Assessing the Potential of Integrating Automation and Artificial Intelligence across Sample-Destructive Methods to Determine Plant Water Status: A Review and Score-based Evaluation

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ABSTRACT

Sample-destructive methods for the determination of plant water status have been the primary reference for various agronomic practices over the years. Several recent technological advancements in automation, robotics, and artificial intelligence (AI) have helped make progress toward more resource-efficient water management. However, several methods, especially those conducted in situ, still require considerable labor and can be further improved via the integration of automation. To this end, this review article has a twofold aim. 1) To point out relevant aspects and technological considerations of sample-destructive methods for determination of plant water status in comparison to proximal and remote monitoring technologies, while also illustrating interrelations among the different measurement practices. 2) To evaluate the potential of current methods to be automated and endowed with AI capabilities that can further enhance the methods' outcomes such as accuracy, precision, and consistency. To address the first objective, 97 articles were downselected and included in a meta-analysis performed in this review article from an initial literature survey comprising 550 articles related to the determination of plant water status over a ten-year time frame. The methods developed and reported within the selected articles were classified based on several key features such as type of measurements, required equipment, sampling time, location of measurements, need for calibration, and affordability. To achieve the second aim, an automation score based on several key metrics was proposed and then used to rank the different methods in terms of potential for automation. This work can spark further discussions within the agricultural engineering community at a time when automation and AI efforts in agriculture create new challenges and opportunities for improving the determination of plant water status in support of more resource-efficient agricultural water management.

1. Introduction

Accurate water management for specialty crops in semi-arid agricultural production areas is critical to achieve profitable yields of market-demanded quality, while also enabling growers to attain highly-productive use of land, water, energy (Rossello et al., 2019) and labor. Field assessment of plant water status has been employed over the last century to inform efficient and timely irrigation scheduling decisions. To determine plant water status, several recent endeavors from academia and the agricultural industry have focused on the development of sensors and algorithms capable of assessing and, at times, predicting plant water status in crops without physical contact or sample handling. Despite the large number of methods being developed and tested, conventional *sample-destructive* methods are still

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commonly used worldwide to determine plant water status. Further, the need for field validation after calibration against conventional methods such as the pressure chamber (Boyer, 1967) still emphasizes the importance of these manually-operated, in-situ techniques as a “ground truth" reference.

The various methods and tools for assessing plant water status in agriculture can be distinguished and classified based on the level of interaction between the measurement device and the plant, and the “destructiveness" (if any) of plant samples (leaf, stem, etc.) after performing the measurements (Fig. 1). The various methods and tools can thus be classified as:

- Physical Methods: Direct contact with the plant is needed to either detach a sample or utilize the probe for measurement. Physical methods can be subdivided into sample destructive and semi-destructive. The former considers cases like the complete detachment of samples (e.g., leaves and shoots) from a plant, whereas the latter involves localized damage (e.g., insertion of an instrument into the trunk of a tree).
- Proximal Methods: The measurement device can be placed in the vicinity of the plant to obtain the desired measurement, but no direct contact is required. Proximal methods may be categorized as non-destructive.
- Remote Methods: Data are streamed from sensors either deployed in the field (but not coming in direct physical contact with the plant) or mounted onto remote/proximal platforms, such as unmanned aerial vehicles (UAVs).
- Learning Tools: Artificial Intelligence (AI) models trained on data from the aforementioned methods can enable the prediction of plant water stress levels given a set of bio-physical characteristics, such as relative water content. methods.

Sample-destructive methods are generally labor-intensive. They require in-situ trained and skilled personnel who may need to work for several hours in the field under various weather conditions and while often carrying equipment that may be borderline portable. In addition, in several cases, multiple daily measurements must be gathered to obtain accurate data from sufficiently large samples. Some methods are also susceptible to how meticulously an operator performs measurements; if not done properly, this can lead to considerable errors and deviations from actual plant water status values. Given their widespread use and their role in grounding and calibrating other methods, it is important to identify ways to improve some of these limitations of sample-destructive methods. To this end, automation and AI can be a potential solution.

Semi- or fully autonomous methods can promote a tight integration among different techniques and improve measurement consistency, accuracy, and precision. In turn, these may improve the utilization of resources such as water, energy, and labor, as well as result in higher-quality specialty crop production. Prior literature review efforts from other groups have focused mostly on discussing state-of-the-art sensors and methods, as well as remote-sensing and novel

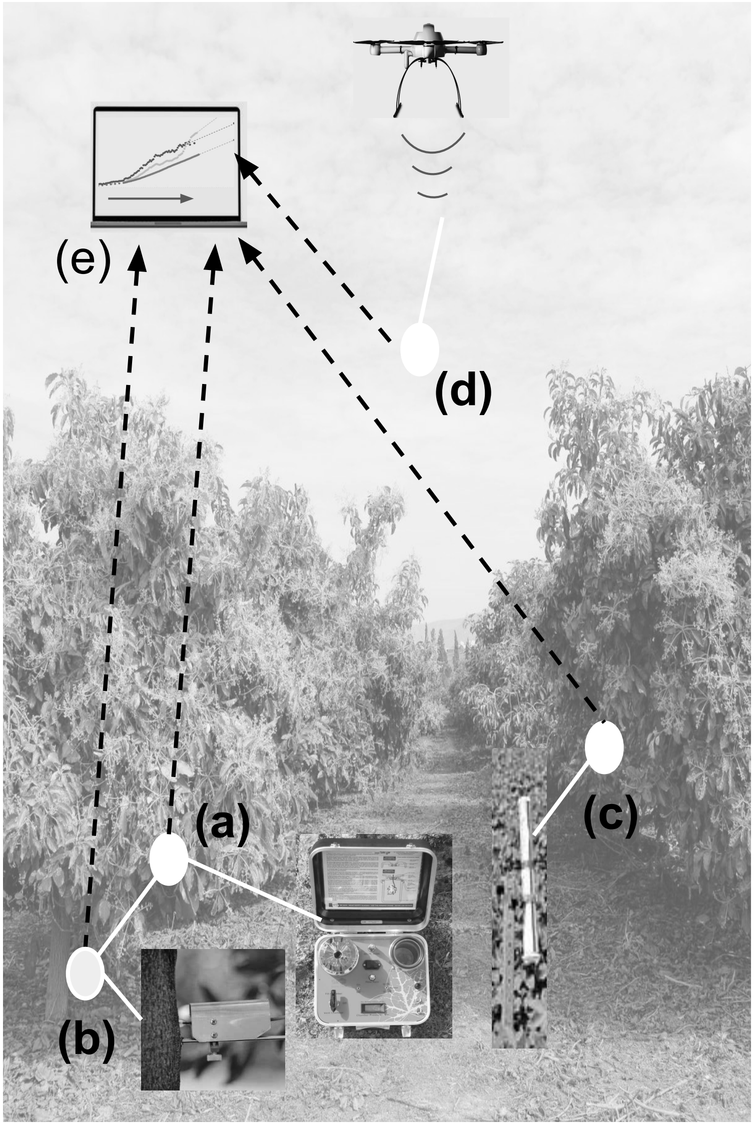

Figure 1: Distinct methods for assessing plant water status. (a) Physical methods (sample-destructive) such as the pressure chamber (or Scholander chamber) method. (b) Physical methods such as the Microtensiometer and Heat-pulse velocity methods. (c) Proximal sensing methods including ground infrared thermal imaging. (d) Remote sensing utilizing platforms such as UAVs equipped with thermal or RGB cameras. (e) Learning tools can utilize destructive, semi- or non-destructive methods and determine or predict plant water status.

technological solutions for plant water status determination and assessment (e.g., Sibanda et al. (2021); Ishimwe et al. (2014); Dean et al. (2014); Maes and Steppe (2012)). Although conventional techniques are discussed to some extent in those prior surveys, no in-depth analysis has evaluated the potential for automation and AI applications regarding sensor placement, measurement, maintenance, and inspection for either destructive or semi-destructive methods.

