AI tools in Agri DSS pipeline - the case of irrigated sugar beet

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Abstract.
Precision and Smart irrigation are based on Decision Support Systems, allowing growers a sustainable use of the water resource and uniform and high level yield quality, a fundamental aspects in sugar beet supply chain. Irrigation scheduling in the case of sugar beet is a critical issue, because of sensitivity of the sucrose yield to non optimal water availability. For this reason, starting from an analysis of the supply chain actors, literature has been analysed to identify available tools already used in water management and in particular the use of AI. They emerge several Machine Learning approaches, already used in several crops can be used in sugar beet irrigation scheduling, and some already in the sugar beet. They mainly include fuzzy logics for recipe application, supervised learning to estimate crop evapotraspiration and recursive neural nets to estimate soil and plant water status. The analysis also envisaged the possibility to adopt other techniques already applied in precision agriculture, as LLM to include growers knowledge in managing to prevent conditions favourable to diseases.

Keywords.
Precision Irrigation, Decision Support System, Machine Learning.

Introduction

Sugar beet (*Beta vulgaris,* Sb) is one of the two main crops used for sugar production. To achieve yields of high quality, a correct water management is essential. Achieving this objective, which is already complex for sugar beet - where yield is determined by both biomass and sugar content - becomes increasingly challenging in the context of a changing climate and the need to address sustainability concerns (Zarsky et al., 2020).

Optimisation of irrigation is commonly addressed by:

- Precision irrigation - based on updated geo-spatial information of the planted surfaces, including remote sensing data, using it to verify the distribution of crop water availability on medium-to-large surfaces and aimed at reducing spatial yield gaps (Sharma et al., 2020, Abioye, 2022).

- Smart irrigation systems - based on automated water supply irrigation systems, relying on irrigation technology designed for specific cropping systems (Younes et al.,2024). Such systems are becoming popular thanks to the increased popularity of the IoT (Internet of Things) technology (Liu et al, 2023).

A modern irrigation service is expected to be Precise (in distribution and timeliness) and Smart (timeliness and automated) to make a safe and sustainable water use. To attain such objectives an integrative approach is searched (Liang et al, 2020), where Decision Support Systems (DSS), Precise and Smart Irrigation combines to allow Real-Time Data Integration from different sources (sensors, remote survey, weather forecasts). Their popularity, motivated by the need of a sustainable water usage, has grown because of the availability, reliability and accessibility of data from:

- local probes, remote surveys, weather networks and forecasts
- crops characterisation, soil parameters, geomorphology and subsurface hydrology
- irrigation efficiency, losses, costs, etc.
- field information such as geometries and agronomical activities

These sources of data are commonly used in DSS, which are harnessed by services mainly for Irrigation Scheduling purposes (generating recommendations and alerts), while taking into account high level considerations, as the area water availability and the needs of other compartments (mainly civil, industry).

However, the complexity of irrigation frameworks results in multiple weaknesses, bottlenecks and inefficiencies in water uses.

Despite significant advancements in data integration methods(data assimilation), there is a growing interest in enhancing the optimisation process using Artificial Intelligence tools (Umutoni & Samadi, 2024, Gao et al., 2023).

The integration of AI and agriculture holds significant potential for transformative impacts. The usage of different data sources, such as remote sensing or meteorological data, can be used to benefit farmers' interests and enhance agricultural practices. The aim is maximizing crop yields, while optimizing water and fertilizers usage. AI technologies are pivotal in agricultural monitoring and management, (Hassan et al.,2023).

In this regard, Large Language Models (LLM) are proving to be a valuable tool, already employed in agriculture for developing chat-bots that assist in answering farmers' questions and making knowledge more accessible**.** In addition, Machine Learning (ML) algorithms are widely accepted in Weed Identification (by Convolution Neural Nets - CNN) and in Forecast of weather, yield, water availability, etc. (by Time series analysis performed using Recursive Neural Nets - RNN).

In this paper we analyse the AI-based solutions in Irrigated Sugar Beet supply chain, to identify more suited solutions. In the first section we will analyse the supply chain actors and their role, the approach to water exploitation and management and the sugar beet irrigation approaches. Then, we will analyse the role of DSS in Sugar beet irrigation and the tools adopted in managing and scheduling irrigation. Lastly, we offer a summary of major AI approaches adopted in Sugar beet irrigation DSS pipeline and produce a comprehensive overview

The Sugar Beet Supply Chain

To capture the complexity of the sugar beet supply chain in an irrigated scenario aimed at locating the critical points where AI has already proven be beneficial, an ontological approach has been adopted[1]. At a first glance, the stage of the Sb supply chain appears to be taken by five actors (fig.1) - actors are described hereafter.

