OVERVIEW AND POTENTIAL OF DIGITAL DECISION SUPPORT TOOLS IN PROMOTING AGROECOLOGICAL IRRIGATION

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DECLARATION

I hereby certify that this work is my own, except where otherwise acknowledged, and that it has not been submitted previously for a degree at this, or any other university.

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Overview and Potential of Digital Decision Support Tools in Promoting Agroecological Irrigation

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Abstract. Understanding how digital decision support tools can potentially promote agroecological irrigation is of great significance in light of the need to promote sustainable agricultural practices, considering that the irrigation demand is increasing with scarce water resources as exacerbated by climate change. In this study, the existing digital DSTs in France were characterized in order to provide insights on the type of tools that widely used new technologies, and their utility based on the spatial and temporal scales of recommendation. It also synthesized the motivations and potential benefits, sustainability features and improvements that the conceptors considered for these DSTs. Using a real plot, three DSTs were tested to assess the tools' irrigation recommendation and determine how it is affected by different soil types and maize varieties. It was found that DSTs in France has been widely and increasingly used for the last 10 years, with majority of these DSTs using new technologies as vectors, such as sensors and satellite data, primarily targeting field crops and market gardening, and with majority of the 64 identified DSTs having plot level and real time spatial and temporal scales of recommendations, respectively, with some overlaps. Additionally, the interviews with six of the DST conceptors highlighted the primary motivations, including maximizing water efficiency and water saving potential, achieving better yield margin, and promoting better decision-making process and agroecological adaptation. These DSTs support sustainable practices and agroecological agriculture through and optimization of energy and resource use in the manufacture, and adoption of carbon neutral technologies and climate-friendly features. However, some improvements were emphasized to enhance ease of use and advice, such as the numerical aspect of the model, data and modules integration, and climate change and irrigation constraints enhancement. Finally, testing of the three DSTs, including Irre-LIS, NetIrrig, and Pixagri Wago, indicates that the three tools are sensitive, although in varying degrees, to the three different soil types and, with exception of Pixagri Wago, to the three different maize varieties in terms of recommended irrigation needs in mm averaged in the period considered. Also, comparison of the tools' irrigation recommendation to the actual irrigation consumption of the study plot suggests an overestimation in Irre-LIS and Pixagri Wago, and underestimation in NetIrrig.

Keywords: agroecological irrigation, decision support tools, digital agriculture, precision agriculture

CONTENTS

1 INTRODUCTION

There is a growing consensus that climate change is imminent and affecting natural systems, including the food and agricultural systems, since water scarcity is one of the potential challenges posed by the scenario. The situation could even be exacerbated, especially for the water-scarce farming regions in many parts of the world. Hence, the adoption of sustainable agricultural practices that increase water use efficiency and optimize crop production is important. Modern agriculture that uses digital tools is considered a panacea in driving efficiencies across different farming models (Abdulai, 2022). The tools that this type of agriculture offers, including digital decision support tools (DSTs), have the capacity to provide farmers with tailored agronomic advice and help them make informed decisions about irrigation practices. By utilizing agro- and hydrometeorological-related data and information, coupled with crop models, these digital DSTs can advise farmers in real time on the timing and the amount of irrigation water to apply for a crop (Lin et al., 2017), thus, providing them more informed decisions (Cetin et al., 2021) and consequently driving efficient water use.

The potential of the DSTs in promoting agroecological irrigation in France in the context of climate change and often dwindling water resources can likely be significant. In addition to efficient water use, DSTs can possibly improve in reducing water waste, thus, mitigating the unfavorable environmental impacts of irrigation practices, since most of these tools use advanced mathematical models and machine learning algorithms that enhance the accuracy of water need predictions. Agroecological irrigation is an important movement that highlights the strong interconnection between the natural ecosystems and sustainable water management, and it is an important aspect of France's efforts to transition towards more environmentally-friendly agricultural practices (Niturkar, 2021; Addulai, 2022). Along this line, digital DSTs could help in achieving this goal, providing benefits to farmers in better managing their risks and natural resources (Vlasova, 2019).

However, the full potential of the digital DTSs is faced with several key challenges that need to be addressed. Firstly, the conceptors of these tools need to improve the ease of access and user-friendliness of these technologies, which pose a significant challenge to the strong uptake by the various farming population with different socio-cultural backgrounds, preferences and skills (Anastasiadis et al., 2018). Some of these technologies could be complex and require a level of technical expertise that all farmers may not readily have (Abioye et al., 2020), which can likely be addressed through provision of training and support to farmers. Additionally, there are also concerns over data privacy and security, data accessibility and interoperability that can likely make a farmer reluctant to adopt these technologies (Anastasiadis et al. 2018). There are also challenges being pointed out concerning the integration of multitude of agronomic, climatic, financial, and social factors that affect irrigation decisions (Cetin et al., 2021; Chowdhury et al., 2023; Mulele et al., 2023; Hedley et al., 2009), which also have some uncertainties pointed in the literature.

Understanding the potential benefits of digital DSTs in irrigation in promoting agroecological irrigation in France is an increasingly interesting domain. However, there are still knowledge gaps and thus, this study aims to characterize the existing digital DSTs in France. Additionally, it explores to identify the motivation of the conceptors in creating these DSTs and understand the issues on utilization, potential benefits, agroecological features, level of communication extended to the users, and the needed improvement. Further, it aims to determine how some of these DSTs perform in the farm by testing them on a plot level, specifically identifying how the tools respond to different soil types and maize varieties, the inter-tool variability in terms of irrigation recommendation, and on how the tool's recommended irrigation is compared to the calculated water needs. It is assumed that the DSTs in France are evolving and that the conceptors motivations in creating them are also aligned with agroecological principles, utilization and level of communication is improving, and that there are still needed improvements. Finally, it is assumed that when tested, the DSTs will respond differently to various soil types and maize varieties, the inter-tool variability is consistent for each soil type and maize variety, and the recommended irrigation would be comparable to the actual irrigation consumption of maize in the plot.

2 LITERATURE REVIEW

2.1 Climate projection, water scarcity and agriculture

The impact of climate change on water scarcity has become a pressing concern. Although uncertainties exists in the predictions and models used, changes in precipitation and other climatic variables have been observed, which pose a significant threat to water supply in many regions in the world (Schewe et. al., 2013). These changes include extreme events that can impact negatively the natural systems. Approximately four billion people experience water scarcity at some point during the year (Mekonnen and Hoekstra, 2016), and this could be exacerbated by population growth and an uptick in food and energy demand (Schewe et al., 2013; He and Rosa, 2023).

Recent studies would suggest that the impact of climate change on water resources in France is significant, hence, it poses an important implications to the country's water management, planning and adaptation strategies as far as ensuring its long-term water security is concerned (Azhari and Loudyi, 2021; Schilling et al., 2020; Erraioui et al., 2022; Ougougdal et al., 2020). The country's climate is projected to undergo significant changes in the future (Ceglar et al., 2020), marked by an increase in temperature by several degrees Celsius, with more frequent and intense heatwaves based on climate models (Wasimi, 2010), alongside contrasting increasing precipitation events in certain areas (Ribes et al., 2019) and with the latter having a significant effects on crop yields and productivity (Ceglar et al., 2020).

Water scarcity reduces photosynthesis and hinders nutrient uptake, thus, leading to nutrient deficiencies and affecting plant's growth (Oliveria et al., 2012). Without enough water needed, the plant experiences water stress leading to wilting, reduced leaf expansion, and even cell death (Volaire et al., 2023). Along this line, without enough adaptation measures, including the use of efficient digital technologies, there would be lower crop yields, especially for water-intensive crops like maize (Gonzales-Camacho, Mailhol, and Ruget, 2008). In addition, it may alter the types of crops that can be grown in certain regions of France (Altieri et al., 2015), since the crops would be substituted with those that can withstand high water stress.

The economic impacts of climate change-induced water scarcity issues can be significant, characterized by the decrease in production output, reduced contribution of the agriculture sector in the Gross Domestic Product, fluctuating food and market prices, that can potentially increase a number of people at risk of hunger and food insecurity based on the State of Food and Agriculture report by the Food and Agriculture Organization (Neufeld, 2020), which is consistent with a study found in Pakistan on how the life, biodiversity, and socio-economic activities have been affected (Mehmood, 2021). However, due to the interplay of complex environmental and agronomic factors, modelling the impacts of climate on major crops (Celgar et al., 2020), and consequently, quantifying the economic impacts in French agriculture is challenging.

2.2 Agroecology and the future of irrigation

Globally, irrigation demand is projected to increase although there is difficulty in pinpointing the exact figure. However, the expansion in the irrigated agriculture lands indicate the demand for irrigation water will increase, as the irrigated area could expand by 32 million hectares by 2050 as estimated by the Food and Agriculture Organization of the United Nations, or a potential expansion of at least 70 million hectares for the same period given that recent studies suggest underestimation by the models being used (Rosa et al., 2020). Conversely, there are limitations that can hinder translating this increased projection into a reality, such as reversion of irrigated areas to rain-fed agriculture due to impact of climate change (Rosa et al, 2020), and the depletion of groundwater resources, which irrigation is highly reliant to, hence, a serious sustainability issue (Hejazi, Edmonds, and Chaturvedi, 2012)

In a nutshell, in France, four scenarios characterizing the different pathways relative with carbon neutrality were considered in projecting water demand by 2050. Among the four scenarios, S3 and S4 indicate the highest consumption of irrigation water by major agricultural crops, such as maize, legumes, cereals and fruits for the period (ADEME, 2022). S3 scenario is where technological development is juxtaposed in addressing environmental challenges, while S4 is a repairing bet scenario with preservation of the lifestyles of the early 21st century in addition to putting global ecological issues as triggers to economic and technological progress (ADEME, 2024).

Irrigation demand is increasing, but water resources are potentially dwindling in many regions. Hence, it poses a great challenge on the sustainability of irrigation practices. For instance, ground water is a major water resource contributing about 60% for human consumption with a significant amount allocated for irrigation in France (Roux, 1995). However, those areas dependent on these water resources, such as those with semi-arid and arid climates, are already experiencing water stress, and the situation is expected to be exacerbated by climate change (Pradipta et al., 2022).

To address the sustainability in irrigation practices, the agroecological transition has become an integral component, highlighting its currency in the mitigation and adaptation strategies. This transition adopts the ecological principles in order to achieve a resilient and productive agricultural systems (Desa and Jia, 2020; Loconto, 2020). As far as water resources is concerned, it aims to transform the irrigation practices by addressing water waste, nutrient depletion, and environmental degradation, and thus, promotes more efficient irrigation techniques that reduce water usage and improve water distribution (Dittmer et al., 2023). Through the National Strategic Plan for the Common Agricultural Policy 2023-2027, France is supporting for the roll-out of European Union's agricultural policies, highlighting the adoption of agroecological principles at the national level (Ministry of Agriculture and Food Sovereignty, 2023). Additionally, the government's strong commitment to agroecology is manifested in its investments in research and development programs in this area (Bellon and Ollivier, 2018).

While the benefits of agroecological transition are present, there are also hurdles to overcome. Changing to more efficient systems comes with a cost (Schaible and Aillery, 2012), which can be prohibitive given the different circumstances of the farmers (Ward et al., 2016). Also, there are technical and technological issues (Pradipta et al., 2022) that require a certain degree of expertise, and supportive policies and market structures, such as those policies that incentivize efficient water use (Grafton et al., 2018).

2.3 Agroecological Transition and the Use of Technology

Achieving agroecological transition is replete with promising innovations. In the agriculture sector, the aim is to provide sustainable, nutritious food for a growing population amidst some constraints and limitations. Among various means, the potential of technology to aid en route agroecological pathways is significant, especially when the benefits can be properly leveraged and valorized on the ground. At present, technology is advancing in a faster pace, with promising innovations that can be of great help. For instance, precision agriculture has been trail-blazing, improving water use efficiency, reducing water wastage and energy consumption (Hakkim et al., 2016), and thus, promoting sustainability because of its ability in decreasing environmental footprint of agricultural production (Shannon et al., 2018).

Gaining strong currency in the modern agriculture are the digital decision support tools (DSTs). These DSTs offer innovative solutions to farmers looking to optimize resource management and enhance productivity (Lima et al., 2020). In particular, it can optimize irrigation management and enhance its efficiency (Imbernon-Mulero et al., 2023; Ososanya et al., 2015). In a larger scale, they have the potential to address global challenges related to water scarcity, food security, and environmental sustainability (Lima et al., 2020; Fernandez, 2017; Karunathilake et al., 2023). Because it is able to provide a useful decision support, recommendations, and insights, it helps the user in terms of the amount of irrigation water to be applied at different growth stages of the crop taking into consideration the regional climate conditions and cropping systems (Neupane and Guo, 2019). This capacity is enhanced with the increasing use of machine learning algorithms that analyze sensor data and other various types of data in order to identify patterns for irrigation decisions (Chaterji et al., 2020).

There have been several successful use cases of the digital DSTs in irrigation. Some of these include DSTs used in the Zhanghe Irrigation System in China using weather forecast and sensors (Wang et al., 2019), in Mekrou river basin in Africa using a tool that ultimately improve crop productivity (Udias et al., 2018), the low-cost system in the northern Italy that showed significant water savings (Viani et al., 2017), the web-based DST "Fruchtfolge in Germany (Pahmeyer, Kuhn, and Britz, 2021), the AQUATOOL DST in an Andalusian basin using hydrological and water management models (Ruiz-Ortiz et al., 2019), the LIFE 4Doñana project using crop needs prediction models (Proyecto LFE 4Doñana, no date), and the ISSCADA System in the U.S.A. (Evett et al., 2020).

While DSTs have various accounts of success, there are also cases where they have failed to deliver the expected benefits because of some challenges in both the implementation and adoption. Cantor et al. (2021) noted that some DSTs use a multitude of data and analyzing them is sometimes a difficult task and that there are still gaps in the existing systems (Zaman and Swaminathan, 2018), such as on how these systems integrate the various factors affecting irrigation management (Neupane and Guo, 2019), including involvement of the various stakeholders in the process, as characterized by situations where these systems are not in tune to the needs of the end-users, because these systems are in themselves often complex (Arsene et al., 2020). In a study of farmers in the Herault department in France, the main barriers identified in the adoption of advanced monitoring tools include cost, lack of time and labor, and the absence of water shortages (Meyer, no date). Lastly, the accuracy of these DSTs are not fool-proof, since, readings can be influenced by sensor placement, calibration, and interference from environmental conditions for those that are using sensor data, although this has been addressed by advanced machine learning algorithms (Shah and Das, 2012), computational intelligence and agro-hydroinformatics with information technology (Abioye et al., 2022). Still, the complexity of the irrigation system is in itself a challenge (Karar et al., 2020), in addition to the fact that the data being used are variable and heterogenous for the machine learning algorithms to fully capture them (Abioye et al., 2022), and, hence, these are the constraints that the DST conceptors have to address in order to improve the reliability and accuracy of these tools.

3 MATERIALS AND METHODS

3.1 Characterization of the Digital DSTs

In characterizing the digital decision support tools, an inventory was carried out through online using the already existing surveys conducted, including those from the initial work of Leroux (2023) and AgroTIC (2024), as primary sources, while also expanding the search through snowballing (Ghent University, 2023; Wohlin, 2014). Only existing DSTs in France were considered, and those in the lists but which do not have any information available online were excluded. Information that provide better understanding of the DST were gathered, and each DST was defined based on the model and data used, the inputs, interface, outputs, spatial and temporal scale of recommendation, targeted crops and the year that the DSTs were introduced in the market so that their evolution can be observed.

3.2 Motivation of the DST Conceptors and Other Features

To better understand the motivation in the creation of the DST, issues on utilization, potential benefits, agroecological features, level of communication, and the needed improvements from the conceptor's perspective, we first contacted all the manufacturers of the DST included in the inventory list whose tools have been used in France, and those who favorably responded to the invitation were interviewed. Using a structured set of questions, the interviews were conducted online and the transcriptions of the interviews were automated using a transcriber with artificial intelligence (AI) by TurboLearn LLC (2024), which has a 99.8 per cent accuracy. Another AI tool, the Insight-lab by data IQ (no date), was also used to generate the knowledge graphs on specific themes from the interviews.

3.3 Desk Testing – Simulation of the DSTs

For the desk testing and simulation of the models, three tools, namely, Irre-LIS, NetIrrig, and Pixagri Wago, were selected from the inventory of the existing DSTs in irrigation in France. To test the tools, we used the plot with an area of about 147,620 m^2 (perimeter of 1,575.38m) located near Vinon-sur-Verdon in the southeast of France, with geographic coordinates 43.73273418417999, 5.803116291785647, as shown in Figure 1. The plot, named as Nicolas Gassier plot, has been using a conventional tillage management system, which "involves moldboard plowing and harrowing" (Wahl et al. 2004, p.821). Based on field assessment and observation, the soil typology of the study plot is predominantly silt loam with an available water capacity of 175mm over 120cm considering the soil texture and using pedotransfer functions. Maize is the crop being cultivated in the said plot.

As already presented, one of the aims of the study is to determine how some of these DSTs perform in the farm by testing them on a plot level, specifically identifying how the tools respond to different soil types and maize varieties, the inter-tool variability in terms of irrigation recommendation, and on how the tool's recommended irrigation is compared to the actual irrigation consumption. Specifically, it would be interesting to investigate the sensitivity of each DST selected for desk testing to different soil types and maize varieties, because each soil type and each maize variety requires specific water needs or irrigation based on, among other factors, its soil texture or structure and its agronomic characteristics, respectively, according to available literature.

Figure 1 shows the test plot and its location in Vinon-sur-Verdon named as Nicolas Gassier plot with an area of about 14.7 hectares (https://earth.google.com and NetIrrig).

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The plot was parameterized for every simulation to provide consistency and comparability of results. Since the three tools required various information, the same input information and data available in the tool's model were used, or the closest data required between and among the tools were adopted from one simulation to another, while selecting the parameters that best represent that soil or maize variety selected from one DST to another for every specific plot configuration.

Three crop varieties, P7326, P0725, and P0937, with different maturity characteristics, identified as early variety, medium variety, and late variety, respectively, were used for the three soil types, namely, silt loam, sandy clay and sandy loam, and the comparable soil types and maize varieties for the other DSTs were used as detailed in Table 1. These three soil types are common in the area and also in France, where maize is suitable for cultivation, with varying effect to yield (Biberdzic et al., 2018).

	Irre-LIS	NetIrrig	Pixagri Wago
Soil			
S1	Silty clayey (silty alluvium) with an RU Max of 80mm	Clayey silt under silty textures	Silt loam
S2	Clayey under other with an RU Max of 125mm	Sandy clay under clay-sand textures	Sandy clay
S3	Silt sand under other (silt sand) with an RU Max of 80mm	Medium silt sandy under silt sand textures	Sandy loam
Maize Variety			
V1	P7326 (Early variety)	Low water requirement ETM grain corn (reference)	Grain Corn (Early)
V2	P0725 (Medium maturity maize variety)	Grain corn 0.8 ETM Allier department	Grain Corn (Semi-early)
V3	P0937 (Late variety)	But late grain G4 420-460 Drome department	Grain Corn (Late)

Table 1 shows the comparable soil type and maize variety used in the testing for the three DSTs.

Using the same plot, with an area of 15 hectares, 7.31 hectares, and 7.0 hectares for Irre-LIS, NetIrrig, and Pixagri Wago, respectively, a total of 27 plot configurations for testing was used with every tool having 9 plot configurations each (Table 2). One plot configuration corresponded to one simulation of the tool.

Tool	S1 constant	S2 constant	S3 constant	
Irre-LIS	S1V1	S2V1	S3V1	V1 constant
	S1V2	S2V2	S3V2	V2 constant
	S1V3	S2V3	S3V3	V3 constant
NetIrrig	S1V1	S2V1	S3V1	V1 constant
	S1V2	S2V2	S3V2	V2 constant
	S1V3	S2V3	S3V3	V3 constant
Pixagri Wago	S1V1	S2V1	S3V1	V1 constant
	S1V2	S2V2	S3V2	V2 constant
	S1V3	S2V3	S3V3	V3 constant

Table 2 details a total 27 plot configurations used in the testing, with each tool having 9 configurations

It is important to clarify that the discrepancy in the area of the plot used in Irre-LIS, as indicated in Table 3, was due to the two different estimates of the area made using GoogleEarth. Also, the discrepancies of the areas of plots used in NetIrrig and Pixagri Wago to that of Irre-LIS was mainly due to practical reasons, since using the whole area, especially for Pixagri Wago, was expensive – the tool provided and used was a trial/testing version, which was only limited to a maximum of 10 hectares, and it would be more expensive to use more than 10 hectares for the simulations of the remaining plot configurations. However, regardless of the discrepancies in the plot areas used, the location of the plots is what greatly determines the irrigation recommendation of the DST, since DSTs are generally location-dependent, rather than area-dependent. Additionally, these tools rely on real-time data collection about crop water and nutrient requirements (Plascak et al., 2021), which would suggest that optimal irrigation application is based on regional climate conditions and cropping systems (Neupene and Guo, 2019), where exact plot location influences factors such as soil moisture, nutrient availability and microclimate (Neupane and Guo, 2019; Plascak et al., 2021), although larger plot areas may exhibit a different heterogeneity in soil properties, crop growth, and water requirements, thus affecting irrigation strategies (Neupane and Guo, 2019), but clearly not the irrigation recommendation provided by a DST.

