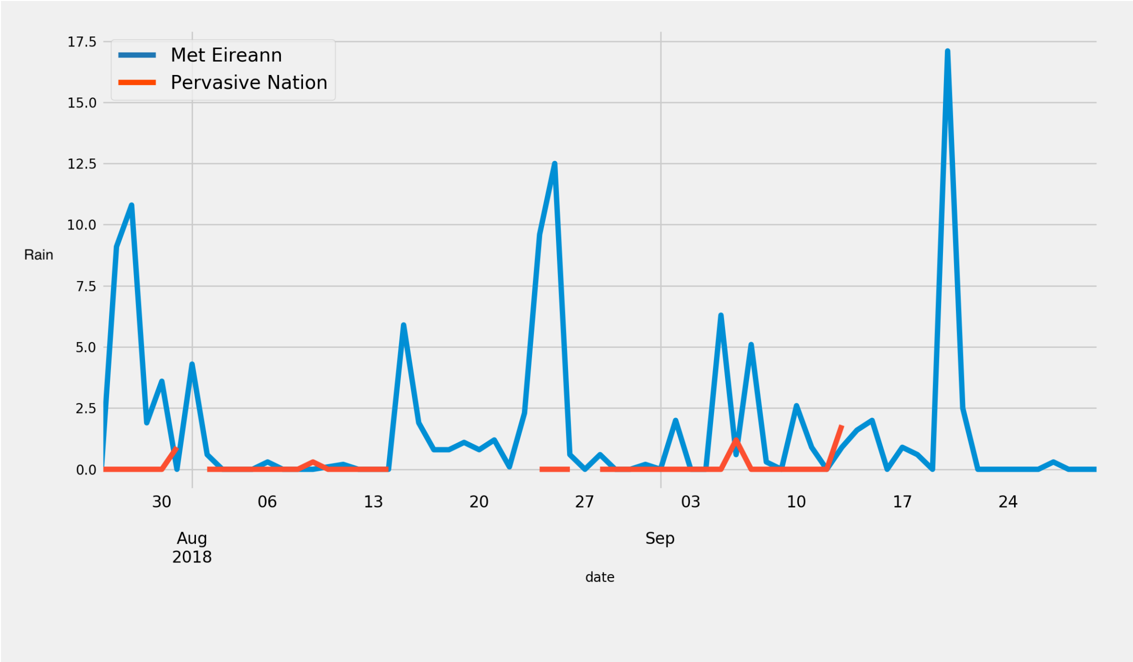

Figure 5.7: Ballymun 25 (PN) vs Glasnevin (ME) 2018 July - September. Correlation r of rainfall is -0.108865.

The next batch of graphs that will be discussed is analysing the accuracy of the reported data from Pervasive Nation sensors. Fig 5.7 shows the sensor 'Ballymun 25' against the nearest Met Eireann sensor, being 'Glasnevin'. The times that the data coincided with one another was only during the months August and September in 2018. Because of this, substantial/significant analysis could not be carried out but it does highlight that even when Ballymun 25 reported data, it did not report the same amounts as reflected at the beginning of August. It also shows how frequent the data was for this short amount of time. For all of the following graphs, Pearson's correlation was used and the null value were ignored as the data that was reported was what is being analysed. The correlation between the two sensors was -0.108865.

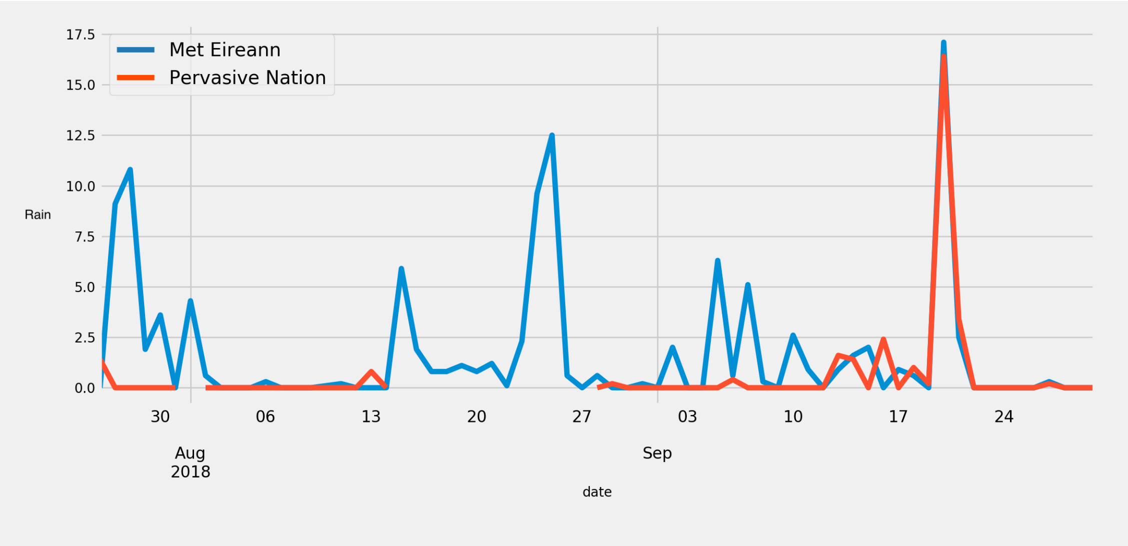

Figure 5.8: Ballymun 26 (PN) vs Glasnevin (ME) 2018 July - September. Correlation r of rainfall is 0.676623.

In Figure 5.8, Glasnevin Met Eireann sensor is used again for the sensor ‘Ballymun 26’. Unfortunately, as stated, this was the only data that coincided with one another (the Glasnevin Met Eireann sensor ended in September 2018). In the previous graphs, the sensor ‘Ballymun 26’ seemed promising but missing data occurred so once again a full analysis could not be completed. One encouraging feature is that at the end of September the PN value matched the Met Eireann reported value. However, between the 27th of August and 17th of September they did not report the same values. Because it had the same spike, and matched Met Eireann during a few days in August, the computer correlation was 0.676623.

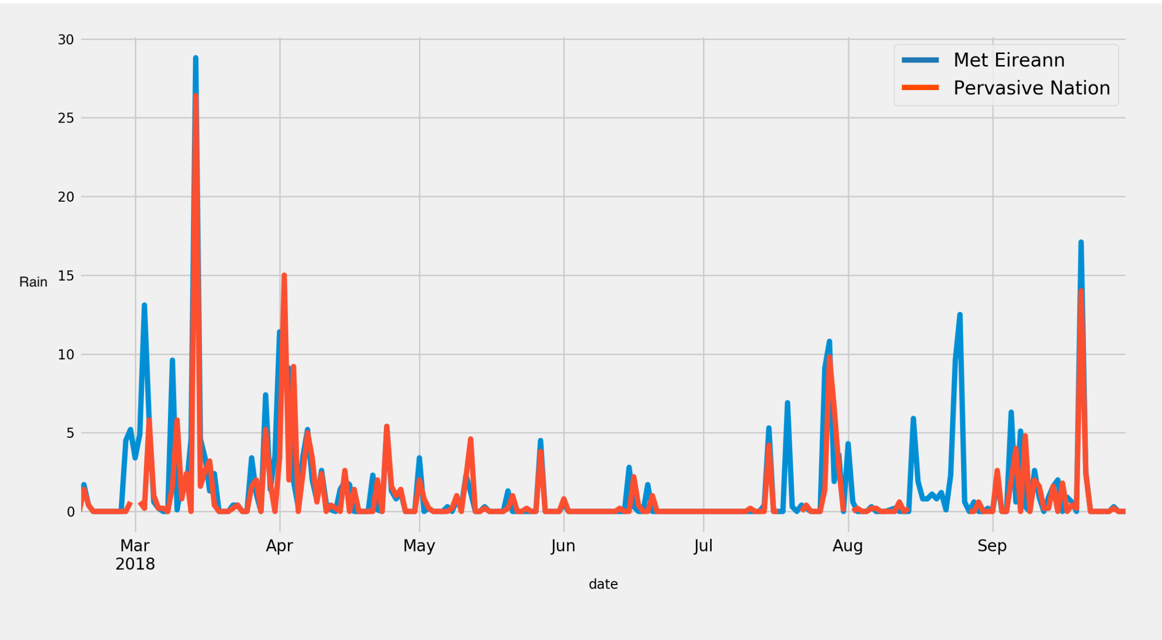

Figure 5.9: Bannow 1 (PN) vs Glasnevin (ME) 2018 March - September. Correlation r of rainfall is 0.765637.

Glasnevin was used again for the closest sensor for PN's Bannow 1, as seen in Figure 5.9. The two sensors matched well with one another, apart from the differences at the start of March 2018. Again, missing data is reflected at the end of March. Overall, this graph looks quite promising as the two sensors are not placed in the same site. The correlation between the two sensors was 0.765637.

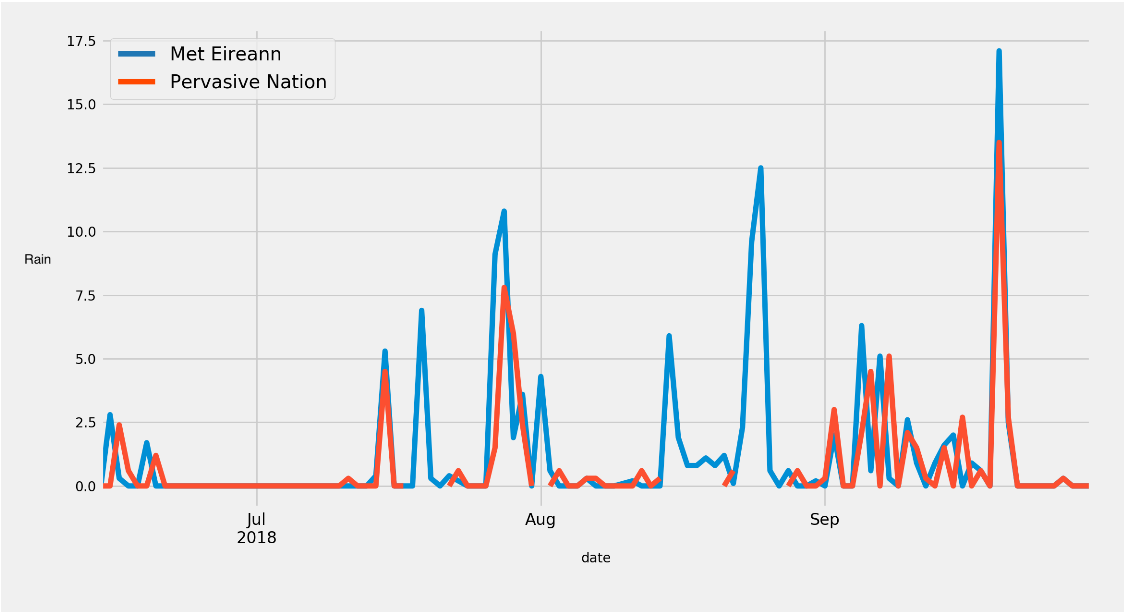

Figure 5.10: Bannow 3 (PN) vs Glasnevin (ME) 2018 June - September. Correlation r of rainfall is 0.748866.

The PN sensors Bannow 3 was the next to be analysed, as shown in Figure 5.10. Less data was available for this sensor and only the months of July to September 2018 were useable. Again, it is clear that missing data occurs at the same times as the previous evaluations. It is also noted that at the start of September, the data does not quite fit with one another indicating that there was a time-lag in the data being received. The correlation of the graph was 0.748866.

The next three sensors analysed are the Poolbeg sensors. Figures 5.11 and 5.12 shows the Poolbeg 27 sensor against both the Met Eireann Ringsend gauge and the Met Eireann Merrion Square gauge. This was because both Ringsend and Merrion Square are located close to the Poolbeg sensor. However, and as can be seen, thorough analysis could not be conducted on these sensors because of the missing data. As stated, 'Poolbeg 27' suffered the most days during which no data was reported and this is evident in Figure 5.11 and 5.12. It is also clear that when the sensor did report data, it did not match what Met Eireann was reporting. The correlation of the PN 'Poolbeg 27' sensor with Ringsend was 0.29368 and with Merrion Square was -0.187706. 'Poolbeg 28' could not be compared with Met Eireann's Merrion Square gauge as there not enough data coinciding with each other. Poolbeg 28 was compared with Ringsend, as seen in Figure 5.13. Here, the same values are not being reported when the peaks are examined but it does appear to report the same rainfall value on the 26th of November. The correlation between the two was 0.465719.