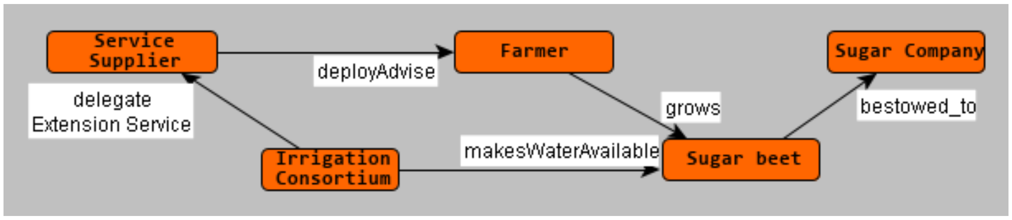

Fig 1. Onto-graph representing actors of Irrigation System

- Irrigation Consortium (or similar agents like Land Reclamation Boards) - when the water resource is shared with other actors, a political-administrative-technical organisation is commonly supervising water exploitation (and taxation); such an organisation manage for a sustainable use of water in agreement with other agents mediating the need for water of civil and industrial purposes, which also involves waste-water treatment. The Irrigation Consortium also manage context with permanent or occasional water excess by drainage infrastructures aimed at guarantee safety for population (floods) collaborating with other hydrological land management organisations.
- Service Supplier - recently the need of enhance water use efficiency and optimise irrigation scheduling, allowed the diffusion of service companies, delegated in collecting information (satellite, weather forecast, land and farm-scale data, water availability on distribution network) and develop irrigation assistance. The activity requires a detailed information about grown crops and irrigation technology, and a follow-up from farmers about the water usage. Currently those recommendations are weekly-based and with a regional scope which lacks the potential to identify field-specific issues and field-specific water recommendations.
- The farmer (or grower) is a key character in the irrigation stage - he is in charge of deciding the cropping scheme, therefore the quota of surface to reserve to Sb growing. As a contractor of Sugar Production Holding, he is normally given the seed (a crop variety optimal of the area) and further direction in Sb cultivation, together with a technical support. However it is his duty to control (distribute) the optimal amount of production factor, included water. When no other actors are involved, he should also manage for water exploitation (Yetik et al., 2022). In areas with water scarcity such as the Mediterranean area, the farmer has a limited allocation of water resources for his entire farming operation, necessitating careful management and efficient use of water to sustain crop growth. Regardless, increasing sugar ratios were reported with decreasing irrigation water quantities in arid climatic conditions with appropriate irrigation scheduling (Li et al. 2019). However, in other regions with greater access to water resources, appropriate water use should also be deleterious, as excessive irrigations increase sugar beet yields but reduce the quality and sugar ratio (Masri et al. 2015).
- Sugar beet (Sb), meant as the crop grown, is undoubtedly the main character of the scene (Fig.1). Sb is one of most diffused industrial crops grown for white sugar production (Tuğrul,2022). Sb is a biannual species (reproduce in the second year) grown for its main root, whose axis may reach 2-3m depth. Sb water requirement is about 900 mm to 1200 mm (Dunham 1993)., and irrigation is quite common also in continental areas to compensate rainfall distribution (Zarski et al, 2020). Though in terms of water management and agronomic conditions (e.g.climate, plant density) Sb have several similarity with Tomato (Solanum lycopersicum) and Cotton Gossypium spp.), more similar crops are represented by Potato (Ipomoea batatas),Topinambur (Helianthus tuberosus) and Cicory (Cichorium intybus var. sativum). Sub-optimal soil-water conditions (dry soil or over-wet conditions) promote the

[1] Ontologies are semantic annotated dictionaries - each entity has a definition clarified by examples (use cases) and links to other entities by links. They can be easily represented in terms of graphs: entities as nodes - links as directed annotated edges.

diffusion of pathogens (Paul, 2022), as:

Rust (*Uromyces beticola*) - moist weather Temp 15-20°C and most intense when dew persists for long periods

Downy mildew (Peronospora farino*sa*)

Powdery mildew (*Erysiphe betae*) - Temp c.ca 20°C with dew at night

Ramularia (*Ramularia beticola F&L*)- Temp c.ca 17°C and humidity > 95%

Leaf Spot (*Cercospora beticola*). - humid conditions

Root-rot (Rhyzochtonia), due to water ponding / stagnation conditions, mainly of concern in tropical areas (Misra et al., 2023)

Root madness (Rhyzomania)

Virus Yellows

Recently several resistant varieties have been selected and in use (Abu-Ellail, 2024), however the extreme scenarios related to the climate change increases the risks in growing such a crop (Rajabi &Taleghani, 2022), and an increasing capacity to manage uncertainties is required (Garcia-Vila et al., 2019).