Irre-LIS	
Postal code	83560
Municipality	Vinon-sur-Verdon
Tool Parameters	Information and Data
Date Week/pl	5-May-24
Previously Irrigated	Yes
My previous (crop)	Mais Grain
Rain zone area selection	Zone 1
Irrigation equipment	Other (sprinkler irrigation)
Irrigated area (ha)	15
Previously irrigated	Yes
Irrigation dose (mm)	427
Duration of water tour (days)	2
Type of water resource	Watercourse or alluvial aquifer (individual)
Area of Plot used	14.7ha+
NetIrrig	
Stone rate %	10
Maximum exploitable soil depth	150cm
Settlement rate %	10
Number of days needed to water the plot	2
Type of irrigation	Sprinkler irrigation
Fixed irrigation capacities	
Area of plot used	7.31ha
Pixagri Wago	
	October 3 (Early variety)
	October 23 (Medium)
Harvest date	November 2 (Late)
Maxium irrigation dose	427
Number of days per water cycle	2
Irrigation system	Spray irrigation
Area of plot used	7ha

Table 3 shows the additional parameters required for Irre-LIS, NetIrrig and Pixagri Wago, while using the comparable soil type and maize variety respective to every plot configuration, with the same sowing date, number of watering cycle and type of irrigation for all DSTs for those DSTs with the same input parameters, while all other parameters are specific to the that tool.

The irrigation being recommended by the tools to avoid water stress was determined starting from the period when water stress was evident. To get the total irrigation applied for every tool starting from sowing, a common reference end period of irrigation application, which was July 18, 2024, was selected, since it was the maximum date common to all three DSTs where irrigation recommendations could be predicted when the simulation was run. Based on the design of the tool, a water stress would be avoided if the line would be kept above the readily available water (RUF) curve, which is addressed by applying irrigation to provide the optimal water requirement of the crop. The sowing date was set on May 5, 2024, coinciding the same sowing day from last year for the study plot.

Two scenarios were considered, pre-optimal and optimal. Pre-optimal scenario refers to the initial simulation of the tool given the inputs used, where field variability, amount and magnitude of the water stress, and irrigation strategies were evaluated before implementing them in the field (Lin et al., 2020; Neupane and Guo, 2019). This scenario also provided information and timing to commence irrigation application. On the other hand, optimal scenario refers to a complete simulation when the irrigation recommendation was applied for the study period to avoid high water stress of the crop, wherein the tool's water balance was also recalculated every irrigation application. Sensitivity analysis was conducted to determine what DST is affected by the type of soil and variety of maize crops in terms of irrigation advice being provided. The computation and visualization of the sensitivity of the tools in terms of irrigation application advice with respect to soil type and maize variety for every tool was automated and coded using Python and run using PyCharm Community Edition 2020.3.3. Finally, the difference between the DST irrigation recommendation root and the actual irrigation consumption of the plot was determined to assess whether the DST is underestimating or overestimating.

4 RESULTS AND DISCUSSION

4.1 Characterization of the Digital DSTs

Initially, two main families of DSTs were identified, namely, those that are using a water balance model and those that are based on the plot-level measurements each with different advantages and disadvantages (Gendre, 2021). However, the inventory and characterization of the existing DSTs in France indicate that there are emerging DSTs using advanced technologies, which necessitate to expand the categorization of families of DSTs. This is likely due to the speed of innovations in this area. In addition, the literature indicates a growing focus of development and implementation of DSTs in France, although the exact available area affected is yet to be determined (Neupane and Guo, 2019; Plascak et al., 2021). Spatially, of the total 64 DSTs, majority of the DSTs have a plot-level recommendation with 45 of them, and with the least number focusing at the territory level, where fiver of them were identified (Figure 2). Moreover, some DSTs overlap, as some provides plant-plot spatial scale of recommendation, with 5 of them; plant-farm, 2 ; plot-farm, 7; plot-territory, 4; and plot-farm-territory, 2. DSTs specific only to a particular spatial scale were as follows: plant level, 5; plot level, 31; farm level, 10; and, territory level, 1.

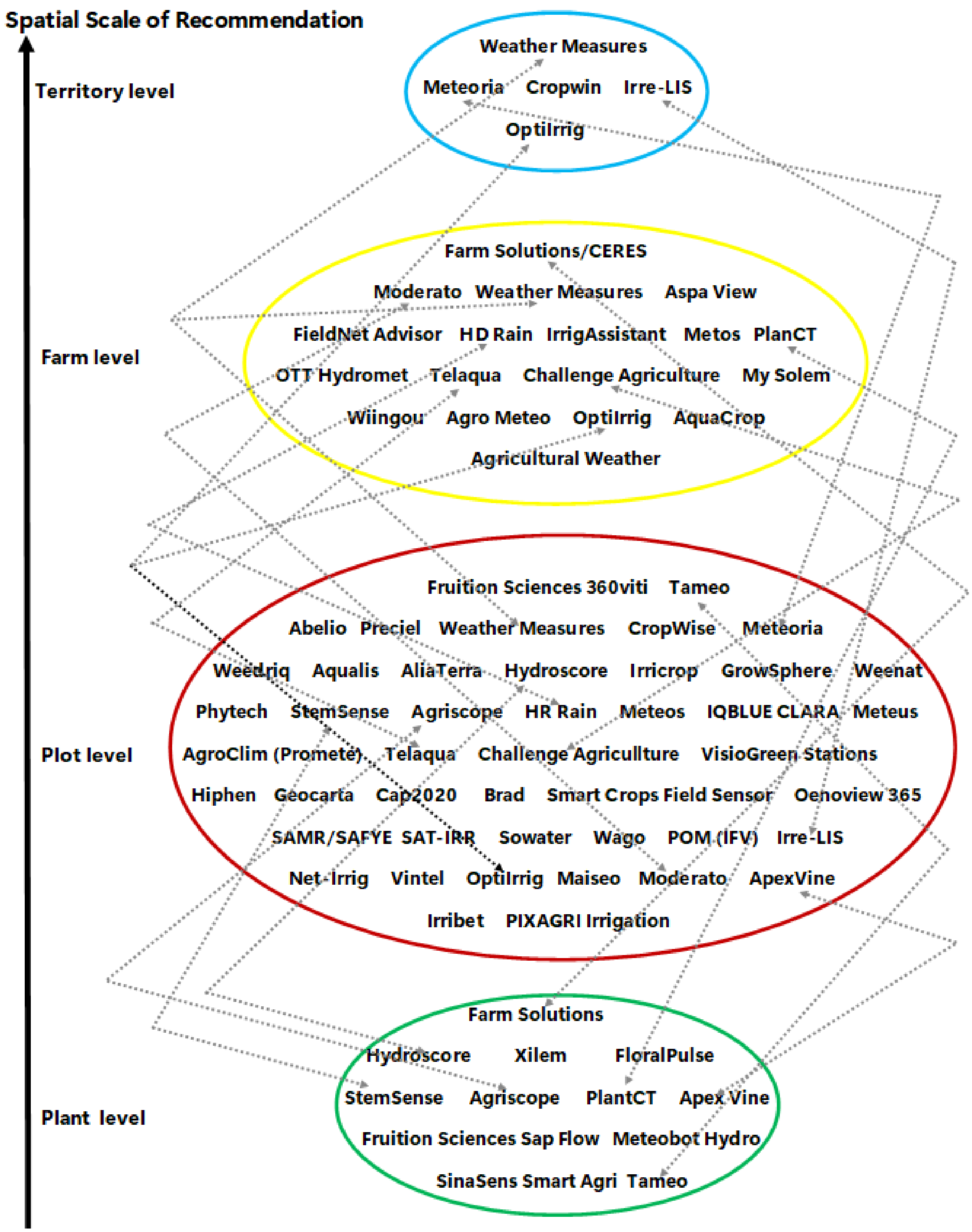


Figure 2 indicates that the plot-level spatial scale of recommendation is where most of the DSTs are concentrated.

Temporally, a significant number of DSTs provide real-time recommendation or status of the field and plant conditions with 15 of them, followed by DSTs providing daily recommendations with 11 (Figure 3). It is important to note that these DSTs also use predictive models in order to provide advance irrigation recommendations to the farmers. Some of these DSTs also overlapped in their temporal scale of recommendation, such as, five-minute recommendation, 15-minute, and up to 7 days, with one DST; real-time and three-day, 1; real-time, daily, and seven-day, 1; daily and seven-day, 1; 10-day, 30-day, and one-year, 1.

Temporal scale of recommendation

1 year : Agricultural Weather

30-day : Agricultural Weather

2 to 3 weeks : Farm Solutions/CERES

15 days : Weenat

10-day : Agro Meteo, Agricultural Weather

9 days ahead : Maiseo

9-day : Tameo, Cap2020

7 days ahead : AgroClim (Promete), Challenge Agriculture

7-day : GrowSpehre, Wago, Net-Irrig

6-day : Sowater

5-day : Irricrop, Brad, Oenoview 365 HYD, MySolem

3 to 7 days : Metos

3-day : IrrigAssistant (with Columbus)

Daily : Abelio, Weather Measures, FieldNet Advisor, Aqualis, AliaTerra, Irricrop, Xilem, FloraPulse, StemSense, Agri scope PIXAGRI Irrigation

3 to 6 hours : Preciel

Every hour : Weather Measures, FieldNet Advisor, Brad, Agricultural Weather, Phytech

15 minutes : Preciel, Metos, Fruition Sciences Sap Flow,

10 minutes : Meteobot Hydro

5 minutes : Metos

Every minute : PlanCT

Real time : CropWise, Meteoria, Aqualis, AliaTerra, Hydroscore, IrrigAssistant (with Columbus), Weenat, HD Rain, IQBLUE CLARA, Meteus, Fruition Sciences Sap Flow, OTT Hydromet, SinaSens Smart Agri, Hiphen, Geocarta,

No specific (information) scale, dependent on the OAD connected: Fruition Sciences 360viti, Wiingou, POM (IFV), Vintel, AspaView

Figure 3 illustrates the wide ranging temporal scales of recommendations provided by the DSTs, with majority having a real-time recommendation.

Sensors have become an indispensable tool that provide input data to the DST, and about half of the existing DSTs are either stand-alone, or are used together with crop model and satellite data, as shown in Figure 4. Moreover, a crop model is usually coupled with in-situ sensors, satellite data, or is used alone.

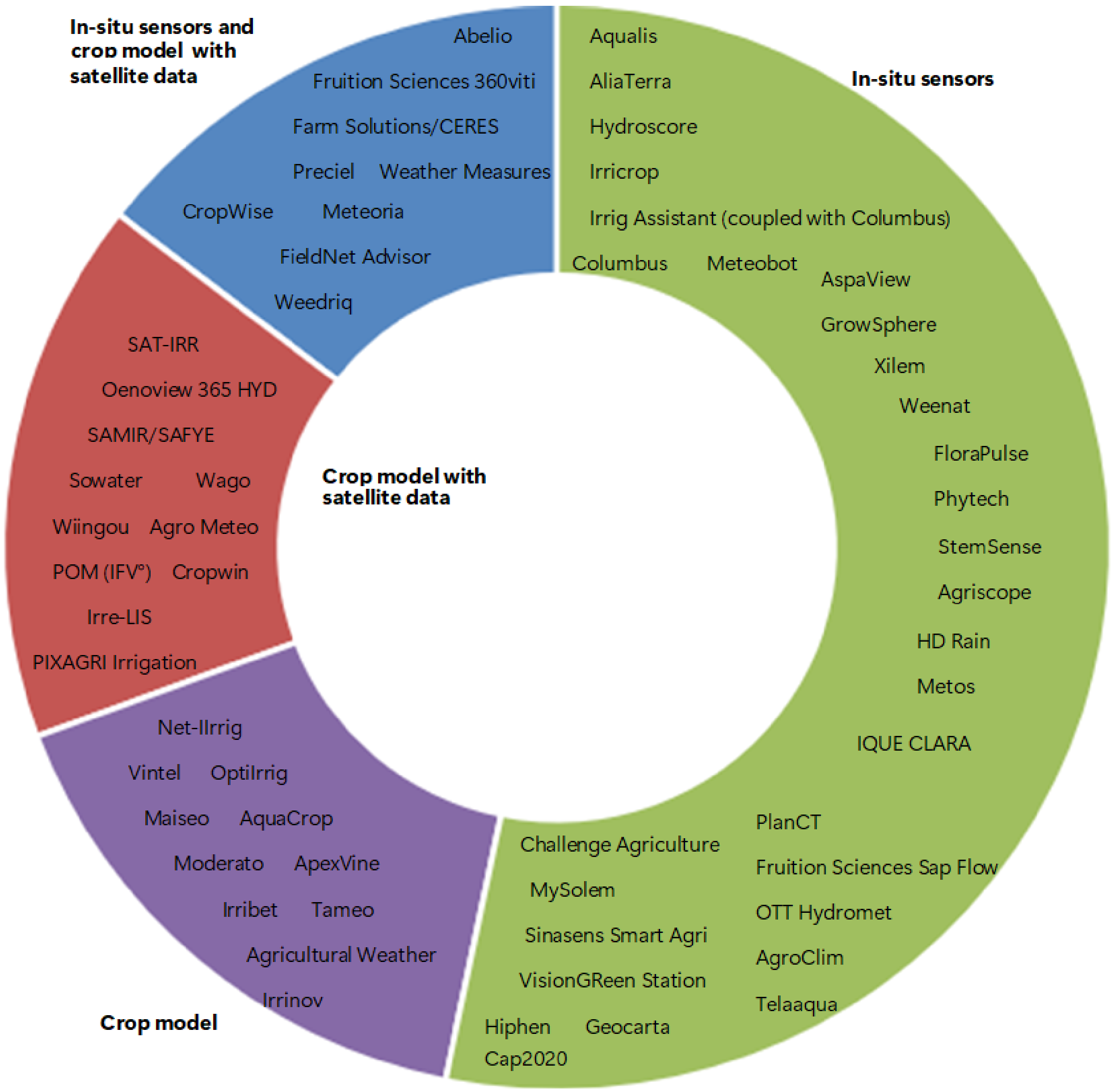


Figure 4 classifies the DSTs according to the different vectors, with majority of them using sensors.

Majority of the crops targeted by the DSTs are field crops and market gardening crops, such as maize, cereals, sorghum, wheat, barley potato, spinach, peas, soybeans, tobacco, onion, sunflower as indicated in Table 4. In general, the DSTs have put their focus in providing irrigation recommendation for field crops, market gardening, and arboriculture.

Name of DST	Targeted crops				Others
	viticulture	field crops/market gardening	arboriculture	horticulture	
Hydroscore, Wilem, Fruition Sciences Sap Flow, Geocarta, Oenoview 365 HYD, POM (IFV) ApexVine, Vintel					
FloraPluse			orchards		
PlantCT			apple and stone fruit		
StemSense	includes wine grapes		orchard	apple, peach, citrus, avocado, cherries, nuts, and more).	
Meteus			tree crops		
AgroClim (Promete)		potato, onion			
SinaSens Smart Agri			walnuts, olives, etc.		green spaces
Net-Irrig		cereals, corn, peas, sunflowers, soybeans, sugar beets, sorghum		canned vegetables (beans, peas, flageolets, salsify, carrots, vegetables (beetroot, asparagus, potatoes, onion	
Meteobot Hydro			tree crops		
Condiditons)					
Farm Solutions/ CERES			orchards, tree nuts, grapes, citrus crops,		
Agriscope (Dendrometer)			tree crops, i.e. apple, apricot, etc.		
AspaView				production	big cultures
Irribet				beet	
Sowater			orchards, i.e. citrus, pomegrate, etc.		
Phytech			tree cops		
Challenge Agriculture		cereals, corn	fruits, i.e. melon, etc.	vegetable, seeds	other irrigated crops
MySolem					
Abelio		corn, soybean, sunflower, wheat, green bean and potato			
Preciel		corn and wheat			
CropWise		large crops			specialty crops
SAMIR/SAFYE		wheat)			
Cropwin		soybean			
Maiseo		corn, popcorn and all types of waxy.			
Moderato		maize			
Tameo		soft winter wheat, corn, barley, other new species			
Irre-LIS		(straw) cereals, soya/soybean, wheat, durum wheat, corn (fodder), seed maize, potatoes, spring barley, tobacco,			
Optilrrig					seasonal crops
Wago		corn and wheat			annual crops; large crops and industrial crops
PIXAGRI Irrigation		all types of corn, wheat, cotton, vegetables			

Table 4 classifies the crops targeted by the DSTs, with a significant number focusing on field crops/market gardening. The blank colored boxes refer to the general crop category given in the heading used by the online sources, and did not mention any specific crop with that category.

Name of DST	Other targeted crop categorization
VisioGreen Stations, Cap2020, Aqualis, IrrigAssistant	All crops
Weedriq, Columbus, Metos	All irrigated crops: (potatoes, onions, shallots, garlic, vines, vegetables, big cultures)
Weather Measures, Meteoria, FieldNET Advisor, Irricrop, Weenat, OTT, Hydromet, Brad, Hiphen, Smart Crops Field Sensor, SAT-IRR, Agricultural Weather, HD Rain, Wiingou, Agro Meteo, Telaqua	Various crops (specific crops not identified)
AliaTerra	Customizable according to agricultural activity: mangoes, olive, apples, almonds, pineapples, watermelons, salads, cabbage, tomatoes, etc.
GrowSphere	Perennial crops (open field even greenhouse: 40 crops)

Table 5 provides additional categorization of the targeted crops of the DSTs that are not using the standard crop categorization.

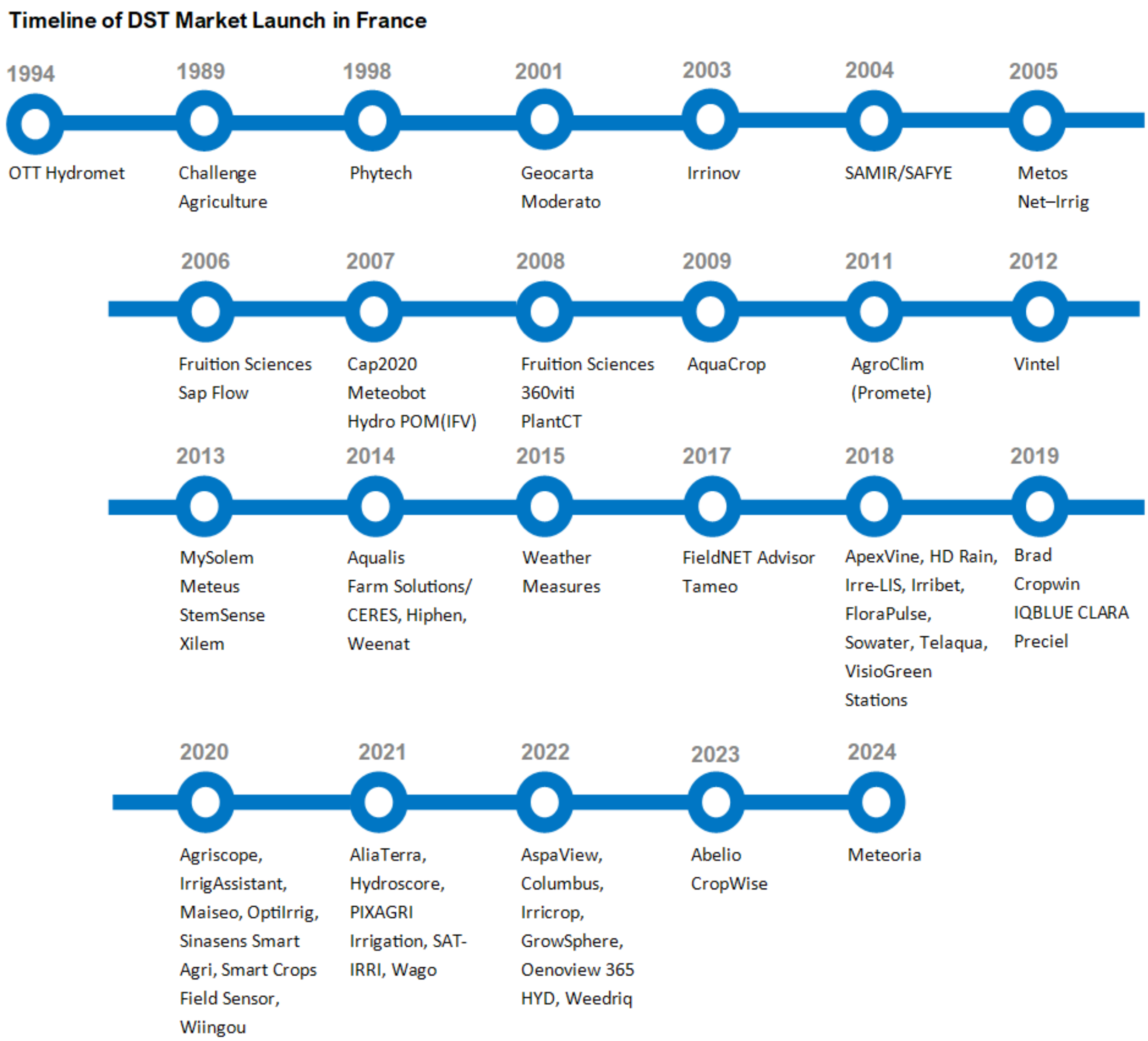


Figure 5 shows the chronology of the market launch of DSTs in France, indicating the increasing presence of DSTs for the last 10 years.