The present review article aims to inform agricultural engineering researchers, growers, crop and irrigation consultants, and practitioners, as well as agronomists and horticulturalists on 1) the characterization of conventional and novel methods for determining plant water status, and 2) how possible future developments on integrating automation and AI could elevate conventional methods to yield more consistent, accurate and precise measurements. From an initial pool of 550 articles, 97 articles were selected and reviewed in detail to explore conventional methods to determine plant water status, which can be automated and allow integration with AI. These methods were classified according to various technical aspects and considerations, as well as requirements to make proper measurements, and resulting metrics. The need for validation after calibration was given specific consideration and served as the means to indicate inter-relations among certain methods; an additional benefit of such considerations is that they can also enable an appraisal of how automated systems can benefit newly developed technologies.

In addition, this review paper presents findings from a meta-analysis of the selected articles and proposes an *automation score* exploring the aforementioned aspects and technical considerations of each method, as well as their inter-dependence due to calibration needs. Based on the attributed automation score, a follow-on discussion emphasizes the likelihood of partially or fully automating these methods on a physio-mechanical level utilizing various hardware components, and suggests different configurations per tasks that are derived from applicable methods as potential solutions for the automation goal. The potential of integrating AI and machine learning techniques into the proposed automation scheme on a case-by-case basis was also presented. Finally, the article presents a discussion of recent findings from one case study where some of the processes related to the pressure chamber method for determining stem water potential were automated.

2. Background and Motivation: Methods to Determine Plant Water Status

Plant water status, measured on a leaf, can be referred to as water content and water energy (or potential) in the leaf tissues. An overview and discussion on the general concepts of leaf water content and stem water potential is presented, highlighting that in many identified articles from the reviewed literature discussed next, the terms leaf water potential and stem water potential are used interchangeably. While inter-related (see for example Suter et al. (2019)), leaf water potential (measured at predawn) may overestimate soil water availability when there are underlying heterogeneous conditions in soil humidity (Améglio et al., 1999). Stem water potential, in contrast, is assessed around midday when the environmental conditions are typically more stable, which makes the measurement procedure more easily implementable (Intrigliolo and Castel, 2010).

2.1. Leaf Water Content

To determine the absolute leaf water content (LWC) one can take a leaf and immediately measure its weight, and subsequently subtract the weight obtained when the same leaf is dried out, thus using a gravimetric method. Some methods estimate water content based on a validated relation between the content and reflectivity of light, such as transducers (Kong et al., 2017), image analysis, and hyperspectral data (Corbin, 2015). The high accuracy of the gravimetric method makes it a calibration reference for other methods. Furthermore, novel methods have recently been developed as non-destructive alternatives for determining leaf water content, such as standing wave radio (SWR) (Gao et al., 2019), wavelet analysis (Cheng et al., 2012), and terahertz quantum cascade lasers (Baldacci et al., 2017), including terahertz radiation spectroscopy using single (Browne et al., 2020) or multiple (Li et al., 2020) frequencies. A more specific determination of plant water status is leaf relative water content (RWC) (Mullan and Pietragalla, 2012), which relates the measured water content with its maximum value at full turgidity, and also considers the osmotic adjustment (OA), an important hydration mechanism for plants under drought that is not considered when determining the absolute water content. Assessing RWC is less common compared to LWC since turgor weight (TW) determination requires elaborate laboratory procedures (Corbin, 2015; Sancho-Knapik et al., 2010).

2.2. Leaf/Stem Water Potential

The water potential is calculated according to Eq. 1 (Jones, 2007) as:

$$\Psi = \Psi_o + P + \Psi_g + \Psi_\tau \tag{1}$$

where Ψ_o is the osmotic potential (due to dissolved solutes), P is the hydrostatic pressure (turgor pressure or pressure potential), Ψ_g is the gravitational potential due to elevation differences between measured samples and soil, and Ψ_τ is the matric potential (often combined with the osmotic potential). To illustrate the concept of water potential, consider for instance a tree as a vertical pipe, with a pump and tank system (Fig. 2), where water moves from the soil to the leaves to convey nutrients, overcoming gravitational effects and pipe resistance (friction) against it. To do so, a negative pressure gradient between the leaf, roots, and soil is necessary. Even when the soil is saturated a leaf still requires water (usually transferred to the atmosphere). This negative pressure generates a tension along the soil-plant-atmosphere continuum, moving water (as well as ions, and nutrients) from the soil to the leaf for photosynthesis and carbon assimilation. Therefore, the lowest potential in the atmosphere engages the leaf to act as a “suction pump" (hence building up the highest water tension within the plant), and the water potential subsequently increases at the stem and root (pipe), and then soil (tank) which also demonstrates the highest water potential (lowest water tension).

An important distinction when determining plant water status is the necessity of a sample, and if the procedure requires additional handling or modification during preparation or measurement itself. Sample-destructive methods require direct contact of a user with the sample, during collection and/or measurement stages, and consequent destruction of the sample after the measurement is conducted. These methods are generally the most accurate, given the physical proximity of the measuring instrument and sample, which allows for a direct measurement of the sample's physiological properties.

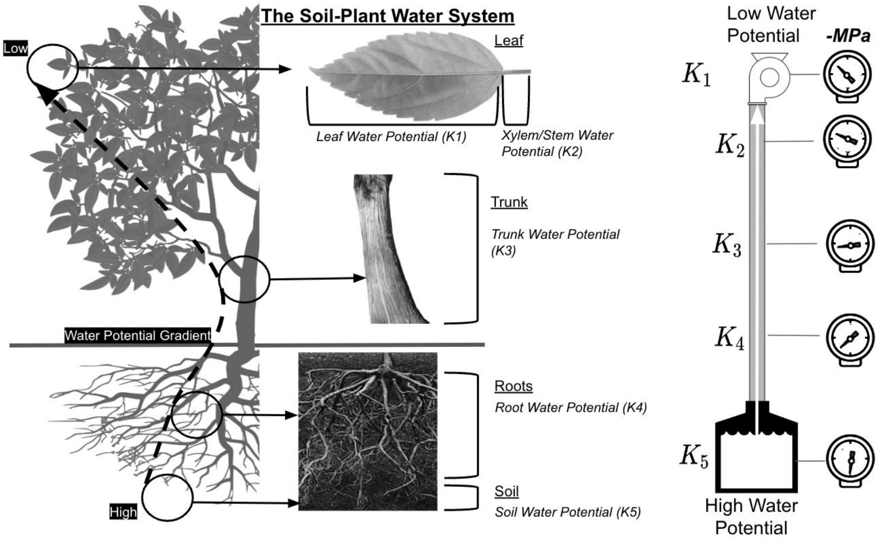

Figure 2: Overview of water potential within a tree. The image on the right demonstrates a vertical pipe analogy, where the highest water potential (least negative pressure value) will be at the tank (soil) whereas the lowest water potential (most negative pressure) will be at the leaf (pump).