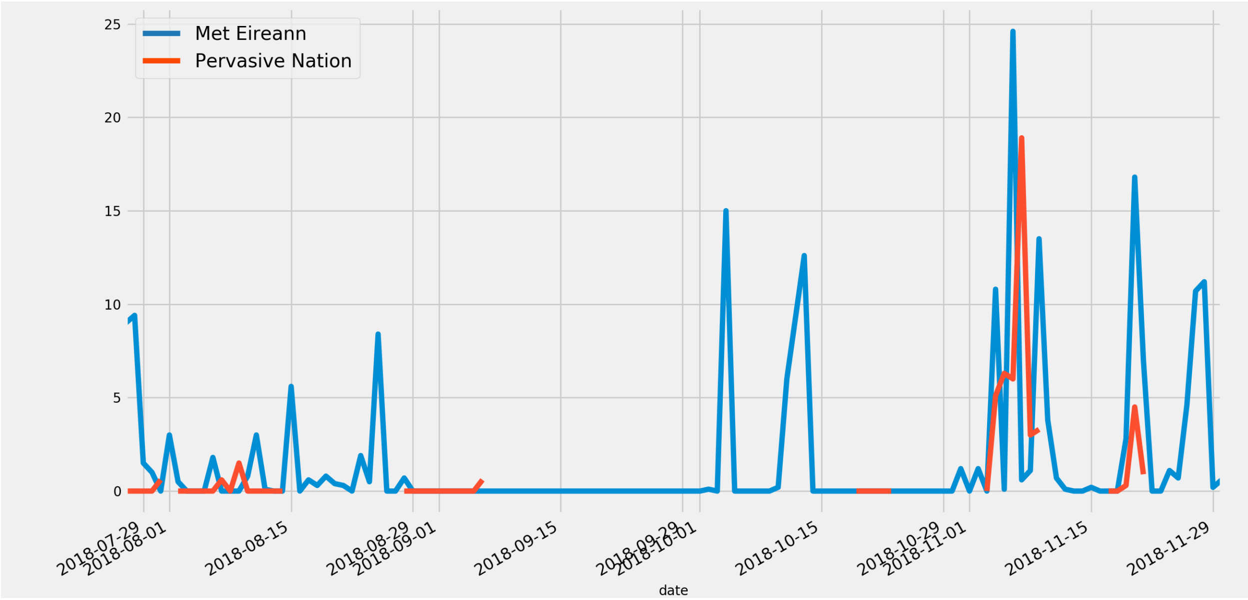

Figure 5.11: Poolbeg 27 (PN) vs Ringsend (ME) 2018 July – November. Correlation r of rainfall is 0.29368.

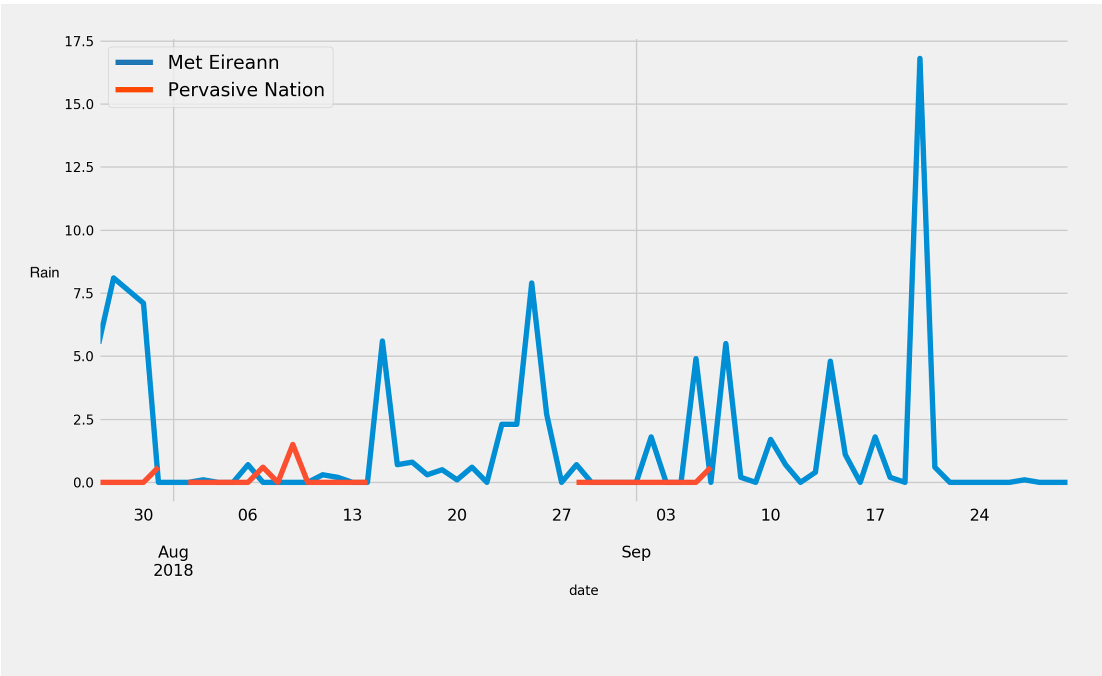

Figure 5.12: Poolbeg 27 (PN) vs Merrion (ME) 2018 July – November. Correlation r of rainfall is -0.187706.

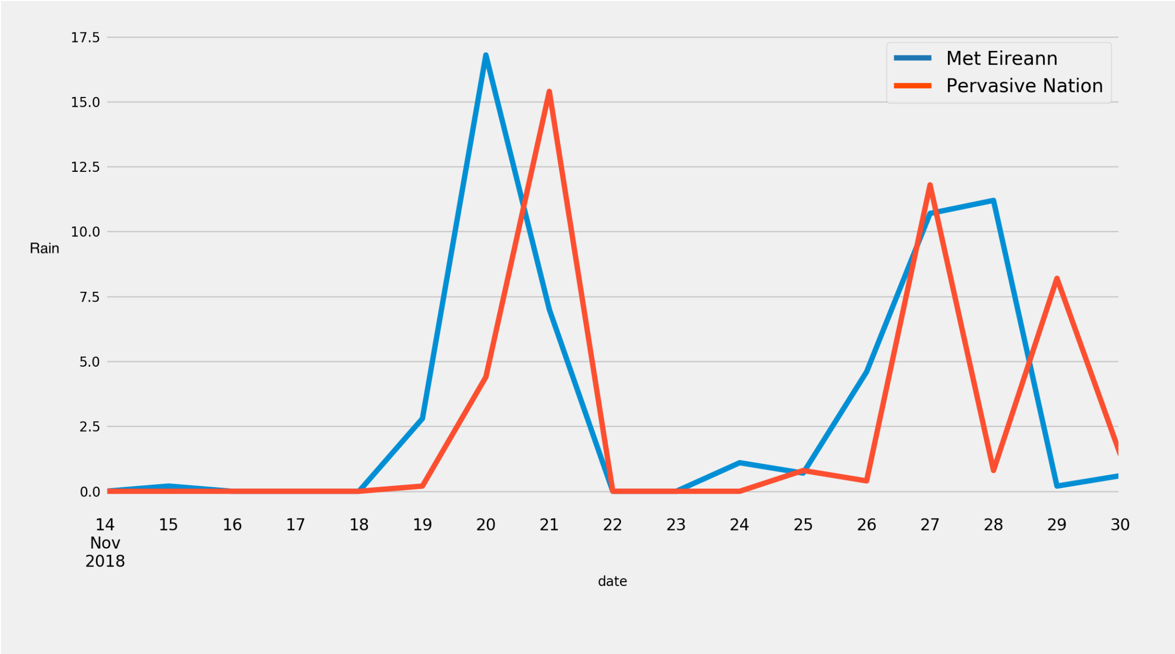

Figure 5.13: Poolbeg 28 (PN) vs Ringsend (ME) 2018 November. Correlation r of rainfall is 0.465719

The PN 'Woodquay 29' and 'Woodquay 30' were the next sensors to be analysed. Figure 5.14 shows the 'Woodquay 29' sensor against the Merrion Square gauge from August to September 2018. The correlation between these was 0.753661 but this does not reflect the true description between the data. For most days, 'Woodquay 29' did not report anything close to the Met Eireann values except during the peak between 10th and 17th of September as well as 17th and 24th. Figure 5.15, shows PN's 'Woodquay 30' with Met Eireann's Merrion Square gauge. 'Woodquay 30' behaved much the same as 'Woodquay 29', except that 'Woodquay 30' had a greater number of missing values. It also had a lower correlation value of 0.673063.

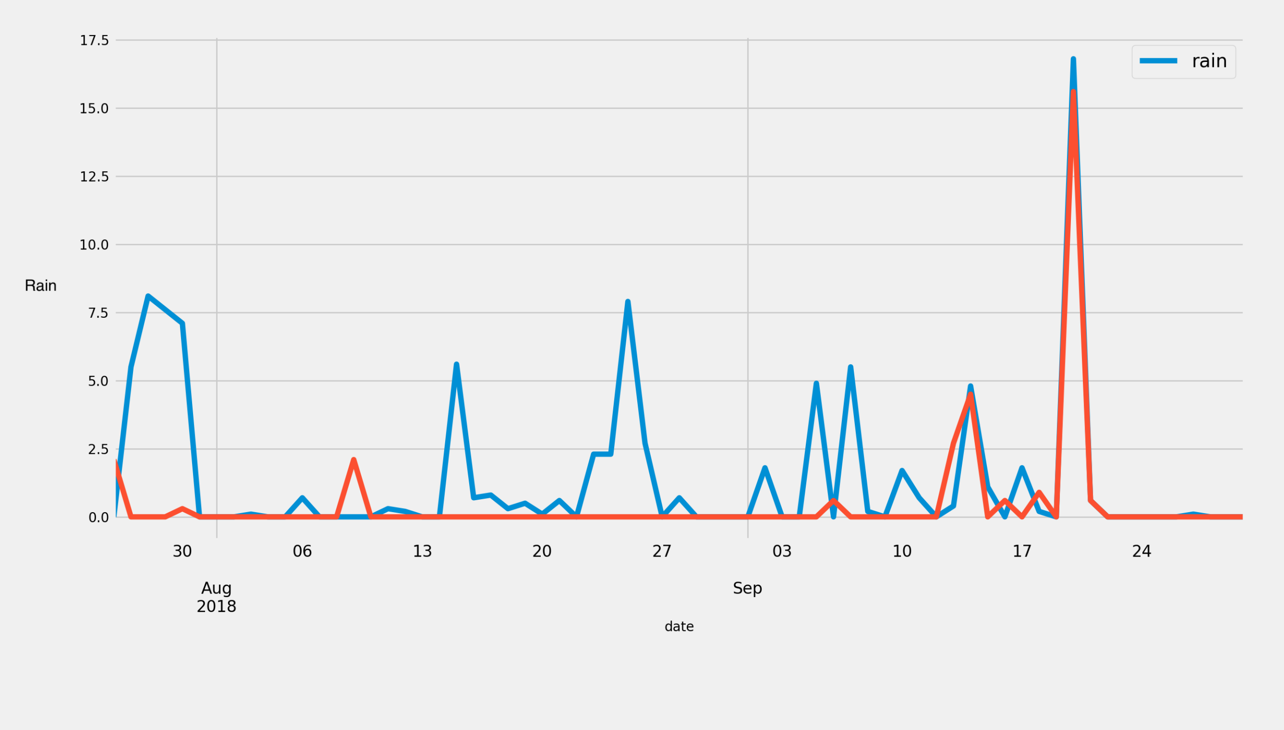

Figure 5.14: Wood Quay 29 (PN) vs Merrion Square (ME) 2018 August – September.Correlation r of rainfall is 0.753661

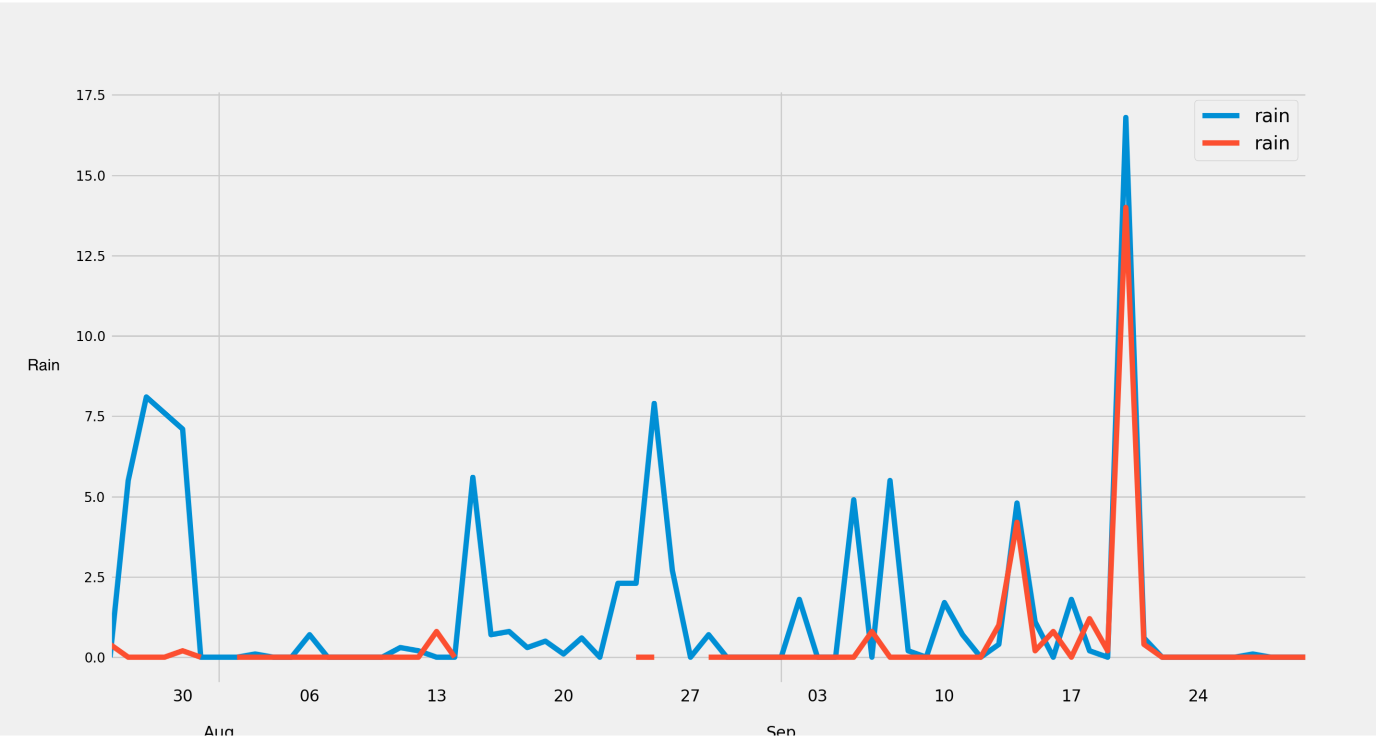

Figure 5.15: Wood Quay 30 (PN) vs Merrion Square (ME) 2018 August - September. Correlation r of rainfall is 0.673063.