4.2 Synthesis Interview with DST Manufacturers

Based on the interviews with the six DST conceptors, including Irre-LIS of Arvalis, GrowSphere, Aqualis (Agralis), Hiphen, Vintel, and NetIrrig (Seabex), their responses provide useful insights on the motivation behind these tools, the ease and level of use, the potential benefits, sustainability and agroecological features, the way of communicating about these DSTs, and improvements.

4.2.1 Motivation for the DST Conception

Questions: *Why did you come up with this DST? What are you trying to address with this DST? What needs or issues are you trying to meet and address at the microcosm (farm) and macrocosm level (societal)? How this DST will be able to address those needs or issues? What are the specific and important features of the DST for it to be able to meet or address those needs and issues?*

The development of Decision Support Tools (DSTs) in agriculture is primarily motivated by the need to specifically directly help farmers decide when and how much to irrigate, and consequently, enhance water efficiency, optimize irrigation practices, and, address challenges related to water scarcity, climate change, and technological advancements in the agricultural sector. These tools aim to assist farmers in making informed decisions about irrigation, crop management, and resource utilization. The key objectives of DSTs include improving crop yields, promoting sustainability, and contributing to environmental conservation efforts.

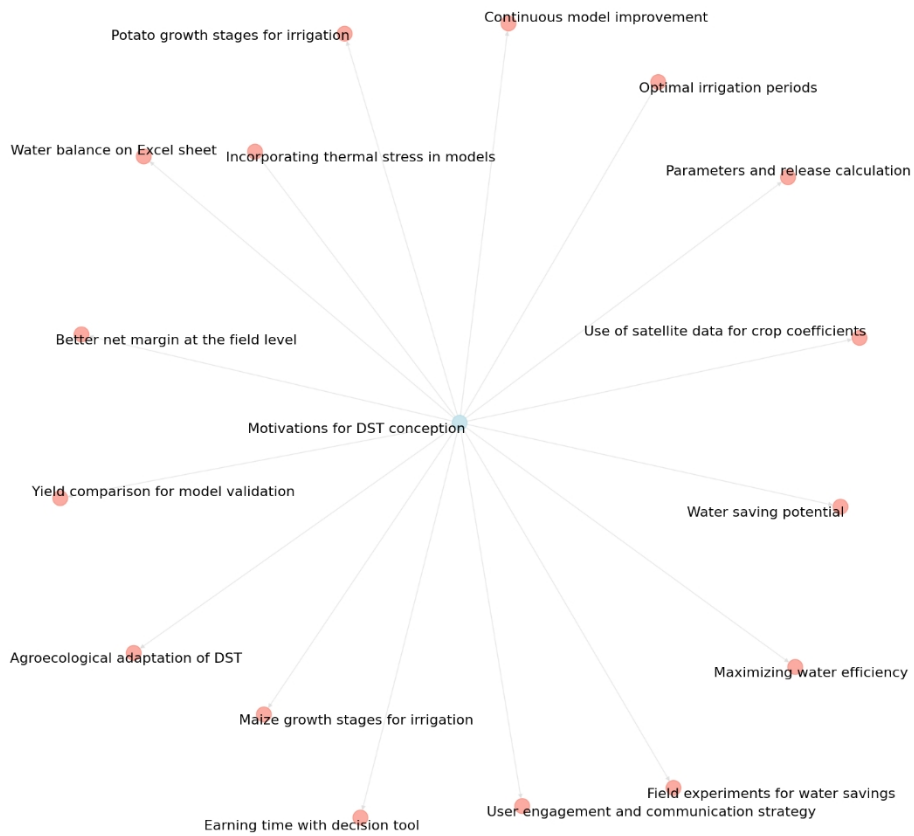


Figure 6 is the AI-generated knowledge graph, highlighting the major themes on motivations, which shows that some of the major motivations behind the creation of the DSTs are to maximize water efficiency, water saving potential while assisting as well field experiments in this area, better yield margin at the field level, and promote better decision-making process and agroecological adaptation through the use of satellite and crop data, water balance model and other important parameters.

At the farm level, DSTs like Irre-LIS, GrowSphere, and Aqualis aim to enhance decision-making processes related to irrigation, crop rotation, and water management. By providing personalized recommendations based on real-time and/or historical data, these tools empower farmers to optimize their irrigation strategies, leading to increased efficiency, profitability, and resource conservation. The integration of economic indicators, agronomic models, and strategic tools in DSTs facilitates a holistic approach to water management, benefiting both farmers and the larger community.

Societally, DSTs play a crucial role in promoting sustainable water management practices, addressing water scarcity issues, and contributing to broader environmental goals. By improving water efficiency at the farm level, these tools support societal concerns related to water conservation, climate change, and food security. The integration of databases, meteorological data, and crop information in DSTs simplifies decision-making processes for farmers, leading to reduced water usage, increased crop yields, and enhanced environmental sustainability.

Figure 7 shows the needs and issues to be addressed, including research and development, such as accurate integration of thermal stress and hydric stress in the model and on how to meaningfully integrate yield data and other data in the tool, and the tool's ability to provide advice on water saving and water efficiency maximization.

To address the needs and achieve the objectives outlined above, DSTs incorporate specific features such as comprehensive monitoring and control systems for irrigation, automated valve operation, sensor integration for real-time data collection, and crop models for tailored recommendations. These features enable farmers to make informed decisions about irrigation practices, optimize water usage, and enhance crop productivity. Additionally, DSTs offer modules for limiting volume management, cover crop modeling, and economic analysis, enhancing their utility and effectiveness in addressing water efficiency and sustainability challenges.

In summary, DSTs in agriculture are essential tools for modernizing farming practices, improving water efficiency, and promoting sustainable agriculture. By leveraging specialized knowledge, collaboration with technical institutes and organizations specializing in various crops, and incorporating advanced technologies like drones, sensors, and real-time data analysis, DSTs contribute to enhancing crop management, increasing productivity, and supporting environmental conservation efforts. The continuous improvement and innovation in DSTs ensure their relevance and effectiveness in addressing the complex water management needs of modern agriculture, benefiting both farmers and society as a whole.

4.2.2 Ease of Use

Questions: *What feedback do you receive from your users in terms of the ease of use of the DST and the application (hardware and software)? In terms of DST features, what makes it easy to use for the farmers? Are there any features of the DST, both hardware and software, that you find or consider challenging for the farmers/users? At what length do you provide technical assistance to your users/farmers?*

The interview with the above-mentioned DST respondents provided valuable insights into the feedback regarding the ease of use of DSTs and their applications, focusing on both hardware and software aspects. The feedback highlighted user experiences, features contributing to ease of use, challenges faced, and the level of technical assistance provided to users for each tool.

Starting with Vintel, the feedback emphasized positive user experiences, particularly in terms of irrigation advice and disease management. Users found the tool user-friendly, with essential information displayed clearly. Features like a FAQ section, webinars, and step-by-step guidance enhanced usability. However, challenges were noted in the water features, indicating areas for improvement. Vintel aims to enhance the irrigation module by focusing on cover crop management and nitrogen fertilization. Technical assistance is primarily provided through email and phone support, with a collaborative approach between the support and development teams to address user queries effectively.

Moving on to NetIrrig, the respondent highlighted the ease of use of their DST, with over 380 customers finding the platform user-friendly. Training videos and a mobile app facilitated access to information, reducing help requests. Challenges included adjusting growth stages and understanding recommendations, which the company is addressing through satellite imagery and generative AI modules. Technical assistance is provided through phone support, video tutorials, and webinars, ensuring timely help for users.

The interview with GrowSphere focused on irrigation and fertigation management. The system aims to make irrigation easier and more efficient for growers, with features like alerts and recommendations. Challenges included the level of involvement required from farmers in maintaining the hydraulic system. Technical assistance is provided through training and support, adapting to the specific needs of farmers in different regions. Ongoing developments include integrating remote sensing and satellite data for more accurate recommendations.

Aqualis highlighted that their digital DST is designed for effective irrigation management. Users appreciated the robustness and longevity of the tool, with customization options available. Challenges were noted for older farmers in using smartphones and the app, requiring technical assistance. Aqualis provides support through a technical hotline, tutorials, and email assistance. Hardware features like Sentek probes offer precise soil humidity measurements, aiding in water consumption data collection.

Figure 8 highlights the issues in the DSTs and other challenges concerning and affecting ease of use, including difficulties in field experiments and in knowing total available water in the soil, concerns on crop coefficients and evapotranspiration, and lack of thermal stress for hot temperatures in the model.

The Irre-LIS tool highlighted challenges in understanding total available water in the soil for effective irrigation management. A web application is being developed to address this challenge. Technical assistance is provided through training sessions and an online platform for calculating total available water. The tool focuses on maximizing water efficiency and improving net margins for farmers, with ongoing efforts to enhance the model and incorporate agro-ecological considerations.

Lastly, Hiphen's DST, used by breeders and research centers, offers a user-friendly platform named Cloverfield for data sharing and analysis. Ongoing efforts focus on improving the processing chain and visualization of results. Technical assistance is personalized, with campaign managers assigned to projects for direct support.

In conclusion, the feedback on the ease of use of DSTs varied across tools, with common themes of user-friendly interfaces, challenges in specific features, and ongoing improvements. Technical assistance was provided through various channels, ensuring users receive adequate support in utilizing the tools effectively. The insights from the interviews underscore the commitment of these companies to continuous improvement and user satisfaction in the agricultural sector.

4.2.3 Potential Benefits

Questions: *How are the DSTs able to translate to these benefits? In specific terms, at what stage of the crop you find the DST most useful/beneficial to the farmer, and/or at what stage it is frequently used (peak utilization)?*

Collaboration between farmers, technical experts, and researchers is essential to translate these benefits into actionable strategies for improving crop health and overall agricultural outcomes.

In terms of peak utilization, DSTs typically align with critical stages of the crop cycle, such as planting, irrigation, and harvesting, where timely information is crucial for maximizing productivity. Specific stages of the crop cycle where DSTs are most beneficial include critical growth periods or in response to environmental factors like drought or disease outbreaks. For example, during key stages like bud break, flowering, or periods of heightened stress, DSTs provide valuable insights for farmers to make timely decisions and optimize crop health. By utilizing DSTs during these peak utilization periods, farmers can proactively address stress factors, minimize crop damage, and maximize yields.

Figure 9 summarizes additional specific benefits of DSTs, such as enhancing quality and aromatic profile of the crop, and savings in money and resources.

The use of DSTs in agriculture offers practical solutions to complex decision-making processes, benefiting both individual farmers and the agricultural sector as a whole. These tools provide accurate recommendations, adjust growth stages, integrate weather data, and leverage advanced technologies to enhance usability and effectiveness. By focusing on improving sustainability, incorporating artificial intelligence, and integrating satellite imagery, DST providers continue to evolve to meet the changing needs of farmers and contribute to a more sustainable future for agriculture.

4.2.4 Sustainability and Agroecological Features

Questions: *How did you integrate sustainability in the manufacture of the DST in terms of resource and energy use from manufacture to use in the farm? Do you consider any opportunities to make the design and manufacture of the DST more sustainable/agroecological, and what are those opportunities?*

Responses from the DST conceptors provided valuable insights into the integration of sustainability in the manufacture and use of digital DSTs in farming practices. These discussions emphasized the importance of continuous improvement, user feedback, and data-driven enhancements to optimize resource and energy use while promoting eco-friendly farming practices.

GrowSphere highlighted the significance of data collection to track user interactions with the DST, enabling analysis to optimize performance. The tool's global reach and collaboration with manufacturers underscored a commitment to sustainability and innovation. Aqualis focused on sustainability through repairability, energy-efficient manufacturing, and user engagement. Efforts to enhance the DST included incorporating AI to further improve the tool’s capacity for data analysis and improve accuracy and reliability in providing water management recommendation

Hiphen's collaboration with industry actors aimed to enhance tools like Irre-LIS for irrigation support, focusing on improving data fusion capabilities and visualization for accuracy and efficiency. On the other hand, Irre-LIS highlighted challenges in soil data accuracy and the importance of water efficiency for better net margins. Efforts were made to adapt the tool to cover crops and non-soil work, aligning with agroecological principles.

NetIrrig emphasized sustainability through carbon-neutral cloud providers and advanced technologies like AI to optimize recommendations and reduce water consumption. The company aimed to scale the impact of their DST across agricultural value chains, promoting sustainability practices. GrowSphere focused on optimizing water, fertilizer, and energy use through their DST, aiming to reduce water consumption while maintaining crop yields.

Vintel's reliance on existing weather data and minimal hardware requirements inherently contributed to environmental sustainability. Opportunities for enhancing sustainability included cover crop management, irrigation optimization, and addressing local constraints. Irre-LIS prioritized water efficiency, collaboration with research institutions, and incorporating agroecological principles for sustainable farming practices.

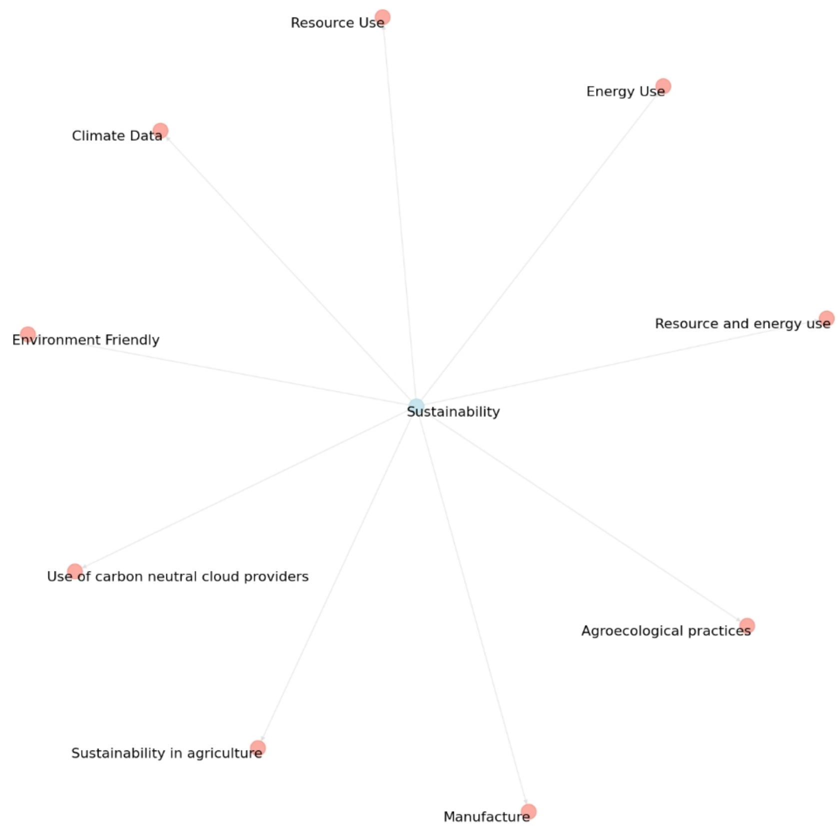


Figure 10 shows that the major sustainability features incorporated in the DSTs include climate-friendly features, use of advance technologies provided by carbon neutral cloud providers and optimizing the use of energy and other resources, specifically in the manufacture of the tool, and adapting the tool in order to promote sustainable and agroecological practices in agriculture by integrating climate and other data in the tool.

Overall, the interviews highlighted a collective effort towards sustainability in DST manufacturing and use. Key themes included optimizing resource and energy use, enhancing user engagement, and continuous improvement based on feedback and data analysis. Opportunities for making DSTs more sustainable and agroecological included incorporating advanced technologies, improving water management recommendations, and adapting tools to cover various agricultural practices.

In conclusion, the integration of sustainability principles in DST manufacturing and use is crucial for promoting eco-friendly farming practices and resource optimization. By leveraging user feedback, data-driven enhancements, and collaborations with industry partners, DST manufacturers are actively working towards a more sustainable and agroecological future in agriculture. The commitment to continuous improvement, innovation, and environmental responsibility showcased in these interviews signifies a positive shift towards sustainable farming practices globally.

4.2.5 Communication

Questions: *How do you keep your users engaged with your product in terms of information accessibility and availability? Are the level of information about the DST and communication with your users sufficient?*

DST providers shed light on how these tools engage users through information accessibility and availability. The DSTs prioritize user engagement by offering a range of resources, such as websites, training videos, mobile apps, social media, webinars, and partnerships with agricultural organizations. The companies emphasize continuous improvement in communication to ensure users have the necessary information to maximize the benefits of the tools. While the level of information and communication is considered sufficient by some companies like NetIrrig, others acknowledge the need for ongoing enhancements in this area. For instance, Vintel conducts training sessions to familiarize users with the tool and improve user proficiency over time. The tools like Aqualis and GrowSphere focus on sustainability and user-centric design to enhance user experience and address irrigation challenges effectively. The companies value user feedback and incorporate suggestions for continuous improvement, ensuring that users receive relevant and timely information. The DSTs collaborate with technical institutes and research centers to enhance their tools based on industry insights and user needs. Overall, the DSTs prioritize user engagement through personalized features, robust technical support, and proactive communication strategies to optimize irrigation management practices and decision-making processes.

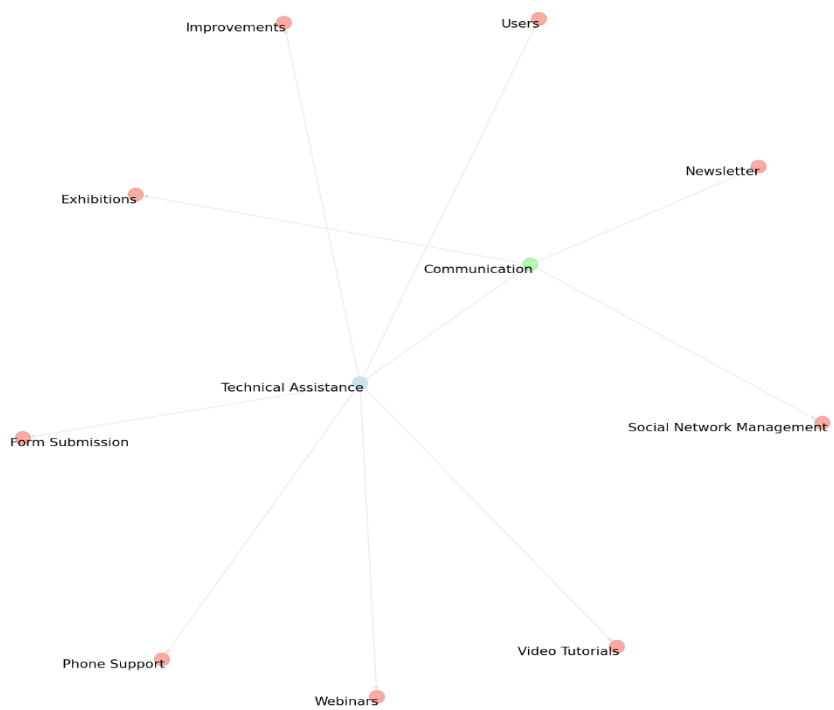


Figure 11 shows that DSTs employ different strategies in providing technical assistance, and to improve engagement and communication with its users by utilizing different modalities, including, but not limited to, video tutorials, webinar, phone support, form submission, exhibitions, social network management.