On the other hand, non-destructive methods can take advantage of distal sensing technologies such as imaging and thermal radiation (among others) to appraise plant water status in leaves, canopies, and even entire orchards. The non-destructive methods have recently gained traction and interest owing to the development of novel mobile platforms, such as low-cost UAVs and various multi-spectral imaging sensors. Despite their versatility, non-destructive methods may not be as accurate as the sample-destructive ones and still require some level of calibration routines against the latter.

2.3. Sample-destructive Methods

2.3.1. Isopiestic Psychrometer (IP)

The psychrometer method is widely adopted due to its versatility in measuring water status in plants, soil, and any water-containing media. The operating principle (IP, Fig. 3) relies on the evaporation and resulting humidity level of a substance or sample containing water in a sealed chamber, and its subsequent comparison with a substance of known humidity (e.g., the air). The vapor pressure of the sample can therefore be calculated (through measurements on a transducer converting temperature to voltage), and water potential is then determined. Some of the conditions required for measurement include:

- Humidity conditions near saturation (or near 100% relative humidity) as the method relies on water evaporation.
- Maximum temperature variation inside the sealed chamber limited to $10^{-3}\ {}^{o}C$, such that the relative humidity reflects the condition of the sample being measured.

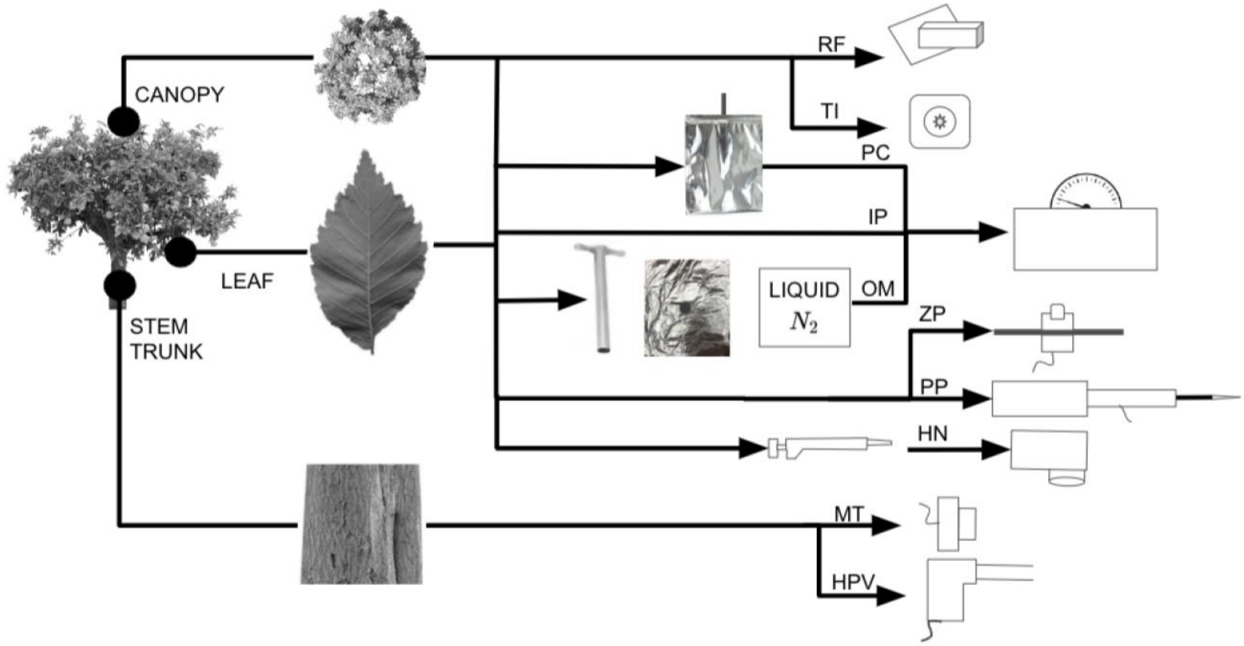

Figure 3: Various methods for determination of plant water status: (RF) Radio-Frequency Santos et al. (2021), (TI) Thermal-Imaging, (PC) Pressure Chamber, (IP) Isopiestic Psychrometer, (OM) Osmometer, (ZP) Zim-Probes Zimmermann et al. (2008), (PP) Pressure-Probes, (HN) Hydrogen-Nanoreporters Jain et al. (2021), (MT) Microtensiometer Blanco and Kalcsits (2021), and (HPV) Heat Pulse Velocity Forster (2017).

- Scale for measurement of about 10^{-9} Volts using a thermocouple.

For the isopiestic condition, while pressure is maintained equal, the thermocouple is reinserted on a solution of known water potential. This reinsertion will determine the actual water potential of the sample, which will be the same as that of the chosen solution. Despite being one of the most accurate methods of determining water potential, with pressure tolerances around 10^{-2} MPa, small temperature variations (of about $10^{-2}\ ^{o}C$) can lead to water potential variations of about 0.1 MPa.

2.3.2. Osmometer

The working principle of an osmometer (OM, Fig. 3) relies on the pressure build-up (or turgor pressure) on the concentrated solution of a plant cell membrane, until equilibrium is achieved. The method relies on the linear relationship between plant water to solute in determining osmotic potential (freezing point depression method). By tracking the solution freezing point decrease (as a result of increasing the solute), the osmolality can be precisely determined.

2.3.3. Pressure Probe

A pressure probe can directly determine the turgor pressure of a plant (PP, Fig. 3). The device, which resembles a micro syringe, contains a relatively incompressible fluid (silicone oil) that moves according to the pressure applied by the plunger (relative to the sap of the plant cell, initially at lower pressure). When the boundary between sap and silicone oil returns to the tip of the probe, volume is restored and the pressure values of the capillary and inside the cell are equal. Hydrostatic pressure can therefore be measured using a pressure sensor. Limitations of the method are mainly correlated with the size of the plant cell, as well as leakage potential or non-penetrability of the capillary into the cell.

2.3.4. Pressure Chamber

A conventional and perhaps the most well-known and commonly applied method for determining stem water potential is the pressure chamber (PC, Fig. 3), also called the Scholander chamber (Scholander et al., 1964). It relies on the pressure exerted on the leaf to counterbalance the tension (or negative pressure) with which water is retained by the leaf tissues. The method considers the partial sealing of the leaf inside a pressure chamber up to the xylem, which is exposed and held by a rubber gasket. A prerequisite before measurement consists of bagging the leaves utilizing reflective bags (placed around the leaf for about ten to thirty minutes). This procedure insulates the leaf against thermal effects and consequently transpiration of water into the atmosphere. After the leaf is separated from the tree by an incision at the stem, water distributes itself by osmosis through the xylem to the surrounding living cells. Initially, the xylem appears to be dry, but by increasing the pressure inside the chamber, the pressure state before the incision can be achieved, and the pressure required for it is annotated as the balancing pressure (or end-point).

One key working assumption is that the leaf will be in pressure balance with the stem and the rest of the plant; when that happens, the measured value of water potential will reflect the value for the entire plant as opposed to that of the leaf alone. Such an assumption may not be accurate in some regions of the world (such as California in the United States) where higher night temperatures may prevent the occurrence of equilibrium and plants may be under stress before the measurements are performed. Additionally, if leaves are not bagged, the respective water pressure will be more negative than if bagging is done, and the measurement will instead quantify the water potential of individual leaves in their specific conditions. The pressure value at shaded parts of a tree will also be different than values obtained in leaves exposed to direct sunlight.