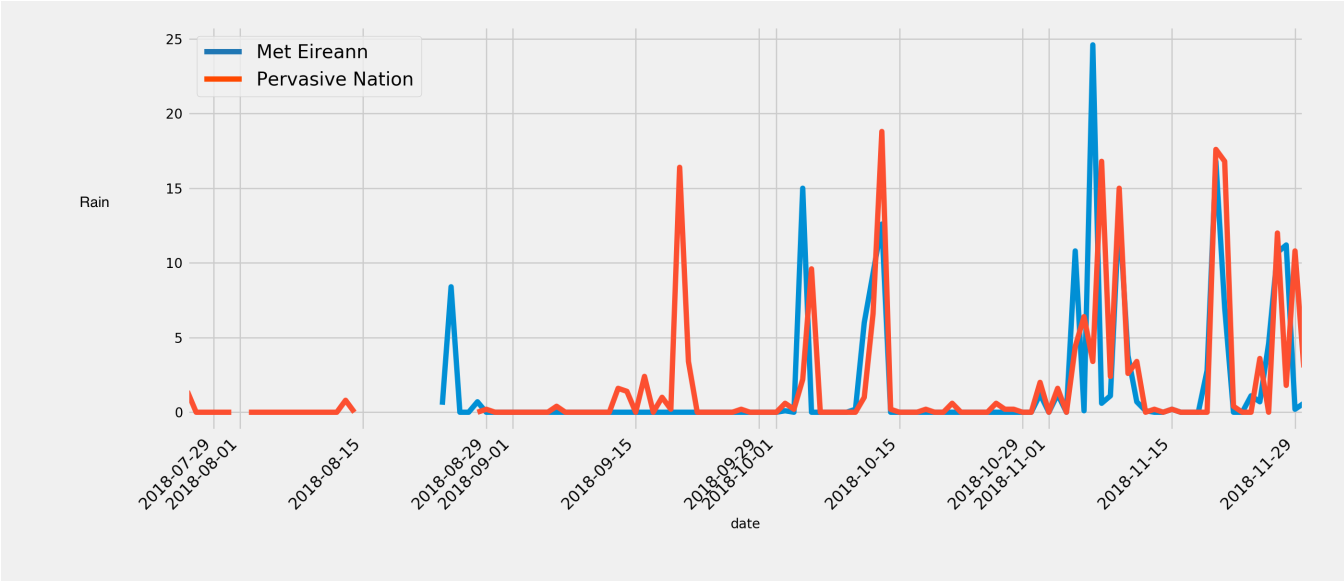

Figure 5.16: Shrewsburry 4 (PN) vs Ringsend (ME) 2018 August - November. Correlation r of rainfall is 0.540492.

Figure 5.16 shows PN's 'Shrewsbury' sensor against Met Eireann's Ringsends gauge. One notable difference is that in September, the PN sensors reported nearly 20mm of rainfall when Met Eireann did not report anything. During mid November, the PN sensor was also inaccurately reporting values. The correlation between these two sensors came to 0.540492.

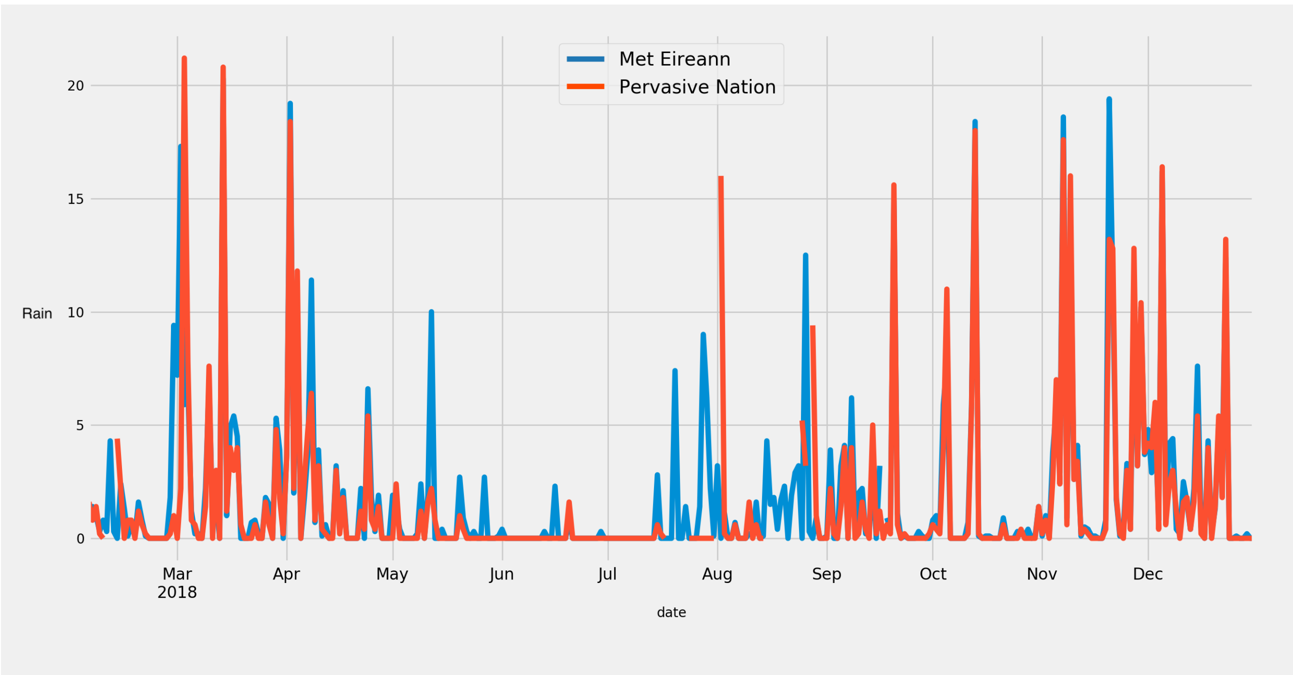

Figure 5.17: Chapelizod (PN) vs Phoenix Park (ME) 2018 April - December. Correlation r of rainfall is 0.815652.

The last Pervasive Nation sensor to be analysed was the Chapelizod sensor. The Phoenix Park Met Eireann sensors were used to compare the values which can be seen in Figure 5.17. At first glance, the PN sensors seem to be quite accurate when compared with the Phoenix Park station. There are some inconsistencies, one of which can be seen at the start of May, where 10mm of rain was reported but the PN sensor reported less than 5mm. Out of all the Pervasive Nation sensors, the Chapelizod sensor seemed to have performed the best, achieving a correlation of 0.815652. It was also the sensor that had the most data submitted and, to this day, the Met Eireann Phoenix gauge continues to still report, as opposed to the rest of the Met Eireann gauges used for this analysis.

5.2 Analysis of Dublin City Council Sensors

In this section, the rainfall sensors used by Dublin City Council will be discussed. Because Dublin City Council did not have missing values and that sensors always reported information when they were configured, no analysis was carried out to investigate the network. In this section DCC sensors are compared against the nearest Met Eireann sensors. Surprisingly, there were not many Met Eireann stations which could be compared against due to insufficient data coinciding with one and other. For this analysis, Phoenix Park and Ringsend will be studied.

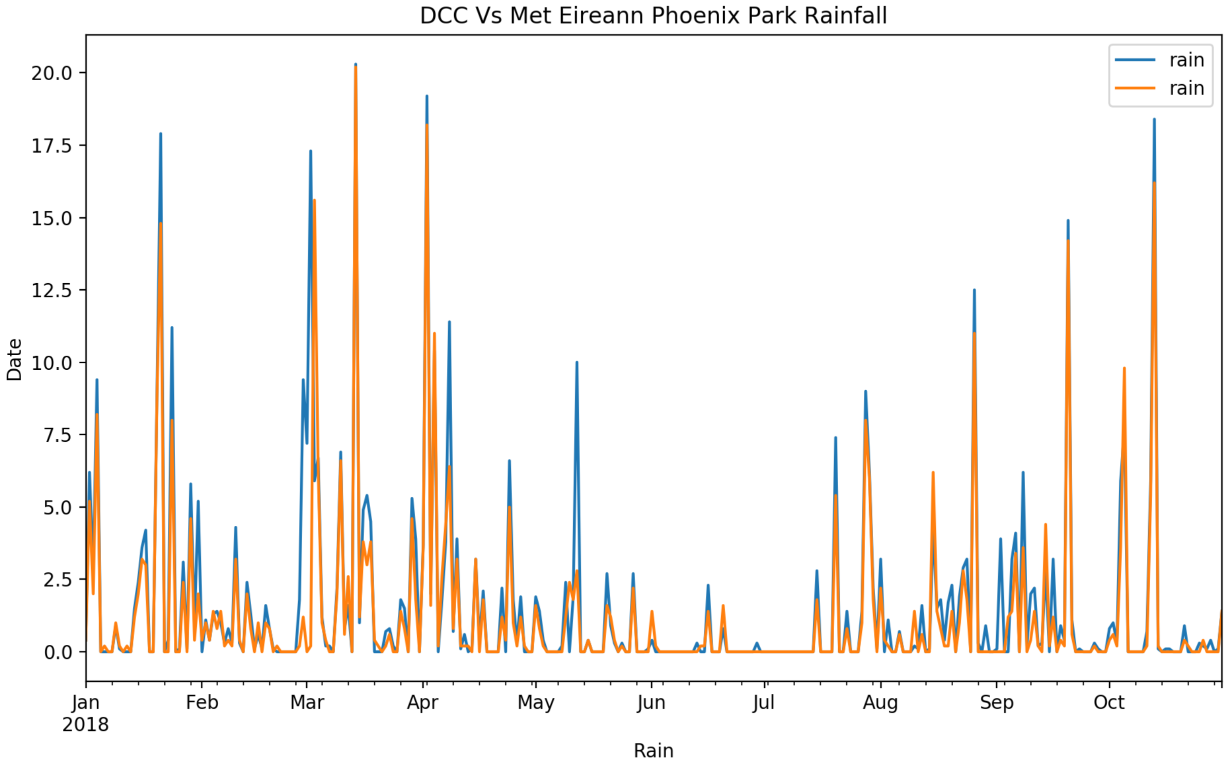

Figure 5.18: This graph depicts the daily rainfall of the DCC rain gauge and the Met Eireann rain gauge. There is a correlation of 0.884714. Blue indicates Met Eireann and Orange indicates DCC.

Figure 5.18 depicts the DCC Chapelizod sensor against the Met Eireann Phoenix Park rain gauge. The two datasets appear to be following the same trends with the most noticeable outlier being in the start of May. Interestingly, this outlier also occurred for Pervasive Nation meaning, perhaps, that the rainfall at that time was much more localised where the Met Eireann sensor was. Another interesting observation is that the DCC sensors continually reports a lower value when the peaks are inspected (i.e. the 5 highest peaks between July and October). This graph had a correlation of of 0.884714, suggesting that the DCC sensor was more accurate than the Pervasive Nation sensor.