4.2.6 Improvements

Questions: *Are there any existing features of the DST you consider require further improvement or upgrade? What additional features or improvements would you like to do in order for the DST to perform better and better (i.e. numerical model/aspect, etc.)?*

Common themes across the interviews include the need to enhance the numerical aspect of the models used in the tools to provide more reliable and tailored recommendations. The importance of refining the models to improve accuracy and effectiveness was emphasized to better support farmers in managing irrigation and fertigation on their fields. Additionally, the interviews highlighted the significance of incorporating considerations for climate change and irrigation constraints to ensure the DSTs remain relevant and valuable in the agricultural sector.

Furthermore, the interviews underscored the importance of user feedback and engagement in refining the DSTs. By analyzing usage data and comparing it to recommendations, insights can be gained on how farmers interact with the systems and where improvements are needed. This feedback loop can help developers tailor the systems to better meet the needs and preferences of users, ultimately enhancing their performance and usability. The collaboration with technical institutes like Arvalis and ITB was also highlighted as crucial for progressing in stress detection and assessment, indicating the significance of external expertise in enhancing the capabilities of the DSTs.

In terms of additional features or improvements needed, the integration of remote sensing data, such as satellite data, was discussed as a future development to enhance the systems' capabilities. The goal is to make the systems more autonomous and user-friendly, allowing farmers to make informed decisions based on the data provided by the DSTs. Moreover, there was a focus on enhancing the integration of data sources for more accurate recommendations and actively seeking feedback from users to drive continuous improvement. By addressing these aspects, the DSTs aim to become more efficient, user-friendly, and effective in supporting farmers in optimizing their agricultural practices.

The interviews also highlighted ongoing efforts to enhance the DSTs by focusing on improving the irrigation modules and diversifying cover crop management options. Additionally, considerations for managing irrigation recommendations based on constraints, such as water availability during specific periods in certain regions, were discussed as valuable enhancements for users facing similar challenges.

Figure 12 shows that the needed major improvements identified in the DST conceptors include the numerical aspect of the model, other modules and features, climate change and irrigation constraints, and how other data can be integrated in the model in order to provide accurate, actionable, and meaningful recommendations.

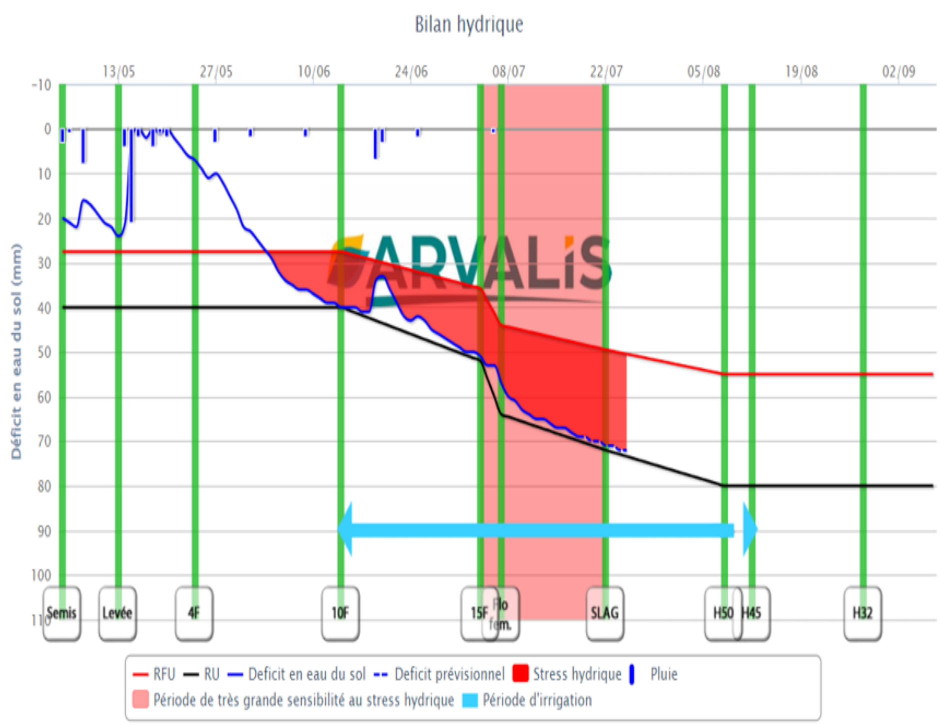
Overall, the interviews emphasized the continuous development and enhancement of DSTs to meet the evolving needs of farmers and stakeholders in the agricultural sector. By addressing the identified areas for improvement, such as enhancing the numerical aspect of the models, incorporating considerations for climate change and irrigation constraints, and actively seeking user feedback, the DSTs aim to optimize water efficiency, support sustainable agricultural practices, and provide valuable decision-making support to farmers globally.

4.3 DST Simulation and Desk Testing of the Models

4.3.1 Pre-Optimal Simulation

As already presented, pre-optimal scenario refers to the initial simulation of the tool given the inputs used, where field variability, amount and magnitude of the water stress, and irrigation strategies were evaluated before implementing them in the field (Lin et al., 2020; Neupane and Guo, 2019). This scenario also provided information and timing to commence irrigation application. For the tools being tested, the pre-optimal simulation provided information on the magnitude and start of water stress for each plot configuration with a defined soil type and maize variety. In addition, it allows to detect two important information, including the start dates of the onset of water stress and the high sensitivity to water stress.

Water stress generally begins when the amount of depletion exceeds the readily available water in the soil, and in the DST simulation, it is reflected when the depletion curve or water stress curve is being crossed, a scenario which would result to incipient stomatal closure, which reaches its maximum at crop's wilting point (Ramadas and Govindaraju, 2015). Knowing when water stress occurs is important to generally help the farmer or user decide when, and where to apply how much irrigation water at different crop growth stages to optimize water use and crop production (Neupane and Guo, 2019). In Irre-LIS, the onset of water stress was detected when the readily available water (RFU) curve crossed the soil water deficit curve. Figure 13 (topmost) shows Irre-LIS simulation for S1V1, and we can see in this figure that the start date of water stress was on June 5, 2024, when the figure is zoomed in the tool's online interface. In Net-Irrig, the start of water stress was recorded when the water depletion curve crossed the minimum threshold of easily usable reserve curve (orange-colored curve), as shown in Figure 13 (middle) for S1V1 simulation, and the start date of water stress in this figure was on July 4, 2024. Meanwhile, for Pixagri, the water stress started to occur when the water depletion curve crossed the readily available soil water curve, as illustrated in Figure 13 (bottom), with a start date on June 3, 2024 for S1V1 simulation.



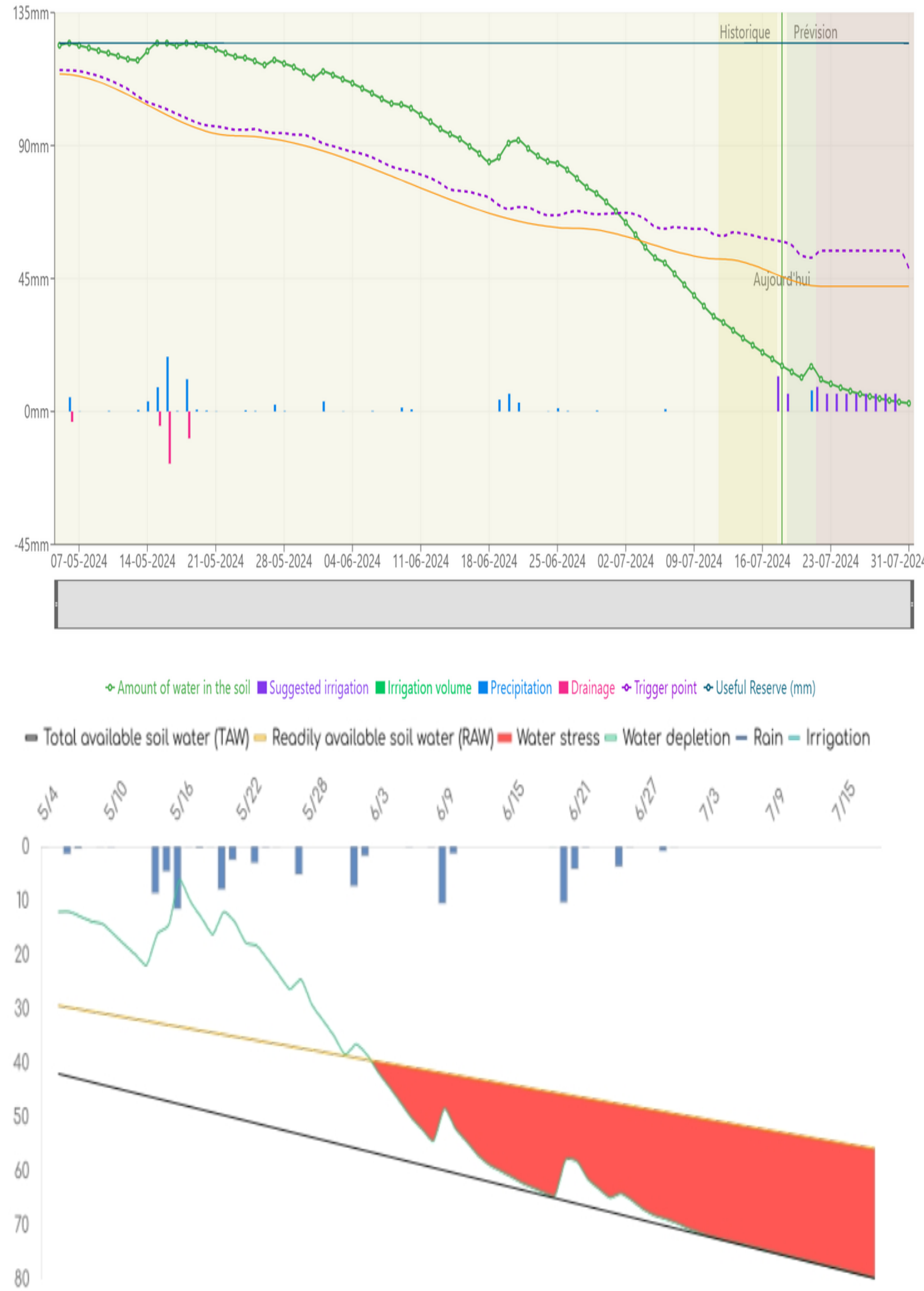


Figure 13 shows the S1V1 simulations for Irre-LIS, NetIrrig and Pixagri (top to bottom) when the readily available soil water or the minimum threshold of easily usable reserve curve was crossed detecting the onset of water stress, indicating the onset of water stress.

The start dates of water stress for all combinations of soil and variety for each DST are gathered in Table 6.

Plot Configuration	Irre-LIS		NetIrrig		Pixagri Wago	
S1V1	Blue line (soil water deficit) to red line (RFU)	05 June ‘24	Green line (amount of water in the soil) to yellow line (RFU)	04 July ‘24	Green line (water depletion) to Yellow line (RUF/ or total available water)	03 June ‘24
S1V2		04 June ‘24		12 June ‘24		03 June ‘24
S1V3		04 June ‘24		29 June ‘24		03 June ‘24
S2V1		08 June ‘24		03 July ‘24		26 May ‘24
S2V2		08 June ‘24		11 June ‘24		26 May ‘24
S2V3		08 June ‘24		28 June ‘24		26 May ‘24
S3V1		04 June ‘24		07 July ‘24		04 June ‘24
S3V2		04 June ‘24		03 July ‘24		04 June ‘24
S3V3		04 June ‘24		01 July ‘24		04 June ‘24

Table 6 shows the start date when RUF curve was crossed for each combination of all the DSTs indicating the onset of water stress.

On the other hand, the period of high sensitivity to water stress, which usually follows after the onset of water stress, is when the plants may exhibit reduced growth, wilting, and decreased photosynthetic activity, with impacts on crop yield and quality (Seleiman et al., 2021), and this type of sensitivity is influenced by crop type, growth stage, and environmental conditions (Osakabe et al., 2014). In the same manner, identifying the period of high sensitivity to water stress is crucial in making more informed decisions about when and how much water to apply, resulting to improved water use efficiency and crop production considering the crop’s water requirements at different growth stages (Neupane and Guo, 2019; Zhang et al., 2020), thus, enabling the effective use of the tool (Parkash and Singh, 2020). The period and the start date of this period of high sensitivity to water stress was automatically indicated by each DST. In Irre-LIS, it started on July 4, 2024 for S1V1 simulation, as shown in Figure 13 (topmost), in light red-shaded bar; July 12, 2024 for NetIrrig SIVI simulation (Figure 13, middle), in light brown-shaded bar; and, June 18, 2024 for Pixagri Wago S1V1 simulation (Figure 13, bottom), identified when the cursor was moved in the online interface of the tool.

Table 7 list the information on the start date of high sensitivity to water stress for all combinations of soil and variety for each DST.

Plot Configuration	Irre-LIS	NetIrrig	Pixagri Wago
S1V1	04 July 2024	12 July 2024	18 June 2024
S1V2	27 June 2024	12 July 2024	18 July 2024
S1V3	27 June 2024	02 July 2024	19 July 2024
S2V1	04 July 2024	12 July 2024	19 July 2024
S2V2	27 June 2024	12 July 2024	19 July 2024
S2V3	27 June 2024	02 July 2024	19 July 2024
S3V1	04 July 2024	12 July 2024	19 July 2024
S3V2	27 June 2024	12 July 2024	19 July 2024
S3V3	27 June 2024	02 July 2024	19 July 2024

Table 7 lists the start date of high sensitivity to water stress for each simulation in all of the DSTs.

Among the three DSTs, the early onset of high sensitivity to water stress was observed in Pixagri Wago on June 18, 2024 for the silt-loam and early grain corn (S1V1). Moreover, the same was observed for the onset of the water stress, with the earliest recorded in Pixagri Wago on June 3, 2024, mainly for silt-loam soil with all of the maize varieties (S1V1, S1V2 and S1V3). Similarly, Pixagri Wago also had the latest onset of high sensitivity on July 19, 2024 for all other plot configurations, excluding silt-loam – early grain corn (S1V1) and silt-loam – medium grain corn (S1V2).

In terms of the onset of high sensitivity to water stress and water stress per tool:

- Irre-LIS had the earliest occurrence of high sensitivity on June 27, 2024 for almost all plot configurations, except silt-loam – early grain corn (S1V1), sandy-clay – early grain corn (S2V1), and sandy-loam – early grain corn (S3V1), with these three having started high sensitivity on July 4, 2024. The earliest start of water stress was on June 4, 2024 for silt-loam – early grain corn (S1V2), silt-loam – late grain corn (S1V3), sandy-loam – early grain corn (S3V1), sandy-loam – medium grain corn (S3V2), and sandy-loam – late grain corn (S3V3).

- The earliest high sensitivity for NetIrrig was on July 2, 2024 for silt-loam – late grain corn (S1V3), sandy-clay – late grain corn (S2V3), and sandy-loam – late grain corn (S3V3), while earliest water stress was on June 11 and 12, 2024 for sandy-clay – medium grain corn (S2V2) and silt-loam – medium grain corn (S1V2), respectively.

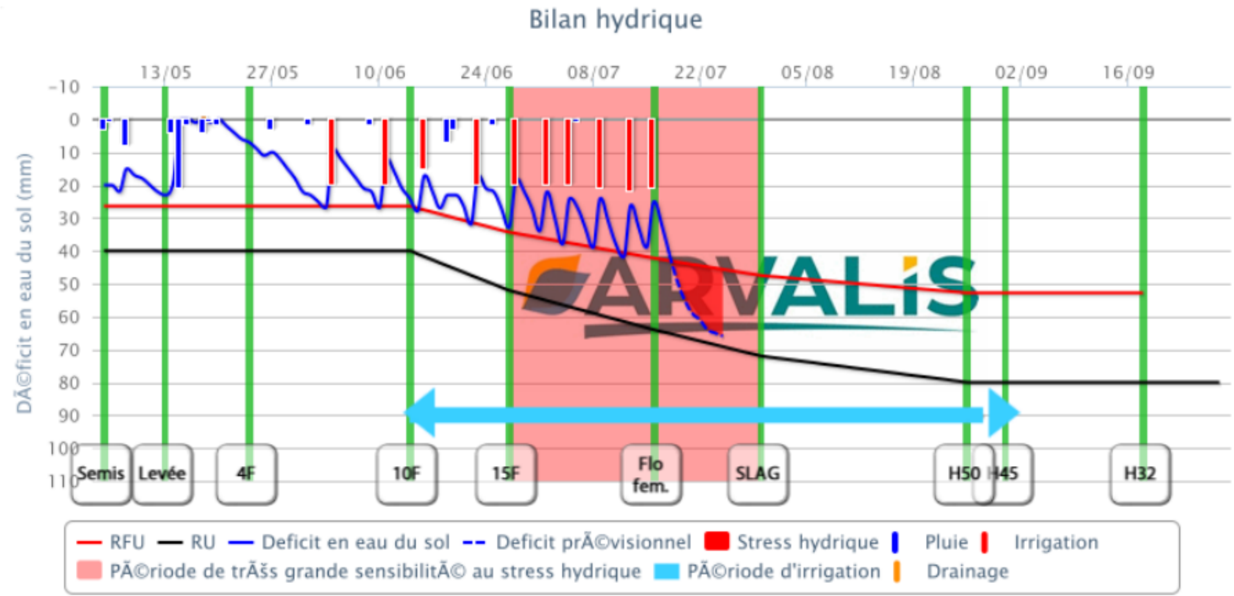
- Again, the earliest high sensitivity was on June 18, 2024 for Pixagri Wago for silt-loam – early grain corn (S1V1), with the earliest water stress occurring on May 26, 2024 for sandy-clay – early grain corn (S2V1), sandy-clay – medium grain corn (S2V2), and sandy-clay – late grain corn (S2V3).

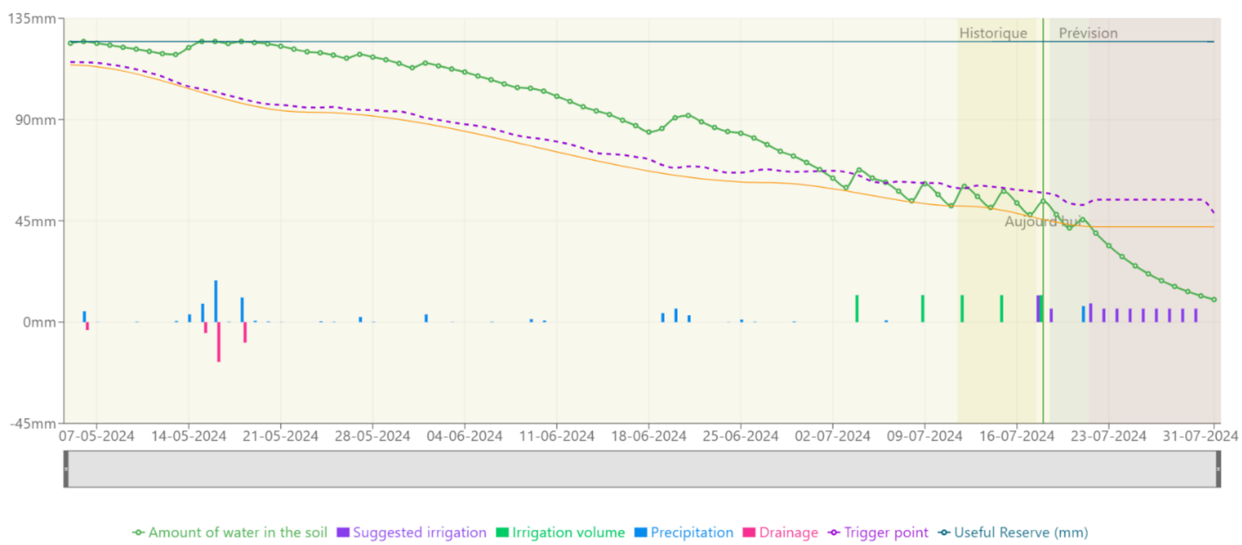
4.3.2 Optimal Simulation

The pre-optimal simulation provided the initial information on the date that water stress occurred, when irrigation should be applied, and the visualization of the magnitude of water stress.

It is important to note that optimal simulation is a scenario when the soil-plant-atmosphere continuum is accurately represented, considering factors such as weather conditions, crop growth, and water availability, so that the most efficient irrigation schedules can be recommended (Shi et al., 2021; Tolomio and Casa, 2020). Hence, to be optimal, efficiency of irrigation schedules, covering the timing and the amount irrigation water, is a pivotal criterion.