Major irrigation techniques adopted for Sb crops are represented by furrow, sprinkler and drip irrigation. The benefits of drip irrigation Sb has been tested in major production areas [Topak et al., 2011]

- Transformation Holding (Mill) - Sugar beet is commonly grown in medium-large scale compartments (for logistical reasons). Contracts with farmers rule income which strictly depends on quantity and quality of produce - harvested roots should bestowed in the transformation site in short time as roots left on the field border may deteriorate in adverse circumstances. The sugar producer takes in consideration and bring together every issues appearing along the supply chain, and agronomic issues often fade away in the big view (Bily & Passel, 2018). In some agreement schemes, the mill is required to audit irrigation practices, which is an unmanageable task if inspections are conducted physically.

DSS for Irrigation

A Decision Support System is an information system designed to assist decision makers in organizations in the process of making complex, semi-structured decisions. The DSS provides tools, as well as data and analytical models to help analyse information, evaluate options and support decision making. These systems are designed to address specific business problems and often involve the interaction between people and information technologies. A DSS is useful to a holding in a variety of decision-making contexts, including strategic planning, human resource management, financial planning, and many other business areas where in-depth analyses are required to make informed decisions. Key features of DSS include:

- Data Access & Integration, providing quick and easy access to relevant data from various sources (internal and external to the organization), e.g. weather forecast information.
- Analytical Tools & Modelling, for processing and interpreting data, such as reports, graphs, dynamic tables, and visualization tools - including simulations to explore future scenarios and evaluate the impacts of alternative decisions.
- Support for Decision Structuring and Collaborative decision-making processes, used for displaying information, models and analysis results.
- User Interaction, offering interactive and user-friendly user interfaces, allowing decision

makers to explore data, perform analysis and make informed decisions efficiently.

In an agricultural framework, DSSs are key tools for optimizing agricultural practices, helping in improving efficiency, productivity, and sustainability (Martin-Clouaire, 2017; Zhai et al., 2020).

DSSs are a cornerstone of Precision Agriculture (Nowak, 2021). They enable farmers to make data-driven decisions aiming for yield and quality increases, adopting a more targeted and sustainable approach, including spatial and temporal variability together with variable rate application, by means of optimizing the use of water, fertilizers, and pesticides (Fountas et al.,2006). Spatial analysis methods can be used to interpolate measurements to create a continuous surface map or to describe its spatial pattern (Fortes et al., 2015), contributing to this improvement of decision-making.

A Real-Time Decision Support System (RT-DSS) is designed to provide timely information. In Smart Agriculture it includes Real-Time Field Condition Monitoring (including Crop, Water Quality, Disease and Pest) and weather information to make immediate decisions in response to sudden climate changes during critical stages of crop life cycle (e.g. germination), to give automatic notifications and alarms to farmers for immediate action. A RT-DSS is also useful for machinery monitoring, to collect real-time operational data from agricultural machinery, enabling more effective management and preventive maintenance. Many components embedded in RT-DSS (as models) are today reused in the area of Digital Twins (Verdow et al., 2021).

Precision Irrigation - Grower associations and extension services provide farmers with recipes for irrigation about local crops. In the case of Sb, in Mediterranean areas (dry summer), pre-sowing irrigation ensures sufficient soil moisture for proper irrigation, while post-sowing irrigation supports the early establishment of the crop. For loose soils, irrigation frequency may be required every *5* days, whereas for heavy textured soils, a *10* day interval may be sufficient. Frequent and short irrigations are suggested to maintain an optimum soil moisture. Finally the irrigation has to be stopped at least *2* to *3* weeks before harvesting (i.e. for hot dry periods, Sb is almost dormant, and a sudden water supply may induce Sb to restart vegetating using sugar reserves, thus reducing yields (= biomass x sugar content). If at harvest the soil is too dry / hard an irrigation is recommended (TNAU, 2024).

