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# Energy-Efficient Operation of IoT Sensors in Precision Agriculture

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Master's Degree in Telecommunication Engineering

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**Problem description:**

IoT technology is starting to play a key role in many fields, one of them is precision agriculture. Several kinds of sensors are helping farmers to check different parameters of their crops in real time, giving them a very useful decision support to know when irrigation is needed, detect plagues, etc. However, these sensors have a limited lifetime due to its battery or power supply limitations, moreover, in most cases the selection of the sampling rate (the parameter with highest influence in power consumption) is left to be set by the farmer, adding difficulty to the use. In general terms, this work aims to analyze moisture monitoring sensors and systems to obtain certain conclusions and rules to be used as base in the implementation of smart soil moisture sensors with adaptability and intelligence to auto determine when to measure, making them more efficient and easy to use.

The first stage of this thesis will study the state of the art in smart agriculture, and more specifically the use of soil moisture sensors. Class, applications, price, autonomy and other qualities of the sensors will be studied, as well as opinions from farmers and smart irrigation companies to determine the ideal requirements in a possible smart system. After that, some experiments with commercial sensors and products will be held in order to obtain raw data to work with. The sensors will be placed in an experimental soil during several wet-dry cycles and configured with a high sampling rate storing all the data for future analysis, soil temperature will be studied at the same time. The analysis will reveal how to reduce the number of samples without reducing the utility of the system, presumably that means to reduce the sampling rate when moisture values are not significant and increase it when they are close to critical values for the farmer (irrigation threshold, over wetting, etc.) but conclusions won't be clear until the analysis is done. Finally, possible improvements in power consumption will be accounted to discuss possible implications of this (better autonomy, smaller devices etc.).

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## Abstract

IoT devices aim to have significant relevance the next big revolution in the field of agriculture. Sensor-based irrigation, disease prediction or custom super-localized weather forecasts are just some examples of what IoT can provide to agriculture. For this thesis we put the focus on soil moisture sensors in the context of sensor-based irrigation. These sensors provide the farmers with real-time data of soil moisture from their crops. This data can be used to make decisions like start or postpone an irrigation event finding the optimal moment. This decision support helps the farmer not only to optimize water management but also to save labor avoiding unnecessary trips to the crop since irrigation can be automated or taken remotely.

IoT technology has evolved a lot during the last years increasing battery-life of the devices. However, IoT sensors are still energy constrained. Some devices include solar panels to be self-sufficient but they present some drawbacks. Long periods of darkness can exhaust the battery and interrupt the flow of data. To solve that manufacturers increase the size of the batteries or the solar panels. This solution increase also the price and size of the devices making them less interesting for the user. For this work we acquired a product largely used by farmers to measure soil moisture remotely. Checking the its operation and exploring other options in the market we discovered that there is big room for improvement in the energy management of these devices.

The goal of this thesis is to discuss how the energy-operation of IoT soil moisture sensors could be improved. For that we propose to replace static sensing strategies based in a fixed sampling frequency by energy-smart sensing policies able to adapt the sampling frequency to the relevance of the data. We will study the state of the art of sensor-based irrigation interviewing also stakeholders to define the user requirements. We will use these requirements to understand what makes some moisture measurements more valuable than others. Once we understand which moisture measurements are valuable and which not we will explore different smart sensing strategies able to skip not valuable readings. In other words, sensors exchange energy for information, our objective is to optimize that trade-off by avoiding irrelevant data collection. Finally we proved that energy-smart sampling policies based in the relevance of the measurements are a valid solution to reduce the use of energy while keeping similar quality of information.

# Preface

First of all I would like to express my gratitude to Frank, my supervisor in this work, he gave me the idea, the media, his guidance and especially the motivation to carry out this project. I would also like to thank Faiga, my co-supervisor, she gave me valuable ideas and opinions that without any doubt have had a great relevance in this thesis.

Thanks of course to my parents and sister for their continuous support during all my stage as student. I wouldn't be here today if it wasn't for them.

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# List of Acronyms

**AHP** Analytic Hierarchical Process.

**AoI** Age of Information.

**AW** Average Weighted.

**ET** Evapotranspiration.

**FAO** Feeding and Agriculture Organization of the united nations.

**FC** Field Capacity.

**GWC** Gravimetric Water Content.

**IoT** Internet of things.

**IT** Irrigation threshold.

**M2M** Machine to Machine.

**PA** Precision Agriculture.

**PR** Recharge Point.

**PWP** Permanent Wilting Point.

**RDI** Regulated Deficit Irrigation.

**SI** Sampling Interval.

**VoI** Value of Information.

**VWC** Volumetric Water Content.

**WC** Water Content.

# Chapter 1
# Introduction

In this chapter we present the motivation, an introductory section about the battery issue of IoT devices, the problem scope and the aim and structure of this master thesis.

## 1.1 Motivation for IoT in agriculture

Many experts estimate the origin of agriculture around 10.000 years ago, since then farming has experienced a large and constant evolution. First records of agriculture improvements belong to ancient civilizations. There are evidences of advanced water management and use of new tools like the roman plow in the Greco-Roman empires or ancient Egypt [31, 20, 14]. After the old age, agriculture evolution slowed down. It was not until 18th century when Modern farming began. Several advances and changes were introduced to agriculture in a short period of time. Some examples are four field rotation system, cross-breeding to create better and bigger crops or methods to replace soil nutrients. These improvements made agriculture more efficient reducing the number of farmers required what promoted the industrial revolution [20]. As consequence of industrial revolution, new industrial processes started manufacturing new tools and machines for agriculture. During the end of 18th and specially 19th century, new devices like reapers, harvesters or seed drillers appeared. They were initially manual or powered by animals and later replaced by steam and internal combustion engines [21, 31]. The next big revolution was between 1960 and 2000, this period called the Green Revolution was characterized by a huge improvement in world food production and distribution. This improvement was a combination of high crop research investment, mechanization and extended use of synthetic fertilizers, pesticides, and genetically improved crop varieties. These advances tripled the production of some crops such as wheat [9].

Nowadays, despite the high efficiency reached, agriculture faces new challenges that threaten human civilization. The worrying increase population and the effects of climate change is forcing the agriculture to find new techniques based in data-driven management and automation to increase production while minimizing the use of resources. This upcoming era aims to put together several technologies like Internet of Things (IoT), artificial intelligence or robotics. Collecting and analyzing several kinds of data will provide the farmers with an optimal decision support while automated systems will reduce the use of chemicals, energy, water or human labour. Within this new scenario, remote sensing for soil moisture aims to change water management in agriculture, saving energy and water while increasing productivity [14].

## 1.2 IoT lifespan issue

Battery life is nowadays one of the biggest constrains for IoT devices. Its batteries has to be replaced on average every three years. In 2020 the number of IoT devices is around 20.4 billions, assuming an average battery life of three years 18 million battery replacements are necessary everyday [13]. Change batteries every three years can look assumable but, when the density of sensors in the system is large, the extra labor of monitoring and replacing the batteries can eclipse the benefit of the IoT sensor itself. This issue is even bigger at sites where the task of replacing batteries is difficult or potentially risky such as offshore wind farms or weather monitoring stations [40, 4].

Better batteries could solve this problem in the future, also battery-less devices based in super-capacitors are an option to be considered [40, 4]. Meantime, there are several approaches to maximize battery life like for example energy harvesting, low power electronics, high-efficiency protocols or low power sensing techniques. Most of the devices based in energy harvesting are designed to be autonomous by collecting thermal or solar energy [41]. However, they need a considerable energy buffer to survive long periods with small or even null power input. A bigger battery or solar panel means more size and price while IoT sensors aim to be as small and cheap as possible. Other problem of autonomous sensors is that unusual long dark periods (or adverse situations) can lead into lack of energy and thus into poor or missing data [40, 4]. Apart from the battery, data handling implications must be considered. IoT sensors usually read continuously or every few minutes from the environment generating a big amount of data. This data has to be either stored, sent or both. More readings or transmissions implies more power consumption.

In agriculture, farmers use IoT sensor networks to check in real time soil moisture, prevent plant illness, optimise water efficiency and many other applications. These sensor networks frequently need to cover huge areas of land, requiring a lot of sensors what makes the maintenance cost high. In other words, lifespan of the sensor's batteries is a critical factor to limit the cost of an IoT network [40]. The techniques mentioned before to enlarge battery life are doing its best, electronics is more energy-efficient every day while protocols are doing the same. However, to ensure a good lifespan in IoT sensors, optimise the energy management is as crucial as having a good battery [40, 4].

## 1.3 Problem scope

We found an unexplored approach for lifespan improvement in the sampling policies of IoT devices. Most sensors right now work with a fixed sampling frequency. This means that the sensor takes a measure from the environment every certain time no matter the relevance of the data or the availability of energy. The sampling frequency can be optimized for each use case, however, it is not easy task. A too short sampling interval consume too much energy and generates too much data but on the other hand an excessive sampling interval can miss relevant events. If we speak about soil moisture sensors, the task to determine how often the sensor should the read is left to farmer in many occasions, who at final instance only wants to know when to irrigate. This task adds complexity to the product and makes it less interesting for the customer.

Another limitation of these smart-less strategies is that they are not energy aware, if it is not changed by the user, measurements will be made with the same frequency no matter the level of the battery. An option would be that if the level of the energy buffer is low, the sampling frequency is reduced progressively until more energy is harvested so, the data flow is not interrupted. An energy-smart sampling policy is an option with huge potential to solve this problem.

The scope of this thesis is based in the premise that less measurements consume less energy. Instead of the smart-less sampling strategies used right now we want to explore the option of smart sampling policies that adapt the sampling interval according to the relevance of the data (domain knowledge) and other involved factors like energy availability. The relevance of the data is related with the decision making of irrigation in agriculture.

The aim is to contribute to the soil moisture measurement in the sensor-based irrigation context. Reducing the energy used in the process while keeping the same value of information obtained from the data collected.

## 1.4 Aim of the project

We assume that the system somehow can optimize its operation if it knows which observations/measurements are actually valuable, and only use energy on those. We want to find out how to determine this value in different use cases in the domain of agriculture. To explain the aim of this thesis we have to start explaining what an **energy-smart sensing policy** is. For us, an energy-smart policy is a policy that has knowledge from its use domain and is aware of the available energy. With this information, the policy adapts the sampling frequency to maximize the energy/information exchange trade-off.

**The aim of this thesis is to understand how to apply the knowledge from the domain of precision agriculture and sensor-based irrigation to the development of energy-smart sensing strategies for soil moisture measurement using remote sensors**.

Is important to clarify that the aim of this thesis is not the creation of such smart sampling strategies but to study how they could be useful and improve the energy operation of IoT moisture sensors in precision agriculture. For that, we will do a research to know the state of the art and contact several stakeholders like farmers and irrigation experts. We will also acquire real products to understand how moisture data is and how it is measured. Together with the information found and the requirements from the stakeholders we will determine the user needs. With the user needs we will define the technical requirements and come up with a potential solution of smart sensing. Finally we will carry out several experiments and simulations to verify that our proposed solution is valid.

At final instance, we want to be able to answer the following 4 questions.

### 1.4.1 Research questions

- **RQ1:** What are the user requirements for a remote sensing system of soil moisture?
- **RQ2:** How can we evaluate the relevance of soil moisture data based in the user requirements and other related factors?
- **RQ3:** How can we use the value of information of soil moisture to develop energy-smart sensing strategies?
- **RQ4:** How energy-smart sensing strategies can improve IoT soil moisture measuring and what implications could have?

## 1.5 Structure

The overall structure of the thesis is formed by 9 chapters. Including the introduction chapter the remaining chapters proceed in this way:

-Chapter 2, Background: Here we present all the key concepts and domain knowledge necessary to develop and understand this project.

-Chapter 3, Methodology: We present the design science method and design cycle followed in this work.

-Chapter 4, User requirements: This chapter includes part of the literature review and interviews with stakeholders done to understand the user requirements.

-Chapter 5, Data collection: We present the hardware used to obtain real data of soil moisture as well as the different experiments of data collection.

-Chapter 6, Models: We present the simulation models that we will use in the next chapters to replace real data of soil moisture and test possible sensing policies.

-Chapter 7, Use cases: We present the three use cases in which we will apply the simulation models.

-Chapter 8, VoI of soil moisture in sensor-based irrigation context: We define a framework to estimate the value of soil moisture data related with other influence attributes.

-Chapter 9, VoI as baseline for energy-smart sensing policies: We use the estimations of value of information from the previous chapter to discuss how could it be useful to develop energy-smart sensing policies. We also include here the conclusions of the project and a proposal of future work.

# Chapter 2
# Background

Precision agriculture combines knowledge from two fields traditionally distanced, agronomic industry and electronics/telecommunications technology. In this chapter we introduce and explain all the concepts from these two fields necessary to understand and carry out this work. We start talking about precision agriculture and the implication of IoT technology on it. The focus will be on the use of soil moisture sensors for sensor-based irrigation. After this we explain what soil moisture is, how it is measured and how these measurements must be interpreted. We also explain how different factors like weather, irrigation technique, type of soil or type of crop can modify the behaviour of soil moisture. Finally, we discuss different sensors and techniques used to measure soil moisture, including the current solutions in the market.

## 2.1 Precision agriculture

**Precision agriculture** or **PA**, is an approach to farm management developed along the last years with the intention of maximize the economic return and quality of the products while minimizing the use of resources, risks and environmental footprint. To achieve that, PA combines several technologies to adapt to spatial and temporal variability of the crops and environmental factors [37].

Selective application of pesticides or fertilizers, automatized irrigation based in soil moisture sensors or selective nutrient supply based in historical data are just some examples of what precision agriculture can do. To understand spacial and temporal variability and take advance from it PA uses several technologies like Global Positioning System (GPS), geographic information system (GIS), automatic control devices, mobile computing, remote sensing, internet of things (IoT), advanced information processing, artificial intelligence, robots, satellite and drone imagery between many others [28, 37].

Farming can look a simple task; Nevertheless, it is extremely complex, spatial variability involves infinity of parameters (e.g. soil moisture, weather situation, terrain features/topography, nitrogen levels, PH, etc.). That variability makes very difficult for the farmer to do an optimal management of the field using only its observation and experience. PA use predictive analysis software to combine all the data available (real-time and historical records) to provide the farmer a decision support that ensures optimal management [28, 37]. Precision agriculture covers such a big number of technologies, parameters and applications that is very difficult to explain in a few paragraphs. In summary, we define PA as application of several technologies and data processing techniques to ensure an optimal farming management. Apart from that, PA also provides traceability and prediction, useful for economical planning.

### 2.1.1 IoT in agriculture

We define IoT as grouping and interconnection of devices and objects through a network (internet or private networks) where all of the devices can interact. IoT devices can be sensors, mechanical actuators, or everyday objects such a smartwatch. Infinity of objects can be connected to internet using what we know as machine to machine connection (M2M) [12].

In agriculture, IoT helps farmers to control their crops and manage them efficiently. The key role of IoT in agriculture is remote sensing and control. The recent improvement of IoT sensors has created cheap, reliable and small devices allowing the deployment of huge wireless sensor networks that can cover big areas of land and provide real time data about soil moisture, temperature, crop height, plague detection etc. These networks provide the necessary data to maintain a decision support system (automated or not) that helps the farmer to know when and how should take actions to keep their crops healthy and productive. An example of this systems and the core of this work is sensor-based irrigation.

### 2.1.2 Soil moisture sensors in agriculture, sensor based irrigation

Moisture sensors are useful for several tasks in agriculture, the most important one is sensor-based irrigation. Current sensor-based irrigation systems work measuring the moisture periodically, according to the sampling frequency. Every certain time, the datalogger connected to the sensors sends the last readings to the farmer by the cloud. If these readings report a soil water content too low, then the irrigation is activated by sending an order to remote actuators placed in valves, sprinklers or pumps. The definition of sensor-based irrigating will be extend in the chapter 4, until then is enough to know these concepts:

- **Sampling frequency or sampling interval (SI):** defines how often the sensor takes a sample from the soil.

- **Irrigation (inferior) threshold (IT):** Level of water content from which the soil is considered dry and irrigation is needed.

- **Superior threshold or irrigation target:** desired level of water in the soil after irrigation.

## 2.2 Key concepts about soil moisture

In this section we introduce some concepts about soil moisture and how it must be interpreted.

### 2.2.1 Soil moisture and water content

Soil moisture has different meanings according to the discipline in which it is used. For example a farmer will use it to know if its plants has enough water to grow healthy. Meantime, for a weather forecaster soil moisture will help to determine the development of precipitations and weather patterns as soil moisture has a huge influence in soil evaporation. Other uses of this parameter are flood control, soil erosion prediction or reservoir management.

Despite all different uses, we define soil moisture as the amount of water stored per metric unit of soil, from now **Water Content (WC)**. **Gravimetric Water Content (GWC)** defines the mass of water per unit of dry soil, while **Volumetric Water Content (VWC)** express the volume of water per volume unit of soil usually as $m^3/m^3$ or percentage [16, 26].

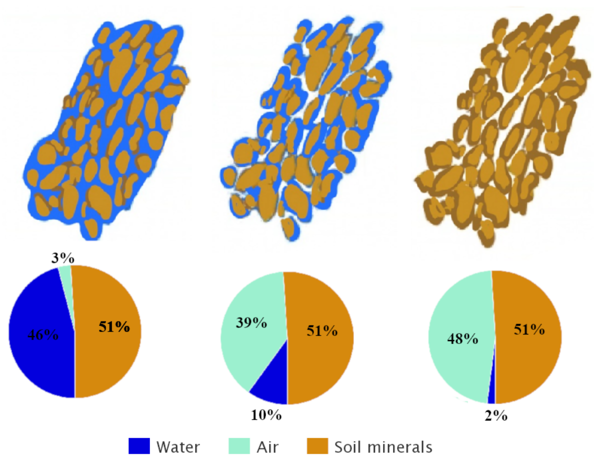



Figure 2.1: Different compositions of soil. Adapted from [26]

### 2.2.2 Evapotranspiration, Saturation, Field capacity, Permanent wilting point and Recharge point

There are some significant levels of soil moisture we must define. After a rain event or irrigation, soil pores will be filled with water, if the watering event is large enough and all the pores get filled with water we say that the soil is in state of **Saturation** or saturated, at this point there is no air left in the soil.

After the watering event stops, water move downward by effect of gravity in a process known as **drainage or infiltration**. During this event, air replace part of the water in the biggest pores while the smaller pores remain full of water. **Field capacity**, **FC** from now, is the maximum amount of water that can be held by the soil after a period of drainage, this point is also the superior limit of available water for the plant optimal for a good absorption of water and nutrients [26, 16].

Once FC is reached, if there is no any watering event, the roots of the plant keep taking water from the soil. That water is used by the plant for its vital processes and then is released to the atmosphere as vapor in a process called **Transpiration**. At the same time, due to atmospheric factors like sun or wind, soil water is converted into water vapor in a process called **Evaporation**. The combination of this two processes is known as **Evapotranspiration**. Evaporation and transpiration has different contributions to soil drying according to the state of the plant and the season [26, 5].

As the drying of the soil continues because evapotranspiration, remaining water will get more and more difficult to be extracted by the plant's roots. At the point when water absorption is not sufficient to satisfy plant's vital needs, the plant starts to dry and if the situation is prolonged, it would die. This point is known as **Permanent wilting point (PWP)**. Permanent wilting point is different for each plant and soil, for example in a sandy soil PWP can be below 1% of VWC while in a clay soil is around 25-30%. An important annotation here is that the plant starts suffering before reaching the PWP, it only indicates the lower limit for which the lack of soil moisture can kill the plant [26, 16].