In this simulation, the three tools required different amount of irrigation water application to avoid water stress in running the optimal models. Specifically, optimal simulation was achieved when the soil water deficit or water depletion curve is kept above the readily available soil water (RFU) curve in Irre-LIS (Figure 14, topmost) and Pixagri (Figure 14, bottom), which simply means deficit is lower than the RFU. For both Irre-LIS and Pixagi, it was achieved by estimating the amount of irrigation to be applied noting the initial parameters yielded in the pre-optimal simulation, or a trial-and-error exercise until the water deficit is above the RFU curve. In NetIrrig Figure 14, middle), optimal simulation was achieved when the amount of water in soil curve is kept above the minimum threshold of the easily usable reserve curve, and this DST readily provided the exact amount of irrigation for the optimal simulation.





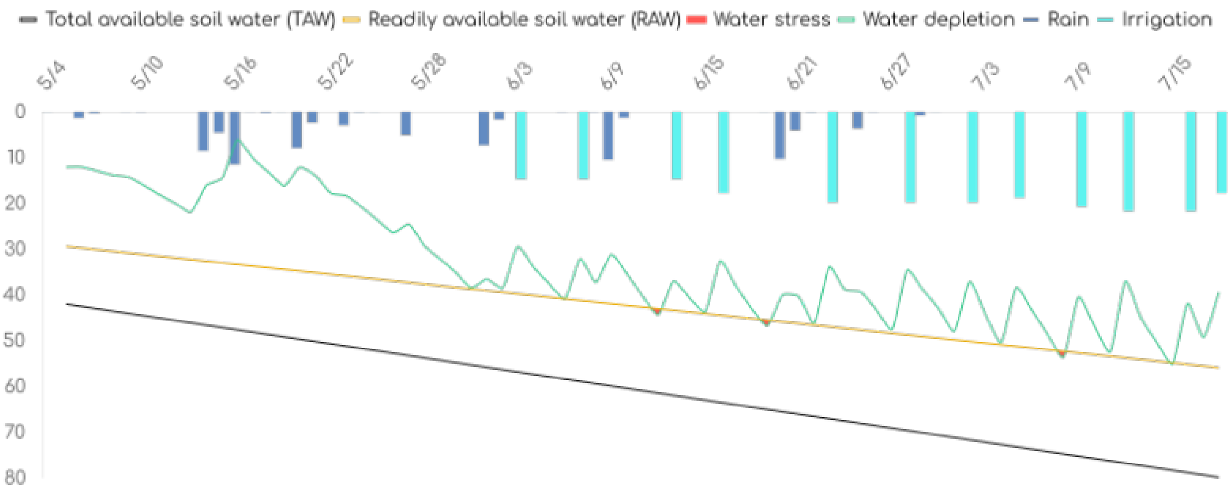


Figure 14. Irre-LIS, NetIrrig and Pixagri Wagi optimal simulations for S1V1.

Conducting the optimal simulations yielded total irrigation for every combination for all the DSTs, covering the May 5, 2024 sowing date until the July 18, 2024 common reference date. We have gathered the total optimal irrigation for each combination and each tool in Table 8.

Plot configu-ration	Irre-LIS	NetIrrig	Pixagri Wago
S1V1	197	60	225
S1V2	197	132	220
S1V3	200	108	216
S2V1	175	60	246
S2V2	184	132	247
S2V3	183	120	255
S3V1	197	60	204
S3V2	200	57	206
S3V3	204	96	203

Table 8 shows the total irrigation performed per plot configuration since sowing until July 18.

Using the Python code, we calculated the average optimal irrigation for each soil type and maize variety with the results in Table 9.

Soil Type/Tool	Irre-LIS	NetIrrig	Pixagri Wago
Silt loam	198.0	100.0	220.3
Sandy clay	180.7	104.0	249.3
Sandy loam	200.3	71.0	204.3
Maize variety			
Early	189.7	60.00	225.0
Medium	193.7	107.0	224.3
Late	195.7	108.0	224.7

Table 9. shows the average recommended irrigation by tool, soil type and maize variety.

Using the same code, the average optimal irrigation for each soil type and maize variety for all DSTs were visualized as histograms and presented in Figures 15 and 16.

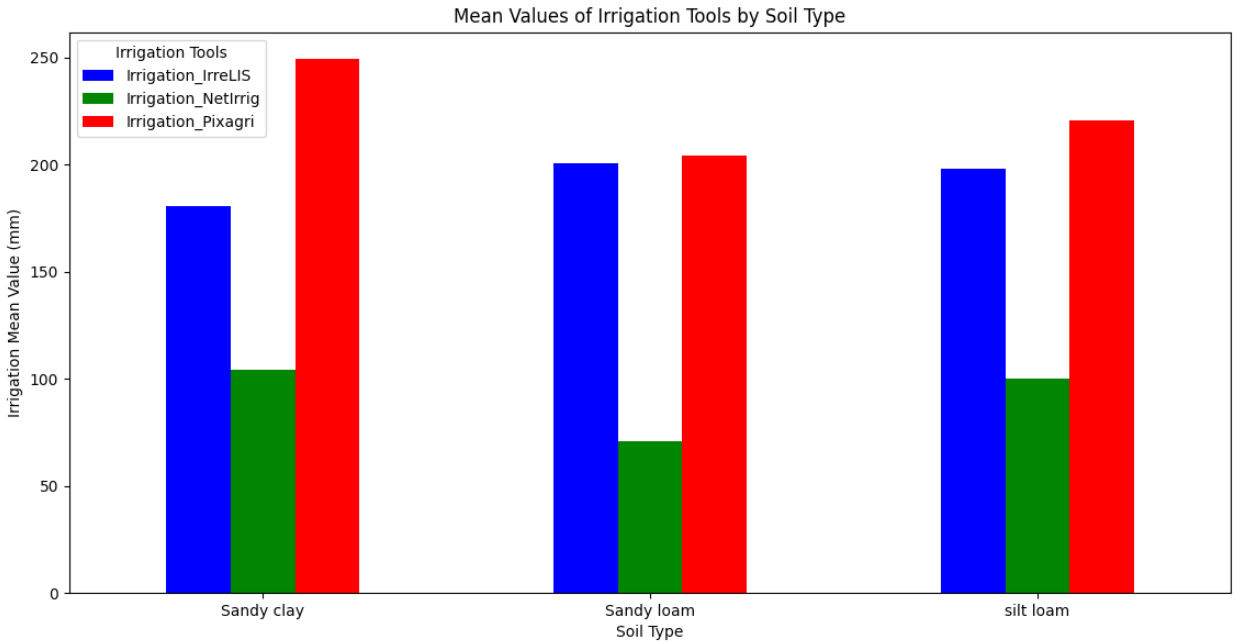


Figure 15 shows the average optimal irrigation for Irre-LIS, NetIrrig and Pixagri Wago, suggesting the tools are sensitive to soil type.

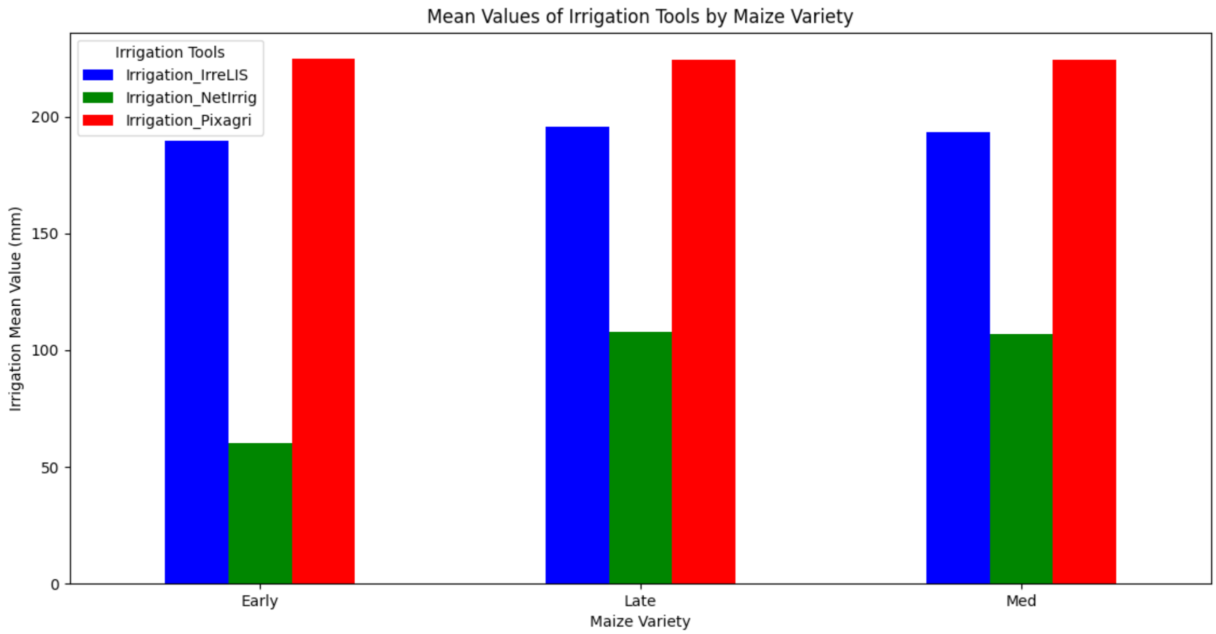


Figure 16 shows the average optimal irrigation of the three DSTs, suggesting that, except for Pixagri, Irre-LIS and NetIrrig are sensitive in varying degrees to maize variety.

Results of the optimal simulation indicate that the three tools are sensitive, although in varying degrees, to different soil types and, with exception of Pixagri Wago, to different maize varieties in terms of recommended irrigation needs in mm averaged from sowing until the reference period. Among the three tools, Pixagri Wago yielded the highest recommended irrigation across all soil types and maize varieties, while NetIrrig provided the lowest irrigation values, with Irre-LIS values lying in between, as presented in Table 8 above.

NetIrrig and Pixagri have the same ranking of irrigation recommendation based on soil types, with sandy clay having the highest value at 104mm and 249mm for NetIrrig and Pixagri Wago, respectively, and sandy loam the lowest (71mm for NetIrrig and 204mm for Pixagri Wago). On the other hand, the highest value for both NetIrrig and Pixagri Wago was the lowest for Irre-LIS at 180.6mm for the sandy-clay soil. All the three tools have silt loam as the soil type with second highest irrigation at 198mm for Irre-LIS, 100mm for NetIrrig, and 220mm for Pixagri Wago (Table 8).

It is important to note which among the three soil types require most, medium or less irrigation water due to its soil texture which affects water holding capacity. Among the three soil types, studies indicate that sandy-clay soil requires less frequent irrigation water to maintain optimal moisture levels (Ahmed et al., 2015), with silt loam suggesting more frequent irrigation than sandy clay (Chu et al., 2020), while sandy loam requiring most water for irrigation due to its low water-holding capacity (Reddy et al., 2018; Chu et al., 2020; Ahmed et al., 2015; Jain et al., 2017; Otie et al., 2022). However, this pattern was not accurately indicated in the results presented in Table 8, with only Irre-LIS providing the least irrigation water with 180.7mm for sandy clay, while other tools did not provide the irrigation pattern for each specific soil type based on the literature.

Further, in terms of maize variety, the results indicate that the three tools are generally not as highly sensitive to different grain corns when compared to the irrigation recommendation for the different soil types. However, for NetIrrig, the sensitivity is strongly contrasted between the early grain corn and both the medium and late corn variety. Sensitivity of Irre-LIS irrigation recommendation to maize varieties is low, while no significant sensitivity can be concluded for Pixagri against different maize varieties, since the simulation was using the grain corn varieties in the Pixagri, where values for agronomic traits and characteristics are not likely or highly contrasted (Figure 16).

Research indicates that among the three maize varieties, the early grain corn has the lowest total irrigation water needs, with late grain corn having the highest and medium grain corn in between the two varieties (Trout and Bausch, 2012; Flynn et al., 2023; Rajasekar et al., 2020). The result of the simulation suggests that the tools, except for Pixagri Wago, is following the pattern, with early grain corn variety having the lowest total irrigation and late grain corn having the highest (Figure 16).

4.3.3 Comparison of the Recommended Irrigation to the Actual Irrigation Consumption

Based on the collected and available actual irrigation consumption of the Nicolas Gassier study plot in 2023, the total irrigation applied from May 5 to July 18 was 145 mm. Again, the soil type of the plot is silt loam and the maize variety cultivated was P0725 (medium maturity variety). The DSTs irrigation recommendations for this soil type and maize was then used and compared with the actual irrigation consumption of the plot in 2023, and the results were gathered in Table 10.

Among the three tools, the irrigation recommendation of the NetIrrig indicates an underestimation when compared to the actual irrigation consumption of the same soil type and maize variety, implying that the tool’s recommendation was rather applying less irrigation, (Table 9). On the other hand, both Irre-LIS and Pixagri indicates overestimation, hence, both tools were recommending more irrigation water than the actual irrigation values for the same soil type and maize variety (silt loam and medium maturity variety).

Average Irrigation for May 5, 2024 – July 18, 2024 (in mm)				Difference from Actual Irrigation Consumption (in mm)		
Soil Type/Tool	Irre-LIS	NetIrrig	Pixagri	Irre-LIS	NetIrrig	Pixagri
Silt loam	**198.0**	**100.0**	**220.3**	**53.0**	**-45.0**	**75.3**
Maize variety						
Medium	**193.7**	**107.0**	**224.3**	**48.7**	**-79.3**	**79.3**

Table 10 shows that NetIrrig is underestimating while Irre-LIS and Pixagri are overestimating when compared to the actual irrigation consumption in 2023.

It would be interesting to note if the same results would be observed when using the 2024 actual irrigation consumption of the plot when available.

5 CONCLUSION

The trajectory of development and implementation of digital DSTs in irrigation is increasing over the last few years in France, and it is expected to continue given the focus on agroecological transition in the face of pressing challenges posed by climate change. There is a great emphasis given by the conceptors on agroecological and sustainable features of these DSTs with additional consideration on the practical and easy utilization by the users, although some needed improvements, such as the level of complexity through communication and technical assistance, enhancement of decision-making processes that accurately integrates factors affecting irrigation management, and maximization of water efficiency, have been recognized.

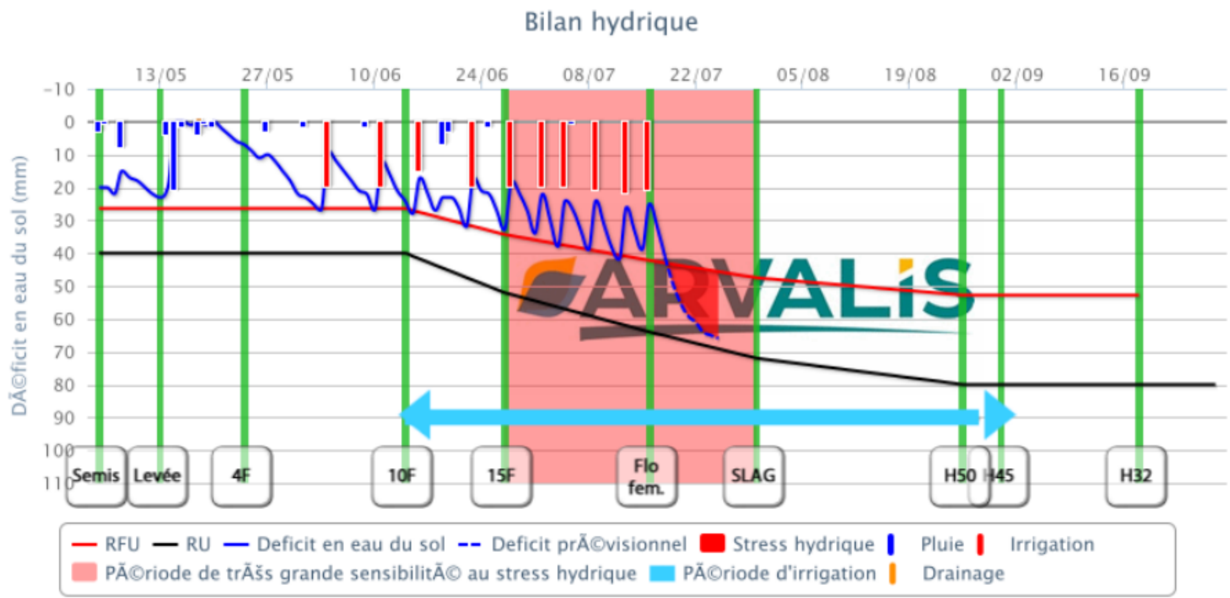
Importantly, results of the optimal simulations indicates marked differences in the irrigation recommendation across the three tools being tested. The tools are sensitive, but in varying degrees, to soil types and, with exception of Pixagri Wago, maize varieties, as indicated in the irrigation being recommended. The pattern for the irrigation recommendation for soil types based on literature was not accurately observed, with only Irre-LIS providing the least irrigation water for sandy clay at 180.7mm. In terms of the inter-tool sensitivity to maize variety, the tools were not as highly sensitive compared to soil types. Further, although some patterns were already observed given that the length of the reference period used was shorter, covering the whole campaign period of the crop would validate these patterns.

There were, however, limitations in this study that should be addressed to ensure better and better results in the future investigations. Again, tt would be interesting to conduct the simulation at the near-end of the campaign to cover the whole cropping period, since the simulations in this study only covered about half of the cropping period, as the tools could only predict few days from the reference date selected when the simulations were run. Also, although the tools have already available values of the parameters in the models, such as for the agronomic traits of the crops, it would help to use values that closely represent, for instance, the agronomic traits of different maize or crop varieties. More interesting is to compare these tools for year 2024 on many plots, for instance, 100 plots located at different points in France, with more crops and more combinations, which are usually determined by the number of soil types and crop varieties. The challenge in doing this kind of study would be - firstly, the parameterization of the tools and in carefully making the parameters as comparable or close as possible from one tool to another; and, secondly, the time and cost involved, in the case of trial version of the tool (as there would be additional cost beyond 10 hectares, in running the multiple simulations, since some tools take time to process the simulation, and some tools do not provide the exact irrigation application amount, hence, it is done on a trial-and-error basis. To address the cost constraint for the trial version, it would help to use the same plot for all the simulations and just change the parameters every simulation. The aim of every DST is to maximize water efficiency, reduce water use, and improve productivity, and it is important that these DSTs perform optimally using accurate parameters and values that represent reality. When these are ensured, the benefits of the DSTs can be significant.