The pressure chamber can also determine the relationship between water potential and relative water content through the calculation of pressure-volume curves (PV or P-V). These are generated by utilizing consecutive measures on a drying leaf, and parameters such as turgor loss point (TLP) (Bartlett et al., 2012b) (i.e., the point at which the value of turgor pressure is equal to zero), so that osmotic potential and bulk modulus of elasticity can be derived. As the pressure chamber method does not require rigorous temperature control or delicate instrumentation compared to the methods previously described, it is a widely adopted technique in various orchards and specialty crops.

2.4. Proximal Sensing Methods

2.4.1. Microtensiometer

The microtensiometer sensor (Pagay et al., 2014) provides real-time monitoring of water potential at the tree stem (MT, Fig. 3). The method applies a miniaturized version of the soil tensiometers and addresses some of the problems of the conventional approach such as the need for large amounts of water to register tension and the high porosity of the tooltip level, both of which combined can lead to bubble formation. However, greater reading variability can be observed in comparison to the pressure chamber, and because of the shrinking and swelling, and photosynthesis of the tree, sensor placement stability can be affected, thus requiring periodic calibration and maintenance.

2.4.2. Heat Pulse Velocity

The heat pulse velocity method (HPV, Fig. 3) can determine sap flow and water content. Since each probe has a small zone of influence (about 5 *mm* radius), the technique can be utilized for plants with stems as small as 10 *mm*. According to recent work of Forster (2017), the method has had satisfactory results when correlating heat velocity and transpiration, but high errors (up to 34%) in determining transpiration alone. Measurement disparities can occur due to limitations in scale, probe misalignment, and wounding of the xylem during sensor placement and the method still requires calibration when determining tree transpiration, but not for measuring sap flow.

2.4.3. ZIM-probes

Magnetic leaf patch clamp pressure probes, or ZIM-probes (ZP, Fig. 3), are alternatives to the conventional pressure probes described in Section 2.3.3, providing continuous monitoring of turgor pressure on a leaf using opposite magnetic probes and a pressure sensor (Zimmermann et al., 2008). For measurements, a small leaf patch, ideally under osmotic and hydraulic equilibrium (early morning readings are recommended), is clamped between two magnets, the offset distance of which can be manipulated to control magnetic pressure exertion. The relative leaf turgor pressure is given by the patch pressure output, while an external magnetic pressure is kept at constant value (Rodriguez-Dominguez et al., 2019). The probes were tested on a variety of herbaceous and woody plant species, and numerous studies combined ZIM-probes with different sensing methods, such as the heat pulse velocity method (Rodriguez-Dominguez et al., 2012) and the pressure chamber (Fernández et al., 2011).

2.4.4. Hydrogel Nanoreporters

The use of hydrogel nanoreporters (HN, Fig. 3) for estimating plant water status through leaf water potential (Jain et al., 2021) is new. It comprises the in-situ insertion of hydrogel into the leaf (limited to the apoplastic space, and not entering the xylem or cytoplasm), the measurement of water potential by different levels of gel swelling, and the correlation of the attained readings to the fluorescent light spectrum. This minimally-destructive method generates negligible effects of temperature and pH on the reporting of water potential, and it is a promising alternative for measuring water potential. The method, however, still requires initial calibration against the pressure chamber before its deployment.

2.5. Remote-Sensing Methods

2.5.1. Thermal Imaging

Thermal imaging (TI, Fig. 3) provides high spatial, temporal, and temperature resolution imaging and has vastly been explored in case studies reported in the scientific literature (Ishimwe et al., 2014). Some direct applications include monitoring of crop health and field conditions, soil salinity estimation, detection of bruises on fruits, and evaluation of irrigation schedules. Particularly, it can use leaf/canopy temperature to provide estimates on water potential and stomatal conductance. Especially when implemented (or deployed) onto mobile platforms such as aerial or ground robots, this method can become quite expensive, thus posing restrictions to its adoption. In addition, temperature variations during the day as well as heating of the thermal camera itself during operation may determine the need for periodic sensor calibration to ensure measurement accuracy; this in turn adds one more activity to be conducted in the field and hence increases its overall complexity.

2.5.2. Radio Frequency

Although not directly related to plant water status, the use of high radio-frequency waves (RF, Fig. 3) and observation of the attenuation signal strength can be an indicator of water content in leaves (Santos et al., 2021). By considering two high-gain antennas and a leaf placed in between, the attenuation of high-frequency electromagnetic signals (about 20 GHz) is shown to be affected by the leaf water content irradiated by the radio beams. The method is non-destructive, can help determine variations of water in a single plant, and can promptly be embedded into various mobile robotic platforms.

2.6. Other Methods

Other important indicators related to plant water status not mentioned above include salinity and soil electrical conductivity, or leaf stomatal conductance. Although out of scope for this review, the authors suggest the following relevant literature and reviews on these respective themes (Volkmar et al., 1998; Parihar et al., 2015; Safdar et al., 2019; Friedman, 2005; Brillante et al., 2015; Gupta et al., 2019; Campbell et al., 2021; Chatziparaschis et al., 2023). Lastly, other methods not discussed in detail herein include sap flow using microneedles (Baek et al., 2018), nuclear magnetic resonance (NMR) (Windt and Blümler, 2015), stem water content with capacitive sensors (Matheny et al., 2017) and thermal micro sensors (Atherton, 2012).

3. Review on Determining Plant Water Status

In this work, an extensive body of literature was considered regarding the scope of the various methods presented in Section 2. Relevant data were extracted and a meta-analysis was performed to group associated methods considering various aspects and technical considerations (see Fig. 8, and Fig. 9). The relevant downselected articles were ranked based on an automation score (denoted K_s) defined in this review, which aims to score both the relevance and potential of automating the methods utilizing current technologies and enhancing their usefulness through AI methods. Although no upper limit was considered for K_s, higher scores would translate to greater propensity to automation and AI integration, and vice versa.

3.1. Methodology

The following criteria were considered when selecting relevant work.

- Literature search was limited to a ten-year time-frame prior to date, and selected using Google Scholar for uniformity and to avoid duplicates.
- Keywords were selected by the authors owing to their expertise and past relevant works, and attempt to encompass the most relevant terms related to indicators of plant water status and the various available methods.

To facilitate synergy and organization, an online collaborative platform (Rayyan [1]) was utilized in this study.

A three-phase pipeline (Fig. 4) attempted to filter out literature based on selected keywords (Keyword Clustering phase), ranking (Top-median phase), and meta-analysis (Methods phase). Given the breadth of the initial selection, focus was given to the top-median results. Although not within the scope of this work, keywords such as “remote sensing” inevitably represented the majority of recent work on plant water status and were also considered for the overall meta-analysis, as discussed below.