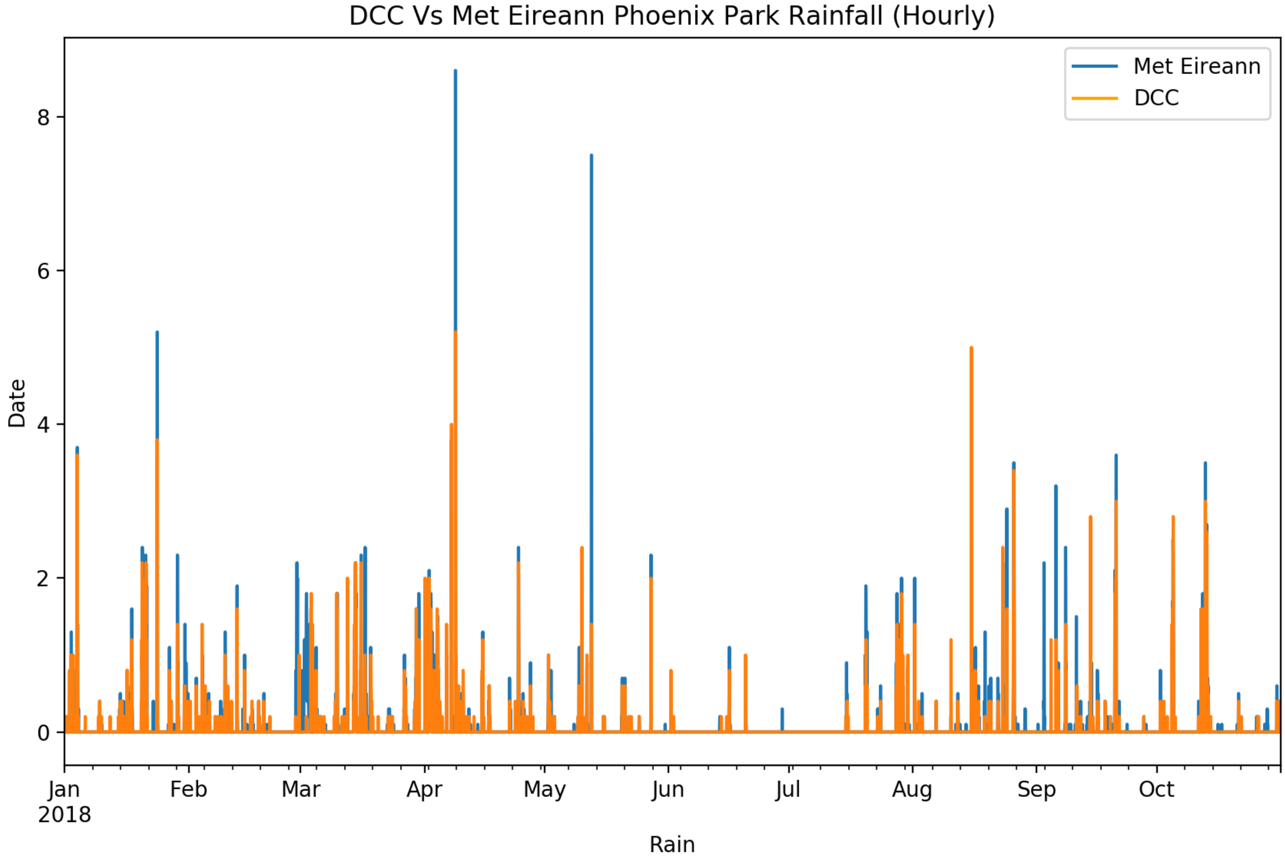

Figure 5.19: This graph depicts the hourly rainfall of the DCC rain gauge and the Met Eireann rain gauge. There is a correlation of 0.749541.

Figure 5.19 shows a more detailed view of the DCC Chapelizod and Met Eireann Phoenix Park sensor as it graphs out the hourly values that were reported by each sensor in the months of January to October 2018. Again, it seems that the DCC sensor continuously undershoots the the Met Eireann an example of which can be viewed in April and May. However, it would not be reasonable to assume that this was because the rainfall was more localised, as the DCC rarely reported more rainfall than the Met Eireann sensor. The correlation also worsened in the analysation, with a value of 0.749541.

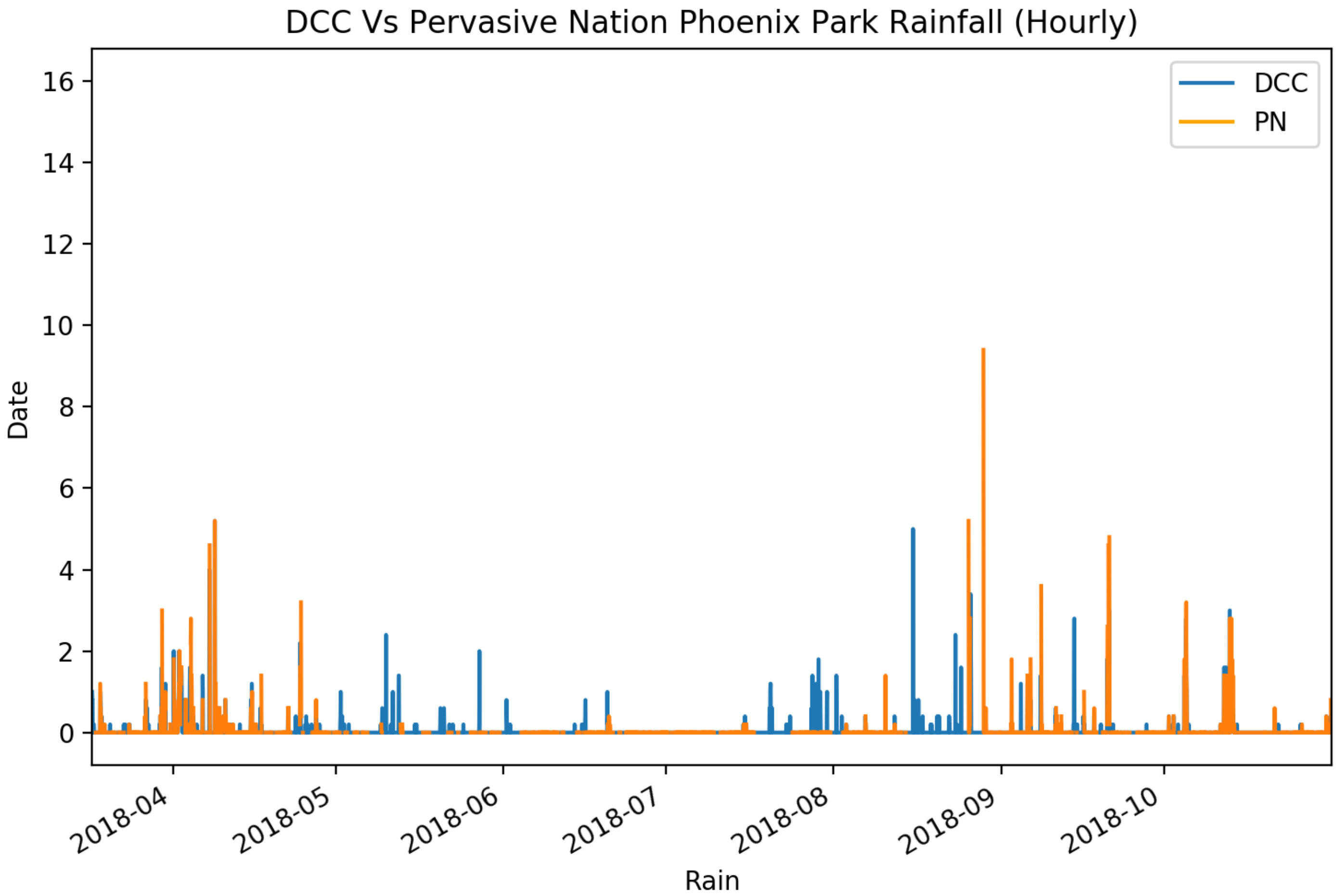

Figure 5.20: This graph depicts the hourly rainfall of the DCC rain gauge and the Met Eireann rain gauge. There is a correlation of 0.424189.

The hourly values of the DCC Chapelizod sensor was compared with the hourly values of the Pervasive Nation sensor for the months of April to October 2018 in Fig 5.20. It appears, at the start of April, that the two sensors were reporting similar values but afterwards it struggled to maintain this trend. This graph also highlights the missing hourly values of the month of May. The relationship between the two sensors was poor and which reflected a correlation of 0.424189.

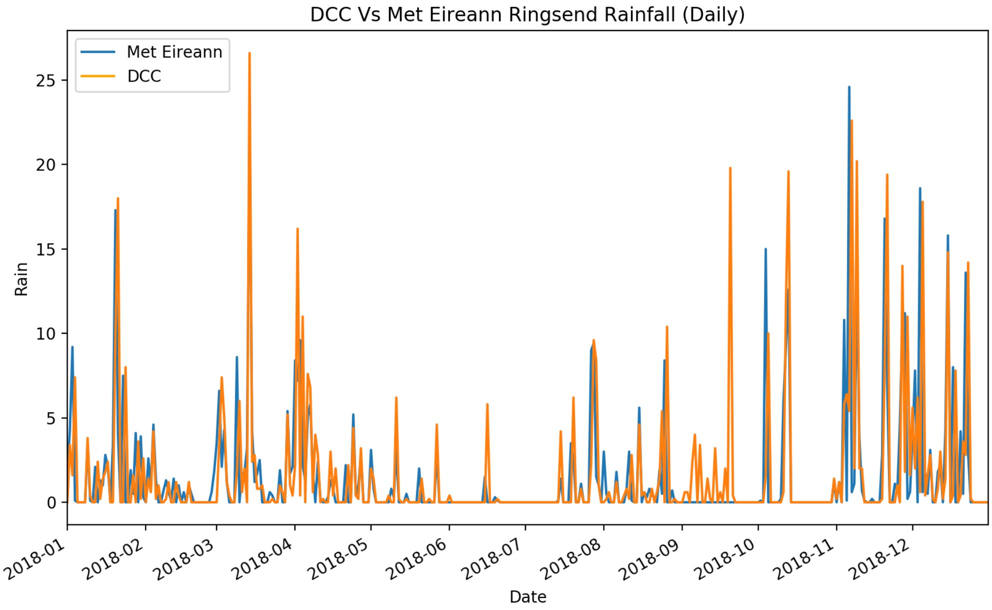

Figure 5.21: This graph depicts the daily rainfall of the DCC rain gauge and the Met Eireann rain gauge. There is a correlation of 0.532424.

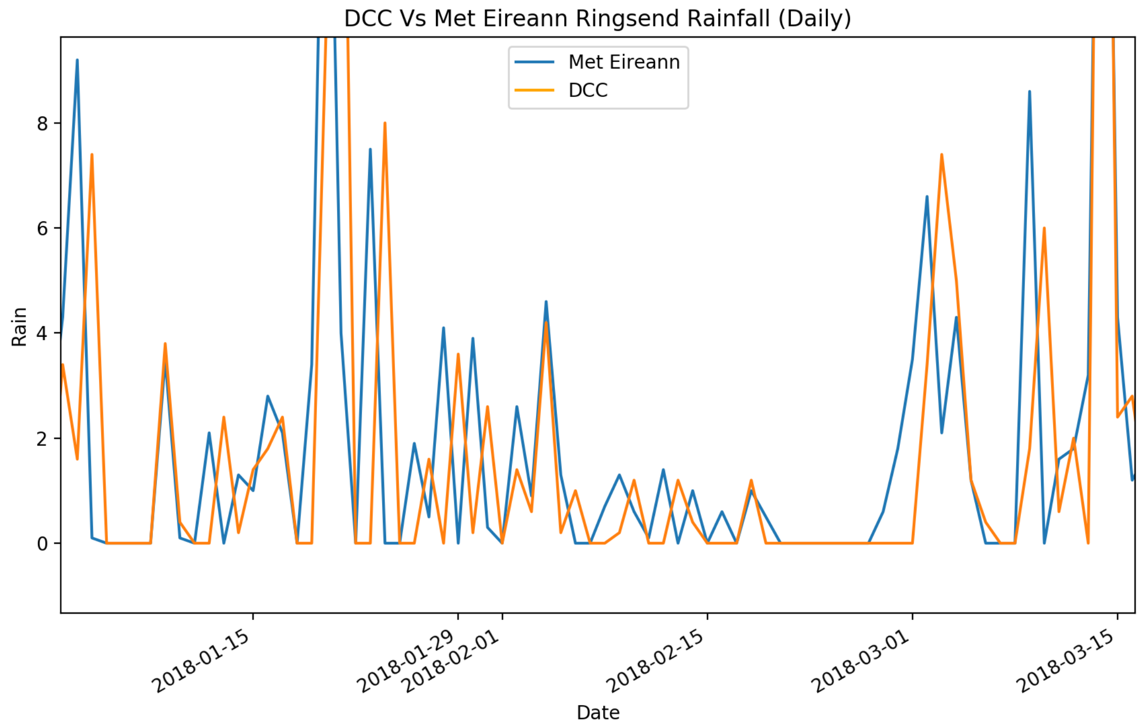

Figure 5.22: This graph depicts a closer view of the daily rainfall of the DCC rain gauge and the Met Eireann rain gauge.

Figure 5.21 depicts the rainfall values between the Ringsend Dublin City Council sensor and the Ringsend Met Eireann gauge. Figure 5.22 shows a more close-up view of the data of Figure 5.21. As depicted, it appears that the rainfall amount reported does not quite line up with the Met Eireann sensor values. A steady 'lag' effect seems to be reflected between the DCC and Met Eireann sensors as the DCC sensors are reporting the same amount of rainfall after the Met Eireann reports. The correlation between the two Ringsend sensors is 0.532424.

5.3 Analysis of SigFox Sensors

This section will now analyse the VT Sigfox river level sensors. There will be a discussion into the effects of rainfall on the river levels. Due to the fact that the only river level data available is the VT and DCC datasets, the accuracy of the river level data will be discussed in the next section.