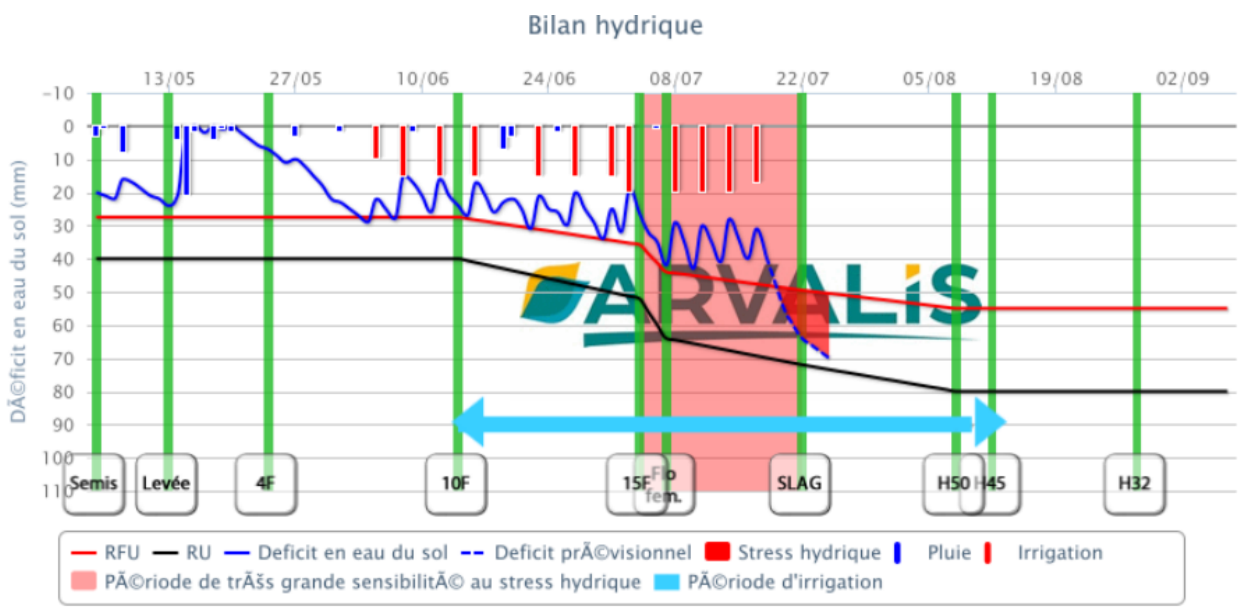
6 APPENDICES

6.1 Optimal Simulation Results

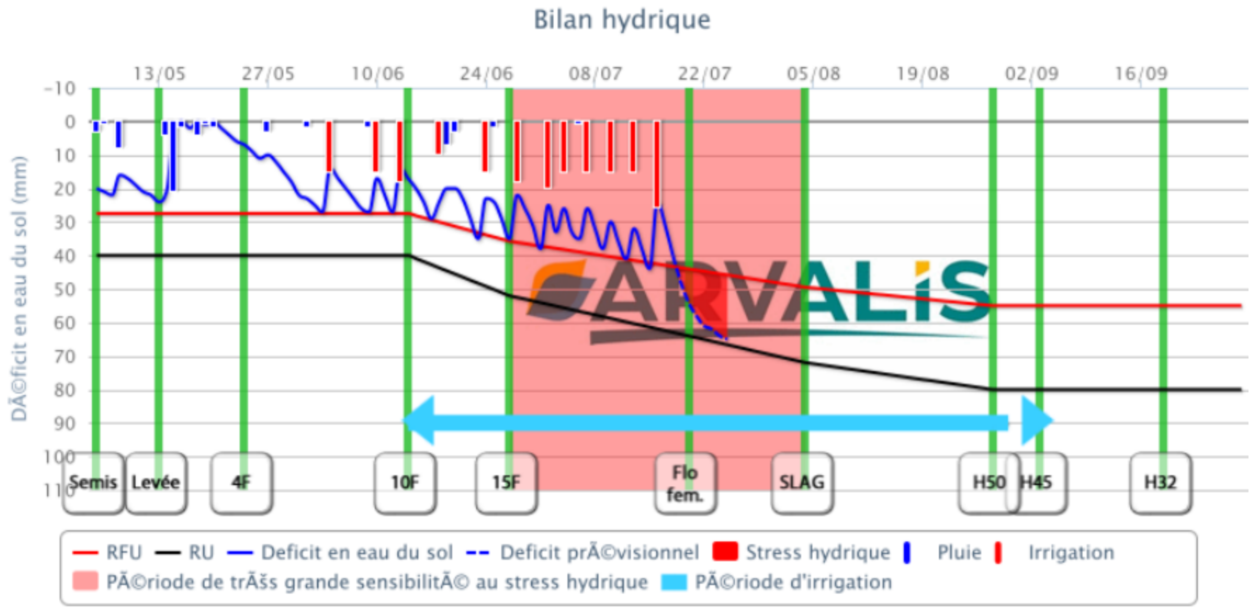
6.1.1 Irre-LIS



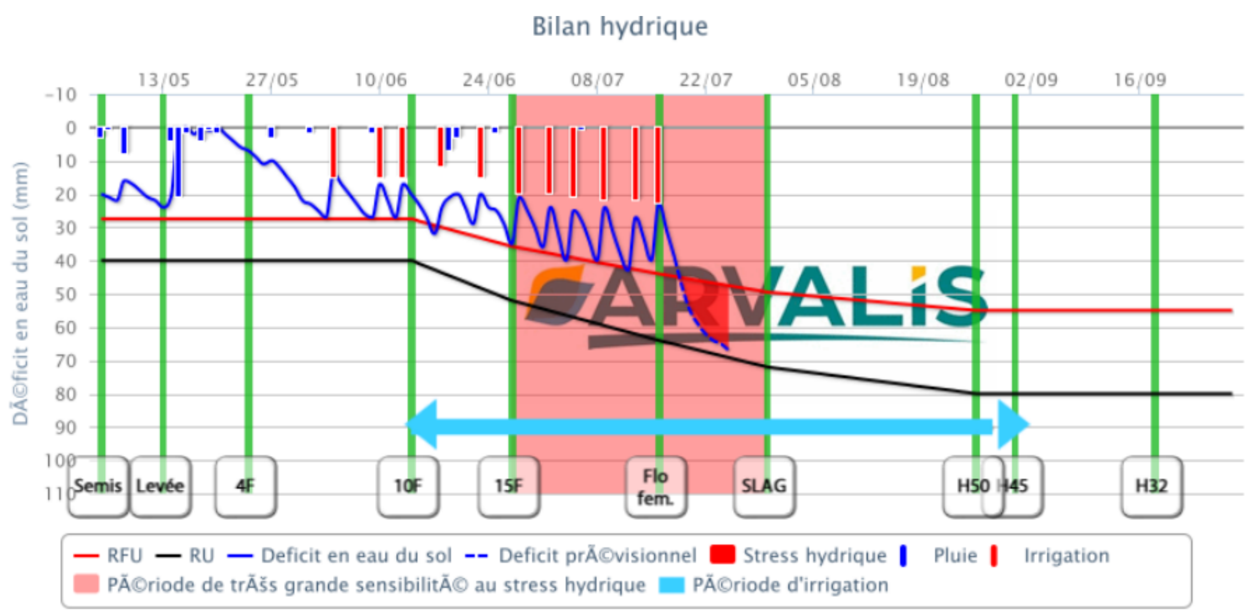
S1V1 Simulation



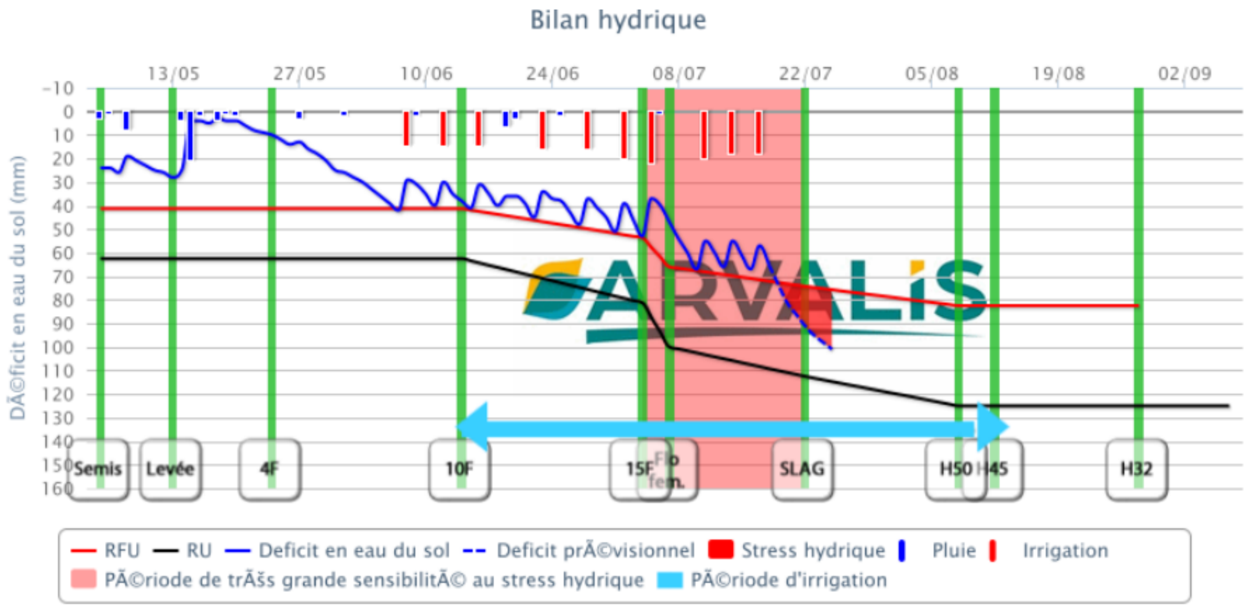
S1V2 Simulation



S1V3 Simulation



S2V1 Simulation



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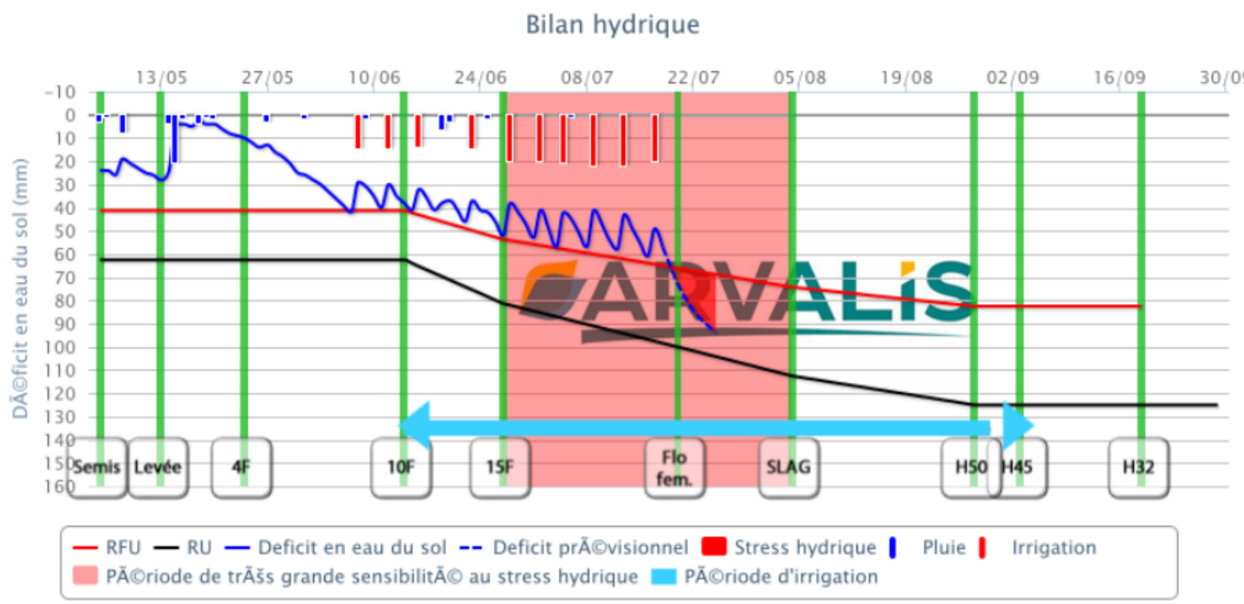
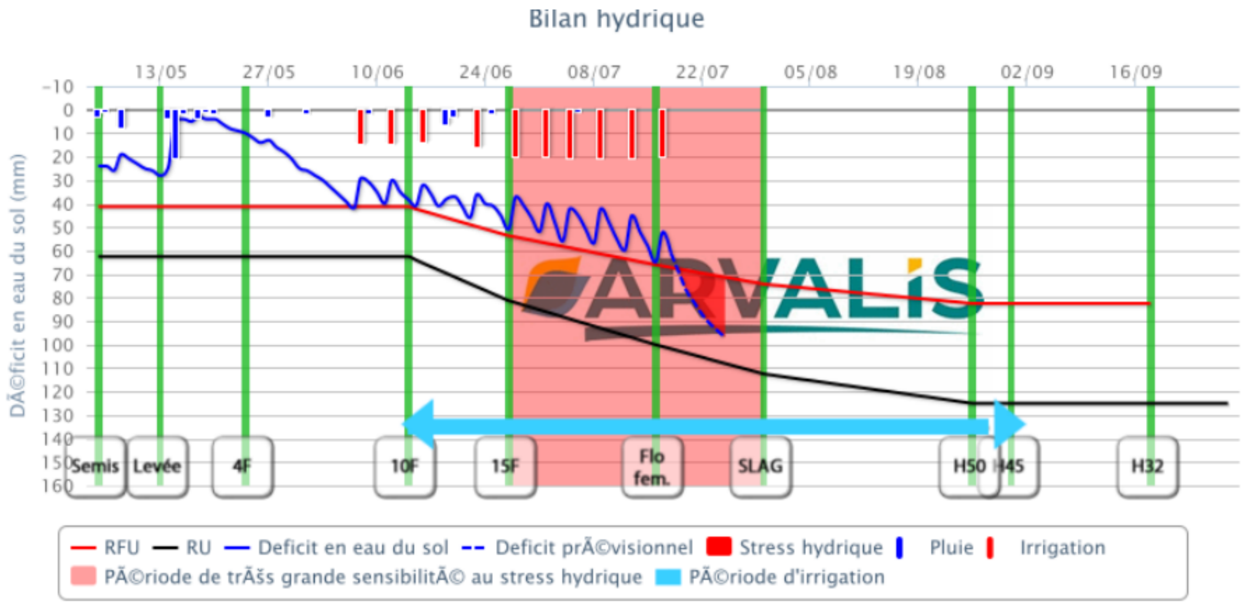
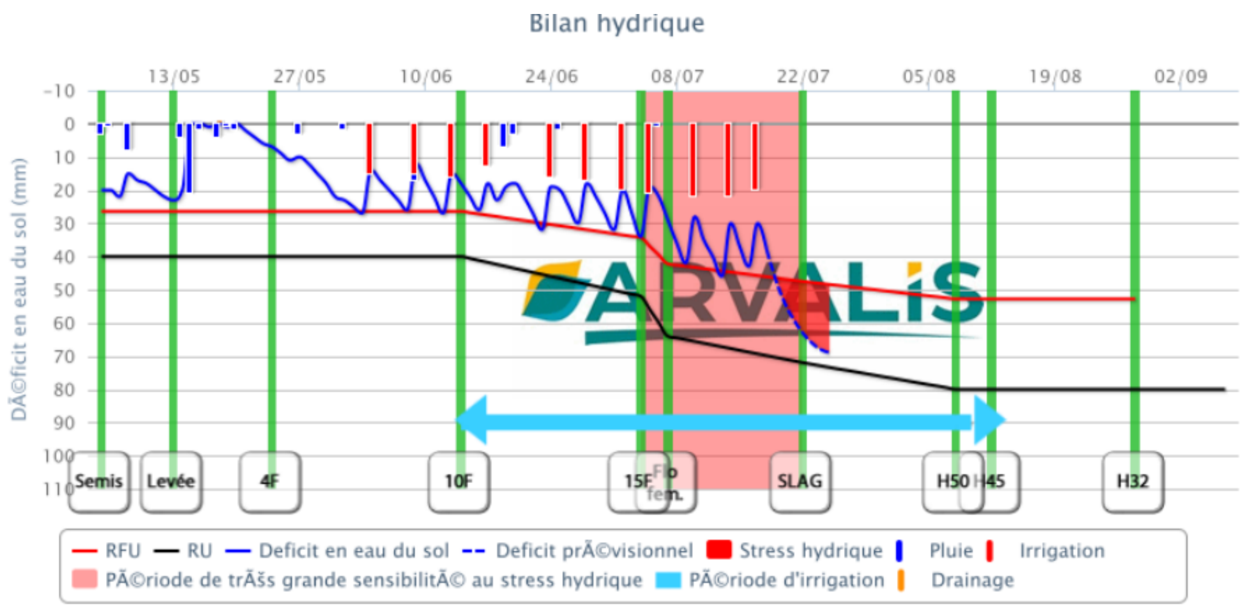