3.2. Keyword Clustering

We have selected 26 keywords, leading to $N = 550$ publications considered initially. Our selection attempted to include most terms directly or indirectly related to the methods discussed in Section 2. We emphasized specialty crops (such as avocados, olives, and grapes), as these tend to require larger volumes of water for irrigation and more attentive water management (Yazdi et al., 2021). Other keywords relevant to determining plant water status, such as stem, leaf,

[1] https://www.rayyan.ai/

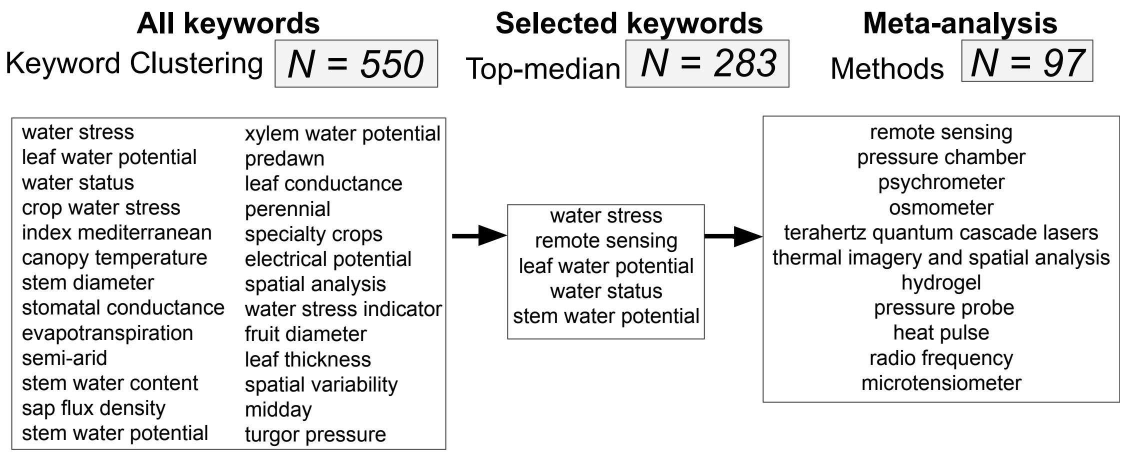

Figure 4: Pipeline for keyword selection and meta-analysis.

and fruit diameter, were included for completeness. The overall statistics of selected literature are shown in Fig. 5, along with a word cloud (Fig. 6), and keyword occurrences (Fig. 7).

3.3. Keyword Selection

We ranked results from the previous stage by keyword occurrences, only selecting the top-median results ($N = 283$). Four keywords prevailed: (plant) water stress, remote sensing, leaf (stem) water potential, and (plant) water status. As mentioned earlier, the appearance of the remote sensing keyword in over half of the results reflects current research trends in exploring alternative methods for determining plant water status, while also implying the lack of discussion on sample-destructive methods over the period considered in this review article.

3.4. Meta-Analysis

Our meta-analysis considered a total of ($N = 97$) final references out of the top-median results based on direct (title) or indirect (text) reference to at least one of the methods for determination of plant water status listed in Section 2. Table 1 lists these references grouped in terms of the method employed for the determination of plant water status in those scientific works. We proposed and calculated an automation score K_s for each method in Section 2, correlating it with aspects and technical considerations such as target measurement (e.g., leaf water potential, turgor pressure), location of measurement (in-situ, ex-situ), and sampling time (Fig. 8, items A to F). For this calculation, we emphasized the sample-destructive methods and proximal-sensing techniques, dropping the terahertz and remote-sensing terms. We also selected different hardware components pertaining to available technology and considered whether or not the method is likely to be adopted to promote automation (Fig. 8, items G to L). Finally, we further considered whether AI can be readily integrated to further promote automation (Fig. 8, item M).

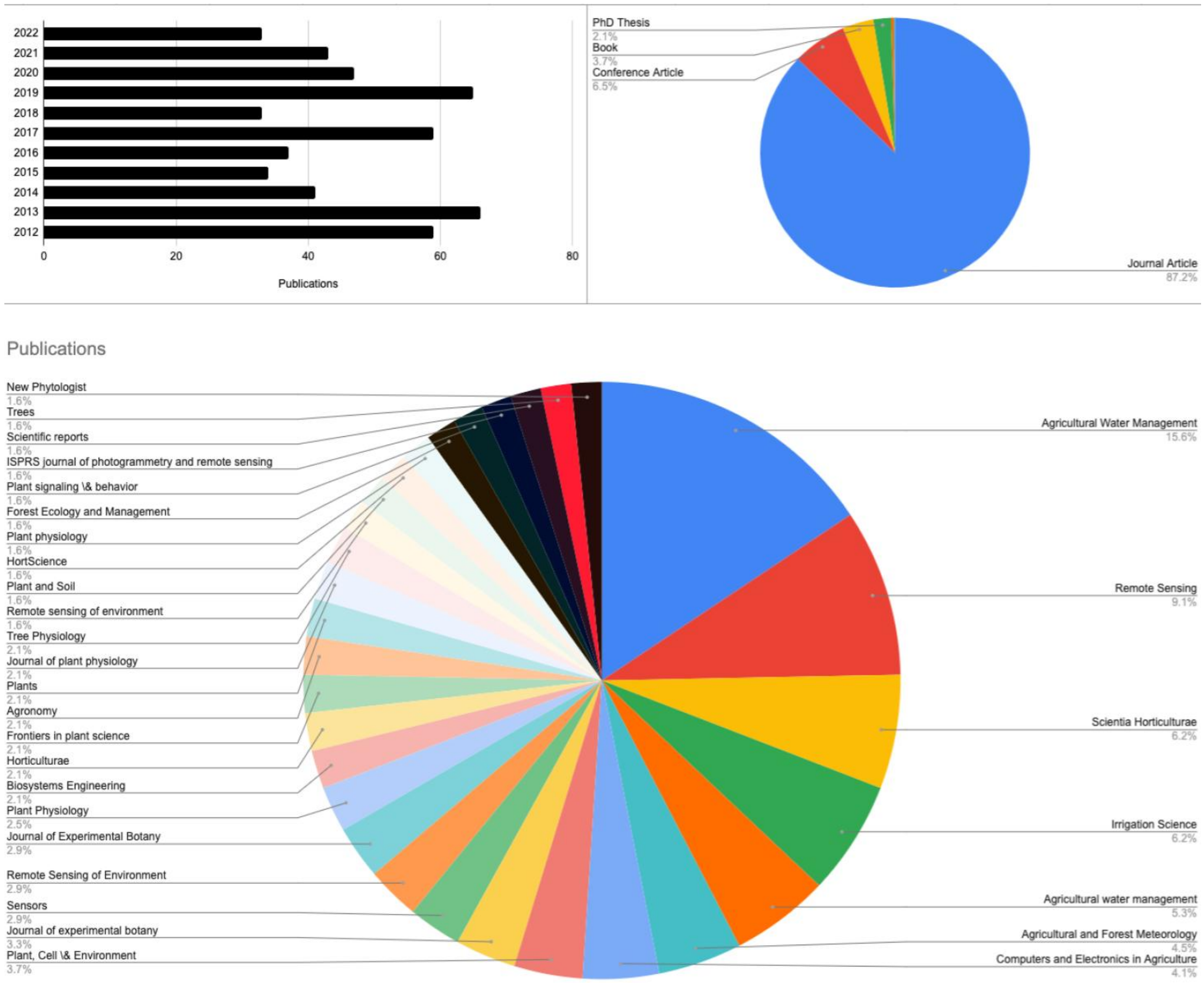

Figure 5: Statistics for the initial selection of literature ($N = 550$): classification by year (upper left), by type of publication venue (upper right), and journal names (bottom).