One quirk about the river level sensors is that the configuration between the sensors and the dashboard are off. Figure 5.23 explains the configuration and note where it says that the diameter of the river level sensor tank is 100cm. When viewing the images of the river level sensor, it is clear that the tank is not actually a metre wide. This could explain why the 'Litres' value of the river level data seems unusually high to the observer. In this dissertation, I was unable to establish the diameter of the tanks, however, this does not affect the results of the analysation because only relationships and trends are studied rather than exact figures. When the real diameter is discovered the values can easily be converted but the correlations will stay the same.

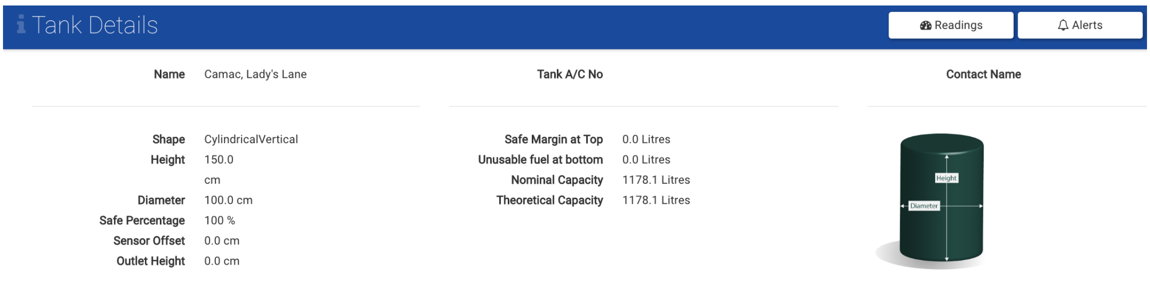

Figure 5.23: VT sensor configurations as displayed on dashboard

Figures 5.24 to Figure 5.33 shows the river levels of each of the VT sensors. Each of these graphs proves that no data was missing and also shows that few outliers are present. Figure 5.33 depicts Ballsbridge and it is important to note that this river is affected by tidal currents and could explain why much more activity is shown in the graph.