The last significant value we highlight is **Point of recharge (PR)**. PR is a water content level between FC and PWP for which the water absorption of the plant starts to decrease significantly. This point defines the moment when plant starts to suffer significant stress due to water deficit, what affects its health or yield. This value is different for every plant and soil but can be estimated in an intermediate point between FC and PWP [8]. This value is specially useful to determine the irrigation threshold. In the table below, we include the VWC values of FC and PWP for different soils, so a specific value of VWC will be considered wet for a type of soil but dry for another.

Table 2.1: FC and PWP in different soils [26].

| Soil | FC | PWP |
|---|---|---|
| Sand | 5% | 1% |
| Sandy loam | 17% | 1% |
| Loam | 27% | 14% |
| Silty loam | 27% | 13% |
| Silt | 24% | 10% |
| Silty clay | 40% | 28% |
| Clay | 42% | 32% |

### 2.2.3 Water content vs available water

As explained in 2.1 VWC reference values are different for different soil what makes them impossible to compare without knowledge of the soil. Nevertheless, there is a parameter directly related with the available water for the plant and independent from the type of soil, this parameter is known as **matric water potential**.

Matric water potential is the potential energy per mole of water referenced to pure water (zero potential). In other words, it is the amount of energy you need to overcome to displace water. Water moves from high energy places to lower energy parts to reach equilibrium [26]. This value indicates also how difficult is for the plant to move the water from the soil to the roots.

As VWC, matric potential can be directly measured from the soil, using a special tool called tensiometer. Matric potential is measured with pressure units, an optimal range for the plant goes from -2 to -5 kPa corresponding with the very wet side, until approximately -100 kPa where the plant will stay healthy, below that plants will be in deficit, and past -1000 kPa they start to suffer damage. Depending on the plant, the permanent wilting point will be between -1000 and -2000 Kpa [26]. We can use the matric potential for sensor deployments in unknown soils, the readings obtained from the tensiometer are useful to determine references of FC and PWP no matter the type of soil.

The picture below shows an example of potential gradient in a plant. As water goes from higher energy places to lower ones, it is possible to deduce that water will pass from the soil to the roots, after that to the xylem and leafs and finally will be released to the atmosphere by transpiration.

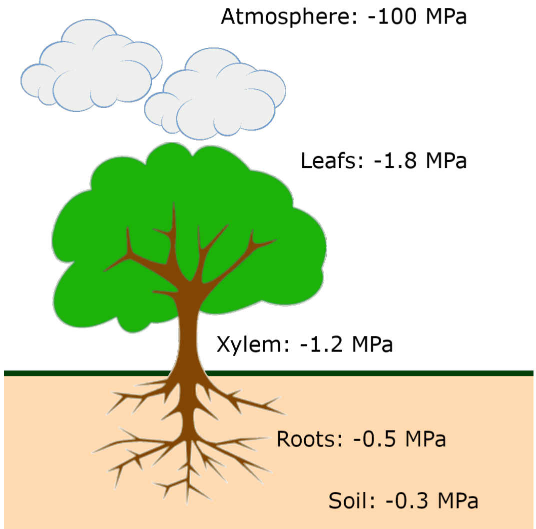



Figure 2.2: Example of water potential gradient in a plant. Adapted from [26].

### 2.2.4 Water deficit and plant stress

Water deficit, also called plant stress or only stress is the lost of yield, production or health of the plant due to absence of available water in the soil. As mentioned in 2.2.2, PWP is the point when plant can no longer extract water from the soil to survive however, the stress starts much earlier, approximately below PR. Moreover, water deficit is also influenced by time. A long period with slight lack of water can be worse and cause more stress than a short period with a very dry soil. Because of that, we will define water deficit or stress as the product of time of VWC below PR and average VWC value below PR during that period.

## 2.3 Factors that affect soil moisture behaviour

A good understanding of the environment is necessary to predict how soil moisture will change. In this section we discuss factors like weather, soil properties, vegetation or irrigation method that determine how fast the soil dries and gets wet.

These factors will be essential to create the soil moisture model in the chapter 6 that we will use in this thesis to carry different simulations. Moreover, if we are able to predict future likely values of moisture this will help us to develop advanced sensing strategies focused in moments when the VWC value is more critical.

### 2.3.1 Soil properties

The first factor that we analyse are the soil properties. When water is supplied to a field, it penetrates into the soil by infiltration. How fast it happens determines the infiltration rate. At the same time it depends on different factors such as soil texture or water content. This parameter will be really useful for us because it is directly related with the drying speed of the soil [5].

#### Soil Texture

In soils with high bulk density, water penetrate and move easily into bigger pores. Because of that, it takes less time to infiltrate into the soil. In other words, infiltration rate is higher for soils with thick grains than for fine textured soils. If the soil gets wet faster, it will also dry faster [5, 1].

These are the characteristics for each type of soil:

- **Sandy soils** usually have very high infiltration rates. That means sandy soils dry out very quickly. Sandy soils can hold few water because the range between FC and PWP is small [10].

- **Silty-loam soils** have moderate infiltration speed. This type of soil holds more water than sandy soils, because of that, drying speed is also slower [10].

- **Clay soils** have notoriously slow infiltration rates. These soils can store much water but also, as infiltration rate is small they can become waterlogged easily. As this type of soil holds a lot of water, the drying process will be slow [10].

- **Containerized soil** works different. Compared to field soils, in containerized production is important to take into account the volume of soil in the pot. The less soil in the pot, the faster it will dry because the absorption of the plant [19].

#### Soil moisture content

The water infiltrates faster when the soil is dry than when it is wet. When the soil moisture is between saturation and FC moisture decrease faster because the effect of infiltration. Between FC and PR, the drying curve has a constant slope (it is linear), after PR the drying speed progressively decreases by the effect of soil depletion, see 6.1.5 [5].

#### Soil structure

Generally speaking, water infiltrates quickly into granular soils and slower into massive and compact soils. Cracks or holes increase the infiltration rate. Also farmer cares to the soil like plowing affect the infiltration rate [5].

### 2.3.2 Crop effect

The crop that covers the soil has really big influence in the evolution of soil moisture. Bigger plants or thick plantations extract a lot of water from the soil by the effect of transpiration. But also, big plants with leaves will shadow the soil decreasing the evaporating power of the sun. This phenomenon is difficult to model. However, the Feeding and Agriculture Organization of the united nations, **FAO** from now, defines a method to estimate this effect as well as specific parameters for each type of crop. All this information is compiled in a guide for determination of water needs of the crop [5]. This guide will be mentioned several times in this thesis as it also covers the effects of the weather.

### 2.3.3 Atmospheric conditions

Weather can affect in two ways to WC. Firs of all rain will obviously increase the WC. In the other side, other phenomenon like temperature, sun radiation, wind or relative humidity determine the evaporating power of the atmosphere. It can seem obvious that higher temperatures or wind speeds increase the evaporation. However, as there are several factors involved it is difficult to model. Again, as for the effect of the crop, FAO's guide define a method to estimate the effect of the weather in the evapotranspiration using the Penman-Monteith equation, it will be explained in the chapter 6, see 6.1.2.

#### Rain

That rain wets the soil is clear. However, rain has other implication, taking into account the rain forecast can make the farmer skip or delay irrigation events in order to save resources and avoid over-wetting the soil. In automated irrigation systems, weather forecast is and important input to plant irrigation events.

### 2.3.4 Irrigation method

We define irrigation as application of controlled amounts of water to crops at desired intervals. How water is applied to soil has a huge effect in how fast moisture increase. If we know the type of irrigation, we will be able to predict moisture evolution with more precision. The most used irrigation methods are described below.

#### Surface irrigation

Surface irrigation is the most used since ancient times. It works distributing the water through channels or furrows arranged along the crop area, if all the area is covered with water it is known as flood irrigation. When the farmers decide to irrigate they let the water flow through the surface and the gravity distributes it into the soil [44]. Surface irrigation floods the soil temporarily so, the soil absorbs water as fast as it can, usually the peak level of moisture is reached after few minutes from the water event.

#### Drip irrigation

Drip irrigation, also known as trickle irrigation, distributes the water drop by drop to the plants using pipes strategically placed on the crop surface. Along the pipe there are several holes or nozzles in the desired irrigation points. Drip irrigation events usually last for hours, increasing soil moisture slow and constantly, because of that it is easy to automate and control to maintain fixed level of moisture. This method is very efficient and is suitable for soils with low water retention [44].

#### Sprinkler irrigation

Sprinkler or overhead irrigation is a system that moistens the soil in a similar way to the rain. Water at high pressure is pumped into pipes, at the end or along the pipes there are sprinklers or spray guns that pulverize the water above the plants. This system is good to cover big areas and is also easy to control and automatize. Irrigation events for sprinkler systems are usually shorter than drip irrigations, normally they lasts minutes but can reach several hours. In general, we expect a faster wetting process than drip irrigation but slower than surface irrigation, it will depend mostly on the flow of the system [44].

#### Subirrigation

Subirrigation delivers the water directly to the plant root zone, recollecting the exceeding water to reuse. This method is mainly used for potted plants in greenhouses. Subirrigation presents several variants with different moisture behaviour between them. Moisture evolution can be from a fixed value with very small variance to periodical irrigation events with fast changes. Moisture sensors can be used to control this method but, as is very difficult to control water absorption they will be only useful to establish an irrigation threshold but not to stop it [35].

## 2.4 Soil moisture measurement

Until now, we have explained what is soil moisture and how it behaves. Now is turn to explain how it can be measured. Even though this work is related with IoT sensors, we consider proper to explain other alternatives to measure WC as well as the different type of sensors available in the market.

### 2.4.1 Direct method, gravimetry

GWC defines the amount of water per unit of soil in terms of mass. It is the most basic method to measure soil water content and is divided in three steps. First of all we need to take a sample of soil and we weight it, after that we dry the sample in an oven until all the water evaporates, finally we remove the dry sample from the oven and weight it again. GWC is calculated as the wet soil weight minus the dry soil weight and then divided by the dry soil weight [26]. Gravimetry is the most precise method and does not require special or expensive hardware. However, is a invasive method that needs a lot of time and labor.

### 2.4.2 Sensors

Measure the water content by GWC technique is precise and simple but not practical in most cases. Sensors instead can read directly from the soil giving in-situ measurements. There are several types of sensors that will be described below.

#### Resistive sensors

Most restive sensors consist in two probes working as electrodes, a voltage difference is set between both probes creating a current flow through the soil. Measuring the current we obtain the value of resistance or conductivity, directly related with the VWC. As the soil is considered as dielectric, current will only flow through water included in the soil, more water means better conductivity.

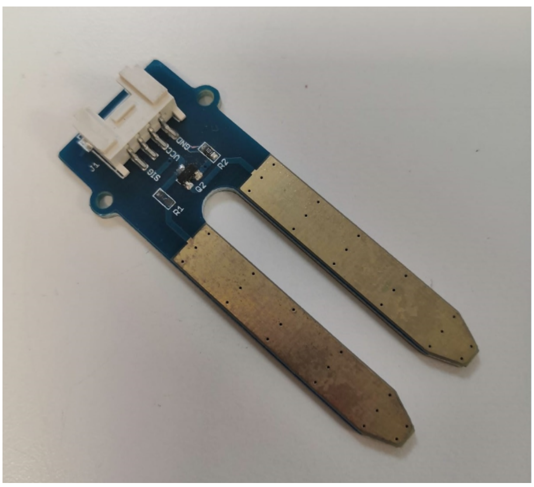


Figure 2.3: Resistive sensor

Resistive sensors are cheap and easy to use but they present a lot of drawbacks. First of all, water itself is a very bad conductor, it needs dissolved salts to be conductive so, current flows through water's ions, water composition and amount of salts can be very different depending on the source; Hence, the sensor will output different values in different soils with the same amount of water if the concentration of salts is different. Another big inconvenient is their low durability due to corrosion, the voltage difference and the metallic composition of the electrodes make them very vulnerable to rust and corrosion, limiting the durability and precision along the time. One last drawback is a smaller area of influence compared with other kind sensors, the measurement is only representative for the soil between both probes.

In conclusion, resistive soil moisture sensors are very cheap and easy to use; however, due to its lack of precision and life are not suitable for research or industrial use. Nevertheless, these sensors can be the best option for home gardening or low cost projects.

### Dielectric sensors

Dielectric sensors measure the charge storing capacity of the soil and relates it with VWC. Soil is composed of solids, liquids and gases. In the same soil, solids will not vary in the short term so only the proportion of water and air change during watering processes. Solids and gases in the soil has in general small dielectric constant compared with water, (air has a dielectric constant $\epsilon_r = 1$ , soil minerals between 2 and 30, and water around 80). As solids do not change, only WC variations will modify the dielectric constant. As explained, only air-water proportion will vary, measuring the changes dielectric constant of the soil is a very good approach to obtain the soil moisture as dielectric of soil is directly related with VWC [26, 24].

Dielectric sensors has a clear advantage over resitive ones. Dielectric sensors use high frequencies (above 50 MHz the influence of salinity is highly mitigated) to polarize water molecules quickly, that aligns them and cause a small charge storage. The good thing is that salt ions are not polarized in that small time, making the measurement less sensitive to the presence of salts [26].

We can distinguish three main types of dielectric sensors:

- **Capacitance:** Capacitance sensor determines the dielectric permittivity of the soil by measuring the charge time of a capacitor in which the soil acts as dielectric element and the metal planks are attached to the sensor.

- **Time-domain reflectometry (TDR):** TDR sensors estimates the VWC by measuring the travel time of a reflected wave along a transmission line, in this case, the soil. The travel time is related to the dielectric constant of the soil and hence to the VWC. These sensors has very high accuracy and fast response time; However, TDR sensors are expensive, complex to set-up and has high power consumption.

– **Frequency-domain reflectometry (FDR):** FDR probes are a variant of capacitive sensors, they consist of two or more capacitors inserted into the soil. The capacitors use the soil as a dielectric, so water content will affect the value of capacitance. The capacitor is connected to an oscillator to form an electric circuit, changes in soil water can be detected by changes in the circuit's operating frequency. FDR sensors are slightly less precise than TDR. Nevertheless, its price is significant lower as well as its complexity and power consumption.

One example of capacitive sensor is shown below. This sensor is a VWC sensor called Teros 11, it also measures temperature from the soil. From the three needles two act as metal ends of the capacitor and the reads the temperature. This is one of the sensors we will use later for data collection.

Figure 2.4: Teros 11 VWC capacitive sensor

### Tensiometer

As explained in 2.2.3, water matric potential is the parameter that can defines available water in the soil. Water potential has several components but in unsaturated soils matric potential is the most significant, tensiometers measure it [26]. There are different types of tensiometers with different construction, each of them is more suitable for different ranges or applications. Tensiometers has different versions but in general typically consists of a tube or container with a porous ceramic cup filled with water. The tube has a needle to measure the pressure inside the tube. The device is buried, and partial vacuum is created inside the tube. As plants absorb water from the soil, pressure inside the tube will decrease. According to its design, tensiometers can be also considered manual devices instead of sensors.

The advantage of tensiometers above VWC sensors is that its readings indicate directly if the soil is dry or wet and how difficult is for the plant to extract the water. Unlike VWC sensors, if we use tensiometers we don't need to know the properties of the soil. The drawback is that tensiometers are more expensive and some models require frequent maintenance. In the picture below we can see the tensiometer Teros 21, a small format tensiometer which will be the second of the two sensors selected for data collection.

Figure 2.5: Teros 21 Tensiometer

### 2.4.3 Other methods

Apart from sensors and gravimetry, there are other available techniques to measure soil moisture.

#### Neutron probe

Due to its complexity and operation, we consider neutron probe as a device rather than a sensor. Neutron moisture probes work throwing fast neutrons, into the soil and then measuring the number of slow neutrons that bounce back. Fast neutrons are slowed down only by large atoms such as Hydrogen, clearly present in water particles. More slow neutrons returned means more presence of water in the soil. First neutron probes were developed in 1950s and since then have been considered a reliable and easy to use measurement method, neutron probes has a good volume of influence and high resolution and are insensitive to salinity. However, the cost is relatively high and as they work with radioactive elements the operator needs special care and licences. Because of that, neutron probes are used only for specific applications or punctual measurements and are not suitable for remote applications or IoT devices [36].

**Satellite:**

It is also possible to estimate soil moisture using satellites; NASA has a satellite called SMAP (Soil Moisture Active Passive) that measures surface soil moisture content and the state of the ground (frozen or thawed). Reading are done around the world frequently and is used to predict forecast extreme weather events, manage water resources or optimize agricultural practices. However, this method measures only wide areas and is not in the ambit of this thesis [29].

## 2.5 Market solutions for soil moisture monitoring

With the current technology, sensors must be connected to a device or datalogger that controls and power them. This device, is also responsible for the transmission of data to the user, cloud or irrigation system. There are several options in the market that include the sensors, the datalogger and a cloud platform to check the data, in this section we describe two of these products.

### 2.5.1 Zentra by Metergroup

Zentra is the name of the cloud used by Meter, the system core is the ZL6 datalogger. ZL6 supports up to 6 sensors which are plug and play and very easy to install. Manufacturer also provides several series of compatible sensors, TEROS to measure moisture and soil properties or ATMOS which includes different weather stations are just some examples. The device is easy to use and configurable via Bluetooth or Web. It integrates GPS, barometric pressure measurement and a Built-in solar panel that gives more than 3 years of power autonomy in a placement with unobstructed view of sun. The sampling interval can be set by the user from 5 minutes to 12 hours, transmissions are fixed hourly but can be more frequent for an extra charge. The communications with the cloud are done via 3G, 4G or 2G (back-up). The price of the datalogger is around 650€ (6500 NOK) and 180 (1800 NOK) the cost of the yearly season pass to transmit the data and use the cloud platform [23].

Figure 2.6: ZL6 datalogger

The picture below shows how the web interface looks like, it includes several features like real-time graphs, online configurations, sensor calibrations or GPS location. The interface holds several dataloggers at the same time and allows to download all the records.

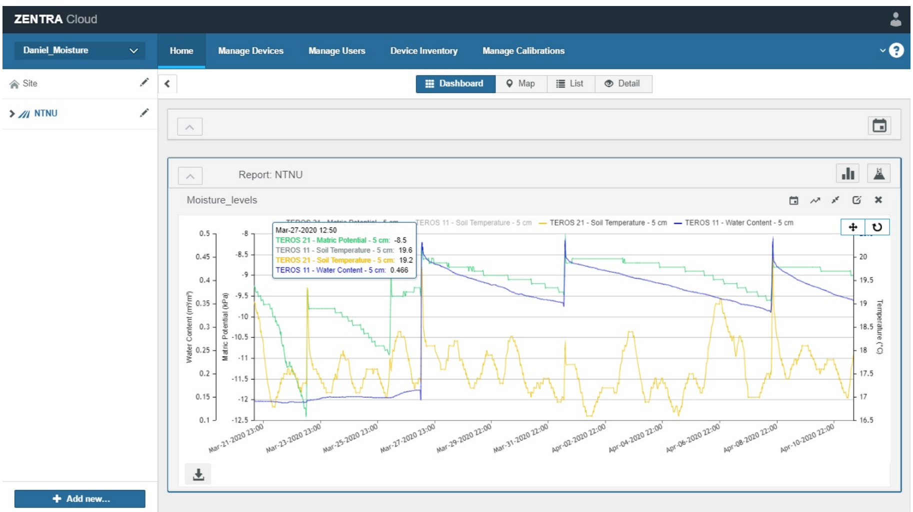



Figure 2.7: Zentra cloud

We will talk more about this hardware later as we chose it for our data collection experiments.