To calculate the automation score, we defined weights $w_i = x$, with index $i = 1, 2, 3...m$ denoting the current aspect being considered (such as target measurement, sampling time, etc.), and x being a weight factor assessed for different metrics that can be improved by automation, as detailed below. As an example, for a total sampling time ($i = 3$) of less than a minute, a lower weight would be given as opposed to higher sampling times, since we assume automation can improve the sampling time. We also introduced w_j as an “interrelation” weight. The motivation was to emphasize how most novel sensing modalities need some sort of in-situ calibration or validation against one or more sample-destructive techniques. The calculation of score K_s was done according to Eq. 2 below:

$$K_s = \sum_i w_i + \sum_j w_j \ , \tag{2}$$

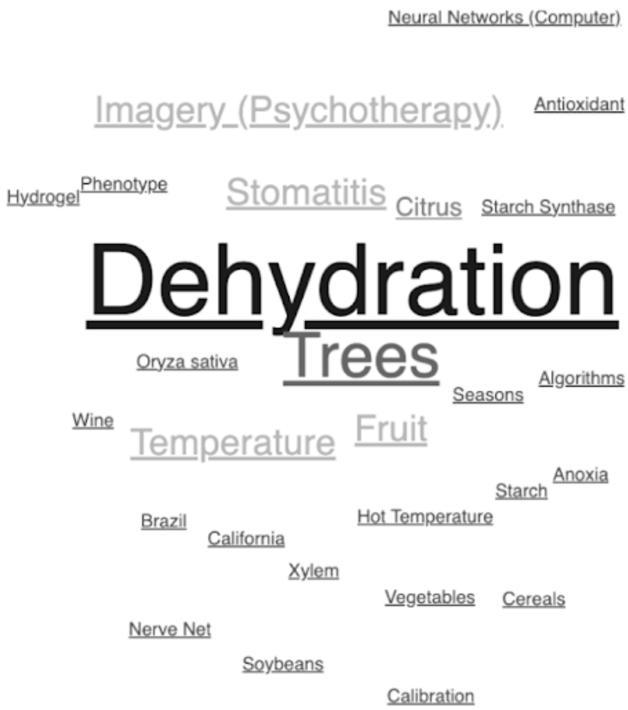

Figure 6: Word cloud for recurring themes of the initial literature selection ($N = 550$).

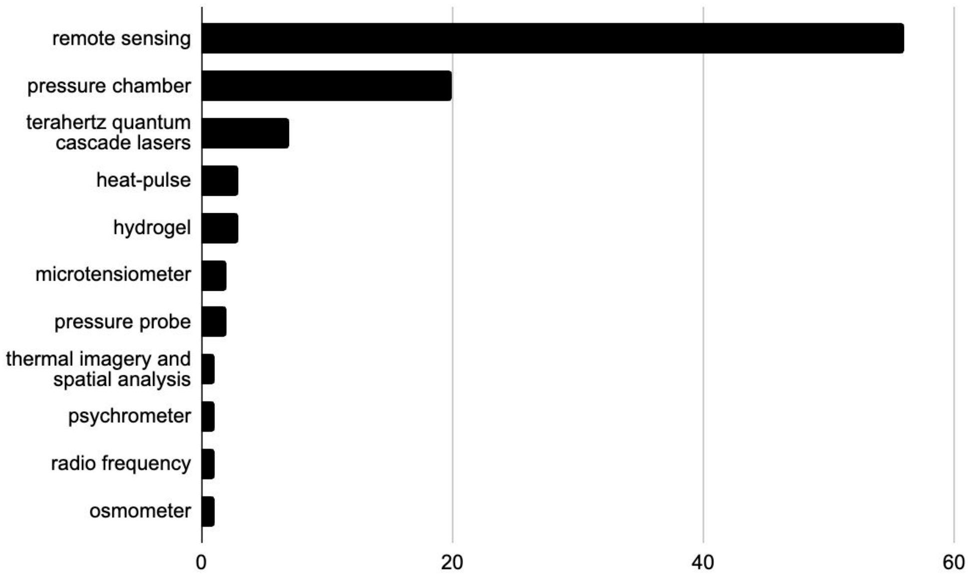

Figure 7: Selected keywords for meta-analysis ($N = 97$).

with a detailed breakdown of weights on different aspects discussed below. Heavier weights essentially demonstrate where there may be more potential for the integration of automation to improve the current standard of a specific method of interest.

Table 1
List of References Focusing on a Method of Interest in this Work.

Method	Reference
remote sensing	Barton (2012); García-Tejero et al. (2012); Stagakis et al. (2012); Qi et al. (2012); Feng et al. (2013); Mulla (2013); Shang and Chisholm (2013); Sui et al. (2013); Yebra et al. (2013); Crawford (2014); Bellvert et al. (2014, 2015); He et al. (2015); Ramoelo et al. (2015); Chuvieco (2016); Thenkabail and Lyon (2016); Yousfi et al. (2016); Wójtowicz et al. (2016); Calera et al. (2017); Khanal et al. (2017); Alvino and Marino (2017); Egea et al. (2017); Romero-Trigueros et al. (2017); Toureiro et al. (2017); Yang et al. (2017); Bhagwat et al. (2018); Damm et al. (2018); Helman et al. (2018); Moreno-Martínez et al. (2018); Matese et al. (2018); Sheffield et al. (2018); Ahmadi et al. (2019); Easterday et al. (2019); Ezenne et al. (2019); Knipper et al. (2019); Konings et al. (2019); Krishna et al. (2019); Maes and Steppe (2019); Mahmoud and Gan (2019); Mendes et al. (2019); Sadaf et al. (2019); Zhang et al. (2019); Zovko et al. (2019); Blaya-Ros et al. (2020); Chen and Liu (2020); Di Girolamo et al. (2020); Inoue (2020); Liu et al. (2020); Na et al. (2020); Chandel (2021); Chandel et al. (2021); Dong et al. (2021); Han et al. (2021); Meivel and Maheswari (2021); Sibanda et al. (2021); Fullana-Pericàs et al. (2022)
pressure chamber	Gaudin et al. (2012); Moriana et al. (2012); Williams et al. (2012); Vandegehuchte (2013); Abrisqueta et al. (2015); Cole and Pagay (2015); Paudel et al. (2015); Mirás-Avalos et al. (2016); Memmi et al. (2016); Cai et al. (2019); Levin (2019); Kumar et al. (2019); Santesteban et al. (2019); Suter et al. (2019); Zahoor et al. (2019); Gips et al. (2020); Hochberg (2020); Jamshidi et al. (2020); Brodribb et al. (2021); Rodriguez-Dominguez et al. (2022)
terahertz quantum cascade lasers	Razavipour (2013); Browne et al. (2020); Li et al. (2020); Tan et al. (2020); Shchepetilnikov et al. (2020); Pan et al. (2021); Zahid et al. (2022)
heat pulse	López-Bernal et al. (2012); Ballester et al. (2013); Forster (2017)
hydrogel	Milliron et al. (2018); Kumar et al. (2020); Jain et al. (2021)
microtensiometer	Pagay et al. (2014); Blanco and Kalcsits (2021)
pressure probe	Gholipour et al. (2012); Rodriguez-Dominguez et al. (2012)
thermal imagery and spatial analysis	Song et al. (2018)
psychrometer	Dainese et al. (2022)
radio frequency	Santos et al. (2021)
osmometer	Bartlett et al. (2012a)

- Target Measurement: $w_i = \sum 0.5$ for each target measurement indirectly determined by the method, and $w_i = \sum 1$ for those directly measured.
- Sampling Time: $w_i = 2$ if no continuous (discrete) data are provided by the method, therefore demanding longer sampling time.
- In/Ex situ: $w_i = 0$ for ex-situ, $w_i = 2$ for in-situ, and $w_i = 3$ for both in-situ and ex-situ measurement locations, prioritizing automation of in-situ methods to assist humans in the field.
- Validation: If validation or calibration of measurements is required using in-situ methods, these received a weight $w_j = 1$ for every occurrence.