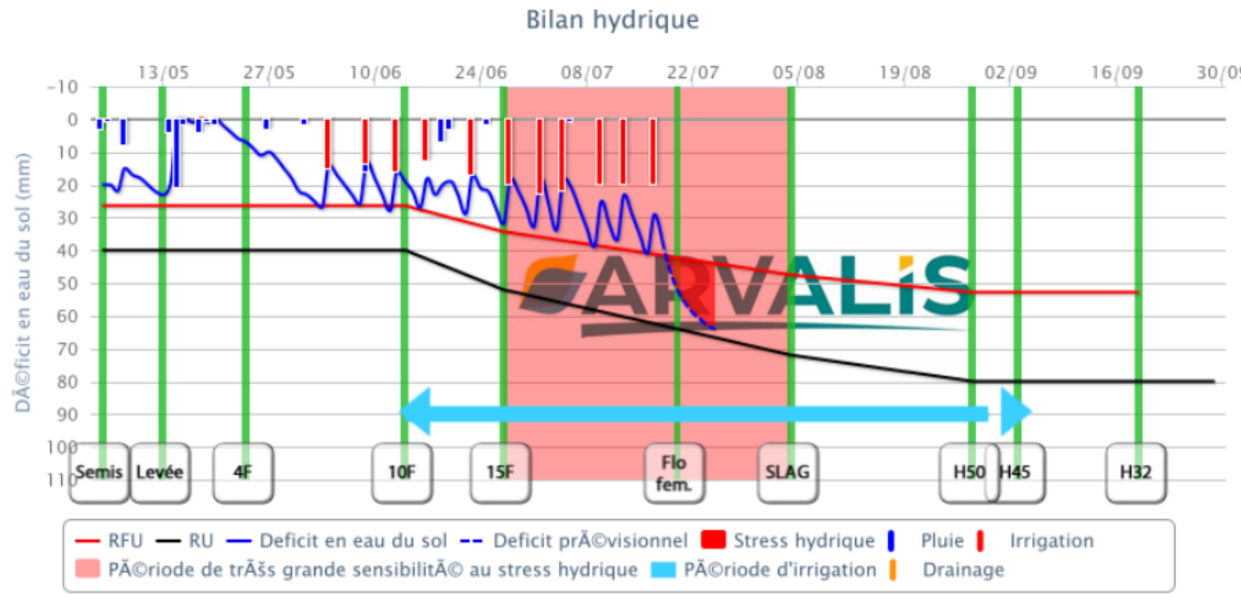
S2V3 Simulation



S3V1 Simulation

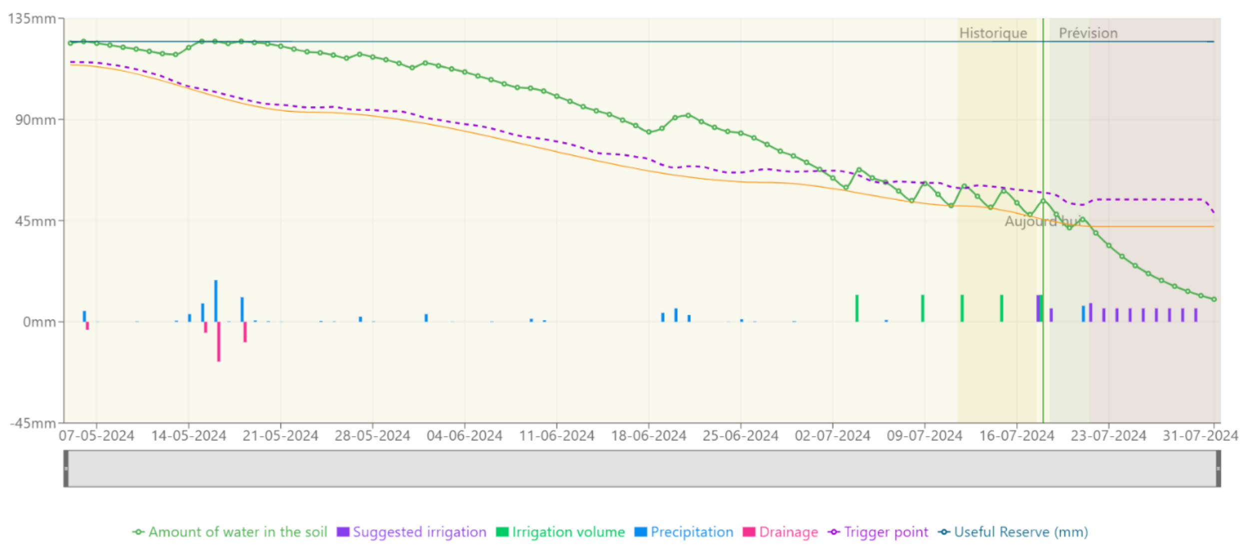


S3V2 Simulation

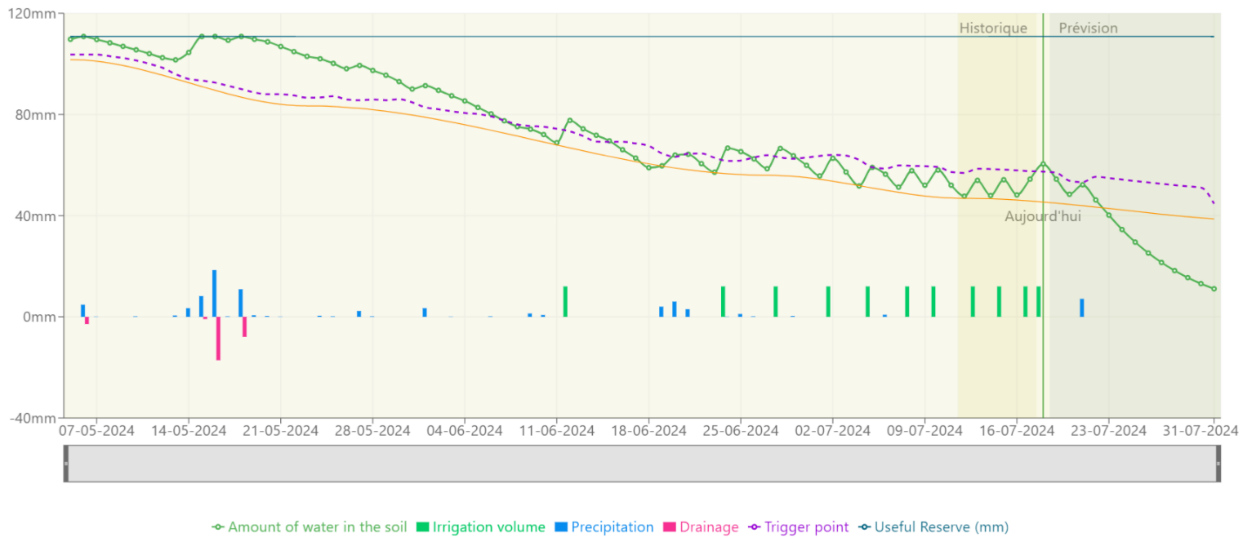


S3V3 Simulation

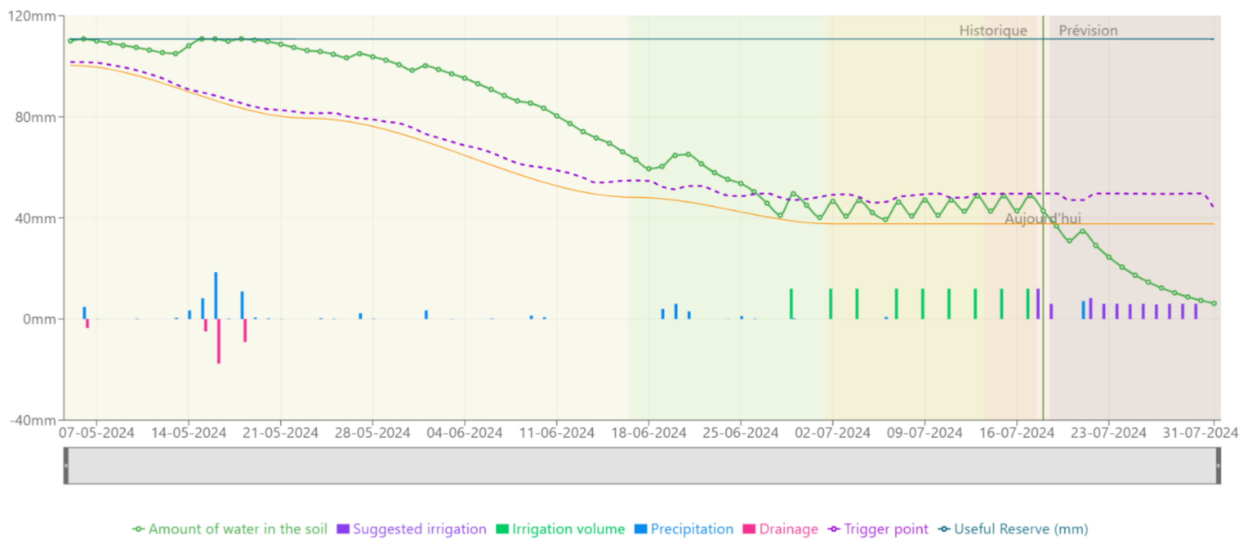
6.1.2 NetIrrig



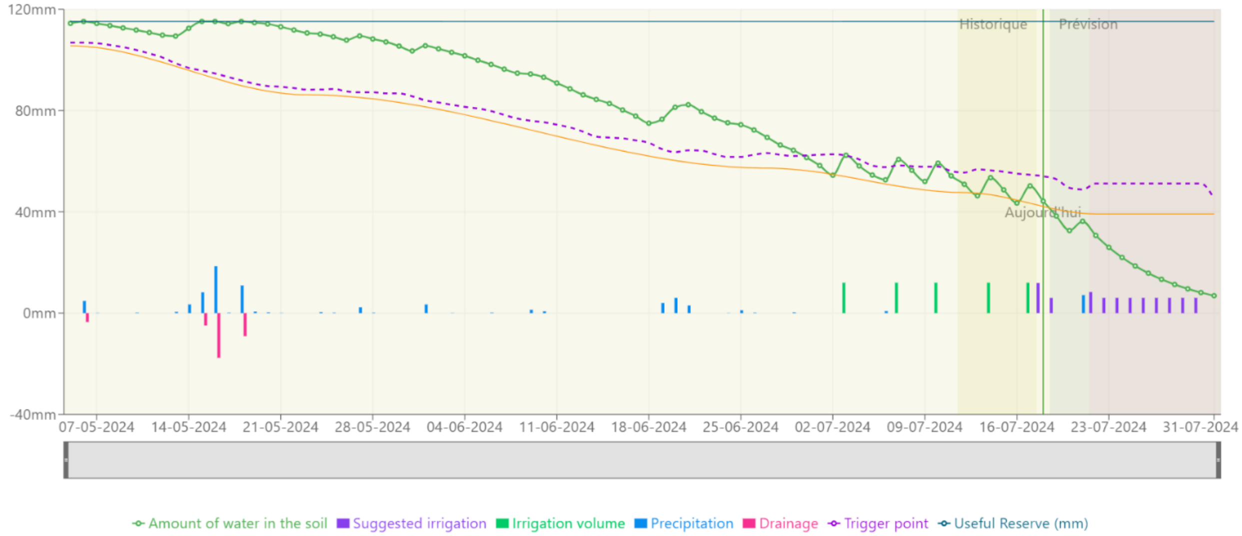
S1V1 Simulation



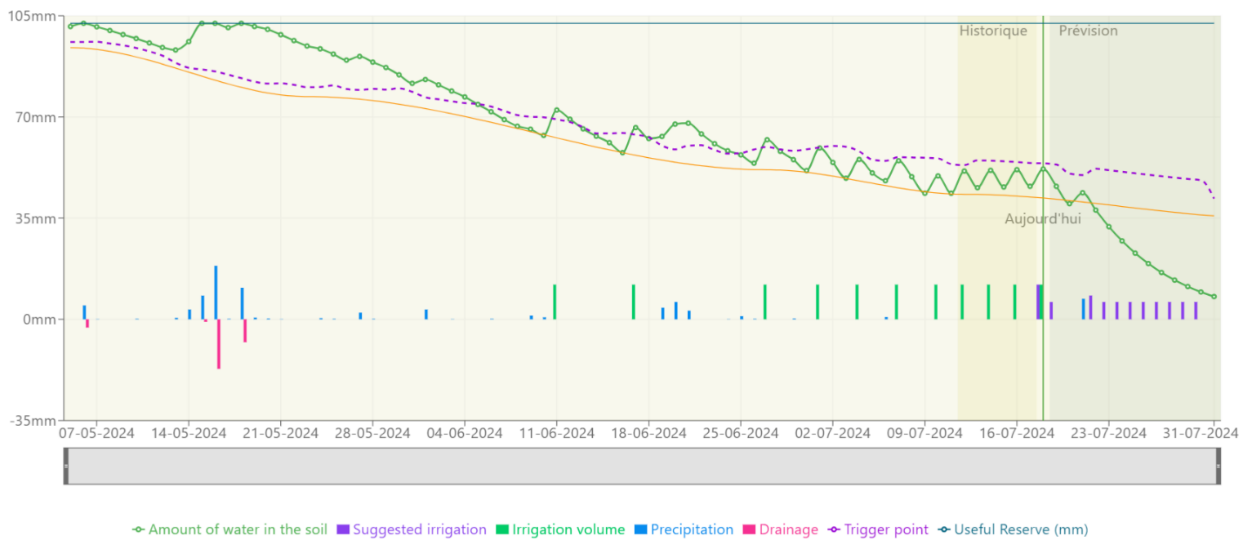
S1V2 Simulation



S1V3 Simulation



S2V1 Simulation



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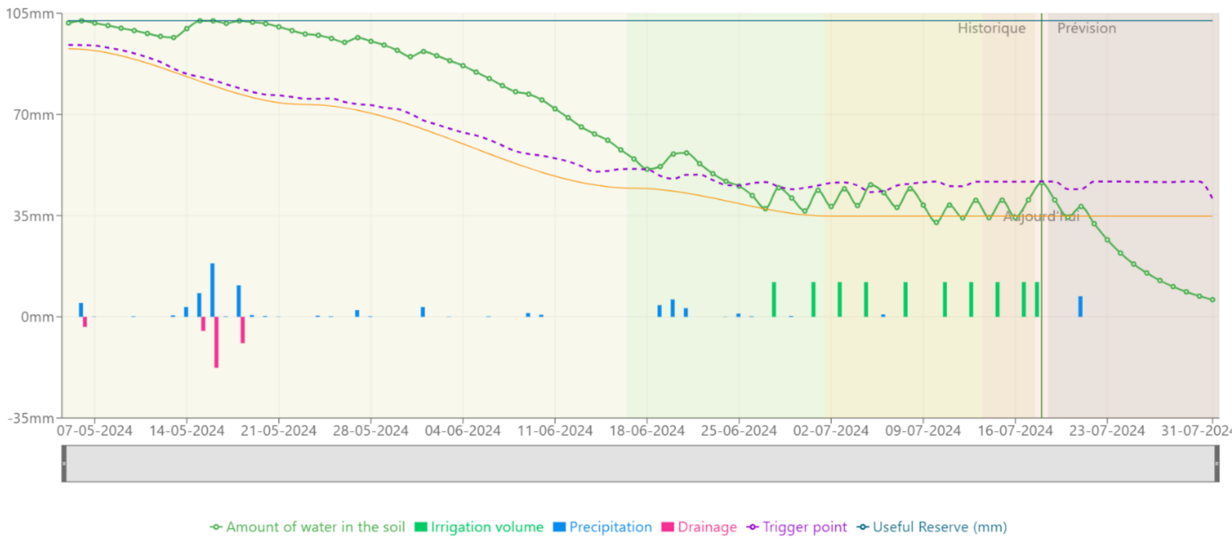
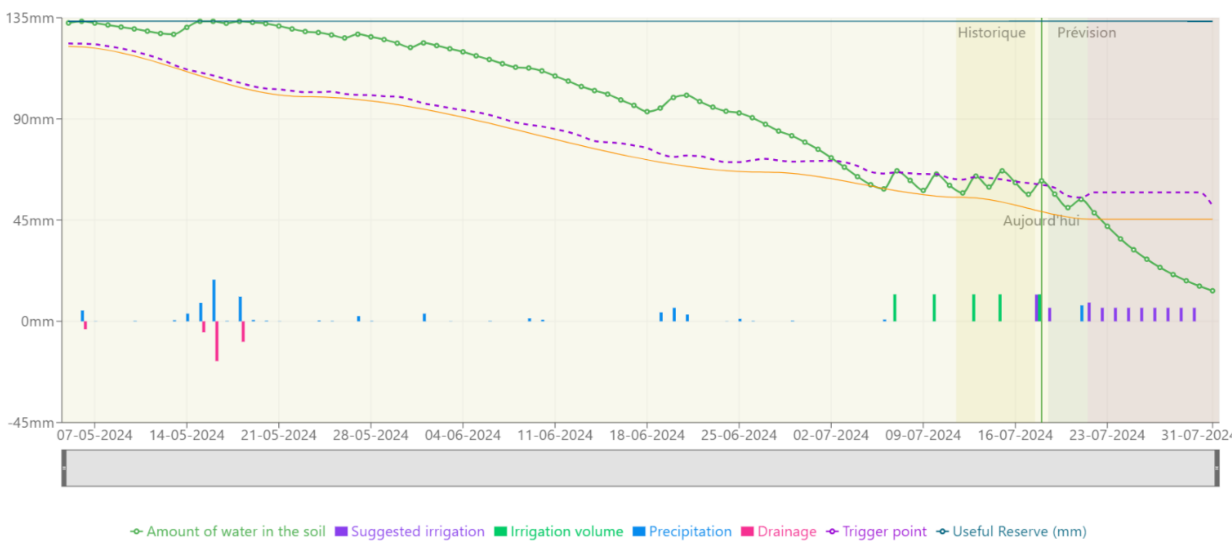


S2V3 Simulation



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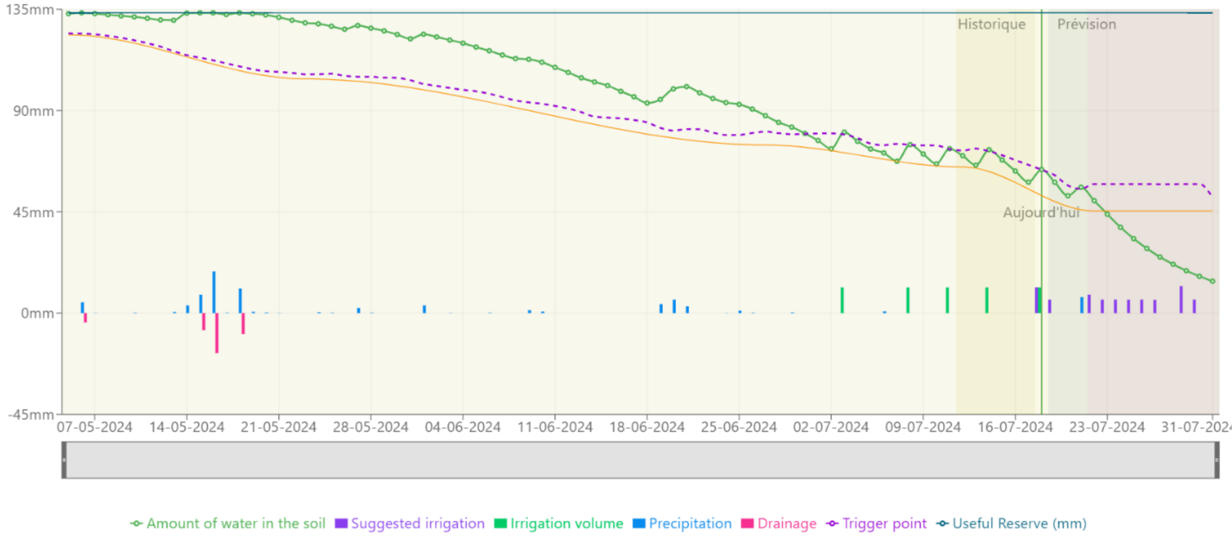
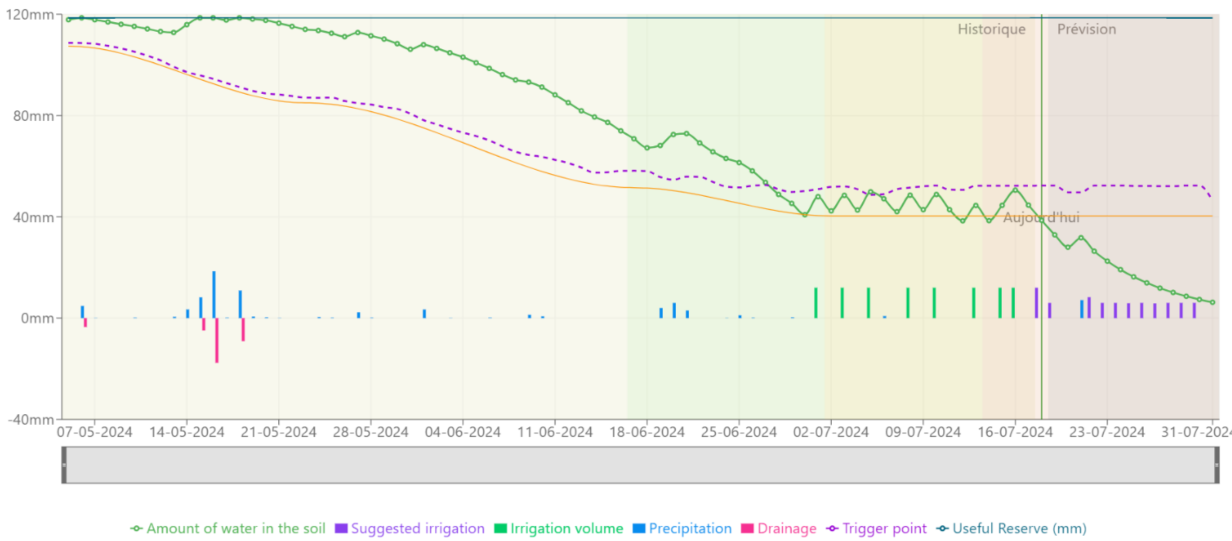
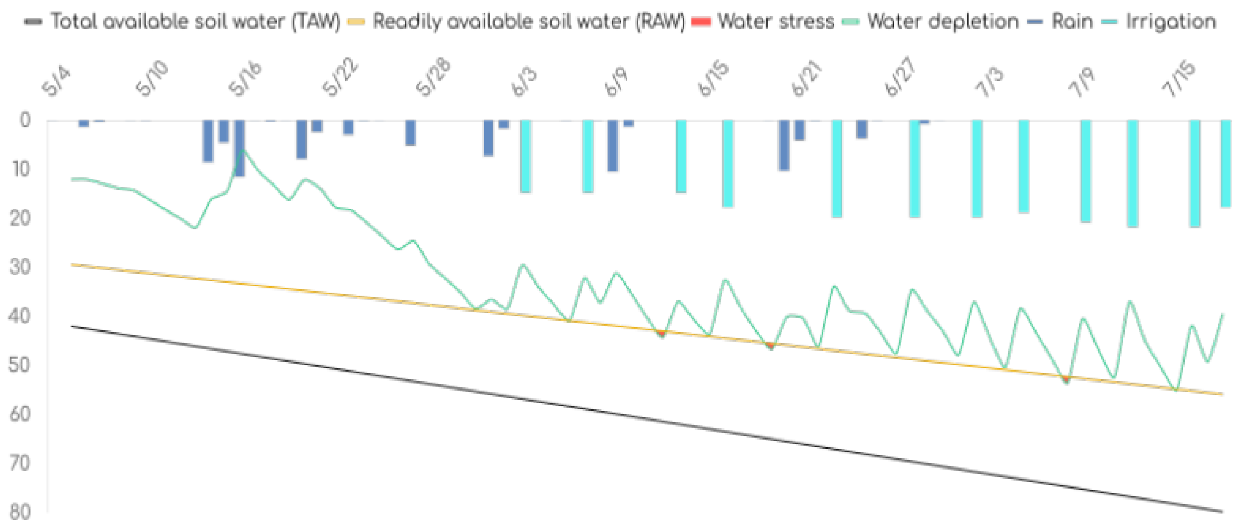