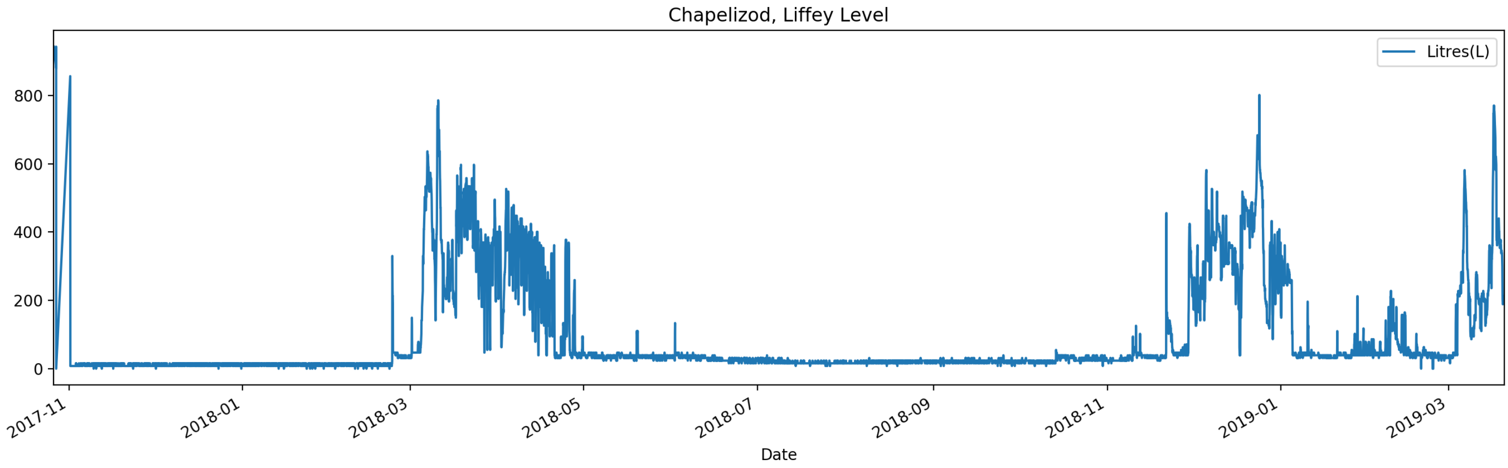

Figure 5.24

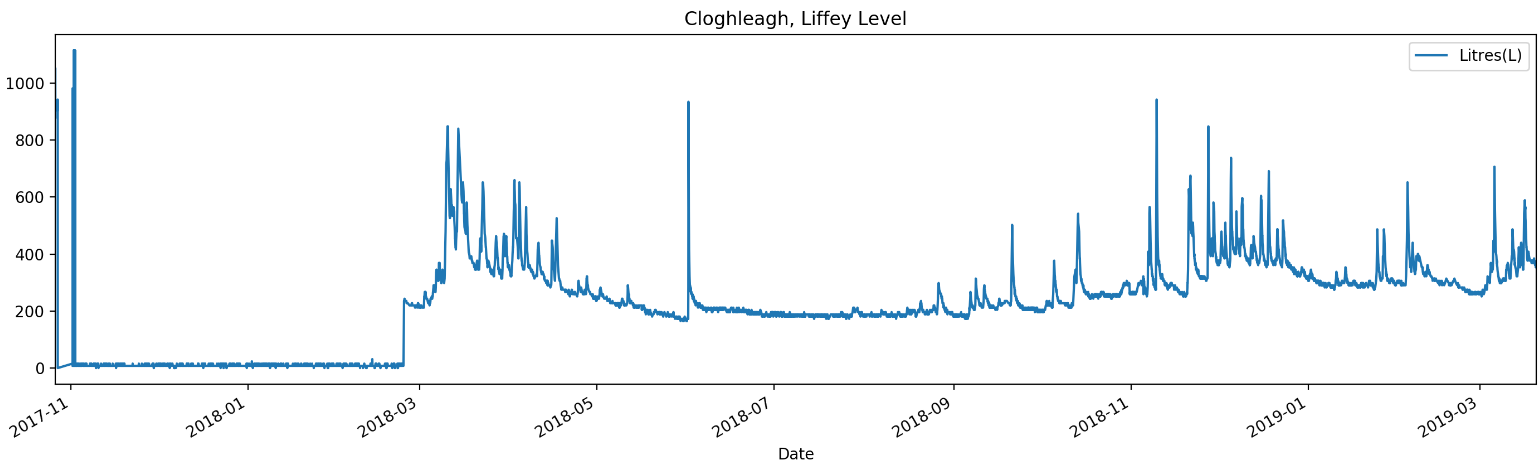

Figure 5.25

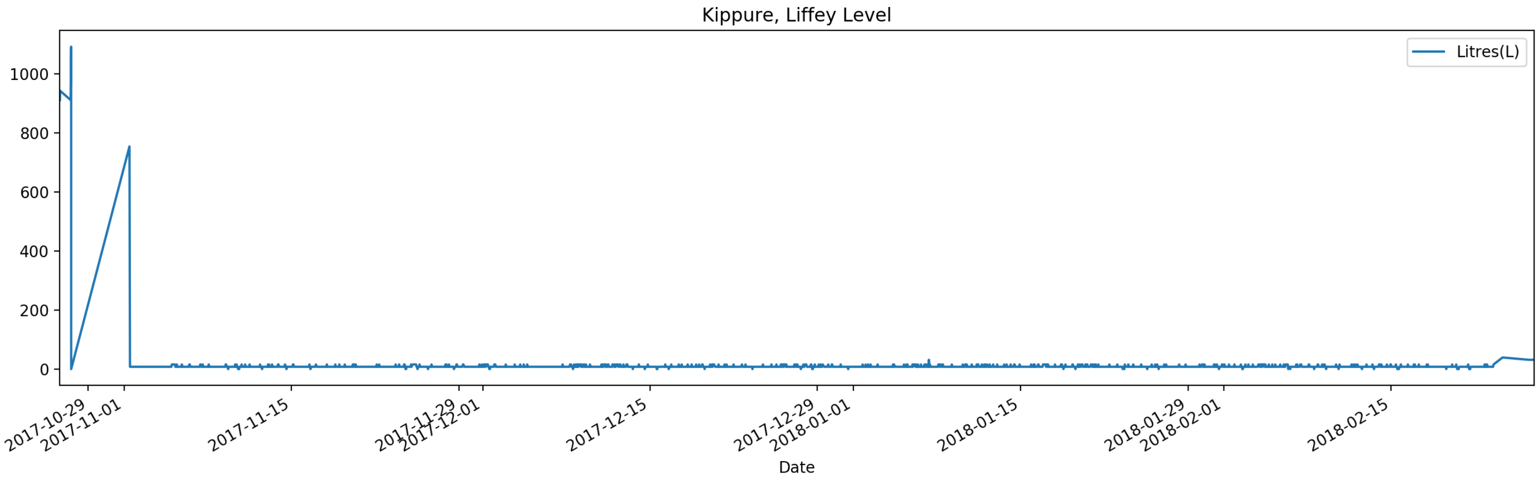

Figure 5.26

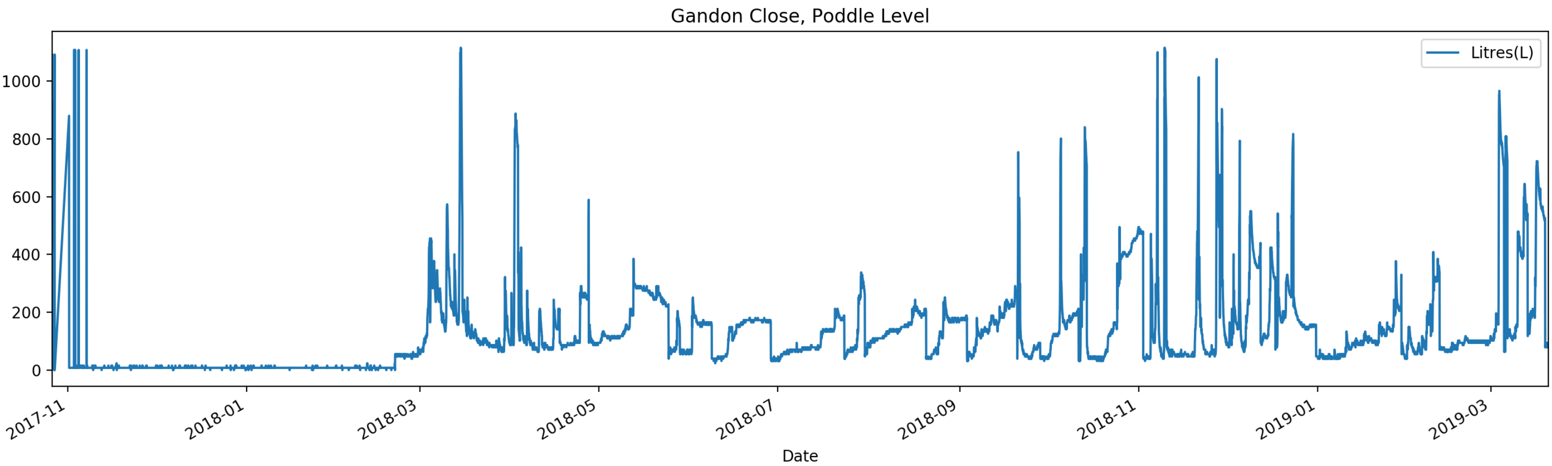

Figure 5.27

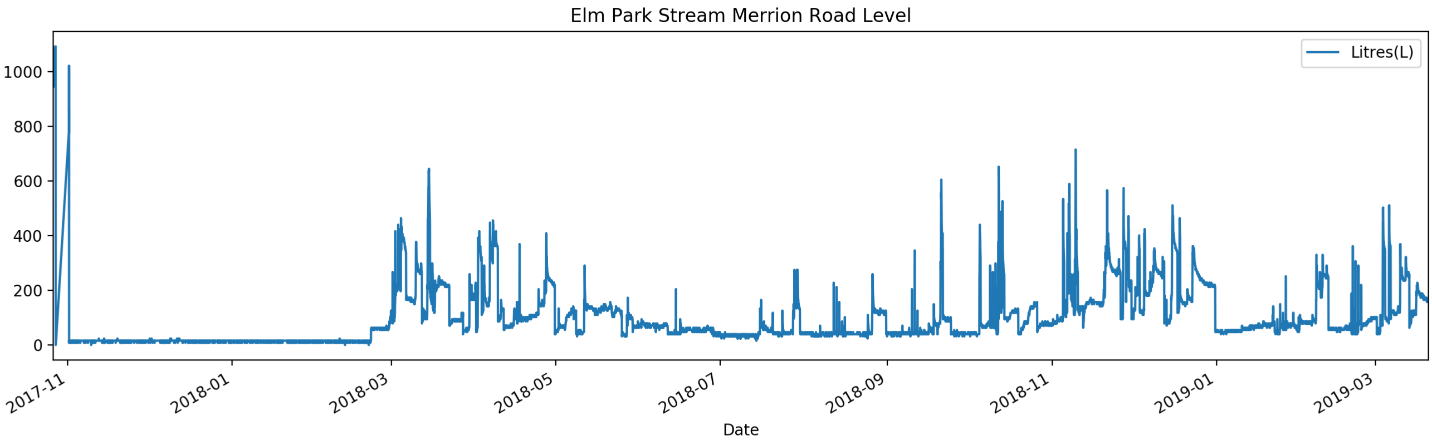

Figure 5.28

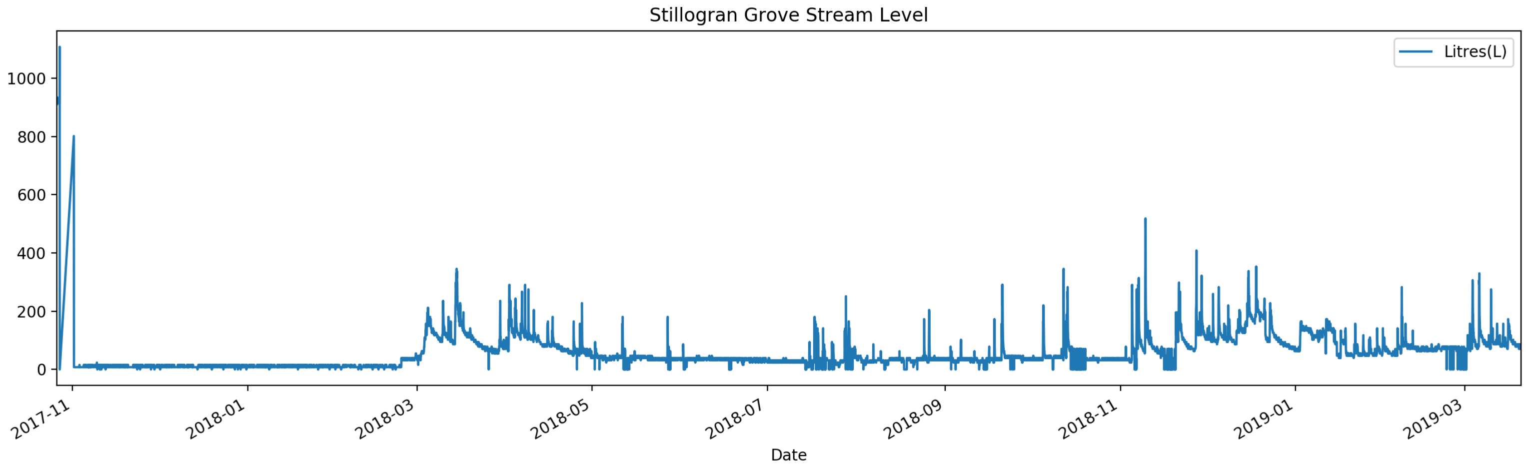

Figure 5.29

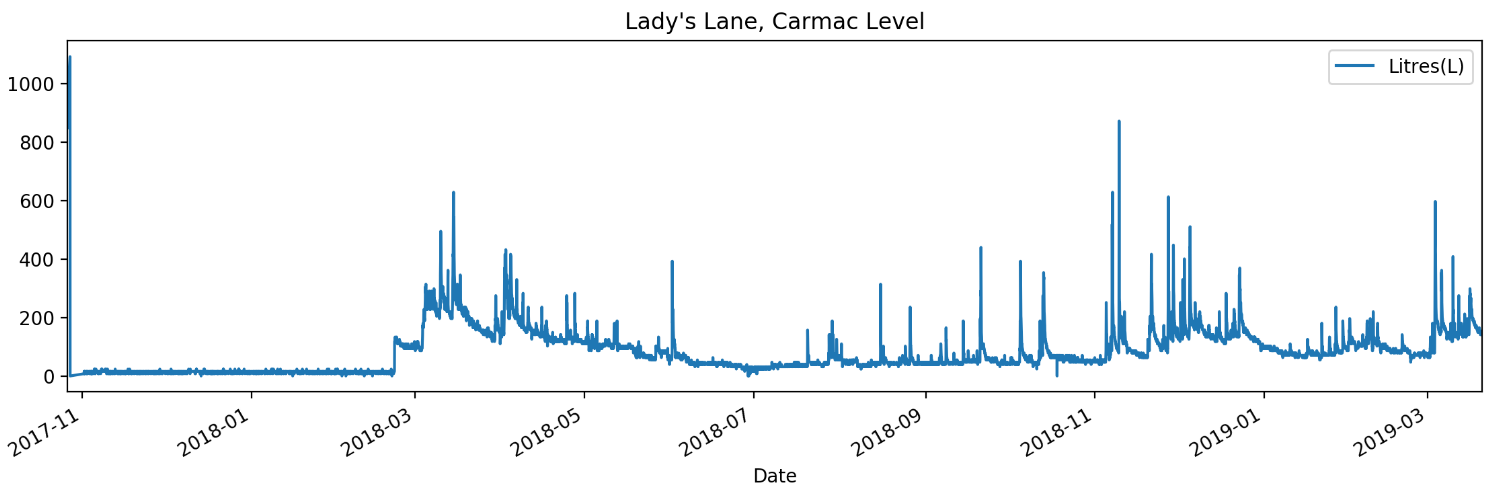

Figure 5.30

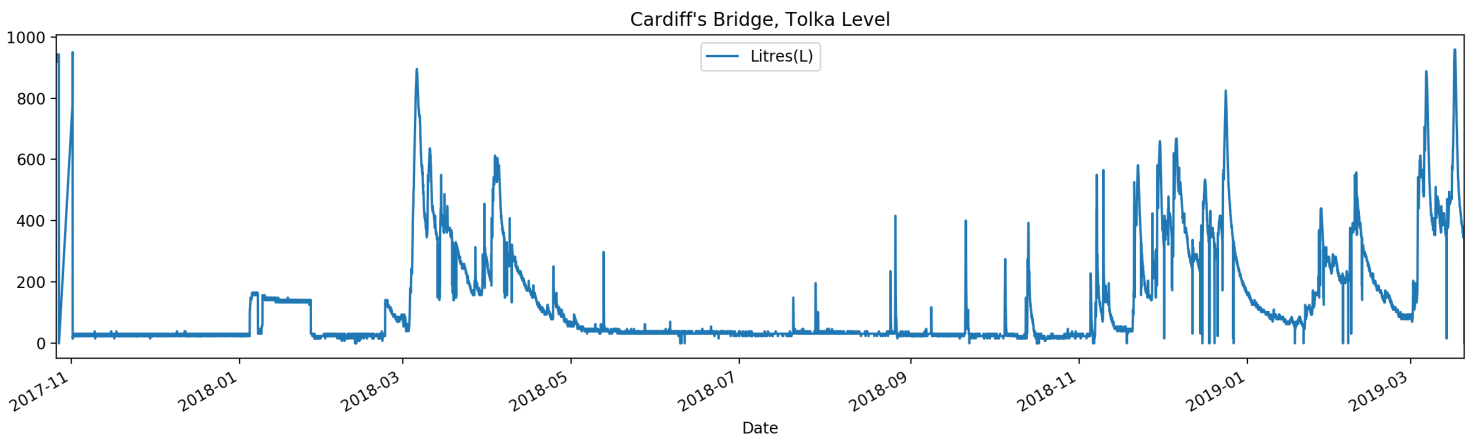

Figure 5.31

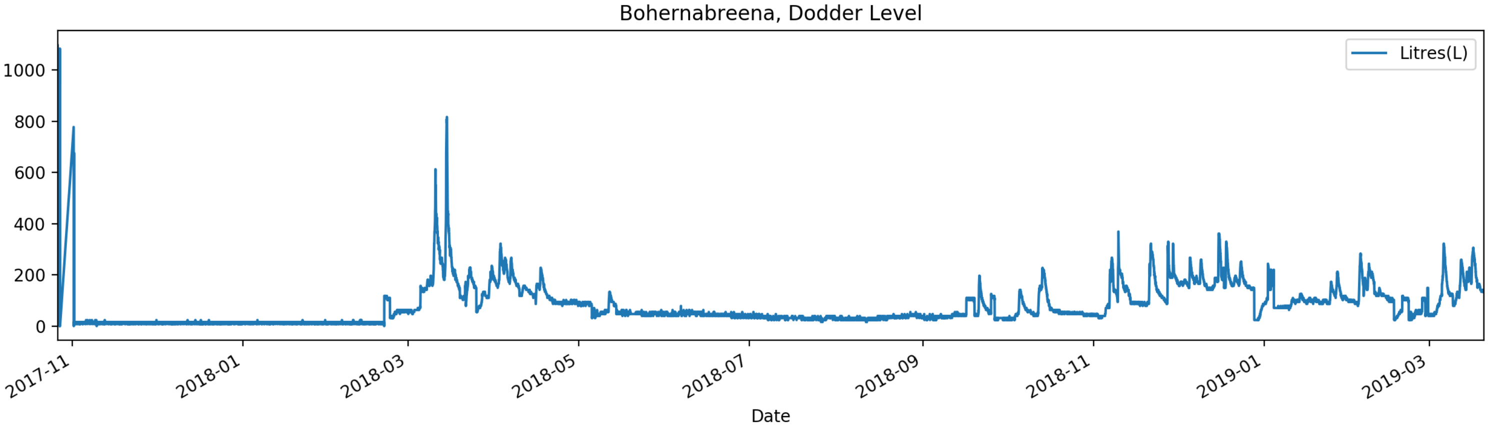

Figure 5.32

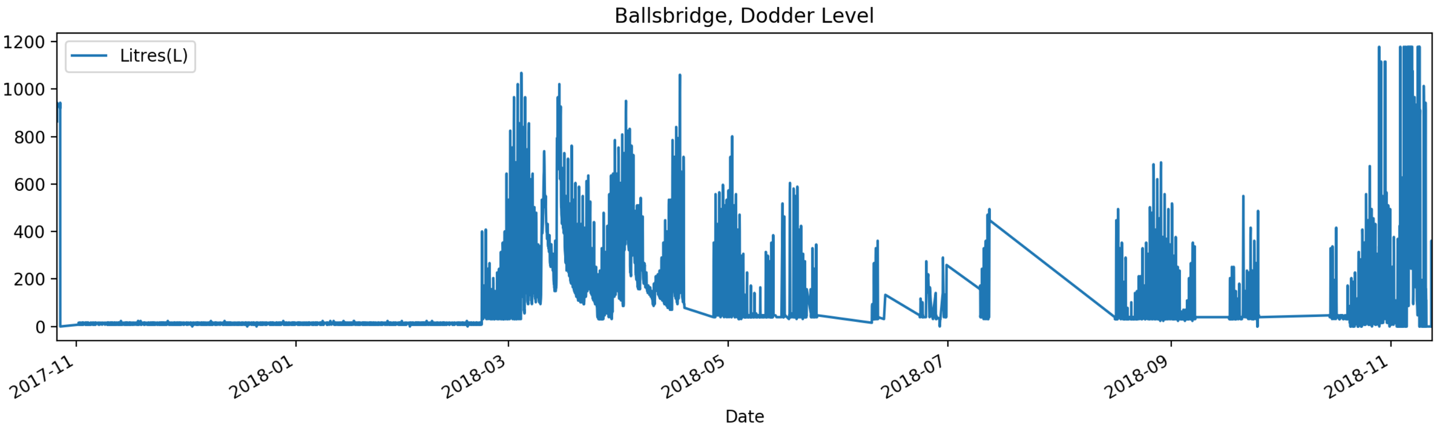

Figure 5.33

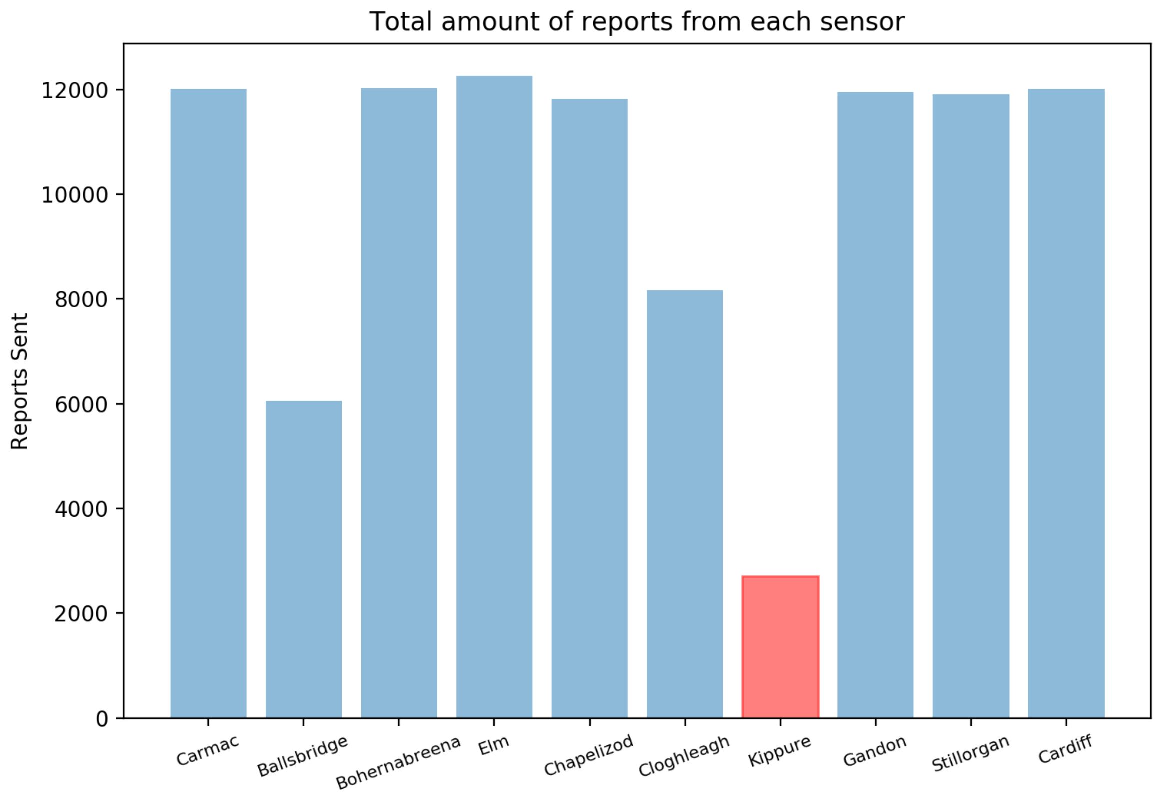

Figure 5.34

Figure 5.34 shows the total reports from each of the VT sensors. This graph is very promising in terms of the reliability of the sensors used and Sigfox network. These sensors are configured to send data either every hour or every two hours. The sensors that have a report count of 12000 send information on the hour, while Ballsbridge and Cloghleagh send reports every two hours. However, and as can be seen in Figure 5.33, the Ballsbridge sensor stopped sending data in the month of November 2018. The reason for this is as yet unknown but due the tidal activity the owners presume that it may well have been washed away. This graph has the Kippure highlighted in red. As can be seen in Figure 5.26, the Kippure sensor ceased reporting data in the month of February 2018. This was caused by the sensor's battery running down. This can be viewed as a disappointing result as the Sigfox network is known for being the top network for battery conservation. Less than 3000 reports were sent by the Kippure sensor.

The next graphs will discuss how rainfall affects the river level. The purpose of this is to investigate what weather variables are needed to predict flooding. If rainfall does have an effect in fluvial flooding the following graphs will prove that precipitation alone is not sufficient to predict flooding. Met Eireann's Phoenix Park rainfall data was chosen as it was the closest rainfall station to have hourly values.

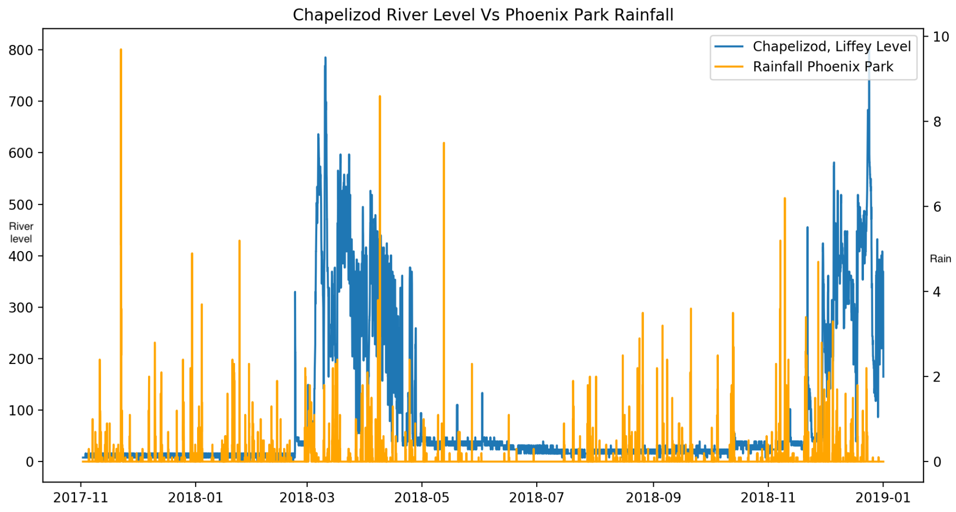

Figure 5.35: Liffey and rainfall

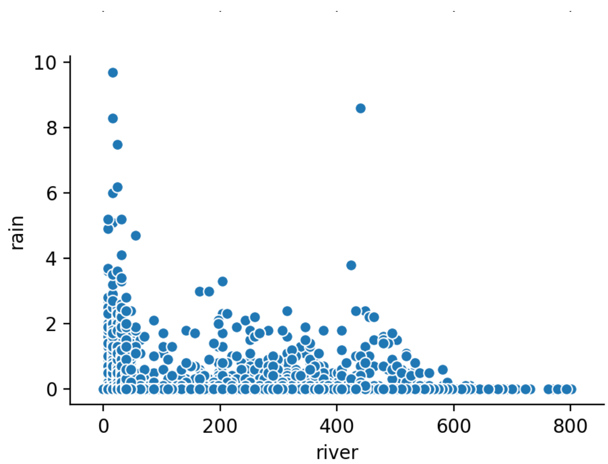