### 2.5.2 Markone, Arable

Arable is a Decision agriculture company that provides *"A global solution to managing weather risk and crop health, delivering real-time, actionable insights from your field"* [2]. Its star product is Arable Mark 2.

Mark 2 has a built-in solar panel and is self-sufficient. It can be used to manage irrigation, predict disease risks or calculate plant stress. The device combines external weather forecast with own measurements using machine learning to provide local forecasting. The device itself is able to measure precipitation, Evapotranspiration (ETc), crop coefficient ($K_c$), solar radiation, plant health indicators, temperature, humidity and atmospheric pressure. For more precision, external sensors like soil moisture probes can be connected to the device. All the readings can be checked using the cloud-based platform. The sampling interval varies based on the property being measured, for soil moisture, soil salinity and soil temperature, Mark 2 devices log data from Sentek soil probes every 5 minutes. The cellular connectivity is done by LTE-M 2G or NB-IOT [2].

Figure 2.8: Mark 2 by Arable. Taken from [2]

This product present some advantages respect other products, it is fully energy-autonomous, it does plant measurements for calculate disease risk, detect changes in plant development, ore read Chlorophyll content evaluate plant performance. Also, the creation of hiper-local forecasts combining reading and third party information is something significant. The main drawback is the higher price compared with other products, Mark2 device costs 1595 $ (16370 NOK) from arable web, year subscription is 699 $ (7180 NOK) and Sentek moisture probes around 300 $ (3080 NOK) depending on the size.

# Chapter 3 Methodology

In this chapter we present the methodology used for this master thesis. The framework that evolves the full project is known as design science. Design science is presented in the section 3.1, in that section we also cover the design cycle, explaining the design process followed in this thesis. Finally, in section 3.2 we explain how we have applied the design cycle and the design science method to solve our problem and answer the research questions from the introduction.

## 3.1 Design science

Design science is a design process that investigate an artifact in its context. The aim of design science is to develop solutions or artifacts in interaction with its environment and influence factors to solve a certain problem [42]. The artifact can be anything created by humans, tangible or not, it can be a software a building or a book, whatever. The context is anything with interaction or influence with the artifact and the problem. Finally, the problem is what we want to give solution to by developing the artifact.

The process of design science is composed by three planes or contexts, the social context, the research part and the knowledge context. The social context include the stakeholders, their problem and their goals. The knowledge context would be all the background knowledge of related with the specific problem including available solutions, designs and knowledge from previous researches. The research plane uses the social context and the existing knowledge and designs as inputs to produce new knowledge or products through the design cycle. The design cycle is explained in the next subsection. The figure below shows a diagram that includes all the design science components.

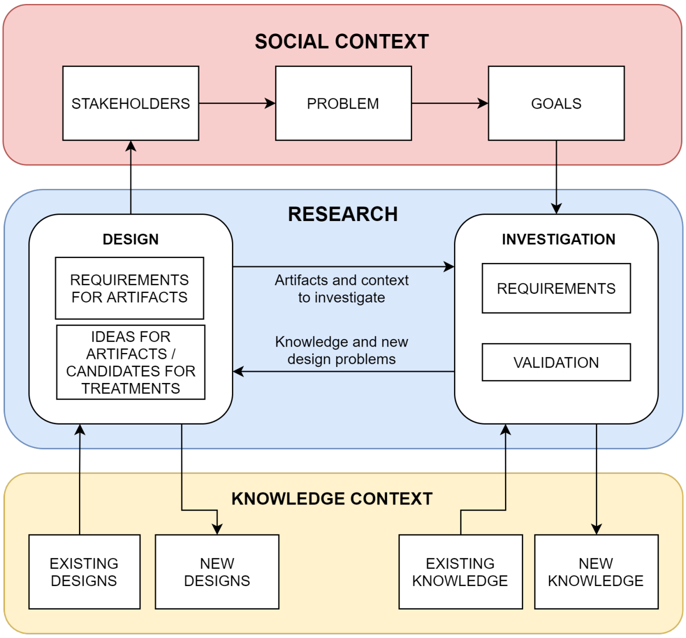



Figure 3.1: Design science framework, adapted from [42]

### 3.1.1 Design cycle

The design of any artifact in the context of design science follows a cycle known as design cycle.

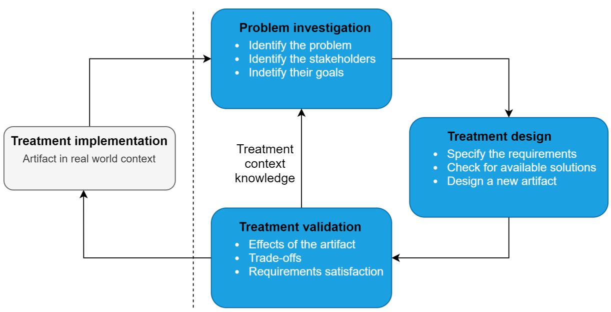



Figure 3.2: Design cycle diagram, adapted from [42]

The design cycle has 4 phases. We start with the problem investigation where we have to answer the question of which problem do we need to solve and why?, here we have to identify the stakeholders and their requirements.

After this, we go into the treatment design. First we have to translate the user requirements into technical requirements and check if there is already a solution that can solve the problem. In case there is nothing, we have to end up with a potential solution that could solve it.

The next phase is the treatment validation, here we have to find out if our artifact works and can solve the problem. In case the artifact does not solve the problem properly or just if we want some improvement, we should do one more iteration to the cycle. The acquired context knowledge from the previous iteration will help us to go in the correct direction and come up with a better solution.

Finally, the last step would be the treatment implementation, it is part of the industry business. It evaluates and implement the artifact in the real world context which it is not in the scope of this thesis.

## 3.2 Design cycle applied to this project

In our case, the artifact is the energy-efficient soil moisture measurement, the context smart-agriculture and sensor-based irrigation and the problem the poor energy management of the IoT sensors. Below we explain how we followed the design cycle and answered the research questions from the introduction.

#### Problem investigation

Our first step was to identify the problem. For that we reviewed and compared several articles, manufacturers web-pages and related literature. That helped us also to identify the stakeholders. We contacted and interviewed some of these stakeholders including users, manufacturers and experts. Combining the knowledge from the literature review and the stakeholders goals we answered the research question 1. *RQ1: What are the user requirements for a remote sensing system of soil moisture?*

#### Treatment design

For the treatment design we translated the goals into technical requirements. We looked for current solutions that could solve our problem. As we did not find any valid solution we started to design a potential artifact. As we developed the potential solution we answered the research questions 2 and 3. *RQ2: How can we evaluate the relevance of soil moisture data based in the user requirements and other related factors?*, *RQ3: How can we use the value of information of soil moisture to develop energy-smart sensing strategies?*

### Treatment validation

Once we had our potential solution we carried out several case-based simulations to verify that our it was valid and able to solve the problem. At this point we did some iterations through the design cycle to improve the results obtained. At this point we also answered the last research question *RQ4: How energy-smart sensing strategies can improve IoT soil moisture measuring and what implications could have?*. We also confirmed the research questions 2 and 3.

# Chapter 4
# User requirements

In this chapter we try to identify the user requirements for soil moisture measurement. First, we discuss different utilities for them in context not only of agriculture. After that we include the main ideas from three interviews with the stakeholders, two farmers and an agronomic expert. Finally, we summarize the principal user requirements a soil moisture monitoring system should cover.

## 4.1 Uses for soil moisture sensors

In this section we evaluate different uses of remote soil moisture sensors, not only in agriculture but other fields like weather modeling or soil studies. To define the user requirements is necessary to know how these devices work in each use case.

### 4.1.1 Irrigation management

Irrigation management is the most common use for soil moisture sensors and the core of this work. The sensors keep track of the soil moisture every certain time, this value helps the farmer to make a good irrigation planning. It also helps to produce healthy and quality crops, minimize costs and allows tailored solutions for specific problems related with soil or nutrients management. IoT soil moisture sensors can have different roles for irrigation management, they are presented next.

#### Irrigation automation, sensor-based irrigation

Sensor-based irrigation, the core of this work is also the most profitable use for soil moisture sensors, it saves not only water and energy but also manual labor.

In sensor-based irrigation, the farmer or agronomic expert defines an optimal VWC inferior threshold for which irrigation should be done, the sensor checks the moisture periodically, sending the readings every certain time. If the last readings indicate that the moisture content is below the fixed threshold, the system will turn on the irrigation system by sending an order to remote actuators placed in valves, sprinklers or pumps. Moreover, for certain irrigation systems like drip irrigation, where watering events lasts for hours and moisture increase slowly, the system is also able to turn the irrigation off when the soil is wet enough 2.3.4. In case, the moisture increases too fast or uncontrollably the solution is to fix the duration of the watering event, as the water flow of the irrigation system is known, farmers calculate how much the optimal irrigation length to reach the deeper roots properly while avoiding infiltration loses due to excessive watering. If the watering events can be divided, and distanced for short periods of time, the sensor can check moisture between them and determine how many times it should be repeated until reach the desired WC value [35].

#### Irrigation tuning

Irrigation can be also automated by using a timer, it is called scheduled irrigation. For this case and even for manual irrigation, moisture sensors can be used to fine tuning the process. Traditionally, the farmer checks manually if the irrigation is poor or excessive just by observation. However, its is not very precise, a temporal deployment of sensors can provide a feedback to farmer very useful to have a reference about how much should irrigate. Once the study is done, the sensors can be removed, so the investment required is reduced.

### 4.1.2 Regulated deficit irrigation, RDI

RDI should be included in the previous section as it forms part of irrigation management. However, due to its relevance in this work, we have included it apart.

Regulated deficit irrigation, RDI from now, consist on reducing the water applied to the plant in phenological periods in which a controlled water deficit does not significantly affect the production and quality of the harvest, saving water and energy [27]. RDI is specially useful in places where the availability of water is limited. Moreover, for some crops, induced period of stress in specific phenological stages can increase the quality of the product [32].

Apart from saving water, RDI allow us to control crop parameters like fruit size, vegetation, light regime, photosynthesis or solids concentration. For example, in vineyards, a period of water deficit during the maturing process of the grape is necessary to produce grapes with the desired concentration of sugars [39]. Across Europe, winegrowers are switching to RDI techniques in order to produce fine wines in a constant and homogeneous way [34]. Other use is for ornamental plants like hibiscus, too big plants are less attractive for the customer so RDI can be used to limit the growth of the plant [35].

An effective way to apply RDI is to change the irrigation thresholds, lowering them if we want to induce some stress to the plant. Control it precisely is only possible using techniques like sensor-based irrigation.

### 4.1.3 Soil erosion, prevention and study

In studies of soil erosion, experts and hydrologists records data like rainfall, wind or soil moisture to make predictions. Infiltration rate, explained in subsection2.3.1 is a function of soil moisture. If the soil is dry, infiltration rate is high so it can prevent soil run-off. However, if the soil is saturated and keeps raining, overland water flow may occur, eroding the soil. Monitor soil moisture is an important input to develop soil erosion models [43].

### 4.1.4 Weather modeling and water prevision from letting snowpacks

Soil moisture and meteorological phenomena are factors with mutual influence at local, regional and global scales. With the time, meteorologist has improved weather models including more parameters and data. Nowadays, most advanced weather stations also include systems to read soil moisture [7].

Other application related with the weather is prevision for reservoir recharge from snowpacks. The volume of the snowpack can easily be estimated. However, the amount of water that will reach the reservoir when the snow melts is highly influenced by soil moisture below the snowpack. A dry soil will absorb a significant amount of water that will not reach the reservoir, while a saturated soil will not absorb almost water causing possible flooding in lower grounds[43].

## 4.2 Interviews to sensor-based irrigation systems stakeholders

To have a better approach of what a real user would want from a sensor-based irrigation systems we did the next interviews. The first two persons are greenhouse farmers from Almería and Murcia, the biggest emplacements of greenhouses in Spain. The last one is with the head teacher of the department of Plant Production in the Polytechnic university of Valencia. We do not include the full transcription of the interview but only the principal conclusions obtained.

**Farmer 1, greenhouse farmer in Murcia**

This farmer worked with a huge variety of greenhouse crops most of them with scheduled automated irrigation systems. He was unaware of sensor-based irrigation systems but provided anyway some interesting conclusions.

- In traditional agriculture, irrigation systems are controlled manually by the user using its experience and observation. In automatized systems, scheduled irrigation is the most used technique, specially in greenhouses.
- Irrigation needs to be specially precise in horticulture because these crops has higher water deficit sensitivity. For example, lettuce has very shallow roots and needs special care.

**Farmer 2, greenhouse farmer in Almería**

As the first farmer, this one works with a huge variety of crops, he admitted that most of his irrigation systems are scheduled based or manual. However, he was aware of sensor-based irrigation systems as he was in contact with some companies to start installing this technology in his farms. These are the most important conclusions he gave to us.

- Irrigation can not be automatized for every crop using scheduling as water needs change along the time due to weather conditions and plant growth. Even for inside crops where there is no rain, the effect of the sun has huge influence in water consumption of the plant in consecutive days.
- Sensor-based systems are a clear solution for the problem mentioned above.
- This technology is more useful and profitable for crops with high sensitivity to water deficit like lettuces therefore, this type of crops is where this technology is being implemented first.
- Irrigation in extensive crops like cereals is easier to manage as they are less sensitive and irrigation events needed less frequently. However, as these crops usually cover big or remote areas, sensor-based irrigation is also been implemented to save time to the farmer.
- In the case of vineyards the quality of the product is much more important than the volume. This quality is highly influenced by the available water during the fruit cycle. Too much water makes the grape excessive big and with lower quality and sugar concentration, water deficit also affects the maturing process. Sensor-based irrigation is a good solution for this, during last years this technology has been deployed in many vineyards in Spain.
- At least in Spain, sensor-based irrigation is something relatively new, the first mass deployments has started during the last two years.

**Agronomic expert, head teacher at School of Agricultural Engineering and Environment, Department of Plant Production, Polytechnic university of Valencia.**

- Irrigation based in soil moisture sensors is a relatively new technology, it is starting to be implemented.
- Most farmers that has installed this technology do not know how to program the system. They just let the technicians do the job.
- Moisture sensors are used to know when to start and stop irrigating, irrigations are done mostly once a day but can be more often if there are infiltration problem.
- Moisture monitoring is more profitable in crops with high sensitivity to moisture deficit and is where is starting to be implemented first.
- Other useful parameter for farmers is electrical conductivity of the soil, it is related with the amount of salts and helps to determine the washing needs of the soil (To keep low the amount of salts). Weather sensors are also used to adapt water needs.
- The price change a lot for every application but he estimates an average of 1.000€/ha (10.000 NOK/ha).
- In their researches they use mostly Teros 10 capacitive probes for in-field measurements.

## 4.3 Requirements conclusion

The interviews and the literature review provide us with a clear conclusion. Sensor-based systems has a proved utility and are profitable for several variety of crops. They will be mass deployed during the next years, however, most farmers are not aware of how do they the work, they will just install it and leave the management to the experts. This make us realize that this systems to automatize irrigation or just to sense soil moisture should be as much autonomous and simple as possible. Settings like sampling frequency shouldn't be decided by the farmer.

In the next chapters, these conclusions will work as baseline for possible smart sampling strategies or management of soil moisture sensors.

Chapter 5

# Data collection

Data collection was specially important for this work because we could not find any moisture data-set. If we wanted to know how soil moisture changes in a real use case and how it is reflected in the measurements we had to do it ourselves. With that aim we acquired two sets of hardware, the first of them was recommended to us by some irrigation companies. The other set is a cheaper solution recommended for home gardening projects. In this chapter we present the selection of hardware and the experiments we did to obtain raw data of soil moisture.

## 5.1 Selection of hardware

The selection of hardware was not easy, there was several options in the market. We asked to some irrigation companies and experts what kind or model of sensors they were using and half of them answered Teros10, a VWC capacitive sensor from the company Meter. We investigated this sensor and its manufacturer and discover that they had a full series of sensors to measure soil moisture content. They also provided the datalogger and a cloud platform for a reasonable price. Because of that we opted to acquire the next hardware.

The first sensor is the Teros11, this sensor measures VWC and soil temperature. This model is easy to install, has a long-life, a good accuracy of $+/-$ 3% in the worst case and $+/-1$ on average but, specially we chose it because it is similar to the sensor recommended by the experts we asked. To complement the readings and have a reference we acquired the tensiometer Teros 21, also easy to install and really useful to obtain references of FC and PWP in unknown soils. We also purchased the cloud season pass to have better access to the data, more detailed information from this hardware is included in the last section of chapter 2, see 2.5.1.

(a) ZL6 datalogger

(b) Teros 11 VWC sensor

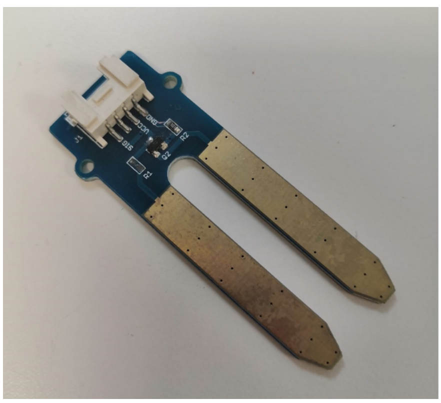
(c) Teros 21 tensiometer

Figure 5.1: Professional hardware for soil moisture reading

Furthermore, to start with, we acquired some cheap hardware. It consisted in two resistance soil moisture sensors of around 20 NOK and a Raspberry Pi 3 b+ to control and store the readings. This combination is usually recommended for home projects of gardening.

The purpose for this hardware was double. First, to get an overview and understand the process of soil moisture measuring and irrigation before start using the professional hardware. The second purpose was to do a side experiment to compare the data obtained from professional and cheap hardware, placing them in the same soil. This experiment would help us to understand the relevance of accuracy in moisture measuring, and also consider the option of reducing costs.

(a) Raspberry pi



(b) Cheap resistive sensor

Figure 5.2: Cheap hardware for soil moisture reading

## 5.2 Cheap sensor with raspberry

To collect the first data, we placed two resistance probes in a little pot as is shown in the picture 5.2 and started reading the moisture content in periods of of 5 minutes.

The first steps to acquire data were frustrating and several drawbacks from the cheap sensors were quickly revealed. In first place the measures needed several hours to stabilize. Once installed, the readings increased slowly for several hours without any kind of irrigation. We also found that there was some offset between both probes even they were placed in the same soil. Other drawback is that the sensor output consist on absolute values that need to interpreted differently for different soils or calibrated using a tensiometer. Finally, after one irrigation, one of the sensors was in contact with water, it was damaged and we had to replace it.

Once everything was installed and the readings stabilised, we left the system acquiring data each 10 minutes. The sensors were reading for a month with a little irrigation event as done in the middle and a big one at the end. The result is shown in picture below.

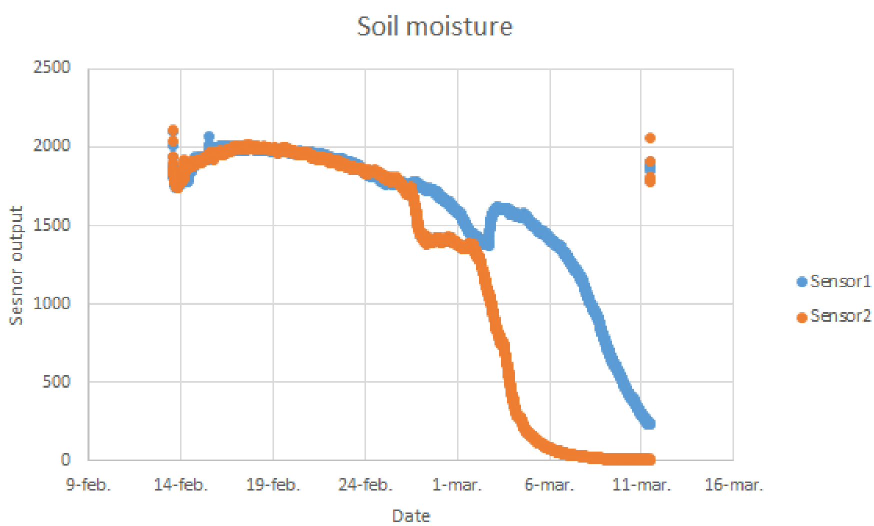



Figure 5.3: Readings from the restive sensors

In the graph we can see all the readings from the pot during a month. Each color represent one sensor. The outputs are represented in the y axis and the date in the x axis.