Similar recipes, coined for different climates, are still in use (Rajabi et al., 2022), however the approach fails in accounting for year variability or anomalous seasons. It is for this reason that, long before the entrance in Climate Change age, a rational use of water has become a relevant aspect (Stewart et al., 1977; FAO, 2024), relying on physical-modelling basis.

Today thereis a growing interest in using DSSs in irrigation (Ara et al., 2021) and most of them include a simulation approach characterising popular models (e.g. AQUACROP by FAO, STICS by CNRS, DSSAT by USDA and APSIM by CSIRO) - figure 2 reports most relevant variables and dynamics relating water availability to Sb yield. On top of figure the variables included in most of models may be easily identified (Prec:Precipitation, W_vel: wind velocity, RH: Relative Humidity, T_air: air temperature, R_sun: solar radiation) the latter ones being required from Penman-Monteith equation for the estimate of potential Evapotranspiration (ETp), while precipitation (and irrigation) is used to estimate soil water content (SWC). Such variables also affect more general aspects of Soil Status and Plant Status, contributing to pathogens development. On the bottom right of the figure the process reporting how water availability affects plant growth are represented, based on a classical parametrization including Leaf Area Index (LAI), crop grow rate (CGR), and crop coefficient (Kc).

Kc is used to adjusts the ETp to the development stage of the crop, soil coverage, and management. It represents the relationship between maximum crop ET (ETc) and the ETp (Kc = ETc / ETp). Traditionally, it has been used theoretically, but thanks to satellite images, it is possible to calculate the current conditions of the crop and determine a Kc adapted to the reality of the plant. The successful use of satellite imagery to calculate the crop coefficient (Kc) was demonstrated by Garrido-Rubio (2015) for maize cultivation.

A non optimal water availability (water stress) is responsible of a reduction of transpiration (Ks =

ETc_act / ETc) which also reflects on the reduction of actual grow rate (CGR_act), estimated from Ky = ETc_act / ETc. Model can be refined with inclusion of the effect of pathogens (yellow labels) and, not to forget, the effects of above mentioned dynamics on sucrose content of roots.

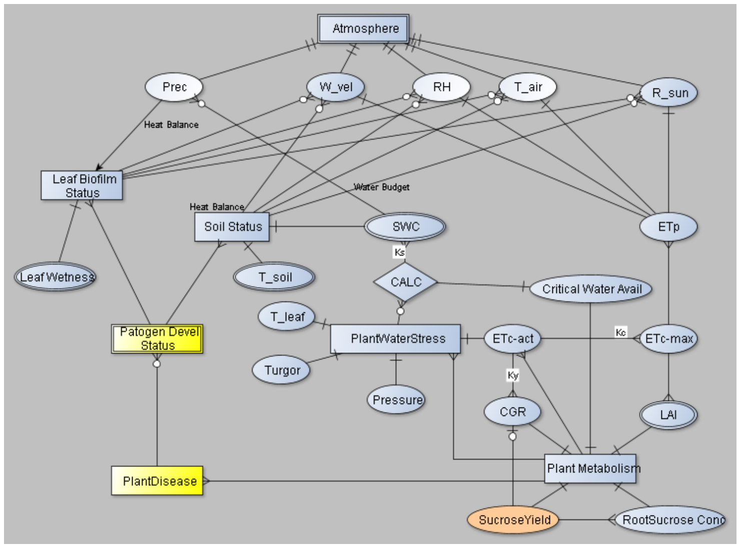

Fig 2. conceptual model relating yield to dynamical environmental conditions

These models are used for irrigation scheduling at crop/field scale. Scheduling is based on:

- Estimating time of intervention **(T)**, by the estimate of the crop water stress (CWS)
- Estimating depth of water supply **(H)**, by the water balance
- Flow intensity **(F)**, based on the estimate of infiltration ratio and run-off.

To correctly estimate H (by ETc_act and Prec - other components as drainage, capillary rise and run-off are seldom considered), empirical crop coefficients are required, which in turn depend on complex soil and crop dynamics, needing time-consuming sensitivity analyses, calibration, and validation based on field experiments, while not granting the generalisation level models were originally designed for.

If from the one hand a rough estimate of H could be irrelevant for a single irrigation, on the other hand the daily error accumulation represents a critical issue in T. For this reason soil data is increasingly used for a direct estimate of T (Datta & Taghvaeian, 2023), inferring Crop Water Status (CWS) from Soil Water Content (SWC) of the root layer.