Figure 5.36: Pairplot between river level (Chapelizod, Liffey) and rain gathered from Met Eireann Phoenix Park sensor. Correlation between rain and river level (Chapelizod, Liffey) is 0.024748172.

Figure 5.35 shows the VT river level in Chapelizod against the rainfall collected at the Phoenix Park rainfall sensor. As it can be seen, it appears that the rainfall does not have any effect on the river level. This is demonstrated again in Figure 5.36, where a scatterplot between the VT Chapelizod and Phoenix Park is shown. This plot demonstrates that there is no relationship between rain and river level and has a low correlation of 0.230323975.

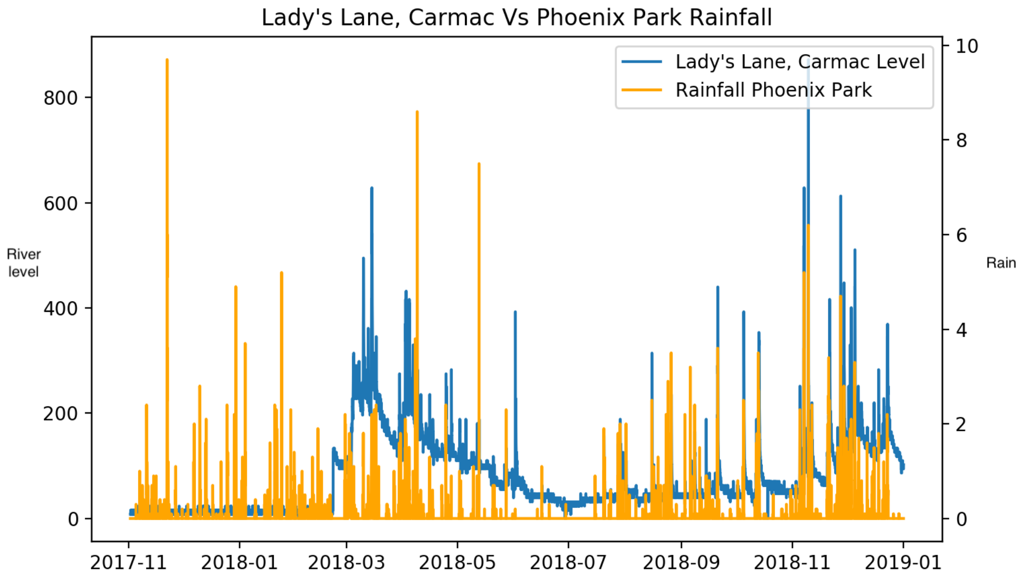

Figure 5.37: Carmac and rainfall

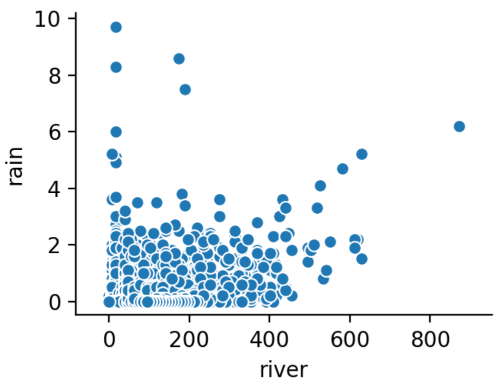

Figure 5.38: Pairplot between river level (Lady's Lane, Carmac) and rain gathered from Met Eireann Phoenix Park sensor. Correlation between rain and river level (Lady's Lane, Carmac) is 0.230323975.

Figure 5.37 shows Lady's Lane on the Carmac river against the Met Eireann rainfall at Phoenix Park. It appears that there is more of a relationship occurring compared to Chapelizod, particularly around the months of September to November. However, the scatter plot between the Carmac river level and Phoenix Park rainfall, reflects no real relationship as shown in Figure 5.38. The correlation between these two variables was 0.230323975.

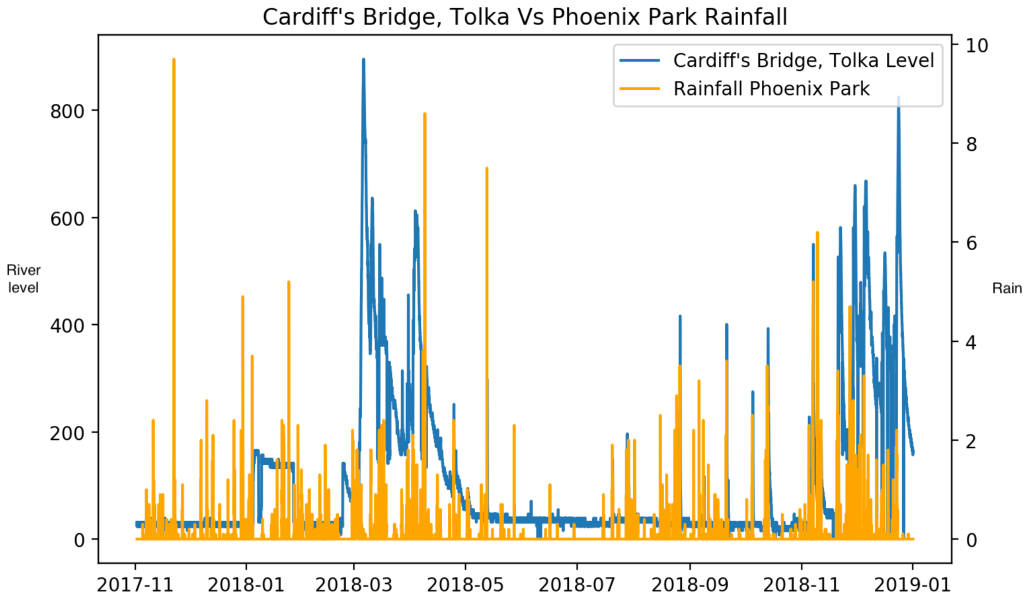

Figure 5.39: Tolka and rainfall

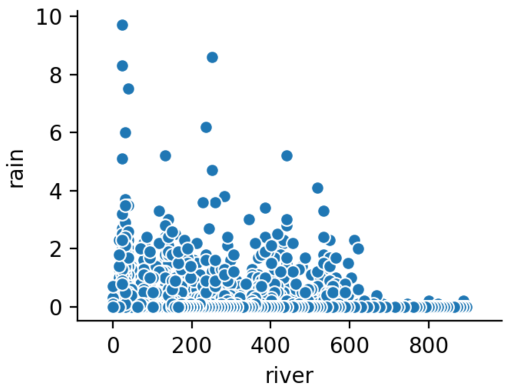

Figure 5.40: Pairplot between river level (Cardiff's Bridge, Tolka) and rain gathered from Met Eireann Phoenix Park sensor. Correlation between rain and river level (Cardiff's Bridge, Tolka) is 0.096935012.

Cardiff's Bridge on the river Tolka was also analysed against the Phoenix Park rainfall. Again, no relationship can be observed as reflected by the scatter plot in Figure 5.40. The correlation between the Carmac river level and Phoenix park rainfall is 0.096935012. Figure 5.41 shows Gandon on the River Poddle and proves once again that rainfall on its own does not have an impact on river level. The correlation of the scatter plot in Figure 5.42 is 0.179729568.