The conclusions we obtained is that the sensors worked more or less properly in the mid-dry range but very imprecisely in the wet end. The maximum output was reached even before reaching FC, very far from saturation. The deviation between the two sensors is also clear. The system is useful to inform about when the soil is dry and when is wet but that's all. The precision is not enough to manage a precise irrigation. The system can be useful in situations where an optimal development of the plant is not critical like home gardening or in crops with very low sensitivity. However, the accuracy is not suitable at all for precision agriculture. Because the low performance of the resitive sensors we decided not to continue with the side experiment and use only the readings from the professional hardware.

## 5.3 First contact with Teros 11/21

For this experiment we used for first time the professional sensors from Metergroup, Teros 11 for soil moisture and temperature and Teros 21 for matric potential. Both sensors were connected to the ZL6 datalogger. This experiment was done to check the correct operation of the system, including the wireless connection, soil calibration and performance of the sensors.

The first contact with the meter system and Zentra cloud revealed an easy handling and a correct operation of wireless transmission. After that, the chosen sensors (Teros 11 and Teros 21) were placed in a pot with 3.8 liters of dry soil. Controlled amounts of water were added periodically to verify the concordance and see the how the wetting process affected the measurements. The system is shown in the picture below.

Figure 5.4: ZL6 datalogger and sensors placed in the pot.

After ten days of readings and irrigations the result obtained is presented below, the left vertical axis shows the matric potential in kPa while the right one the VWC in $m^3/m^3$.

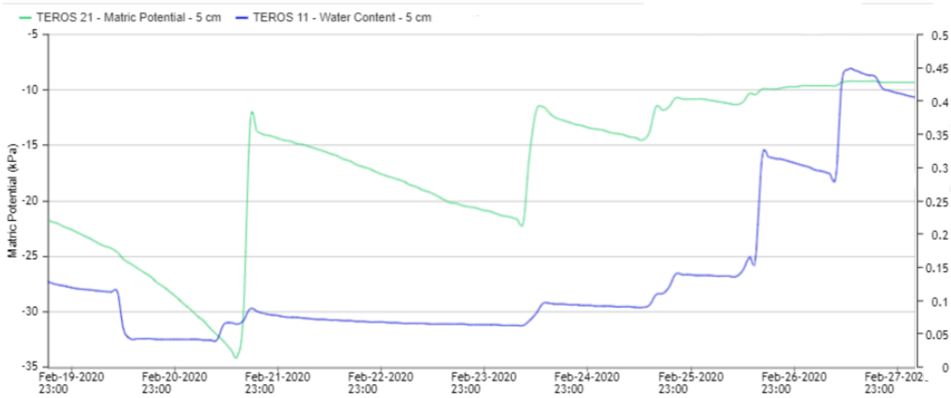



Figure 5.5: First readings from Teros sensors

The following events are shown in the graph.

- Quick drop at the beginning in VWC. We found some discordance between the water added and the readings of the sensor so we changed the soil calibration.
- The first and second jump correspond with irrigations of 125 ml.
- Third and fourth are irrigations of 250 ml.
- The last two are irrigations of of 500 ml.

To test the concordance we did a correlation with the increment in the readings and the real increase, calculated as the initial VWC plus the volume of water added divided by the volume of soil (3.8 l). The results are shown in the table below.

Table 5.1: Teros11 test

| Irrigation | Amount | Initial VWC | Result VWC | Expected VWC | Error |
|---|---|---|---|---|---|
| 24 feb 13:00 | 250 ml | 9.4% | 14.1% | 15.9% | -1.8% |
| 26 feb 10:00 | 500 ml | 16.5% | 31.1% | 29.6% | +1.5% |
| 27 feb 9:00 | 500 ml | 29.2% | 44.8% | 42.7% | +2.1% |

Even though there was no full concordance, we can say that the results are good enough. Any discordance may be because after irrigation, water is not perfectly spread so measurements can result higher or lower than usual. Moreover, the volume of soil is just an estimation as it was calculated by measuring the dimensions of the pot. From this experiment, using the readings of the tensiometer we also verified that there is no linear relationship between VWC and FC as explained in the background chapter.

## 5.4 Garden experiment

After the pot, we deployed the sensors in the faculty garden. It had drip irrigation with frequent watering events so looked as a good option for data collection.

Figure 5.6: Deployment in the faculty's garden

We placed the sensors between the 28th of February and 19th March. The result obtained is presented below, the left vertical axis shows the matric potential in kPa while the right one the VWC in $m3/m3$.

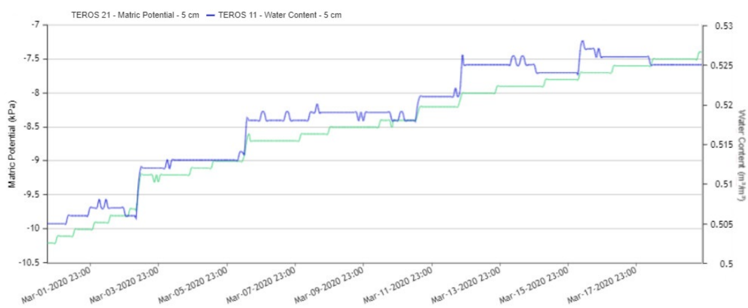



Figure 5.7: VWC and matric potential from garden readings.

The results were not what we expected, VWC was always above 50%, indicating that the soil was almost saturated. The readings from the tensiometer were increasing every day, indicating that more water than the plants used was being applied. Despite the results didn't show any dry-wet cycle, we can have some important conclusions anyway. The irrigation was excessive, using more water than plants needed. If the irrigation would have been controlled by sensors this problem would have been avoided.

## 5.5 Sabuco experiment

Finally we placed the sensors next to a little sabuco tree. First in a pot placed indoors and later, in an outdoor garden directly placed in the soil. We can see the deployment in the next figure. Irrigation events were done roughly every 2-3 days.

Figure 5.8: Deployment of sensors in a sabuco tree

After several weeks we obtained the results presented below, the left vertical axis shows the matric potential in kPa while the right one the VWC in $m3/m3$.

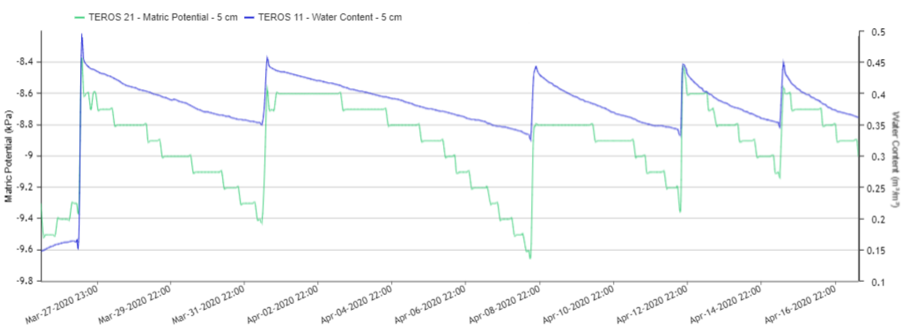



Figure 5.9: VWC from indoor sabuco experiment

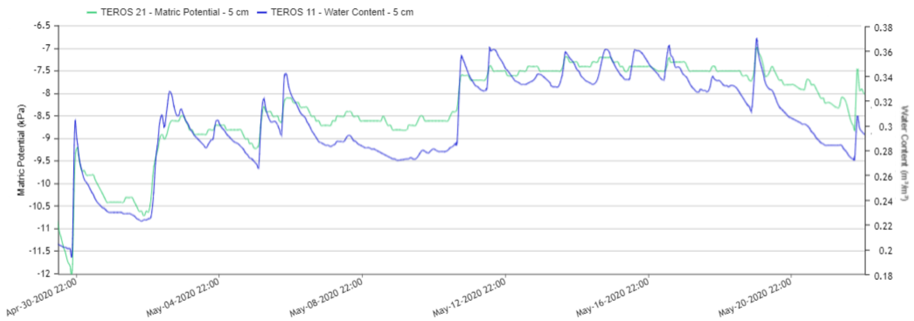



Figure 5.10: VWC from outside sabuco experiment

This experiment was the most useful, both graphs show several dry-wet cycles, necessary to understand how measurements from a real case look like. We also learnt how the effect of infiltration makes the VWC to decrease very fast after each irrigation event. In the other side, the effect of soil depletion is slightly appreciated in some wet-dry cycles, it means that due to lack of water, the plant decrease its activity and thus its water consumption, decreasing the drying speed after a linear period. This dataset will be be used in the next chapter to model the effect of infiltration and soil depletion. We can also see how the effect of the rain in the second graph make the moisture very unpredictable.

Chapter 6

# Models

For this thesis we did not have enough material and time to do a huge deployment of sensors and obtain real data from several crops to work with. Instead, we developed several models that simulate the behaviour of WC and different phenomena involved in the context of sensor-based irrigation. First of all, a model that recreates soil moisture content changes along the time was necessary to have a base to work with and apply possible sensing strategies on it. Moreover, we needed some metrics to check how good a sensing strategy is. For that we developed a stress sensitivity model, that estimates how much damage a plant has suffered due to late irrigations. Finally, as this work is related with energy management, we include the energy model from our hardware that describes the energy required to read and transmit the data. We also include alternative models that covers different energy consumption scenarios.

## 6.1 Soil moisture model

First of all, we developed a soil moisture model [1] that simulates how VWC would change in different use cases. The model is based in the FAO's evapotranspiration guide [5], the data collected and the knowledge obtained from the background investigation.

The model takes the following inputs:

- **Daily Weather data:** maximum, minimum and average temperature, wind speed at 2m, maximum, minimum and average relative humidity, atmospheric pressure, number of sunshine hours per day and latitude.

- **Soil parameters:** Saturation, FC and PWP.

- **Irrigation parameters:** Initial level of water content and upper-lower irrigation thresholds.

[1] All the python models are included in the appendix

- **Crop parameters:** Crop coefficient ($K_c$) for each phenological stage with its respective duration in days and planting date.

### 6.1.1 General expression

Our model calculates VWC every five minutes using the equation below. This equation is a personal adaptation of ET estimation method included in FAO's evapotranspiration guide [5]. From this guide we took the calculation of $ET_o$, the values of $K_c$ and the idea to multiply them to obtain daily ET considering the weather ($ET_o$) and the effect of the plant ($K_c$). Apart from that, we added the depletion and infiltration factors ($K_s$ and $K_i$) that simulates the effect of fast dry after irrigations, and the slower drying speed as WC decreases. The equations to calculate $K_s$ and $K_i$ were develop by hand using the knowledge from the literature review and the observation from the data recorded. Finally, we add the element of rain to simulate how rain events increase WC.

Once we know how much water the atmospheric elements and the plant subtract from the soil daily, we split the value in 5 minutes intervals to calculate the WC in small time steps. The general expression in presented below and the calculation of each element later.

$$VWC(i) = VWC(i-1) - ET_o * K_c(stage) * K_s(WC) * K_i(WC) + Rain(day) \tag{6.1}$$

Where:

- **VWC** = Volumetric water content in %.
- **(i),(i-1)** = Actual moment and previous moment (5 minutes before).
- $ET_o$ = Adapted evapotranspiration to 5 minutes intervals using FAO's evapotranspiration manual [11], based in Penman-Monteith equation.
- $K_c$ = Daily crop coefficient from FAO's evapotranspiration guide [11]. Depends on the actual phenological stage of the plant.
- $K_s$ = Depletion or stress coefficient, depends on the actual level of water content.
- $K_i$ = Infiltration coefficient, depends on the actual level of water content.
- **Rain** = Rain value in mm splitted in 5 minutes intervals during the first three hours of rainy days.

### 6.1.2 Reference evapotranspiration, $ET_o$

Reference crop evapotranspiration ($ET_o$) is a parameter related with the weather and its evaporation power. $ET_o$ is a reference value calculated as evapotranspiration in in a hypothetical surface with standard conditions. This hypothetical surface is covered by grass of certain and constant characteristics. $ET_o$ determines the atmospheric evaporation power for a certain location and period of time. It is calculated using the Penman-Monteith equation included in FAO's guide [11]. The equation is shown below:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{6.2}$$

Where:

- $ET_o$ = reference evapotranspiration ($mm/day$)
- $\Delta$ = Slope of the vapor pressure curve ($kPa/°C$)
- $R_n$ = Net radiation on crop surface ($MJ/m^2day$)
- $\lambda$ = psicrométric constant ($kPa/°C$)
- **T** = average temperature at 2 meters high (ºC)
- $u_2$ = average wind speed at 2 meters high ($m/s$)
- $(e_s - e_a)$ = vapor pressure deficit ($kPa$)
- **G** = Soil heat flux ($MJ/m^2day$)

All this parameters are calculated using weather data. For this work we have used a Python package [17] that directly calculates daily $ET_o$ using the maximum available of the following inputs:

Net radiation (MJ/m2), Incoming shortwave radiation (MJ/m2), Net soil heat flux (MJ/m2), Minimum Temperature (deg C), Maximum Temperature (deg C), Mean Temperature (deg C), Dew point temperature (deg C), Minimum relative humidity, Maximum relative humidity, Mean relative humidity, Number of sunshine hours per day, Wind speed at height z (m/s), z, Atmospheric pressure (kPa), Actual Vapour pressure derived from RH and Latitude.

All parameters can be estimated except maximum and minimum temperature, which are the minimal inputs required. The method will estimate not available parameters using the other available inputs. In our datasets [2] we have data from maximum, minimum and average temperature, wind speed at 2m, maximum, minimum and average relative humidity, atmospheric pressure, latitude and number of sunshine hours per day.

Once daily $ET_o$ is calculated for one day we split it in 5 minutes intervals just dividing it by 288 (the number of 5 minutes intervals in a day) as we explained at the beginning.

### 6.1.3 Crop coefficient, $K_c$

The crop coefficient ($K_c$) defines the difference between evapotranspiration in a specific crop and phenological stage with the reference evapotranspiration ($ET_o$). Kc is divided in four stages and indicates how much water an specific plant in an specific stage of its life-cycle uses. This parameter is thought for optimal conditions of moisture in the soil.

FAO's guide divide plant season in four stages. They provide the duration in days for each stage as well as an initial, medium and end value for $K_c$. Combining these parameters we obtain daily values for Kc as shown in 6.1.

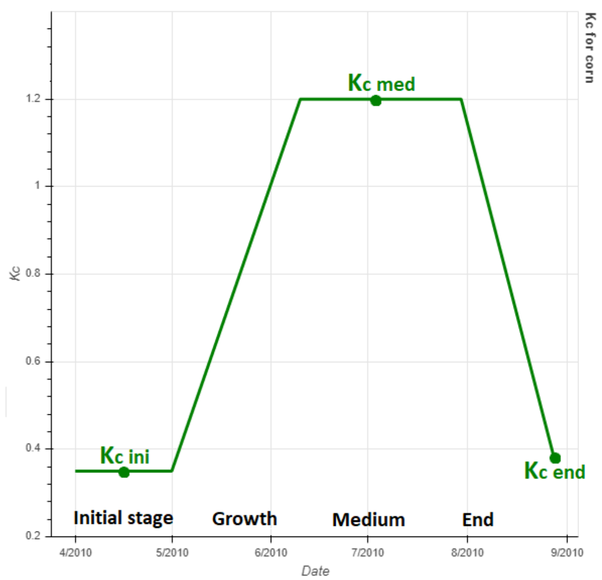



Figure 6.1: Kc daily values for a corn season

[2]The link to the weather datasets can be found in the appendix

$K_c$ indicates how much water a specific plant will consume in a specific stage. We can see the effect in the next graph. The graph shows the evolution of VWC in a field of corn. At the beginning when the plant is small, the ET is low, but as the plant grows, the ET increases accordingly.

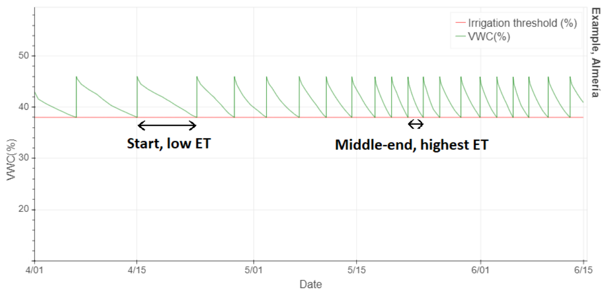



Figure 6.2: Effect of ($K_c$) during corn season

### 6.1.4 Infiltration factor, $K_i$

As explained in 2.3.1, due to infiltration, moisture content decrease very fast when it is between saturation and FC. The effect of infiltration is higher as WC is closer to saturation. But as we get closer to FC, soil attraction can hold all the particles of water, compensating the effect of infiltration. After FC we enter in the linear region, we can see this in 6.4.

We model $K_i$ using the next equation that uses VWC as input. This expression has been developed by hand using the data collected as reference, all parameters must be introduces as percentage.

$$K_i(VWC) = \begin{cases} 1, & VWC < FC \\ ((WC - FC) * 0.5)^2, & FC \leq VWC \leq SAT \end{cases} \tag{6.3}$$

### 6.1.5 Depletion factor, $K_s$

Ks model the decrease of water consumption by the plant caused by stress. As water content of the soil decreases, the plant decreases its vital activity and close its pores in a self-protection technique. It reduces the intake of water and thus the ET. To simulate this effect we add the stress factor Ks in the general equation.

The drying speed function has a linear region between FC and PR. PR determines the level of water content from which the plant starts to suffer stress and decrease its vital processes, for values of Wc below PR the drying speed is not linear anymore. We model it using the next equation taking VWC as input. This expression has been developed by hand using the data collected as reference, all parameters must be introduces as percentage.

$$K_s(VWC) = \begin{cases} 0.1, & VWC < (PWP - 10) \\ 1 - \frac{0.9}{(PR-PWP)+10} * (PR - VWC), & (PWP - 10) \leq VWC \leq PR \\ 1, & VWC > PR \end{cases} \tag{6.4}$$

If PWP is below 10, we would apply this other equation.

$$K_s(VWC) = \begin{cases} 1 - \frac{0.9}{(PR-PWP)} * (PR - VWC), & VWC < PWP \\ 1, & VWC > PR \end{cases} \tag{6.5}$$

The effect of infiltration and depletion factor can be seen in the picture below.