This is today a standard practice in Smart Irrigation (and RT-DSS), where timeliness is fundamental, an approach which is more addressed to orchards and vegetables. In Precision Irrigation the spatial homogeneity of distribution is more relevant, and obtained by remote and proximal sensing observation - in this case, instead of SWC, there is more interest in estimating CWS, using leaf temperature as a sign of a water stress index.

F is still mostly based on irrigation technique and direct knowledge of soil behaviour. Sprinkler Irrigation has an high application efficiency (incl.Sugar Beet), with more than 40% water saving and higher water productivity with respect to gravity-based systems - adding automation can save 20–30% water and increase crop yield by 20–27% (Choudary et al.,2024). However radial distribution of water and overlap of watered areas are stilla challenge (Zhang et al., 2021). For this drip irrigation technology has become popular in certain areas (Yamak et al., 2021).

Finally irrigation scheduling has to be configured in a more complex activity framework (below referred as L) - since water is a limited resource and more agents (or many farmers) are demanding it. Nevertheless, water distribution is delegated to an agency having the task of finding a trade-off between supply and demand. At this level, priority is ruled by complex aspects including: hydrological systems, water collecting infrastructures, and technological limits together with market and policy. L also includes logistic aspects and could be integrated to other services as scheduling of harvest and roots bestowing.

AI in Irrigation DSS

Even though the use of AI in Precision Agriculture is becoming popular (Son et al., 2024, Abioye et al., 2022), applications in irrigation are still limited and are focusing on scheduling irrigation at crop level (points T,H) while applications to activities F and L, even though these are very important, are more sensitive to the adopted technology and the context of irrigation. None the less, despite of a growing interest in Artificial Neural Nets, the fuzzy logic approach is still popular in decision taking (Alvin et al. 2022).

Most of solutions are based on time-series analysis and forecasts and oriented to identification of irrigation strategy (T,H) as:

- a solution has been studied for dry areas based on CSM-CROPGRO simulation model using Reinforcement learning to tune/fit model parameters (Chen et al.,2024, González Perea et al., 2018).

Some solution is more oriented to Smart Irrigation, to forecast soil water content for irrigation scheduling in orchards with drip methodologies (Francia et al.,2022).

Other solutions are more oriented to a spatial water distribution (Precise Irrigation) are investigated for field crops; most of these studies aim at identifying missing observation trying to assimilate multiple information. Some examples are reported.

- Soil Water Content - in Maia et al. (2022) soil matric potential in the plant root zone is estimated from remote sensing data Supervised Learning approaches;

- ETc-act from a reduced amount of environmental data and incomplete weather station coverage. A study on Irrigated Sugar beet Supervised Learning has been used to estimate crop ET (Yamac, 2021);

Finally, another important issue is related to the irrigation survey, a fundamental task of extension services, required to increase the reliability of follow-up from farmers (Radulović et al., 2023)

Perspective

The present analysis draws the big picture of sugar beet irrigation scenario, from which the relevant characters and roles have been identified together with the main tools undergoing an enhancement due to application of AI-based solutions. Existing solutions are oriented to make irrigation scheduling more precise and smarter, by assimilating multiple data for Precise and Smart irrigation schemes.

Together with the identified most important trends, perspective solutions suitable for adoption can be envisaged.

Assimilation/integration of different data e.g. local weather and remote sensing can benefit from RNN used for time series analysis to make irrigation advice more reliable.

A CNN-based system for identification of surface anomalies to trigger the extension service survey by proximal and remote survey to estimate the location of the anomaly and alert a support service for diagnosis and identification of corrective actions [CIT]

LLM-based chat bots used to embed the results of interviews with growers about their irrigation technology and habits, opinions on soil type and susceptibility of varieties to disease and other pests in the different watering conditions. A chat-bot developed to collect, host an increase the amount of knowledge to be integrated in a semi-automatic response system host by the extension service, ready to be consumed by the farmer community, would be helpful. The new role of technicians will be to maintain a personal contact with growers encouraging a constant feed of information to be ingested by LLMs to generate answers to queries. AI is very sensitive to faulty information and quality of labelling for a reliable ground-truth is fundamental to get reliable answers.

Certainly spreading of web/cloud-based solutions & services would benefit from a reduction of the digital divide, which remains relevant in many rural areas.

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