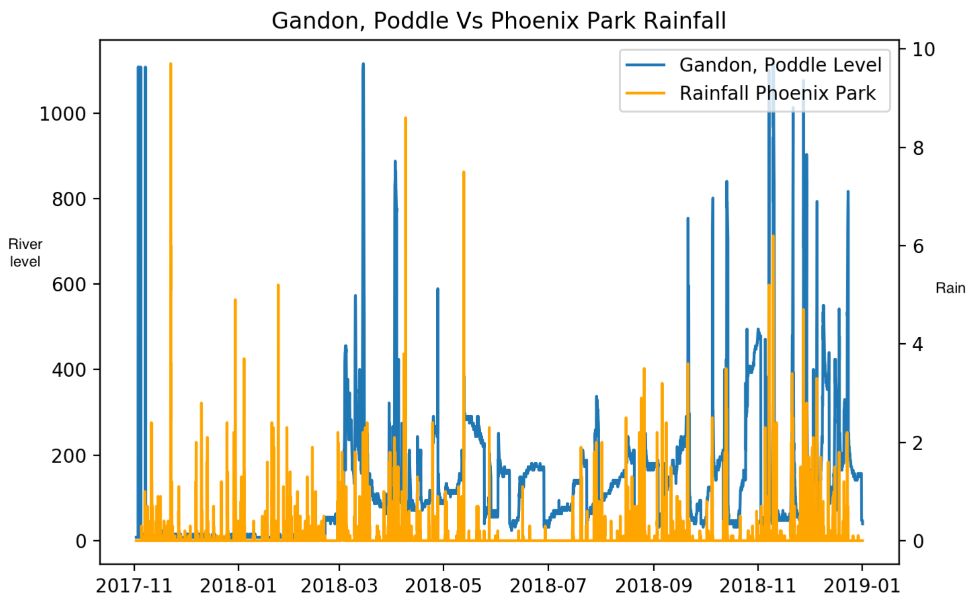

Figure 5.41: Poddle and rainfall

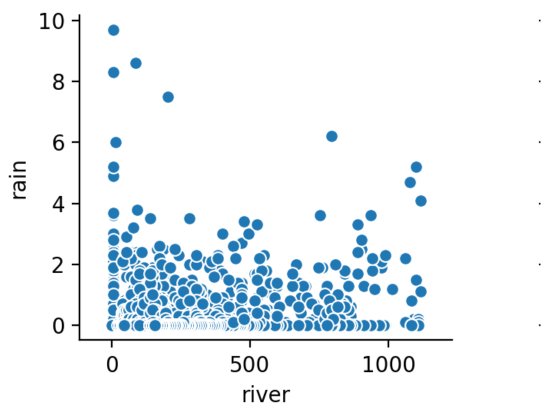

Figure 5.42: Pairplot between river level (Gandon, Poddle) and rain gathered from Met Eireann Phoenix Park sensor. Correlation between rain and river level (Gandon, Poddle) is 0.179729568.

5.4 Dublin City Council River Level Sensors

In this section, the DCC river level sensors are analysed with the VT river level sensors and the Office of Public Works sensor. Many river level sensors were available in the DCC dataset, but because historical river level data is rare, only few could be analysed. Once again, and due to the fact that each of the sensors had reported information when they were configured, there was no need to carry out an in-depth analysis as to the quality of the network and reports. This section will investigate how accurate the reported values were.

Figure 5.43 to 5.47 display scatter plots between the DCC river level value and the VT river level value. As can be seen, each of the plots show a high correlation except for Figure 5.46. Figure 5.46 shows the relationship between the DCC and VT sensor in Bohernabreena. The scatter plot in Figure X shows that the correlation between the two is 0.056016. In this case, perhaps the correlation is not a fair representation of the data, as a visual relationship can also be seen in the data. Another point is that in all of the DCC vs VT graphs, each have the same pattern. That is, when the VT sensors are around zero, the DCC sensors can be any number. However, as the VT sensors value increases, so does the DCC's and a linear relationship can be viewed.

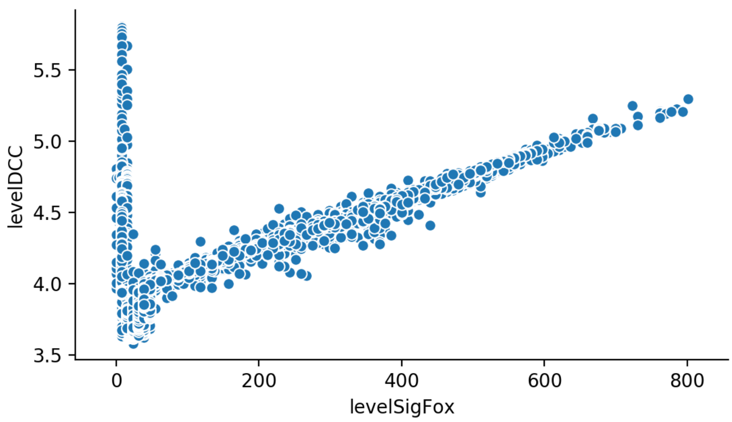

Figure 5.43: Pairplot of river level (Chapelizod, Liffey) between DCC and SigFox. Correlation is 0.732791.

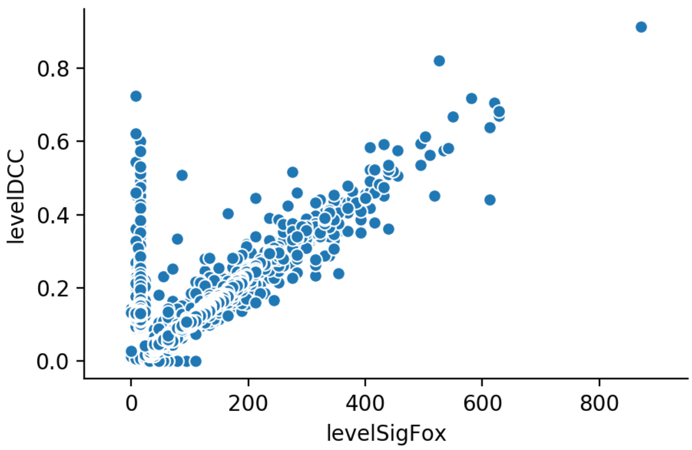

Figure 5.44: Pairplot of river level (Lady's Lane, Carmac) between DCC and SigFox. Correlation is 0.735115.

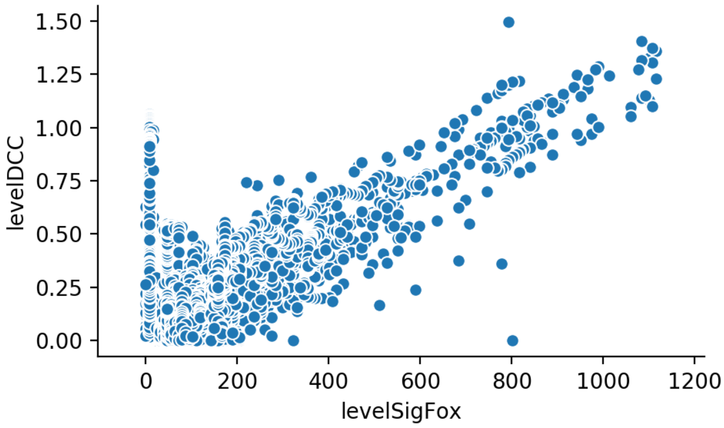

Figure 5.45: Pairplot of river level (Gandon Close, Poddle) between DCC and SigFox. Correlation is 0.681016.

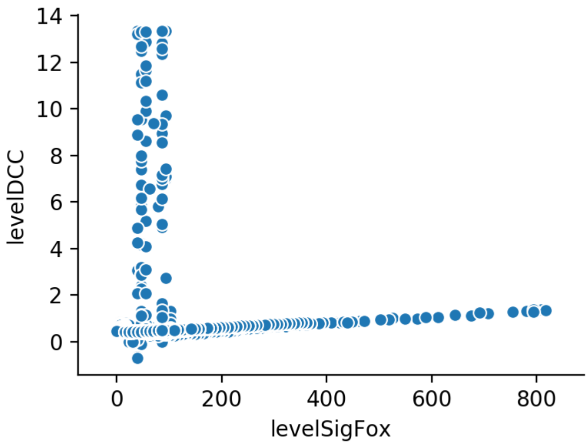

Figure 5.46: Pairplot of river level (Bohernabreena, Dodder) between DCC and SigFox. Correlation is 0.056016.

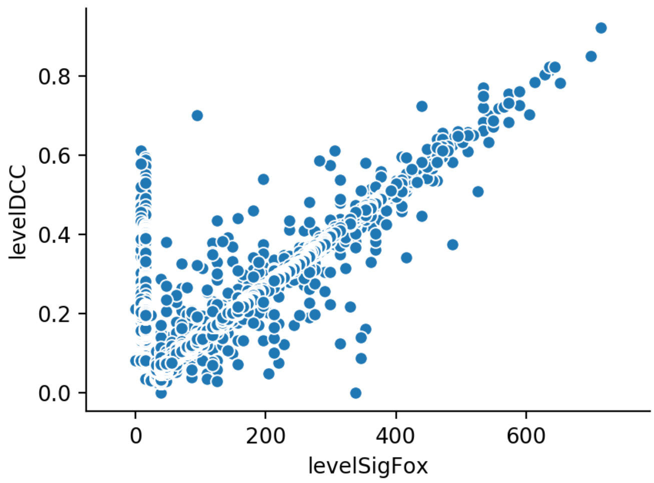

Figure 5.47: Pairplot of river level (Merrion Road, Elm Park Stream) between DCC and SigFox. Correlation is 0.780413.

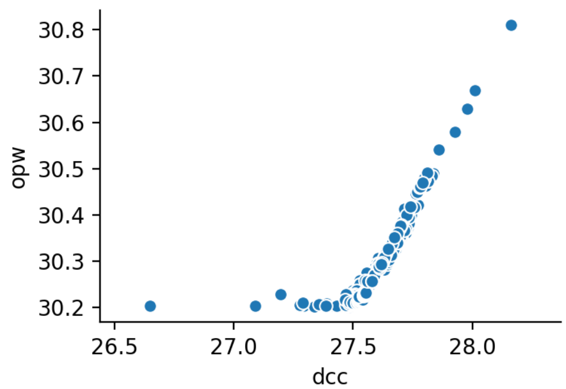

Figure 5.48: Pairplot of river level (Waldon's Bridge, Dodder) between DCC and OPW. Correlation is 0.864924.

Figure 5.48 is the last analysis for this dissertation. This figure depicts the relationship between the DCC Dodder sensors against the OPW Dodder sensor at Waldon's Bridge. As shown, it is obvious that there is a strong relationship between the two. The correlation between the two is 0.864924 which proves again that the relationship is strong. As the Waldon's Bridge OPW sensor is the only official river level sensor which was available in this project, it is a positive for the DCC IoT sensor. It suggests that the values being produced by DCC sensors are indeed accurate.

6 Conclusion

6.1 Findings

As a result of the work that has been completed for this dissertation, a number of important findings have been established. Firsty, the Pervasive Nation sensors are not quite ready to use in a real-time flood monitoring system. This is because the values produced by some sensors did not correlate sufficiently with the Met Eireann sensors. It has also been suggested that the network used is not fully reliable given that, for days at a time, no reports were sent by the sensors. However, some sensors were reliable and achieved strong correlations with the Met Eireann sensors and this suggest that there is a possibility to use these rainfall sensor in an IoT monitoring system.

Secondly, the results of the DCC river and rainfall sensors were positive. The rainfall sensors had high correlations for both the daily and hourly Met Eireann rainfall data. The DCC and VT river level sensors also had high correlation, however, an unusual pattern in the relationship between the two has materialised as a result of the analysation. The most positive result out of the river level sensors was the comparison between the DCC and OPW sensors with a very strong relationship existing between them. Overall, both VT and DCC river level sensors had positive results and it could be suggested that they can be used in a real-time flood monitoring system.

In terms of networks, it appears that the Sigfox network and M2M SIM network are quite reliable at sending data. This was because for both the VT and DCC datasets, very little missing information occurred. Comparing this to Pervasive Nation's LoRaWAN, it could be viewed that this network is not sufficiently reliable particularly in comparison to VT and DCC. This evaluation has been reached given fact that the data that Pervasive Nation's sensor was sometimes unreliable and where days had often elapsed during which no information had been reported.

Analysis was also carried out into establishing what variables are needed when it came to flooding. Unfortunately, due to the limited amount of data, only rainfall could be analysed to discover if it had an impact on river level. The result of this was disappointing, because there was no relationship between the two variables. However, it is important to note that rainfall does have an impact on river levels when it comes to flooding. On the 24th of October in 2011, the Chapelizod river levels were high and flooded the surrounding areas. This was the same day that 71.3mm of rain fell leading one to conclude that rainfall does have an impact, at least to some degree, on river levels. That said, many factors contribute to flooding and the analysis carried out proves that to build a reliable flood monitoring and prediction system, more variables are needed to be measured.

6.2 Future Work

The research aim of this dissertation was to explore the possibility of the Internet of Things being appropriate for use in river and rainfall monitoring. In this regard, at least, it can be said that there is still work to be done in order to establish this proposition. One can only know if an IoT sensor is reporting accurate data is if it directly compared to tried and tested methods. Therefore, the future work for this dissertation is:

- Setting up rain and river level gauges next to the currently active IoT sensors
  - This would be a simple and cost-effective way of measuring and verifying the accuracy and reliability of the sensors already existing. Rain gauges are essentially measuring beakers in the ground and a height chart can be added to a river. This would involve a person checking each regularly to ensure that the values being reported by each sensor match the tried-and-trusted methods of measuring rainfall and river level.
- Installing more sensors
  - Once the accuracy and the quality of the data being reported is ensured, more sensors would be placed around Dublin. For the most part, flooding can occur anywhere in Dublin and, in order to get the best overview of the city, more sensors will need to be installed.
- Setting up a central dashboard of all weather monitoring system
  - This dashboard will allow anyone to easily view all of the sensors available in one place.
- Use the data that was collected to build a flood prediction model and alert system
  - Now that Dublin is well mapped out with sensors, and that all the data is being saved in a database, a predictive flood model using real data can finally be made for Dublin city.

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