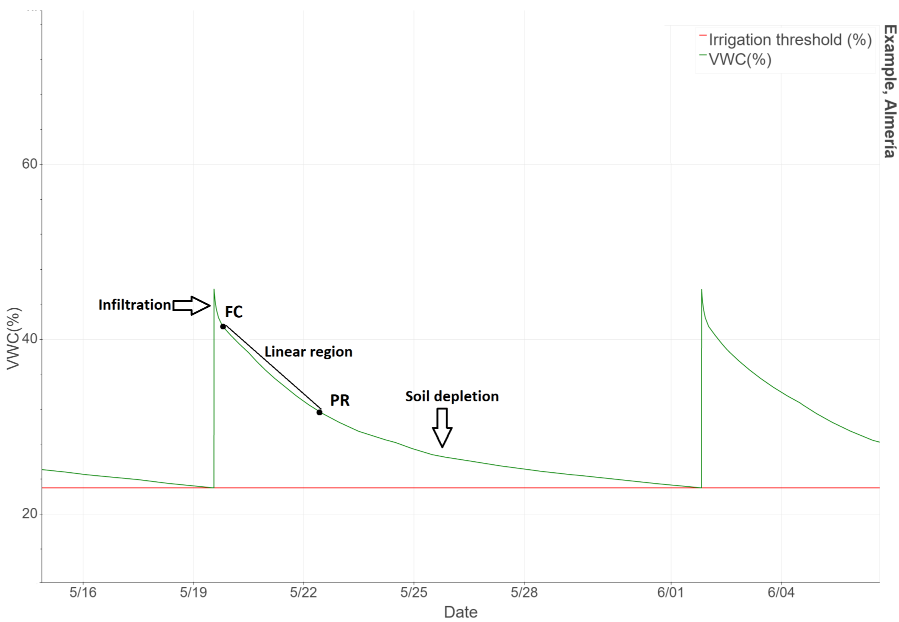



Figure 6.3: Effect of crop coefficient $K_i$ and $K_s$

### 6.1.6 Rain events

The weather datasets we use also include daily records of rain. To include rain in our model, we split daily registered amounts of rain in 5 minutes intervals and add it to VWC during the first 3 hours of each rainy day. We assume that 1 mm of rain increases 1% of the VWC. An example of the effect of rain is shown in the figure below, corresponding with a vineyard field.

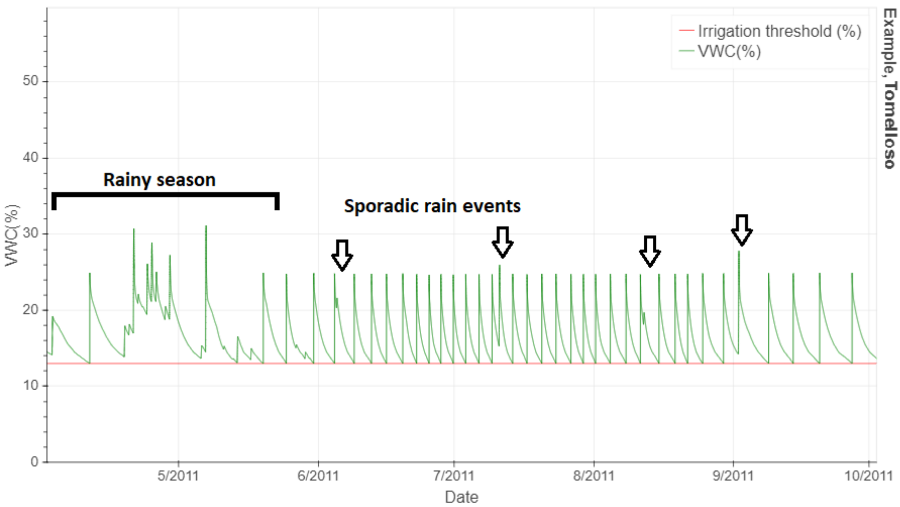



Figure 6.4: Effect of rain during April-June in Tomelloso, Spain

## 6.2 Stress sensitivity model

To evaluate different policies we need to evaluate the health of the plant in terms of available water during its life-cycle. For this, we will use a stress color-map [3] like the one in the figure 6.5.

For some crops like for example vineyards, induced water deficit in some stages is necessary to obtain a good product. If the plant has full availability of water during the season, the quality of the grapes will be affected. But in general water deficit is negative.

Every irrigation event is done when the moisture content is below the irrigation threshold. This value is mostly always detected late. The time delay (difference between optimal moment for irrigation and the moment when low moisture is detected) will also cause a "water content delay" it means, the difference between the irrigation threshold and the value of water content in the moment when low moisture is detected. As both delay components has similar relevance we decided that by multiplying both we would obtain the stress caused to the plant. Depending on the season and sensitivity of the plant, this stress has an effect in the plant health that

[3] The link to the stress color-maps is included in the appendix

corresponds with the stress color-map below. Using the map as function and the stress value as input variable, we can evaluate the damage caused to the plant by a late irrigation. We end up with this model to measure stress using the knowledge acquired from the background investigation.

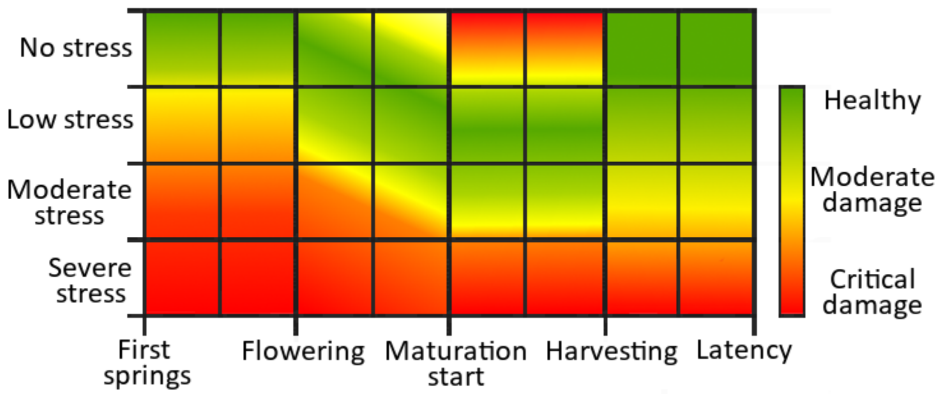



Figure 6.5: Stress map for vineyards

The green range marks the water stress the plant can hold without a significant decrease in yield or production. Yellow defines the transition zone where water deficit damages the plant but has not critical consequences. Finally, the red zone determines levels of stress that would seriously damage the plant and production. The more sensible to water deficit a plant is the narrower the green gap will be. More sensible crops will require a higher sampling frequency to maintain levels of moisture that keep the stress inside the green gap.

The average damage caused to the plant is calculated adding all the damage caused by late irrigations during a full season and dividing it by the number of irrigations. To calculate the damage of a single late irrigation we calculate the stress using the next equation. After this we check the value of damage that correspond with that delay and a specific plant and stage in a table that simulates the stress color-maps. The equation to calculate the stress caused by late irrigations has be developed by hand using the knowledge acquired from the background investigation.

$$Stress(VWCDelay, TimeDelay) = (1 - \frac{2 * VWCDelay}{FC - PWP})^6 * (1 - \frac{TimeDelay}{288}) \tag{6.6}$$

Where:

- **TimeDelay** = difference in minutes between the moment of irrigation and the moment when VWC reaches the irrigation threshold.

- **VWCDelay** = The difference between the VWC in the moment of irrigation and the VWC of the irrigation threshold. VWC is expressed in times one.

***Note:** In the next chapters we will refer to damage caused to the plant just as stress.

## 6.3 Energy models

In this section we evaluate the power consumption from the hardware we chose for the data collection. As well as alternative energy models covering different energy scenarios.

### 6.3.1 ZL6 and Teros energy model

The ZL6 data logger uses approximately 0.228 mAh per transmission, which occurs once per hour for the older 3G cell radio, and 0.083 mAh for the new 4G cellular radios. About the sensors, Teros11 moisture sensor drains 3.6 mA during 25 ms while Teros21 tensiometer drains also 3.6 mAh during 150 ms. Both sensors in sleep mode drain 0.03 mA. All this data was acquired by request to the manufacturer and sensor's datasets [24, 25].

With a nominal voltage of the battery of 7.2V these are the consumptions in Ws:

- 3G transmission: 5.9098 Ws
- 4G transmission: 2.1514 Ws
- Teros 11 reading 0.648 mWs (0.000648Ws)
- Teros 21 reading 3.888 mWs (0.00388Ws)
- Sensors in sleep mode 0.216 mWs (0.000216Ws)

Using the most demanding configuration (sampling frequency = 5 minutes), each sensor will do 12 measurements every hour. Transmissions are done also once an hour. Doing the calculations for one hour, the energy consumption would be 5.9098 w/s from the 3G transmission, 0.05443 Ws from both sensor measurements and 1.5552 Ws to maintain both sensors in sleep mode. Total energy used 7.5194 Ws, 78.59% correspond to the sending, 20.68% to maintain the sensors in sleep mode and only 0.73% to the sensor readings.

In the case with 4G network total energy used would be 3.7610 Ws for the same hourly case, 57.2% correspond to the transmission, 41.26% to maintain the sensors in sleep mode and only 1.54% for the sensor readings.

### 6.3.2 Alternative energy models

The conclusions from the ZL6 energy model are clear, almost all the energy is used to send the data because capacitive soil moisture sensors use very little energy. However, other products in the market may have different energy demands and different configurations (number of sensors, combination with weather sensors, refreshing demand, etc.) that can modify the energy balance. Because of that we will consider more scenarios, covering also the possibility that in the future better protocols like 5G may consume much less energy. The scenarios to consider will be these, to simplify the calculations we use adimensional units for the energy, 1u equals 1 unit of energy.

- **Energy model 1:** Reading energy cost is negligible compared with the used for the transmissions, 0u per reading and 1u per transmission.

- **Energy model 2:** Transmissions are 10 times more expensive than the readings, 0.1u per reading 1u per transmission.

- **Energy model 3:** Similar cost, 1u per reading and 1u per transmitting.

- **Energy model 4:** Readings are 10 time more expensive than transmissions, 0.1u per transmission 1u per reading.

- **Energy model 5:** Transmission energy cost is negligible compared with the used for reading, 0u per transmission 1 per reading.

# Chapter 7
# Use cases

In this chapter we present three different use cases chosen to carry out the simulations that we will use to verify the smart sensing policies. Each case considers an specific crop, soil and location. For each one we explain which factors and characteristics must be considered to manage an irrigation as it will affect a possible sampling strategy. We also include and explain all the parameters and data necessary to do simulations in the next chapters. These parameters are related with the crop, soil, weather and seasonal sensitivity. The table below summarizes the most significant factor to take into account in each use case.

Table 7.1: Use cases summary

| **Crop** | **Drought sensitivity** | **Inside / Outside** | **Health model** | **Main objective** |
|---|---|---|---|---|
| **Greenhouse lettuce** | High | Inside | Constant | Max production |
| **Corn** | Moderate | Outside | Complex | Max production |
| **Vineyard** | Low | Outside | More complex | Max quality |

## 7.1 Use case 1: Greenhouse lettuce

We chose greenhouse lettuce as first use case because its irrigation management is easier to study than for other crops. First of all, inside a plastic greenhouse, rain has no effect so it is not necessary to take into account the rain forecast for the irrigation planning. Secondly, lettuces are recollected when the plant is still green so the final product is the plant's leafs themselves which means there is no process such as flowering or fruit maturation with special watering requirements. We can further assume that the desired level of moisture or maximum water stress is constant and equally important during its whole life-cycle [22, 38, 46, 33]. This simplicity also translates into a more simple sensing strategy.

Lettuce has very shallow roots compared with the size of the plant, making them very sensible to water deficit [38]. Irrigation events must be frequent to maintain a proper level of moisture. An excess of water can be equally harmful for the plant, causing fungus or illness. Lettuce can be irrigated with almost any method. For greenhouses, the most common methods are drip or sub-surface irrigation.

### 7.1.1 Simulation parameters

In this subsection we include all the necessary parameters for the simulations of the following chapters.

#### Crop parameters

According to FAO's ET guide [11] lettuce has a life cycle between 75 and 140 days depending on the season of plant and location. The values of $K_c$ are 0.45, 1, 0.9 corresponding to initial, medium and final stage [22]. For our simulations we will consider a spring cycle of 75 days starting in April in a Mediterranean location. The duration of each stage in days will be 20, 30, 15 and 10, respectively.

Table 7.2: Crop parameters for lettuce

| Initial date | $D_{ini}$ | $D_{grow}$ | $D_{med}$ | $D_{end}$ | $K_{cini}$ | $K_{cmed}$ | $K_{cend}$ |
|---|---|---|---|---|---|---|---|
| April | 20 | 30 | 15 | 10 | 0.45 | 1 | 0.9 |

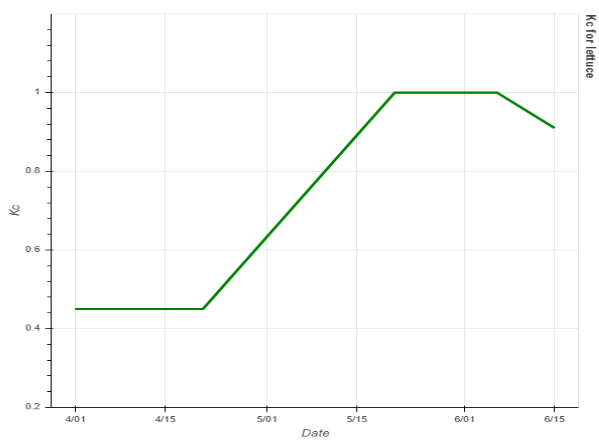



Figure 7.1: Daily $K_c$ for lettuce life-cycle

In the figure above we can see the graph with the daily values of $K_c$ for lettuce in spring cycle.

### Soil and irrigation parameters for lettuce

To manage sensor-based irrigation is necessary to determine the values of FC of the and PWP of the soil, see 2.2.2. Considering those values, the irrigation threshold is set for a value between FC and PWP [46]. The water content between FC and PWP is known as usable water. For sensible crops like lettuce, the irrigation threshold is recommended above a 10-20 % of usable water depletion. For example, if VWC for FC is 35% and 20% for PWP, a 20% of usable water range is 3% so irrigation threshold should be not lower than 32% of VWC [33]. The irrigation target is set slightly above FC to ensure that moisture reaches the plant roots properly.

Table 7.3: Soil and irrigation parameters for lettuce

| FC | PWP | PR | I. Target | I. Threshold |
|---|---|---|---|---|
| 35% | 20% | 27.5% | 37% | 32% |

### Weather data

Weather data correspond with the years 2010-2019 in Almeria, one of the biggest greenhouse emplacements in Spain. Weather data-sets are provided by AEMET, Spanish meteorology State Agency.

The $ET_o$ inside a greenhouse is calculated as a 75% or 60% from open air $ET_o$ depending if the cover is from mesh or plastic [22]. For this use case we consider a plastic cover.

### Stress color-map and sensitivity stages for lettuce

The stress color-map for lettuce is shown below, as lettuce is very sensible to water deficit, the green gap is narrow. Blue shows the ideal level of stress for this use case caused by the irrigation strategy, totally flat meaning no stress at all. It is also possible to see that water deficit has similar consequences no matter the stage of plant.

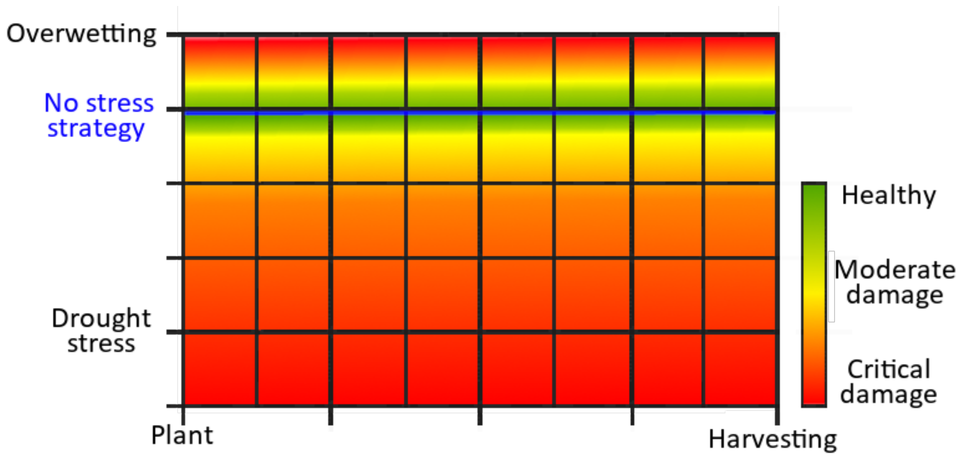



Figure 7.2: Stress map for lettuce

This color-map is translated into a table with numeric values that is included in the footnote. This table is used to calculate the damage or stress caused to the plant by a late irrigation.

### Season relevance for VoI calculation

To calculate the value of information in the chapter 8, crop sensitivity is one of the input attributes as it is directly related with the relevance of the data. This value from 0 to 1 is extracted from the stress color-map. A narrow green range indicates a high value of sensitivity as well as a higher relevance for the data in that stage. Lettuce is the most sensible crop from our use cases, we will give to it the highest value of relevance, 1. As lettuce has constant sensitivity in its whole life cycle, we will consider just one sub-stage.

Table 7.4: Relevance of each stage in lettuce for VoI calculation

| Sub-stage | S1 |
|---|---|
| Relevance | 1 |

## 7.2 Use case 2: Corn

This use case is a bit more complex. First of all corn is cultivated outdoors so, weather is an important factor to take into account. Unlike the lettuce use case, water stress sensitivity is different in some phenological stages like flowering or polinization. Moreover, lettuce is collected still green but corn must be dryed before recollection, because of that some water deficit is necessary at the end of its life-cycle.

### 7.2.1 Corn phenological stages

There is not a single definition for phenological corn stages. But mostly all sources divide corn season it in two parts, Vegetative part (Vn) and Reproductive part (Rn). We will sub-divide this two stages according to their special water requirements. [6, 30, 8]:

**Vegetative stage:**

- **VE-V1:** Germination and emergence, this sub-stage goes from planting to the appearance of the first leaf (V1). In this stage a level of moisture close to FC is recommended to ensure that most grains germinate and produce a plant. Severe water stress here can lead into a low density of plants. Duration 1-2 weeks.

- **V1-V14:** From the growth of the first leaf to fourteenth. Water needs increase as plant grow, but optimal levels of moisture are constant, not far from FC. Water stress here is not critical but can affect the growing cycle of the plant and decrease the size of the ears. Duration 30-40 days.

- **V14-VT:** From the appearance of the fourteenth leaf to start of flowering. It occurs approximately two weeks before flowering. This stage is very sensitive to heat and drought stress. Potential grain number as well as ear size is finally determined here, it is very important to avoid any water deficit, FC must be reached every day. Duration 1-2 weeks.

**Reproductive phase:**

- **R0-Flowering and polinization:** This stage starts when flowering begins and lasts approximately two weeks, after the pollen has fecund the potential grains. This stage is specially sensible and FC must be reached every day so there is no stress at all. A severe stress hear could lead into losses of 100% [8]. Duration 2-3 weeks.

- **R1-Grain development:** This stage includes the development of the corn kernels until they reach its maximum size. Water availability must be enough to generate big kernels. Duration 4-6 weeks.

- **R2-Drying:** After that kernels reach its maximum size until recollection. Water needs decrease, irrigation are severely reduced to consume the available water in the deeper soil layers and dry the grains for recollection. Duration 3-5 weeks.

### 7.2.2 Simulation parameters

In this subsection we include all the necessary parameters for the simulations of the following chapters.

#### Crop parameters for corn

Following FAO's irrigation guide [11], we obtain the following duration in days of the corn stages, the respective crop coefficients and the initial date.