		Pressure Chamber	Isopiestic Psychrometer	Osmometer	Pressure Probe	Microtensiometer	Heat Pulse Velocity	Radio Frequency	Thermal Imaging	Hydrogel Nanoreporters
A	Target Measurement	(Leaf) Water Potential	(Leaf) Water Potential, Osmotic Pressure, Turgor Pressure (indirect)	Osmotic Potential, Turgor Pressure (indirect)	Turgor Pressure	(Xylem) Water Potential	Stem Water Content Sap Flow	Water Content (indirect)	Water Content (indirect)	(Leaf) Water Potential
B	Equipment Required	Pressure Chamber	Sealed Chamber	Osmometer	Pressure Probe	Microtensiometer	Sensor	Radar	Thermal Camera	Injection of nanoparticles, Microscope
C	Sampling Time	Discrete	Discrete	Discrete	Discrete	Continuous	Continuous	Continuous	Continuous	Continuous
D	In situ (I) / Ex situ (E)	I / E	E	E	E	I	I	I	I	I
E	Validation	None	None	None	None	Yes, Pressure Chamber	None	None	None	Yes, Pressure Chamber
F	Affordability	Low	Low	Low	Low	High	High	Low	Low	Low
G	Mobile Platform	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H	Manipulation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
I	Specialized End-Effector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
J	Specialized Sensor	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
K	Pressure/ Temperature Controlled Chamber	Yes	Yes	Yes	No	No	No	No	No	No
L	Teleoperation	Yes	Yes	Yes	Yes	No	No	No	No	No
M	Artificial Intelligence	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Figure 8: Plant water status methods, aspects, and technological considerations.

- Cost: Despite the difficulty in accurately determining costs due to factors such as logistics for sampling, number of personnel involved, and others, a qualitative feature of affordability aimed to capture overall costs. Higher-cost methods (low affordability) received weight $w_i = 2$, as more elaborate methods often require human input, tend to be of higher acquisition cost, and consequently would benefit more from automation (which in turn tends to make processes more affordable).

The technological considerations selected were as follows.

- Mobile Platform: The need for mobility (sample transportation or data acquisition) received a weight $w_i = 1$. It is understood that a mobile platform can also be used to carry heavy equipment for in-situ measurements or any other relevant material.

- Manipulation: If handling is required for sample retrieval or insertion into a measurement device, a weight $w_i = 1$ was given.

- Specialized End-Effector: If the sample or container around the sample needs to be directly manipulated, a specialized end-effector (cutter, vacuum, among others) may be required, and a weight $w_i = 1$ was given.
- Specialized Sensors: Cameras ranging from conventional RGB to thermal imaging devices and microscopes are considered, and a weight $w_i = \sum 1$ is attributed for each sensor required.
- Pressure or Temperature Controlled Chamber: For methods relying on temperature-controlled environments or enclosed chambers, a weight $w_i = 1$ was given, whereas pressure-controlled chambers received weight $w_i = 2$. This attempts to highlight the benefit and increased safety of having pressure chambers handled by an automated process rather than being physically operated by a human. For determination purposes, a capillary is here considered as an enclosed chamber.
- Teleoperation: In-situ methods with frequent sampling may alternatively adopt teleoperation to alleviate challenges imposed on human operators (such as unfavorable weather conditions, heavy equipment, and repetitive motions). A score of $w_i = 1$ was attributed in applicable cases.
- AI Integration Potential: Since most methods rely on visual observation to determine measurements, the potential for automation through artificial intelligence and machine learning is considered. A score of $w_i = 1$ was attributed to the method can leverage learning tools to facilitate measurements or as part of the automation pipeline, beyond the predictive aspect which can generally be applied to all methods.

4. Evaluation and Discussion

A summary of evaluated methods and their respective technical considerations is presented in Fig. 8. The methods are grouped into items G to M due to their commonalities in terms of handling of the sample, sample preparation, observations during measurement, need for a controlled environment, and data analysis potential. A breakdown of each method is proposed that considers various high-level tasks and corresponding groups of hardware configurations (Fig. 9) to enable task automation. From Fig. 9 it can be seen that configurations A through F represent a combination of mobility, vision-aided automation, manipulation, specialized end-effector and chamber design from which each task listed can be automated, as discussed below.

Pressure Chamber ($K_s = 16.5$): The pressure chamber method received the highest automation score since it not only determines stem water potential on its own but also reliably serves as a reference to verify and calibrate other methods. Various stages of the method can be automated:

- Sample selection (which is time and location dependent due to measurement variations) utilizing configuration B, can explore leaf health, size, and light conditions with a certain degree of mobility around the tree. Previous

Task	Configuration	Applicable methods*
Candidate region/tree selection	A	PC, IP, OM, PP, MT, HPV, RF, TI, HN
Candidate trunk/stem/leaf sample selection	B	PC, IP, OM, PP, MT, HPV, RF, TI, HN
Sensor placement at leaf/ stem/ trunk	C	MT, HPV, HN
Sample placement in dedicated container	D	PC, IP, OM
Sample removal from tree	D	PC, IP, OM
Sample placement in/ contact with dedicated chamber	F	PC, IP, OM
Dynamic detection/tracking of water/oil	E	PC, IP, PP, OM
Remote monitoring	A	MT, HPV, RF, TI, HN
Sample transportation	A	PC, IP, OM
Sample disposal and recycling	C	PC, IP, OM

Figure 9: Proposed hardware configurations for achieving tasks common to the described methods of assessing plant water status: Pressure Chamber (PC), Isopiestic Psychrometer (IP), Osmometer (OM), Pressure Probe (PP), Microtensiometer (MT), Heat Pulse Velocity (HPV), Radio Frequency (RF), Thermal Imaging (TI), Hydrogel Nanoreporters (HN).

work developed an autonomous vision-based task with a manipulator and end-effector (D) capable of selecting candidate leaves, retrieving them cleanly from the tree, and storing them into a dedicated container for further analysis (Campbell et al., 2022).

- Time sequencing between leaf bagging, excision, and pressurization can be optimized. Research has shown these timing factors can be quantified for accurate pressure readings, and human interpretation itself may be the highest source of discrepancy in measurements (Levin, 2019).
- Placement of the sample inside the pressure chamber (F), following stem tracking for water appearance during pressure increase (E) can also be done autonomously. The detection itself can be provided by AI-assisted object detection method (M), as described by Dechemi et al. (2023).
- Sample disposal and recycling can be implemented (C).
- One remark for the pressure chamber is the ability to perform measurements in-situ or ex-situ with samples transported under proper conditions to a laboratory.

A future autonomous system should thus have the ability to sample different trees at various hours of the day repeatably and provide consistent readings that can be tracked remotely or logged for subsequent evaluation or comparison with other additional methods.

Isopiestic Psychrometer ($K_s = 10.5$): Similar to the pressure chamber, the isopiestic psychrometer method is also a high-potential candidate for automation in terms of leaf selection (B), sample retrieval, transportation (A), placement in a dedicated chamber (*D*), continuous monitoring of one condition while varying another (*E*), and sample disposal and solution substitution (*C*). However, the need for a temperature-controlled environment limits measurements to be conducted ex-situ, constraining its ability to be deployed along with other sensing modalities in the field. Enhancing automation via AI does not seem immediately viable besides the predictive aspect that can be added in any method in essence.