S3V2 Simulation

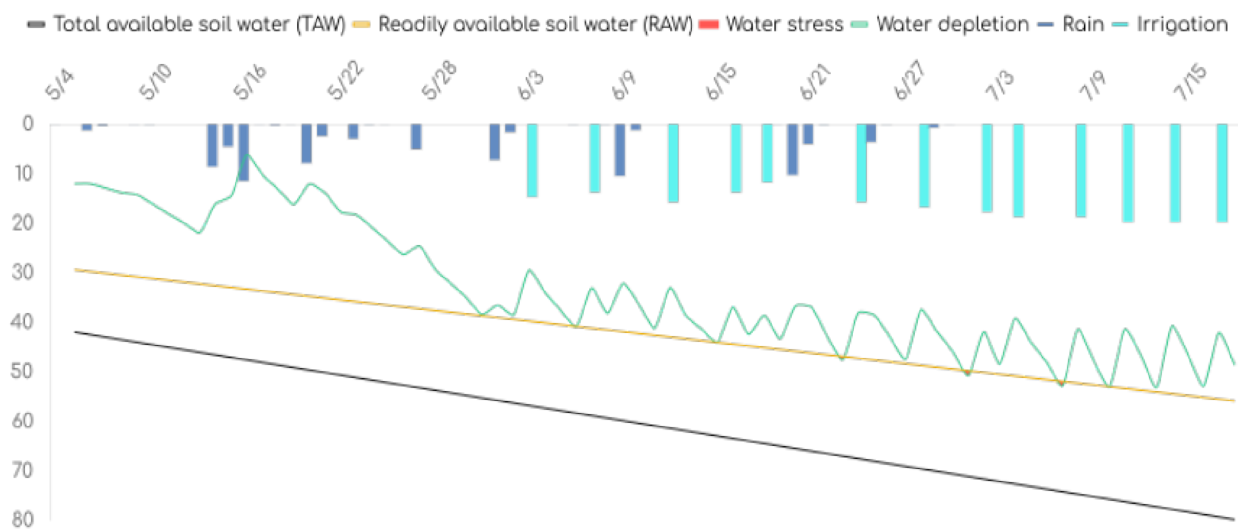


S3V3 Simulation

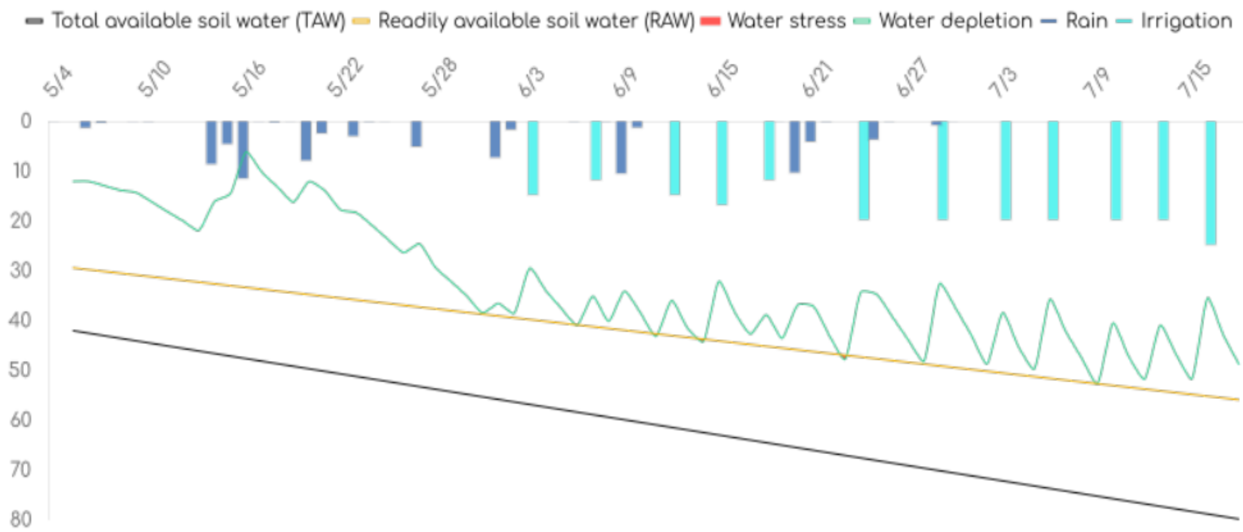
6.1.3 Pixagri Wago



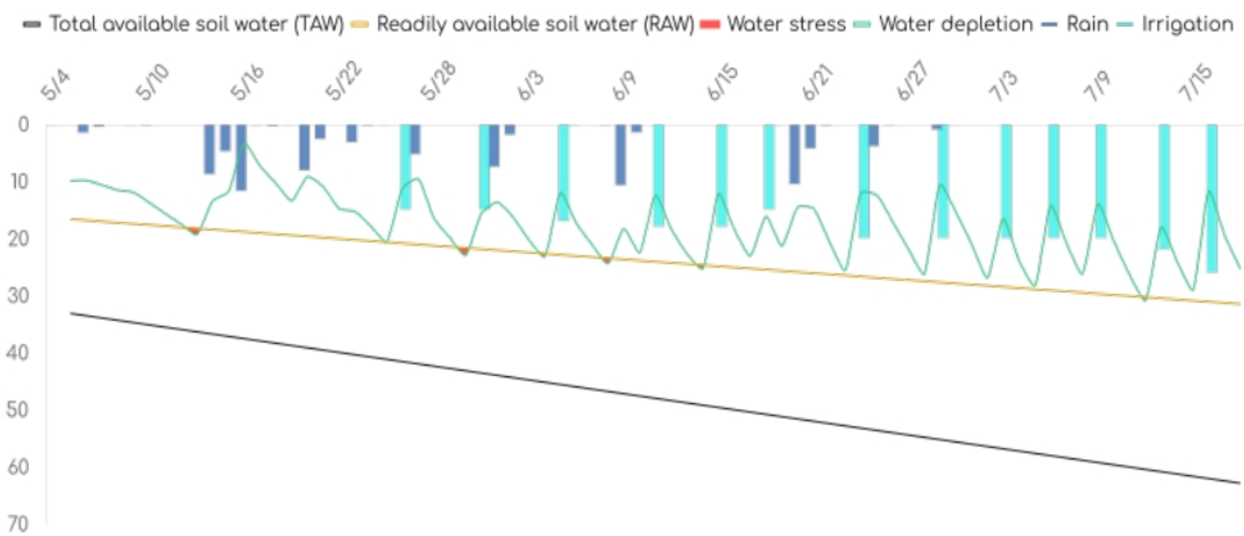
S1V1 Simulation



S1V2 Simulation



S1V3 Simulation



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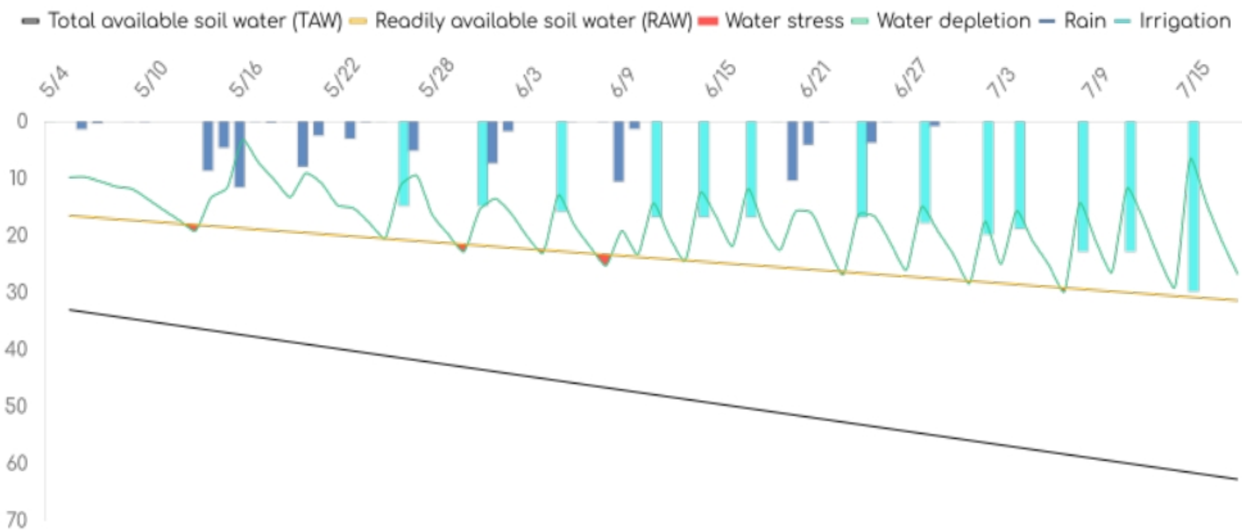

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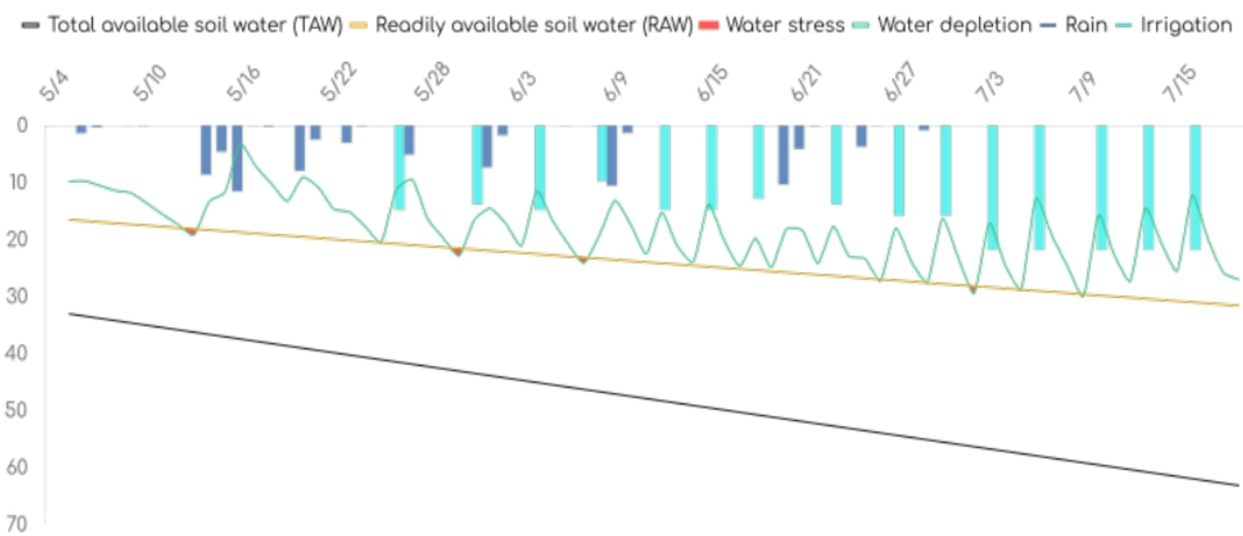
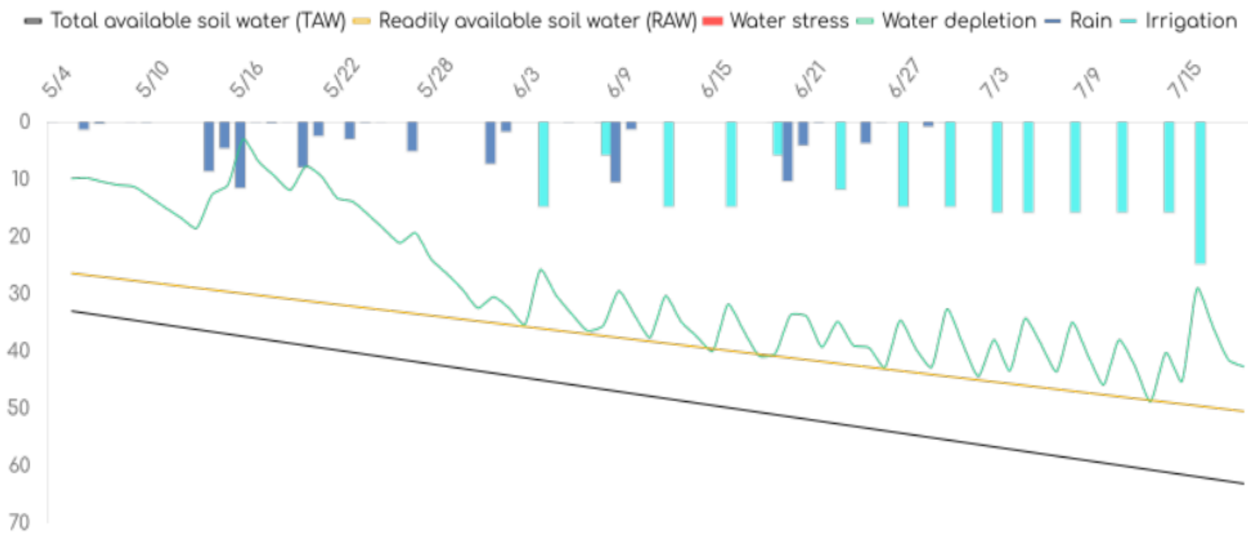
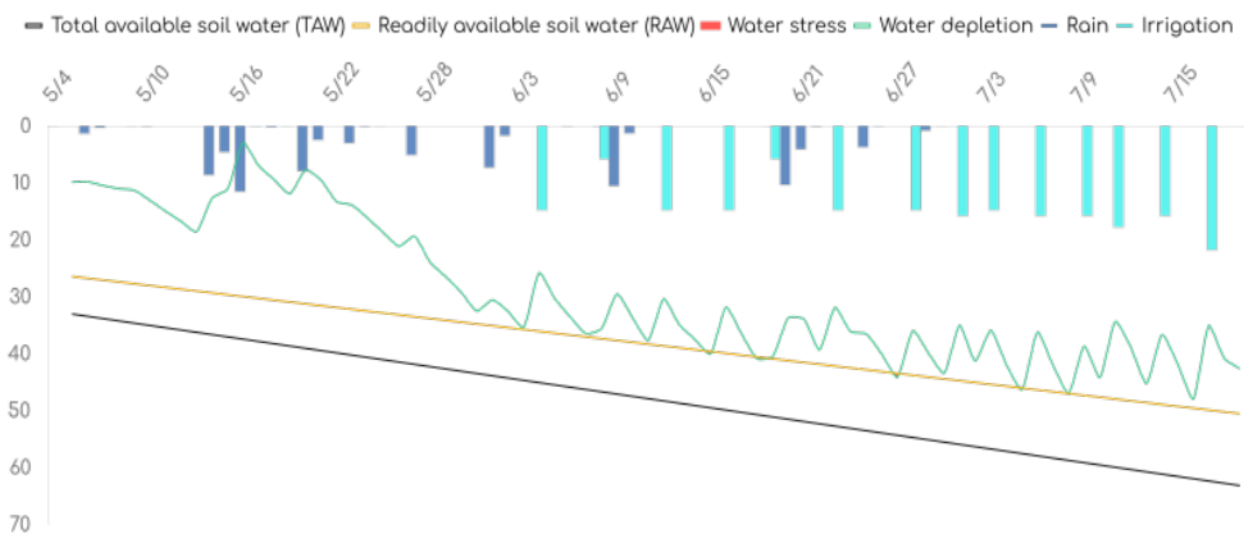


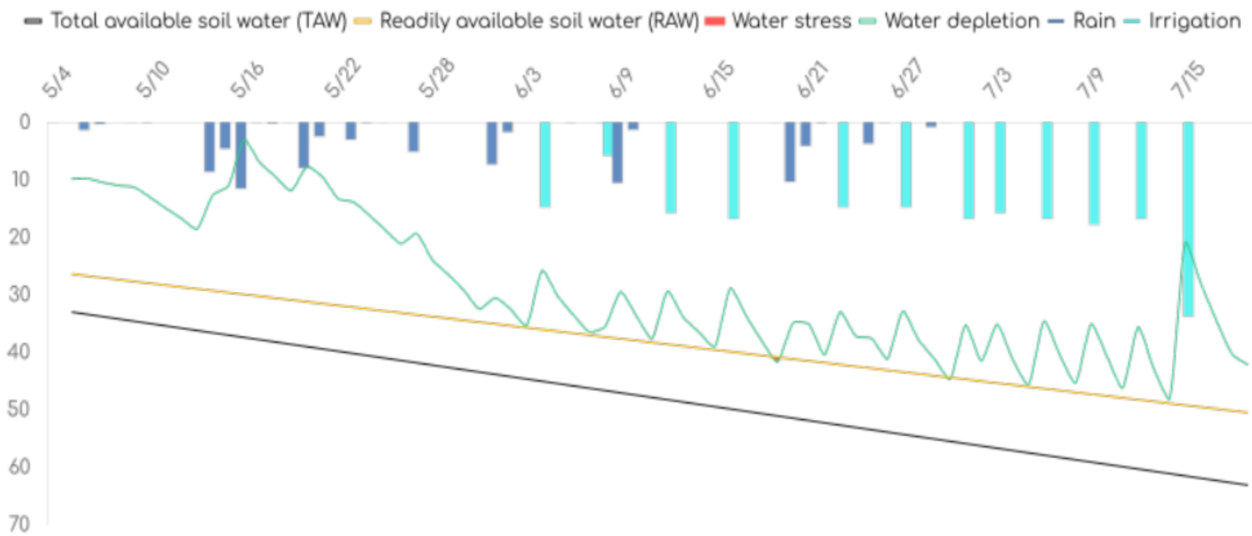
S2V3 Simulation



S3V1 Simulation



S3V2 Simulation



S3V3 Simulation

6.2 Python Code for the Computation and Visualization of DST Sensitivity

```
import pandas as pd
import matplotlib.pyplot as plt

# Your data
Irrigation_IrreLIS = [197, 197, 200, 175, 184, 183, 197, 200, 204]
Irrigation_NetIrrig = [60, 132, 108, 60, 132, 120, 60, 57, 96]
Irrigation_Pixagri = [225, 220, 216, 246, 247, 255, 204, 206, 203]
Soil_type = ['silt loam', 'silt loam', 'silt loam', 'Sandy clay', 'Sandy clay', 'Sandy clay', 'Sandy
loam', 'Sandy loam', 'Sandy loam']
Maize_variety = ['Early', 'Med', 'Late', 'Early', 'Med', 'Late', 'Early', 'Med', 'Late']

# Create DataFrame for Soil_type
data_soil = pd.DataFrame({
    'Irrigation_IrreLIS': Irrigation_IrreLIS,
    'Irrigation_NetIrrig': Irrigation_NetIrrig,
    'Irrigation_Pixagri': Irrigation_Pixagri,
    'Soil_type': Soil_type
})

# Calculate means for each soil type
means_soil = data_soil.groupby('Soil_type').mean()
print(means_soil)

# Create DataFrame for Maize_variety
data_variety = pd.DataFrame({
    'Irrigation_IrreLIS': Irrigation_IrreLIS,
    'Irrigation_NetIrrig': Irrigation_NetIrrig,
    'Irrigation_Pixagri': Irrigation_Pixagri,
    'Maize_variety': Maize_variety
})

# Calculate means for each soil type
means_variety = data_variety.groupby('Maize_variety').mean()
print(means_variety)

######################## First two figures ##################################

# Plotting means by Soil Type
fig1, ax1 = plt.subplots(figsize=(6, 4))
```

```
means_soil.plot(kind='bar', ax=ax1, color=['blue', 'green', 'red'])
ax1.set_title('Mean Values of Irrigation Tools by Soil Type')
ax1.set_xlabel('Soil Type')
ax1.set_ylabel('Irrigation Mean Value (mm)')
ax1.set_xticklabels(means_soil.index, rotation=0)
ax1.legend(title='Irrigation Tools')

# Plotting means by Maize Variety
fig2, ax2 = plt.subplots(figsize=(6, 4))
means_variety.plot(kind='bar', ax=ax2, color=['blue', 'green', 'red'])
ax2.set_title('Mean Values of Irrigation Tools by Maize Variety')
ax2.set_xlabel('Maize Variety')
ax2.set_ylabel('Irrigation Mean Value (mm)')
ax2.set_xticklabels(means_variety.index, rotation=0)
ax2.legend(title='Irrigation Tools')

############################ Figure number 3 ################################

# Plotting means by Soil Type and Maize Variety
fig3, (ax3, ax4) = plt.subplots(1, 2, figsize=(8, 4))

# Plot for Soil Type
ax3.bar(means_soil['Irrigation_IrreLIS'].index, means_soil['Irrigation_IrreLIS'], color='blue')
ax3.set_title('Irrigation_IrreLIS by Soil Type')
ax3.set_xlabel('Soil Type')
ax3.set_ylabel('Mean Value (mm)')
ax3.set_xticklabels(means_soil.index, rotation=0)

# Plot for Maize Variety
ax4.bar(means_variety['Irrigation_IrreLIS'].index, means_variety['Irrigation_IrreLIS'],
color='blue')
ax4.set_title('Irrigation_IrreLIS by Maize Variety')
ax4.set_xlabel('Maize Variety')
ax4.set_ylabel('Mean Value (mm)')
ax4.set_xticklabels(means_variety.index, rotation=0)

############################ Figure number 4 ################################

# Plotting means by Soil Type and Maize Variety
fig4, (ax5, ax6) = plt.subplots(1, 2, figsize=(8, 4))
```

```
# Plot for Soil Type
ax5.bar(means_soil['Irrigation_NetIrrig'].index, means_soil['Irrigation_NetIrrig'], color='green')
ax5.set_title('Irrigation_NetIrrig by Soil Type')
ax5.set_xlabel('Soil Type')
ax5.set_ylabel('Mean Value (mm)')
ax5.set_xticklabels(means_soil.index, rotation=0)

# Plot for Maize Variety
ax6.bar(means_variety['Irrigation_NetIrrig'].index, means_variety['Irrigation_NetIrrig'],
color='green')
ax6.set_title('Irrigation_NetIrrig by Maize Variety')
ax6.set_xlabel('Maize Variety')
ax6.set_ylabel('Mean Value (mm)')
ax6.set_xticklabels(means_variety.index, rotation=0)

############################ Figure number 5 ################################

# Plotting means by Soil Type and Maize Variety
fig5, (ax7, ax8) = plt.subplots(1, 2, figsize=(8, 4))

# Plot for Soil Type
ax7.bar(means_soil['Irrigation_Pixagri'].index, means_soil['Irrigation_Pixagri'], color='red')
ax7.set_title('Irrigation_Pixagri by Soil Type')
ax7.set_xlabel('Soil Type')
ax7.set_ylabel('Mean Value (mm)')
ax7.set_xticklabels(means_soil.index, rotation=0)

# Plot for Maize Variety
ax8.bar(means_variety['Irrigation_Pixagri'].index, means_variety['Irrigation_Pixagri'],
color='red')
ax8.set_title('Irrigation_Pixagri by Maize Variety')
ax8.set_xlabel('Maize Variety')
ax8.set_ylabel('Mean Value (mm)')
ax8.set_xticklabels(means_variety.index, rotation=0)

# Show both figures
plt.tight_layout()
plt.show()
```

7 REFERENCES

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