Table 7.5: Simulation parameters for corn

| Initial date | $D_{ini}$ | $D_{grow}$ | $D_{med}$ | $D_{end}$ | $K_{cini}$ | $K_{cmed}$ | $K_{cend}$ |
|---|---|---|---|---|---|---|---|
| April | 30 | 40 | 50 | 30 | 0.35 | 1.2 | 0.35 |

#### Soil and irrigation parameters for corn

For this use case we are going to consider a plantation of dry corn in a loam soil. Loam has intermediate soil characteristics. Irrigation threshold will be set a little below PR to to take advantage of the rain until the last stages when it will be decreased to dry the kernels. Irrigation target is replaced by a recharge value that indicates the moisture increase after an irrigation event of fixed length.

Table 7.6: Soil and irrigation parameters for corn

| FC | PWP | PR | Recharge value |
|---|---|---|---|
| 35% | 20% | 27.5% | 14% |

We divide the life-cycle of corn in 10 sub-stages to apply different IT, these sub-stages are the same for the sensitivity, they are shown in figure 9.7, each sub-stage corresponds with one column.

Table 7.7: Irrigation threshold for corn in each sub-stage

| Sub-stage | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 |
|---|---|---|---|---|---|---|---|---|---|---|
| IT(%) | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0.2 | 0.18 | 0.16 |

#### Weather data

Weather data correspond with the years 2010-2019 in Huesca, an inland Spanish city with mediterranean climate where corn is typical crop. Weather data-sets are provided by AEMET, Spanish Meteorology State Agency. This climate has very hot months of July and August, sharply raising the demand for water, coinciding with the most critical periods like flowering-polinization. Irrigation will be critical in that period.

### Stress map and sensitivity stages

The stress map for corn is shown below. During the first stages the stress sensitivity is moderate. As it gets closer to flowering an polinization (VT-R1) the sensitivity increases reaching its maximum. Finally, when the corn grains are developed and the plant starts to dry. After that sensitivity decreases very fast becoming irrelevant in the last days before harvesting.

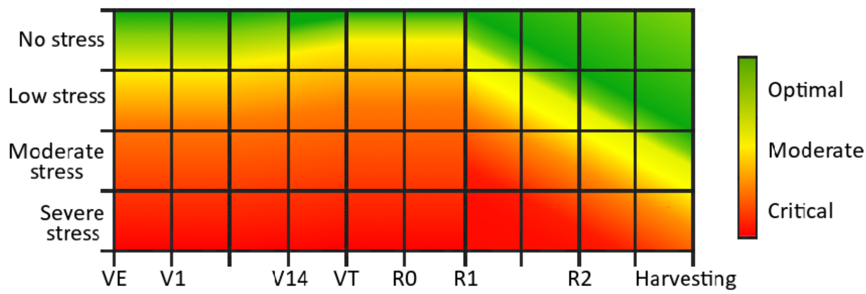



Figure 7.3: Stress color-map for corn

This color-map is translated into a table with numeric values that is included in the footnote. This table is used to calculate the damage or stress caused to the plant by a late irrigation.

### Season relevance for VoI calculation

As explained in subsection 7.1.1, these are the values of relevance for corn in each sub-stage. Each sub-stage has different duration, it is described in subsection 7.3.1.

Table 7.8: Relevance of each stage in corn for VoI calculation

| Sub-stage | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Relevance | 0.5 | 0.5 | 0.55 | 0.65 | 0.8 | 0.8 | 0.4 | 0.3 | 0.2 | 0.15 |

## 7.3 Use case 3: Vineyards

Around Europe, vine is one of the crops where the most sensor-based irrigation systems are placed. It is because vine is a special crop, it is very resistant to water deficit and can survive long periods with very little water available. However, irrigation management is not easy at all. As explained in 4.1.2, vines have to be induced to periods of stress to ensure a good quality in the grape. Furthermore, changing these tailored irrigation strategies it is possible to produce grapes suitable different types of wine. This complex irrigation management is very difficult without sensor-based irrigation systems [34, 15]. Less restrictive techniques produce bigger grapes with lower concentrations of sugars and poliphenols, good for making light wines like table wines. Increase water restriction reduce the size of the grapes but increase the concentration of sugars and poliphenols. Those grapes are useful to make fine wines with stronger taste. An excessive restriction however, produce too strong wines. A good restriction plan is desired to produce a fruit with a balanced concentration of sugars [15]. Induced stress must be done only in some stages of the production cycle. Below we present the main phenological stages of vineyards [15, 39, 3, 34].

### 7.3.1 Vineyards phenological stages

- **Stage 1:** From first springs to flowering the level of moisture needs to be high, close to FC so, the plant has enough water to develop new springs. This phase starts approximately in April and lasts for around two months.

- **Stage 2:** From flowering to start of maturation. Water needs increases a lot after flowering. During the period of flowering and curdling of the grapes the plant is specially sensible to water deficit and can reduce the number of grapes or grow them smaller. Once grapes are curds, irrigation must be reduced progressively. Excess of water make the leafs grow too much, covering the grapes and affecting the maturing process. An excess of water can also cause an excessive growing of the grapes, decreasing its quality. This phase lasts for around two months.

- **Stage 3:** Once grapes has grown, they start maturation, this phase lasts until recollection. For a good maturation, water deficit must induced to the vine so, sugar concentration increase in the fruit. The amount of water applied in this stage will determine the properties of the grape. This phase lasts for around three months.

- **Stage 4:** From recollection to latency of the strain, in this phase the plant lose the leafs. Irrigation and moisture levels must increase again to enlarge the roots and strengthen the plant for the next season. Applied water must be less than in the first stage. This phase lasts for around one month.

### 7.3.2 Simulation parameters

In this subsection we include all the necessary parameters for the simulations of the following chapters.

### Crop parameters

Following FAO's irrigation guide [11], we obtain the following duration in days of the vine stages, the respective crop coefficients and the initial date.

Table 7.9: Simulation parameters for vine

| Initial date | $D_{ini}$ | $D_{grow}$ | $D_{med}$ | $D_{end}$ | $K_{cini}$ | $K_{cmed}$ | $K_{cend}$ |
|---|---|---|---|---|---|---|---|
| March | 30 | 60 | 40 | 80 | 0.3 | 0.7 | 0.45 |

### Soil and irrigation parameters for vine

Vineyards are usually grown in sandy-loam soils. In this type of soil FC is around 20% and PWP around 10%. Recharge point is around 15% . But, as vineyards are very resistant to water deficit and in many cases rain covers water needs, we will set the irrigation threshold below the recharge point at 13% of VWC [10, 45, 15].

To induce the desired water stress in some stages as explained in subsection 4.1.2 we will set different irrigation thresholds in each sub-stage [3, 15]. At the same time, we won't have an irrigation target, instead we will have a recharge value related with the increase of moisture after an irrigation event. Irrigation length is calculated to reach the roots at optimal depths.

Table 7.10: Soil and irrigation parameters for vine

| FC | PWP | PR | Recharge value |
|---|---|---|---|
| 20% | 10% | 15% | 0.12% |

Table 7.11: Irrigation thresholds in each sub-stage for vine

| Sub-stage | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 |
|---|---|---|---|---|---|---|---|---|
| IT(%) | 0.35 | 0.35 | 0.45 | 0.6 | 0.75 | 0.75 | 0.2 | 0.2 |

### Weather data

Weather data correspond with the years 2011-2019 in Tomelloso, a representative village for wine production in the interior of Spain. The data-sets are provided by AEMET, Spanish Meteorology State Agency.

### Stress map and sensitivity stages for vine

The stress map for vineyards is shown below. It is possible to appreciate four different stages that define the deficit irrigation strategy 4.1.2. In stage 1, FC must be reached frequently to cover plant needs and prepare it for the season. During flowering and curdling, no stress is specially important, after that, water input must be reduced to induce a certain stress during maturation. Finally, before harvesting moisture levels must be increased to prepare the vines for winter.

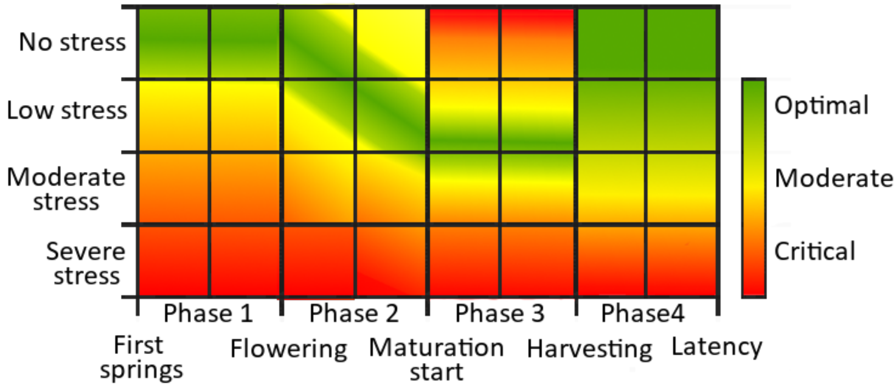



Figure 7.4: Stress map for vineyard

This color-map is translated into a table with numeric values that is included in the footnote. This table is used to calculate the damage or stress caused to the plant by a late irrigation.

### Season relevance for VoI calculation

As explained in subsection 7.1.1, these are the values of relevance for vine in each sub-stage. Each sub-stage lasts one month.

Table 7.12: Relevance of each stage in vine for VoI calculation

| Sub-stage | S1 | S2 | S3 | S4 | S 5 | S6 | S7 | S8 |
|---|---|---|---|---|---|---|---|---|
| Relevance | 0.35 | 0.35 | 0.45 | 0.6 | 0.75 | 0.75 | 0.2 | 0.2 |

Chapter 8

# VoI of Soil moisture in sensor-based irrigation context

In this chapter we explore and discuss the value of information of soil moisture readings in the context of sensor-based irrigation. **Value of Information**, from now **VoI** is a decision analytic method that quantifies how relevant is some data according to a decision making process. The most useful information is the information that can help the decision maker to take an action with regard to its context. We start selecting the attributes that influence this value. Then we explain how to calculate and normalize each one. Finally we describe two methods (AHP and average weighted) to combine the selection of attributes [18].

## 8.1 VoI estimation

In this section we present the attributes that describe the VoI of soil moisture in the context of sensor-based irrigation. Next we explain how to calculate and normalize them. Finally we explain how they should be combined according to its relevance in the decision making process.

### 8.1.1 Selection of attributes

We define VoI according to 4 information attributes. We start with the intrinsic attributes which are the measured value of VWC and the time from last measurement (Age of Information or AoI). Next we describe two extrinsic attributes that does not have direct relation with the measurement but has significant influence in the irrigation decision making. The extrinsic attributes are the rain forecast and the season sensitivity of the crop. The attributes are explained below.

– **VWC measurement**: Difference between the reading of the sensor and the irrigation threshold. This value indicates how far we are from a possible irrigation in terms of VWC. As VWC gets closer to the irrigation threshold, the relevance of the measurements increase. This attributes reach it highest relevance when VWC is below the irrigation threshold, in other words, when irrigation is needed.

- **Age of Information**: Time since last measurement. Even though most measurements won't lead into a decision making, it is important to keep track of the moisture content every certain time. Because of that, if it is been a significant time from the previous measurement the current reading will have a higher relevance. This attribute does not directly influence the decision making of irrigation but helps to keep track of the moisture and make the system more robust.

- **Rain forecast**: Expected amount of rain in mm for the next day(s). A significant event of rain in the next couple of days can postpone an irrigation even if VWC is below the threshold. Irrigate just before a rainy event is a waste of water and energy, and at the same time it can be harmful for the plant due to excessive moisture. For this attribute we consider the rain prediction for the next two days.

- **Season sensitivity**: This attribute describes how sensible is a plant to water deficit in a specific stage of its life. If the plant is in a stage of high sensitivity, it is necessary to check the soil moisture more often to prevent any stress as it would be specially harmful. Different crops in different stages has different levels of sensitivity, we will obtain this value from the relevance tables obtained from stress color-maps in chapter 7.

### 8.1.2 Attributes normalization

To compare all the attributes in equal conditions is necessary to define a framework in which all the attributes are normalized. Following we explain how we calculate the value of each parameter in a scale from 0 to 1. All the methods and equations has been developed manually from research, observation and simulations.

**VWC measurement:**

To model the value of information related only with the VWC value obtained from the sensor we use the following expression.

$$VoI(WC) = \begin{cases} 1, & WC \leq IT. \\ (0.8 * (IT/WC))^2, & WC > IT. \end{cases} \tag{8.1}$$

This equation is the result of different simulations we did to obtain a desired function to model the attribute. The square is because we wanted to increase the VoI for measurements close to the threshold while minimizing for for the most distant measurements. For example, applying the formula to the VWC measurements from vineyard use case during the first week of July of 2011 we obtain the following result.

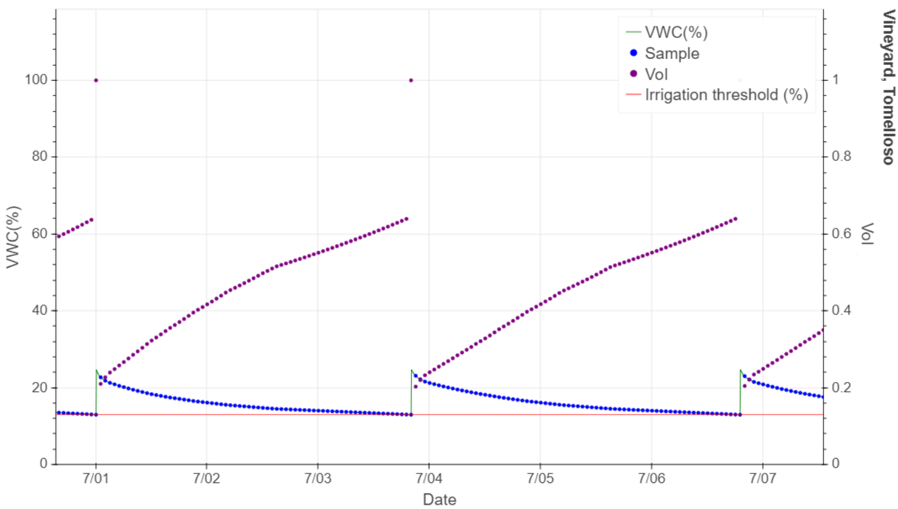



Figure 8.1: VoI based on WC, vineyard use case

It is possible to see that after every irrigation event, the value of the readings suddenly decrease. It is because, the readings of the sensor are used to detect when the soil is dry and needs irrigation, this will never happen just after an irrigation event. It is also possible to appreciate that the reading below the threshold has a value of one, the highest possible. It because it is the VWC value that would trigger irrigation.

**Weather forecast ($VoIforecast$):**

To model the effect of the rain we consider the forecast for the next two days. Only significant amounts of rain can postpone irrigation, we consider a large enough event rain when the accumulated prediction of rain for the next two days is above 15 mm or above 10 mm for tomorrow, in that case the VoI will be 1. On the other hand if the expected rain is lower then it would not affect in the irrigation decision so VoI will be 0. The equation is presented below.

$$VoI(rainforecast) = \begin{cases} 1, & R1 \leq 10 \; or \; R2 \leq 15. \\ 0, & R1 > 10 \; \& \; R2 > 15. \end{cases} \tag{8.2}$$

Where:

- **R1** = Expected rain in mm for the next day.
- **R2** = Expected rain in mm for the next two days.

For example, applying the formula to the VWC measurements from the vineyard use case during the full season of 2011 we obtain the following result. We can see that just before significant events of rain VoI reaches 1 otherwise, VoI is 0.

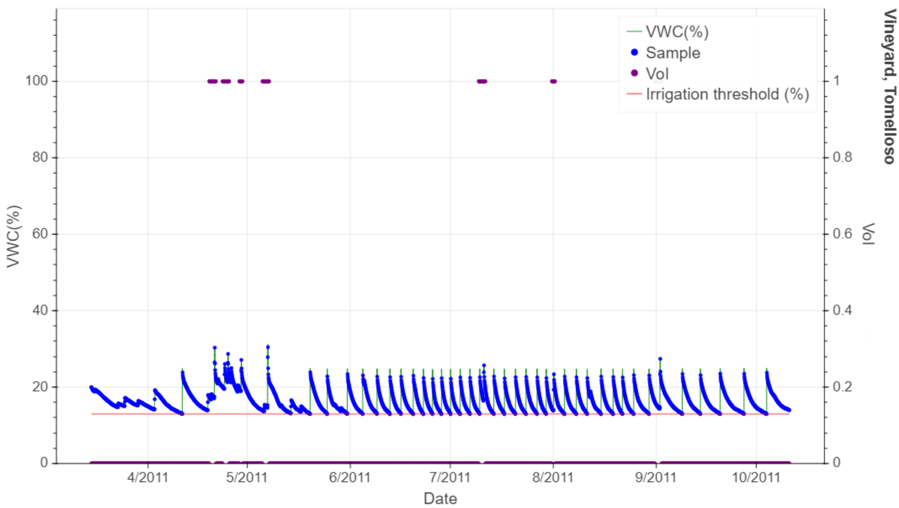



Figure 8.2: VoI based on rain forecast, vineyard use case

**Type and stage of the crop ($VoIstress$):**

To model how sensible a plant is during a specific stage we use the stress color-maps 6.2 from chapter 7. From these maps we obtained the relevance values that correspond with season VoI. These values indicate how sensible is a plant in each sub-stage and thus how relevant are the soil moisture measurements. All the values for each crop and sub-stage are indicated in the table below.

Table 8.1: Season sensitivity based VoI

| Crop | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Lettuce | 1 | - | - | - | - | - | - | - | - | - |
| Corn | 0.5 | 0.5 | 0.55 | 0.65 | 0.8 | 0.8 | 0.4 | 0.3 | 0.2 | 0.15 |
| Vineyard | 0.35 | 0.35 | 0.45 | 0.6 | 0.75 | 0.75 | 0.25 | 0.25 | - | - |

In the next graph we van see the VoI correspondent to each sub-stage of vine during a whole season.

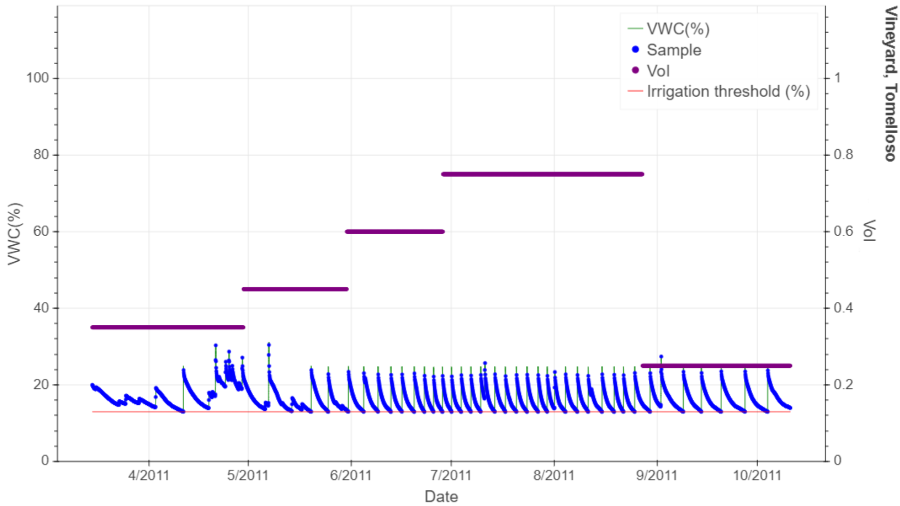



Figure 8.3: VoI based in season sensitivity, vineyard use case

In this graph it is easy to check the significant difference of VoI in different stages. For example, from July to September when the grape is maturing and the irrigation management very critical, the VoI of the measurements is very high, close to one. However, just after the recollection the VoI of the measurements decrease abruptly.

### Age of information (AoI):

The VoI a measurement is influenced by the time difference with the last measurements we call this difference as Age of Information. If the last measurement is very recent then the VoI would be low because it is very likely to be similar. Instead if the AoI is high, then the expected difference between the measurements will be higher and thus the VoI. We propose two possible methods to calculate the VoI from AoI depending on how the irrigation system works. The first one is for a system that forces readings every certain time, what we will call maximum sampling interval. The other one would use the maximum sampling interval just as reference. We have considered both implementations because a system that forces readings every certain time could reduce the effect of a smart sampling policy. Both expressions to calculate VoI are presented below.

$$VoI(AoI) = AoI/MaxSI \tag{8.3}$$

$$VoI(AoI) = \begin{cases} \frac{AoI}{MaxSI}, & AoI \leq MaxSI. \\ 1, & Tsamp > AoI. \end{cases} \tag{8.4}$$

Where:

- **AoI:** Time from last measurement in minutes.
- **MaxSI:** Maximum sampling interval in minutes.

Applying the second equation to the vineyard use case during the year 2011 we obtain the next result:

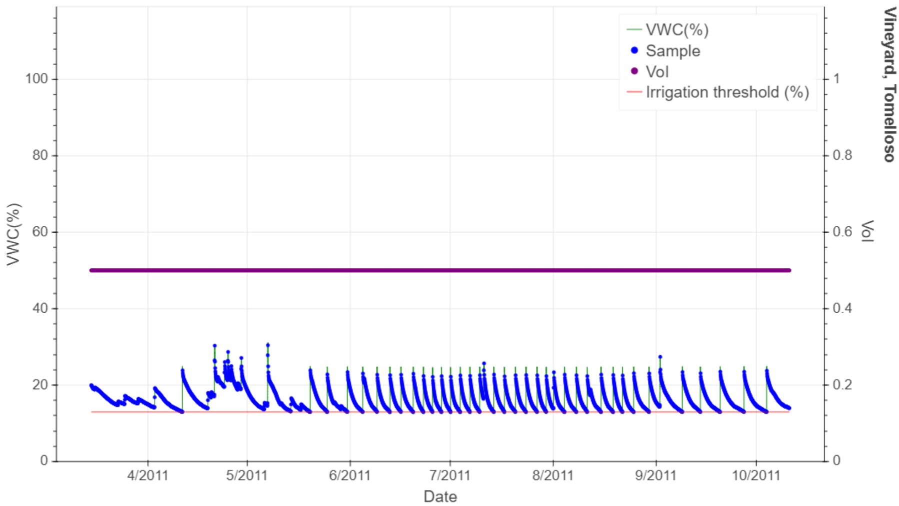



Figure 8.4: VoI based on AoI, vineyard use case

For this case we selected a SI of 60 minutes and a Maximum SI of 120 minutes. As the sensing strategy is constant, then the VoI related with AoI is also constant. Even though in this example this attribute did not have utility (is constant) it will be useful to develop smart policies where the sampling strategy will be no longer static. This will be explained in the next chapter.

### 8.1.3 Attributes comparison, average weighted and AHP

We have now four attributes to define the VoI of soil moisture. As the four attributes make reference to the same measurements we have to combine them in order to calculate a single value of VoI for a single measurement. In this subsection we present two methods to combine the selection of attributes.

#### Average weighted model

As baseline to combine them we can give equal relevance to the four attributes. As the four attributes are normalized we can just make a arithmetic average of them. However, not all the attributes has the same relevance in the decision making process so an arithmetic average would not reflect properly the user specifications.

#### Analytic hierarchy process, AHP

Analytic hierarchy process or **AHP** from now, is an useful tool to deal with complex decision making. AHP is particularly useful to make decisions with several evaluation criteria and alternative options involved. In general, the best option is not the one that optimizes every single criterion. Instead, the best option is the one with the best trade-off among the different criteria [18]. This method was suggested by the co-supervisor of this project M. Alawad to try it out a see if this method fits in the context of soil moisture.

To combine several attributes, AHP reduce the comparison process to a series of pair wise comparisons. The first step is to chose the attributes involved as we did in the first section. After this we put them in a table and according to the decision maker's generate a weight for each pair of attributes. For example in the element $e_{ji}$ we will indicate with a number from 1 to 9 how much more important is i than j, at the same time in $e_{ji}$ we will put the inverse value. Finally, the AHP combines the criteria weights determining a global score for each option.

In our case we assigned manually the values to each pairwise. The result is presented below.

Table 8.2: Criteria comparison

| **Attribute** | **VWC** | **Rain forecast** | **Stage** | **AoI** |
|---|---|---|---|---|
| **VWC** | 1 | 2 | 3 | 3 |
| **Rain forecast** | 0.5 | 1 | 3 | 2 |
| **Stage** | 1/3 | 1/3 | 1 | 2 |
| **AoI** | 1/3 | 1/2 | 1/2 | 1 |

Once we assigned all the values we did the AHP calculations to obtain the following weights.

Table 8.3: Criteria comparison with AHP weights

| Attribute | VWC | Rain forecast | Stage | AoI | Weight |
|---|---|---|---|---|---|
| **VWC** | 1 | 2 | 3 | 3 | 0.448 |
| **Rain forecast** | 0.5 | 1 | 3 | 2 | 0.283 |
| **Stage** | 1/3 | 1/3 | 1 | 2 | 0.163 |
| **AoI** | 1/3 | 1/2 | 1/2 | 1 | 0.106 |

## 8.2 Discussion

Once the weights are calculated, we proceed to simulate how the VoI would behave in a real case. In the next graph we show the VoI for soil moisture values in vineyard, using average weighted and AHP.

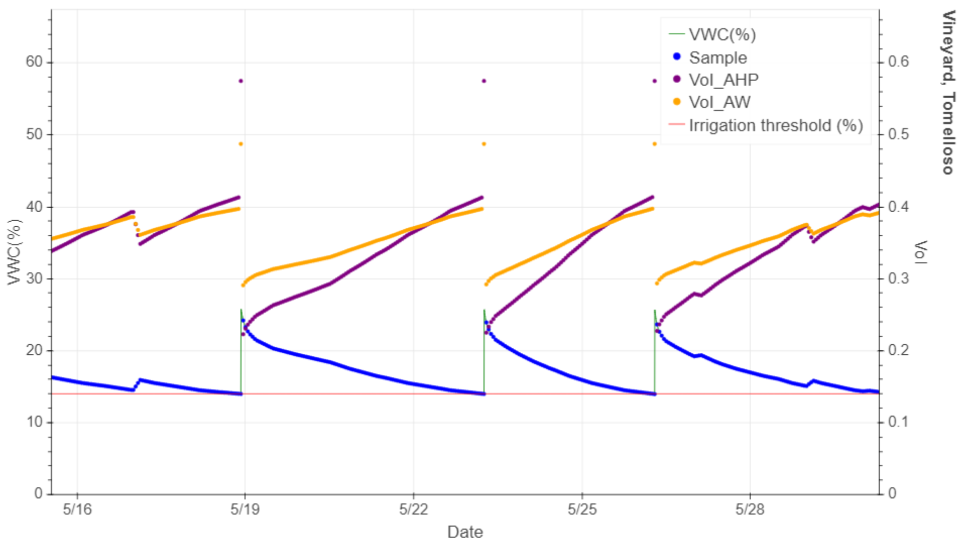



Figure 8.5: VoI calculated as AHP(purple) and Average weighted model (orange)

In the left axis we have the values of VWC (green line), the blue dots indicate each sample of the sensor. The right axis indicates the VoI. Purple dots indicate VoI of each sample calculated using AHP while orange dots show the result from AW.

The first and most significant difference is how VWC affects differently in both models. In the average weighted model the range of VoI is smaller. Moreover as we can see, AW overrates readings of high VWC while underrates readings close or below the irrigation threshold. Instead, the AHP does not have this problem. Values close to to the threshold has a VoI value above 0.4 while non important measurements after irrigation are round 0.25 against the 0.3 for AW.

The present the effect of sensitivity graph below. To make the difference more evident we have calculated both VoI using only the VWC and the season sensitivity.

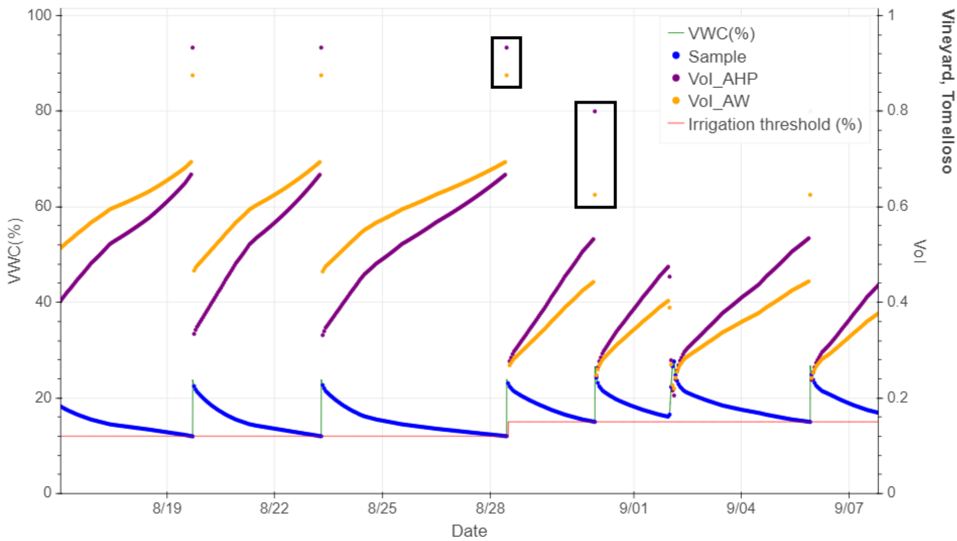



Figure 8.6: Effect of season sensitivity and VWC in AW and AHP VoI calculations

In this case, we can see how AW model gives and excessive relevance to the attribute of sensitivity. If for example we take as reference the values after irrigation when VoI from VWC is equal to one (black boxes) we can see a big drop in both values. This drop correspond with pre and post recollection stages in our vineyard, as we explained, after recollection the water management is not so critical. For AW VoI goes from 0.875 to 0.625, a drop of 0.25 while for AHP VoI goes from 0.933 to 0.8, a difference of just 0.133. This overrating by the AW is normal as the weight for season sensitivity is bigger on it. However, in a real case situation the relevance of the season sensitivity is no so significant.

For the rain forecast there is no a significant difference. Rain has a similar weight in both models (0.25 vs 0.283). As this difference is too small to be appreciated in a graph we have not included any example.

The effect of AoI cannot be appreciated either as the sampling frequency is constant. However, in the next chapter we will see its effect in non-uniform policies.

In conclusion, we have seen that the average weighted model overestimates and underestimates some of the attributes. Because of that the VoI calculated using AW is not as representative as the AHP which grants proper weights to each attribute. For the next chapter and simulations we will use only the AHP calculation for VoI.

# Chapter 9

# VoI as baseline for energy-smart sensing policies

In this chapter we explore the idea of developing energy-smart sensing policies for soil moisture based in the VoI of soil moisture. The objective of this chapter is not the development of such policies but to study how VoI can be used in the process. We also include several simulations to verify the utility of such policies. Finally we include the conclusions obtained from this project.

## 9.1 Toy experiment

One of the first steps of this thesis is explained in this section. Even before doing the full research and identify the objectives, we did this little experiment to get a general overview of soil moisture behaviour and the possibilities of a possible smart sensing policy. Finding a soil moisture dataset to start with was not possible; Instead, we found a graph of soil moisture from a turf irrigation project, we digitalized it obtaining the moisture values for 41 hours with a sampling interval of 15 minutes. The graph included two irrigation events.

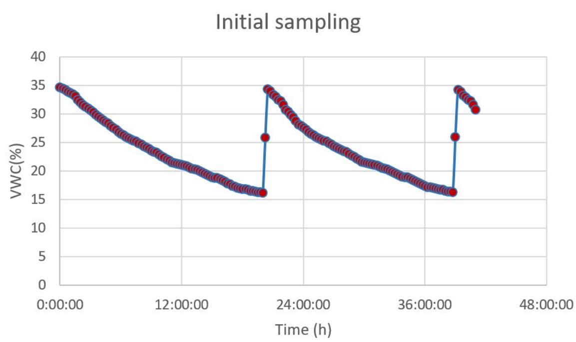



Figure 9.1: Data obtained with SI of 15 min.

The resultant dataset included 165 data or "measurements, to simplify the calculations we supposed every measurement had a cost of 1 unit of energy.

The requirement for irrigation was that this should be done when the value of moisture was between 16 and 16.3%.

With this two premises we did two steps to check if we could use less energy avoiding some measurements while satisfying the irrigation condition. In the first step we reduced the sampling frequency to find the lowest value that satisfies the irrigation condition, we found it as a 25% of the initial frequency, one measurement per hour, a 75% of energy saved.

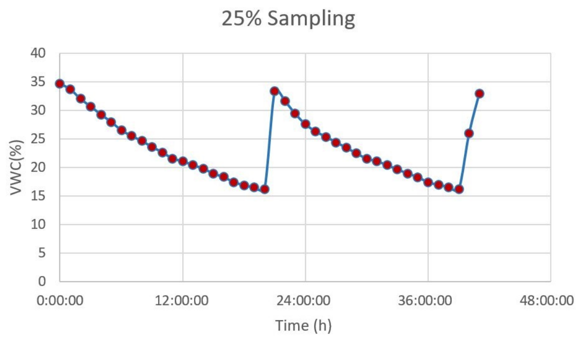



Figure 9.2: Data obtained with SI of 60 min.

To reduce even more the number of samples, we used the premise that only the dry-wet end values are useful to know when we should start or stop irrigation. So we add a very simple constrain, if the last value measured is between 20-30% of VWC, the next sample will be taken within 2 hours instead of one.

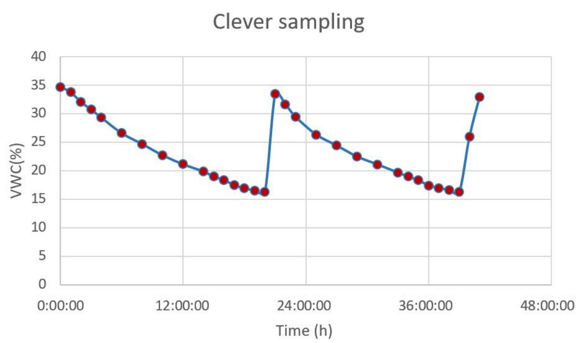



Figure 9.3: Data obtained with clever sampling.

The new constrain reduced the number of samples from 42 to 32, equivalent to a power saving around 80%, improving even more the efficiency than using fixed sampling intervals. Energy saving could be bigger applying more complex and tuned constrains but the aim of this "toy" experiment was only to prove the possibility of power saving using a smart sensing policy and help to dimension the future real experiments.

## 9.2 Static sensing strategies, sampling interval optimization

As we explained in the introduction chapter, sampling strategies based in fixed sampling intervals has a limited energy/information trade-off. However, choose the optimal SI can save a lot of energy. In this section we try to find the optimal SI that maximized the energy/information trade-off. This value will act as baseline for the next sections.

In the following graphs we show the energy consumption and the Stress caused by different sampling intervals in our three use cases during an average season. The SI are between 5 minutes and two hours. The energy consumption is normalized, assuming that energy from measuring and transmission has similar cost and only values below the irrigation threshold are transmitted. The stress level is the average stress for ten years using the method from 6.2, only the months when irrigation is needed are considered. The simulations for each use case span 10 seasons for corn and lettuce and 9 for vineyard. The results are presented next.

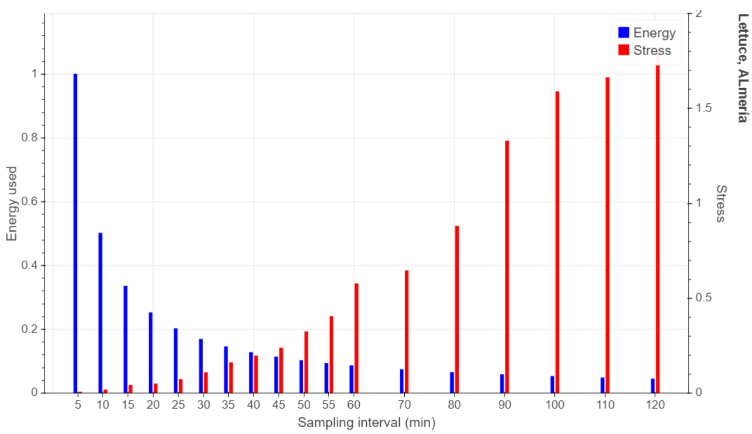



Figure 9.4: Energy used and Stress for different SI in lettuce

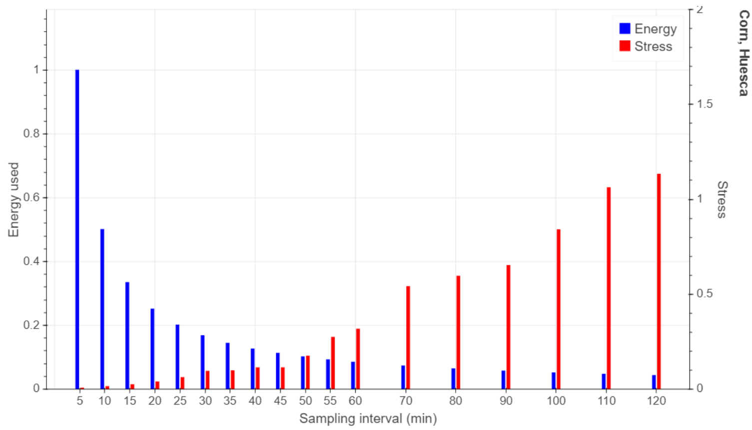



Figure 9.5: Energy used and Stress for different SI in corn

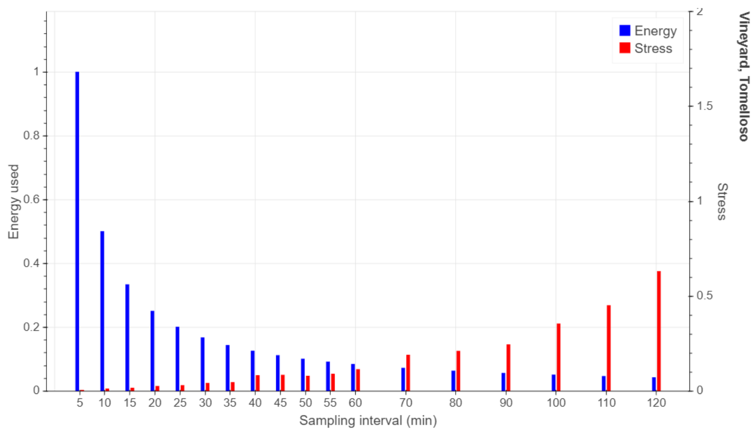



Figure 9.6: Energy used and Stress for different SI in vineyards

As we can see, the same SI causes different level of stress in each crop, it is because each one has different sensitivity, being the lettuce the most sensitive and the vines the most resistant. We opted to show energy and stress together instead as a trade-off value because the energy and the health of the plant has different relevance. The plant must be health no matter the energy required (is cheaper to change the batteries more often than a decrease in the production). So we consider that the optimal SI is the the one that uses the less possible energy while keeping the value of Stress below 0.3. Considering that, the optimal SI for each use case are shown in the table below.

Table 9.1: Optimal SI in different crops

| Crop | Optimal SI (minutes) |
|---|---|
| Lettuce | 45 |
| Corn | 55 |
| Vineyard | 90 |

We also repeated the simulations applying the energy model and sampling/transmission strategy from our hardware explained in 6.3.1. The model consist on a SI of 5 minutes and transmissions every hour. The cost per sample is almost negligible compared with the transmissions. The result was that there was almost no difference of stress or energy between SI from 5 to 60 minutes. The energy consumption was similar as almost all of it was used for the transmissions. The levels of stress has also a similar result as the transmissions are done just hourly. The only benefit of a higher SI in a scenario like that is the possibility to avoid incorrect readings as the system would work with an average of the last samples.

The conclusion from this simulations is that static policies based in fixed sampling interval are inefficient even if they are optimized. An optimal SI is selected in order to avoid periods of stress during the most sensible stages of the crop but, this implies an excessive high number of samples in moments when the readings has low relevance like for example after an irrigation event.

## 9.3 Smart sampling policies based in VoI

In this section we present the process of creation of smart sampling policies for soil moisture using VoI. At the end we explain with examples how each attribute alone would affect a potential policy.

### 9.3.1 Smart sampling policy creation

As we explained we will use the VoI of each moisture measurement to develop the smart sampling policy. The first step is to explore the potential range in which the VoI will move. Once we know the range we can define certain thresholds of VoI that later will determine different SI. After this we define a maximum SI that will be used in the most critical situations (highest VoI readings). Finally we use the VoI mentioned thresholds to skip certain future samples. The higher VoI is the higher number of samples we will skip. This method can look messy and complex but in fact it is quite simple, it will be easy to understand with the following example.

Lets say that in our use case the VoI of our measurements oscillates between 0.3 and 0.6. High values of VoI close to 0.6 are indicative that a irrigation decision must be taken now or in a near future while values close to 0.3 indicate low relevance of the data as a possible irrigation would be far in time. To avoid useless measurements we will skip n measurements according to the VoI and the defined thresholds. In our example n would have the following values for each threshold.

$$n = \begin{cases} 0, & VoI > 0.56. \\ 1, & VoI > 0.54. \\ 4, & VoI > 0.50. \\ 8, & VoI > 0.4. \\ 12, & 0 \leq VoI < 0.4. \end{cases} \tag{9.1}$$

For VoI above 0.56 we will use the maximum sampling frequency to not avoid any relevant event. As VoI decreases we skip more measurements to save more energy.

### 9.3.2 Smart sampling policies based is single attributes

In this subsection we explain how the VoI each attribute alone would be useful or not to develop a smart policy. Even though in some cases the use of a single attribute will lead into a useless or inefficient policy we want to separate them to explain better to the reader the relevance of each one.

The simulations in this subsection will be in the use case of corn. We consider that all the readings are transmitted at the same time and both actions has a similar energy cost of 1 unit.

#### VWC VoI based policy

For the first case we apply the VoI calculated using only the VWC difference to the irrigation threshold.

The first step is to check the range for VoI, in this case VoI oscillate between 0.27 and 0.64 except for the samples below the IT for which VoI is 1. With that range, we establish the next thresholds to determine how many samples the system should skip in each situation.

$$n = \begin{cases} 0, & 0.6 \leq VoI. \\ 1, & 0.55 \leq VoI < 0.6. \\ 4, & 0.5 \leq VoI < 0.55. \\ 8, & 0.35 \leq VoI < 0.5. \\ 12, & 0 \geq VoI > 0.35. \end{cases} \tag{9.2}$$

When high VWC readings indicate that the a possible irrigation is far in time, the system increase the SI, reducing the number of measurements and saving energy. In the other hand when VWC is low the system estimates that a possible irrigation is close so it skips less or none measurements. In other words increases the sampling frequency to avoid any late irrigation. In the picture below its possible to see how the sampling strategy adapts the SI to VoI.

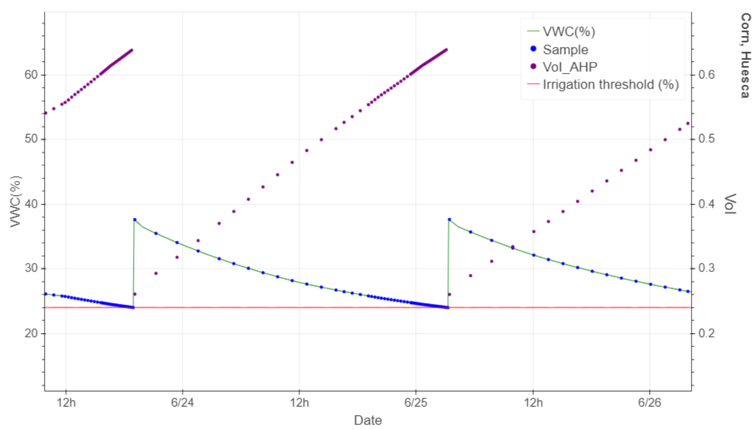



Figure 9.7: Smart sampling strategy based in VWC VoI

We can see that just after an irrigation another event of irrigation is improbable and VoI low, as we are getting closer to the next irrigation, the VoI increases as well as the sampling frequency. In the next table we compare the energy used and the stress caused by the smart policy compared with a static policy which uses a SI of 10 minutes. The smart policy is also based in a maximum SI of 10 minutes.

Table 9.2: Sampling strategy based in VWC VoI result

| Policy | Energy used | Stress | Saving |
|---|---|---|---|
| SI=10 min | 43248 | 0.0139 | - |
| Smart(VWC) | 9686 | 0.139 | 77.6% |

As we can see, the energy-smart policy reduces the energy used while keeping the same level of stress.

**Season sensitivity VoI based policy**

Now we repeat the process considering that VoI is only calculated using the effect of the season sensitivity. In the use case of corn the VoI for the each season oscillates between 0.15 and 0.8 for the least and most sensitive stages respectively. The thresholds we define to skip n measurements are presented next.

$$n = \begin{cases} 0, & VoI \leq 0.7. \\ 1, & 0.6 \leq VoI < 0.8. \\ 2, & 0.45 \leq VoI < 0.6. \\ 4, & 0.3 \leq VoI < 0.45. \\ 8, & 0 \geq VoI < 0.3. \end{cases} \tag{9.3}$$

When the systems detects that the plant is in a sensible phenlogical stage like flowering the VoI is high. It increases the sampling frequency to avoid any possible late irrigation. When the stage has low sensitivity the sampling frequency is decreased as a late irrigation could be assumed. The effect of the policy is shown in the next graph.

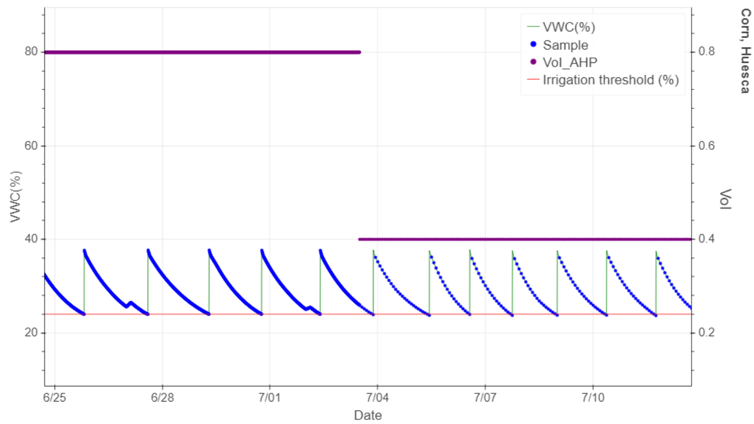



Figure 9.8: Smart sampling strategy based in season sensitivity VoI

In this graph from the corn use case the left side correspond with the flowering and polinization stage, a very critical stage with high VoI and also a high sampling frequency. When this stage ends, the relevance of the measurement decreases as the plant is less sensitive to water deficit, to take advantage of that we decrease the sampling frequency.

In the next table we compare the energy used and the stress caused by the smart policy and by a static policy with a SI of 10 minutes. The smart policy is also based in a maximum SI of 10 minutes.

Table 9.3: Sampling strategy based in VWC VoI

| Policy | Energy used | Stress | Saving |
|---|---|---|---|
| SI=10 min | 43248 | 0.01416 | - |
| Smart(VWC) | 18946 | 0.1103 | 56.19% |

We can see that the energy is significant but lower than for the previous case. It is because if we take only the VoI based in the season we can skip less samples to maintain an acceptable level of stress. We can also see that there are a significant increase in the level of stress but still inside the acceptable range.

### Age of information VoI based policy

A sampling policy based only in AoI lead into a static frequency policy. It doesn't mean that it is useless but, this attribute needs to be combined with other attributes to be useful. The VoI of this attribute does not help to create more energy-efficient policies. It helps to design more robust policies that keep track of the moisture every certain time even if the VoI from the last readings is very low.

#### Rain forecast VoI based policy

We did not simulate a model using VoI from only the forecast because it didn't make sense. Forecast is only a complement attribute that helps to take benefit from the rain reducing the use of water and avoiding damages caused by unnecessary irrigations. In other words, this attribute is very relevant but acts in an opposite way to the other attributes, the more probable the rain is the more possibilities we have to delay the irrigation event even if the VWC is low.

#### Sampling strategy based in AHP VoI

As we explained in the previous chapter, all the attributes could be combined using AHP. It would normal to expect that combining the 4 attributes we would obtain better results than using them alone. However, it is not that easy. Combining the four attributes we obtain a range of VoI with high variability. Furthermore, it is not easy to relate the effect from the rain forecast with the sampling frequency if it ix mixed with the effect of other attributes. Moreover, we know beforehand the sensitivity of each stage and the values between the VWC will move so we can predict the range of VoI resultant from these two attributes. However, the rain forecast and the age of information are only known as we go through time.

To be able to take advantage from the weather forecast and the age of information we would need more complex policies that are able to change the thresholds to skip samples dynamically. This would require too complex functions which are not in the scope of this thesis. For the next simulations we will consider only the VWC value and the seasonal sensitivity to calculate the VoI that we will use for the smart policies creation.

## 9.4 VoI smart policy applied to different energy models

In this section we discuss the effect of a possible energy-smart sampling policy based only in VoI calculated using the VWC value and the seasonal sensitivity attributes. The maximum SI will be 15 minutes and the use case will be the vineyard. We have chosen vineyard as is the case with more variability including several irrigation thresholds and stages with significant difference of sensitivity in just one season. Furthermore, to check the utility of the policy in every possible energy scenario we will consider several energy models and sensing/transmitting strategies which are detailed in the next subsection.

## 9.5 Energy models and sampling/sending strategy

To cover all possible scenarios, we will do the simulations using different energy models and sensing/transmitting strategies. In the section 6.3 we explained what an energy model is and what ones we will use. Here, we include them again. Finally we also include different sensing/transmitting strategies that we will use.

Next we include the energy models to use. To simplify the calculations we use adimensional units for the energy, 1u equals 1 unit of energy.

- **Energy model 1:** Reading energy cost is negligible compared with the used for the transmissions, 0u per reading and 1u per transmission.
- **Energy model 2:** Transmissions are 10 times more expensive than the readings, 0.1u per reading 1u per transmission.
- **Energy model 3:** Similar cost, 1u per reading and 1u per transmitting.
- **Energy model 4:** Readings are 10 time more expensive than transmissions, 0.1u per transmission 1u per reading.
- **Energy model 5:** Transmission energy cost is negligible compared with the used for reading, 0u per transmission 1 per reading.

The sensing/transmitting strategy defines how often the system will collect a sample and how often will transmit the samples already collected. We will consider the following strategies.

- **Simple strategy:** All readings are transmitted when they are collected.
- **Advanced strategy:** readings every SI, transmissions only when the last reading is below the threshold.
- **Market strategy:** custom or fixed SI and transmissions every hour. This strategy is the same that the hardware used for data collection in chapter 5 uses. We have called this as market strategy because most products in the market has a similar setting.

## 9.6 Smart policy simulations

In this section we will carry out all the necessary simulations to verify our smart sampling policy. First of all we calculate the VoI for the full season of vine, it is presented in the graph below.

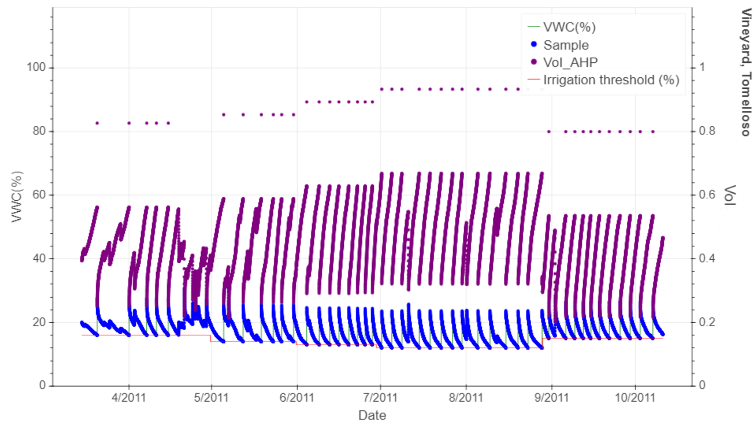



Figure 9.9: VoI of soil moisture for a season in the vineyard use case

As we can see for most measurements VoI oscillate between 0.2 and 0.7. Taking that as premise we propose a smart policy based in the thresholds included below. We remind that n is the number of measurements the system skips if the VoI is low enough.

$$n = \begin{cases} 0, & VoI \leq 0.53. \\ 1, & 0.45 \leq VoI < 0.53. \\ 2, & 0.33 \leq VoI < 0.45. \\ 4, & 0.28 \leq VoI < 0.33. \\ 8, & 0 \geq VoI < 0.28. \end{cases} \tag{9.4}$$

### 9.6.1 Simulation in different scenarios

Now we apply the smart policy detailed above for each sampling/transmitting strategy and energy model. For each scenario we will compare the energy used by the smart policy and a static policy with a sampling interval of 15 minutes.

#### Simple strategy

Reading and transmissions are simultaneous. These are the energy consumption in each scenario. The stress caused by both polices is the same and has a value of 0.01361. These are the results for each energy model.

Table 9.4: Smart policy in simple strategy energy scenario

| Strategy | Static policy | Smart policy | Saving |
|---|---|---|---|
| EM 1 | 20160 | 10761 | 46.62% |
| EM 2 | 22176 | 11837.1 | 46.62% |
| EM 3 | 40320 | 21522 | 46.62% |
| EM 4 | 22176 | 11837.1 | 46.62% |
| EM 5 | 20160 | 10761 | 46.62% |

### Advanced strategy

The readings are determined by the SI, transmissions are done only when irrigation is needed (VWC below the irrigation threshold). The stress caused by both polices is the same and has a value of 0.01361. These are the results for each energy model.

Table 9.5: Smart policy in advanced strategy energy scenario

| Strategy | Static policy | Smart policy | Saving |
|---|---|---|---|
| EM 1 | 44 | 44 | 0% |
| EM 2 | 2400 | 1120.1 | 49.16% |
| EM 3 | 20204 | 10805 | 46.52% |
| EM 4 | 20164.4 | 10765.4 | 46.61% |
| EM 5 | 20160 | 10761 | 46.66% |

### Market strategy

SI of 15 minutes and readings are transmitted only once every hour. These are the results for each energy model. The stress caused for both polices is the same and has a value of 0.1364. These are the results for each energy model.

Table 9.6: Smart policy in market strategy energy scenario

| Strategy | Static policy | Smart policy | Saving |
|---|---|---|---|
| EM 1 | 5040 | 5040 | 0% |
| EM 2 | 7056 | 6116.1 | 13.32% |
| EM 3 | 25200 | 15801 | 37.3% |
| EM 4 | 20664 | 11265 | 45.48% |
| EM 5 | 20160 | 10761 | 46.66% |

### 9.6.2 Discussion

We obtain several conclusions from the simulations. We list them below.

- The smart policy was more efficient than the static one in all the scenarios except the EM1 in advanced and market strategy for which had equal result. It also kept the same level of stress than the static policy in all the simulations.

- The smart policy was more effective in scenarios for which the readings had a higher cost. It is because the policy is designed to reduce the number of samples.

- The sampling/sending strategy has also a very significant effect on the power consumption. Strategies that send the readings simultaneously with the readings or every certain time use more energy. We can say that having a proper sampling/sending strategy is as much important as a having a good sampling policy.

- The scenario with worst performance was the one copied from the market devices. The level of stress produced by that strategy caused more than 10 times the stress caused by the simple and advanced strategies. Furthermore the power consumption was much higher than for the advanced strategy in most scenarios. We can deduce that there is a large room for improvement in the products from the market by using smart policies.

## 9.7 Energy aware policies

Other factor that could be used to improve the sampling strategies is the current and future availability of energy. In the introduction we mentioned that many devices are autonomous. However, during long periods of darkness the battery can run low so data flow will stop.

An energy aware policy could estimate future likely values of available energy in the buffer using the current level of the battery and the weather forecast (sun radiation). If for the next days or weeks, the prediction of solar radiation is low, the system can decrease the sampling frequency in order to save energy and survive during that dark period. Decrease the sampling frequency could cause some late irrigation or a lower density of data for other applications. However, is much better a period with few data than a period of blackout.

## 9.8 Conclusions and future work

From this project we have obtained the following conclusions.

- There is a big room for improvement in the energy-operation of soil moisture monitoring for the IoT devices in the market. This improvement is traduced in a better care of the plants in sensor-based irrigation systems and also into more energy-efficient devices.

- Smart sampling policies based in VoI of soil moisture have turned out to be a valid option to optimize the energy operation of soil moisture monitoring systems.

- Apart from the smart sampling policy, an optimal sensing/transmitting strategy can save significant amounts of energy. Specially if the transmission cost is much higher than the reading cost, which is the actual scenario for many products.

- An increase in the efficiency could allow IoT manufacturers to reduce the size of energy buffers and solar panels of the sensors, making the devices cheaper, smaller and thus more interesting for the user.

To continue with this work, the concept of smart policies and VoI could be used together with artificial intelligence and machine learning techniques to make fully autonomous devices in terms of configuration. Instead of providing the sensor with certain VoI thresholds manually, the sensor could learn from the environment and define its own sampling policy. This would not only improve the performance of the IoT sensor but also improve its handling, if it does not require any special configuration it will be much easier to use for the user.

Another path to improve remote moisture sensing would be the energy awareness of the sensor. We have just mentioned it but it could have a significant effect making more robust systems able to survive longer periods with little energy.

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# Appendix A
# Code and files

All the code used for the simulations is included in the next Github repository: https://github.com/daolgar/Soil-model.git

The repository includes the following files.

– **readme.md:** Text file with all the necessary instructions.

– **color_map_corn.csv:** Table with season sensitivity values for corn.

– **color_map_lettuce.csv:** Table with season sensitivity values for lettuce.

– **color_map_vineyard.csv:** Table with season sensitivity values for vineyard.

– **Almeria10-19.csv:** Weather dataset for the lettuce use case.

– **Huesca10-19.csv:** Weather dataset for the corn use case.

– **Tomelloso11-19.csv:** Weather dataset for the vineyard use case.

– **Soil_model.ipynb:** Jupyterlab notebook with the code to simulate the VWC in the tree use cases.

– **Smart_model.ipynb:** Improved version of Soil_model.ipynb with functions to simulate and plot the energy consumption, the induced stress and the VoI (AW and AHP). Function to simulate smart sampling policies. Also include variable irrigation thresholds to simulate RDI. Include option to simulate and plot the energy used and stress caused by several sampling intervals. Option to simulate several years (available years in the data-set).

Both Jupyter python files uses the python package included in [17] to calculate daily $ET_o$. It must be installed to use the weather forecast, the instructions to install it can be found in https://pypi.org/project/ETo/. Otherwise the function to calculate $ET_o$ can be disabled and a constant value of $ET_o$ assigned manually.