Osmometer ($K_s = 9.5$): Sample selection (*B*), transportation (*A*), placement in a measuring instrument (*D*), and sample disposal (*C*) can be automated. While the osmometer is limited to osmotic potential measurements (and turgor loss point) in ex-situ locations, and as a method has limitations preventing it from being a sole indicator of water status, other tasks such as probing the leaf sample, enveloping it, and placing into liquid nitrogen, measurement of the dried sample (Bartlett et al., 2012a) and chamber sanitation are some procedures that can be subjected to automation. Similar to the isopiestic psychrometer, AI integration does not have any immediate effect on further developing automation of the method.

Pressure Probe ($K_s = 9$): Despite its ability to measure the water status of single cells, the pressure probe method requires precise positioning of the microcapillary into the sample cell, and it is a time-consuming and labor-intensive process, susceptible to vibration and temperature effects affecting measurements. Earlier research efforts demonstrated the feasibility of in-situ measurements (Gholipour et al., 2012) and developed a leaf patch clamp non-invasive alternative for measuring relative changes in leaf turgor pressure (Rüger et al., 2011). One possibility of automation involves dynamic tracking of the cytoplasm/oil meniscus position during cytoplasm motion into the cell, through the microcapillary. An automated system can track the meniscus position while the cytoplasm returns to the cell before puncturing (config. *E*), including integration of AI-assisted approaches (*M*).

Microtensiometer ($K_s = 7$): The fast installation time, ability to stream data continuously, and minimum maintenance requirements are appealing in further integrating automation elements into this method. Deployment of the microtensiometer sensor can be automated (config. *C*) along with remote monitoring for sensor placement and fixture (config. *A*) considering the integration of possible computer vision and machine learning tools (*M*).

Heat Pulse Velocity ($K_s = 9$): The HPV method is versatile in the sense that it can be applied to various plant species, and measure flow with high temporal resolution. Automation can improve the method in terms of sensor placement in the sapwood and periodic monitoring to minimize probe misalignment (config. *C*), and extending points of measurement to the whole plant for remote monitoring (config. *C*). Minimization of probe misalignment can utilize learning tools (*M*) combined with the proposed configurations.

Radio Frequency ($K_s = 7.5$): Despite limitations in utilizing radio frequency as a unique indicator of water status, the possibility of adapting the hardware to a robotic platform can be advantageous for integrating automation elements into this method. Given the ability to select and sample candidate trees autonomously (configurations *A, B*), sample analysis on a mobile platform and continuous monitoring (configuration *A*) will offer additional advantages to the method's adoption. Further, various AI-based techniques (*M*) can positively impact data analysis, complementing and enhancing these configurations.

Hydrogel Nanoreporters ($K_s = 7$): One of the unique features of this method is the possibility of determining water potential gradient along leaf blades while providing real-time, continuous in-situ data. This can allow for the characterization of leaf hydraulics (Jain et al., 2021), which is impossible with other sample-destructive methods. AI tools (*M*) can be an important factor in improving the determination of these gradients. If sensing apparatus (namely fiber-optic probe, clamp, and spectrometer) are embedded in mobile platforms (config. *A*), continuous monitoring can provide a unique level of insight into plant water status beyond other methods described above.

Thermal Imaging ($K_s = 5.5$): Thermal imaging methods are already embedded on mobile platforms (configuration *A*) so the lowest automation score was attributed to the ranking. However, in-situ thermal imaging techniques in combination with leaf-level measurements and fluorescence imaging (Beverly et al., 2020) can allow for prediction models of leaf water potential and allow for prediction of water plant status and stress. Currently, a vast number of AI and machine learning tools (*M*) are directly applied to these methods.

5. Sample-destructive Case Study: Toward Automating the Pressure Chamber Method

The previous discussion suggests that, among sample-destructive methods, the pressure chamber has several potential benefits if automated. In this section, some recent related developments are presented to highlight the suitability and usefulness of some of the tasks illustrated in Fig. 9. In Campbell et al. (2022), the task of leaf-cutting (i.e. sample retrieval in the case of the pressure chamber method) was addressed with a custom-made 6-DOF end-effector attached to a mobile robot, as depicted in Fig. 10. The framework considered a perception-based approach where a three-dimensional point cloud from a depth camera was translated into a six-dimensional pose (position and orientation) of a potential leaf candidate. Then, the mobile manipulator approached the candidate leaf and retrieved it via the specialized end-effector. Experiments conducted with avocado trees on both indoor and outdoor settings led to an overall success rate of detection of about 80%, while 78% of the total 70% leaf captures were successfully cut at the stem. These findings could serve as a basis for enhanced automation integration by enabling AI-assisted leaf detection.

The work of Dechemi et al. (2023) extended the findings of Campbell et al. (2022) by introducing methods to handle additional tasks to complete measurements with the pressure chamber (Fig. 11). Newly proposed tasks included:

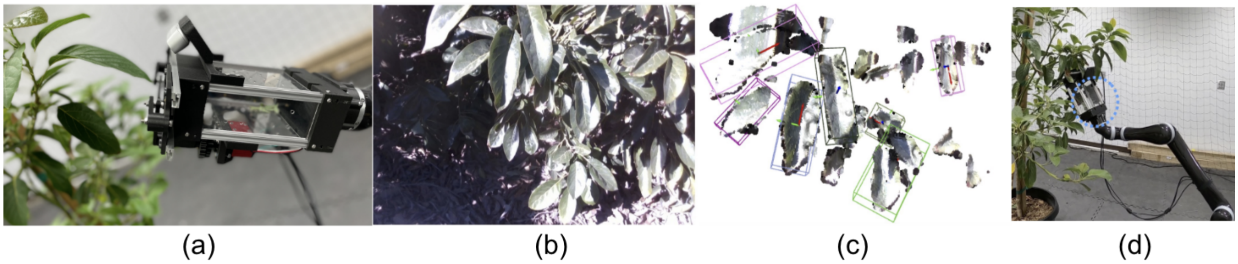

Figure 10: In Campbell et al. (2022) a custom-made end-effector (a) utilized a depth-camera sensor to translate input images (b) to 3D bounding boxes of candidate leaves (c), and a final 6D pose for retrieval utilizing a robot arm mounted on a mobile platform (d). (Snapshots taken from Campbell et al. (2022) with permission from the authors.)

- Informed sampling for tree location and navigation: by utilizing Gaussian processes (GP) and the Rapidly Exploring Random-Exploring-Tree (RRT) motion planning algorithm, the method can assign a path to the mobile robot based on energy budget constraints.

- Machine vision identification of leaf stem wetness in stem water potential analysis: by employing AI-assisted visual perception using a custom dataset from avocado and citrus trees, the method can speed up the process of determining stem water potential.

Field experiments were conducted for both tasks. A demonstration illustrated the overall pipeline in sampling trees from the budged-constrained calculated path. Finally, utilizing the setup on Fig. 11 (bottom left), transferable to both manual and automated pressure chambers, experiments revealed a 98% precision in detecting wet or dry states of the xylem during stem water potential determination. These results confirm the availability of current technology to partially automate the pressure chamber method and allow for future work to utilize these as future references toward automated solutions for the determination of plant water status. This current state of progress could benefit by further integrating joint task and motion planning (Kan et al., 2021), multi-robot system deployment (Kan et al., 2019, 2020), and localization under the canopy (Teng et al., 2023).

6. Conclusion

This work aimed at evaluating different sample-destructive methods for determining plant water status, and proposed a set of tasks common to these methods yielding the potential of being automated. Specifically, this work focused on methods of measuring water status in plants for which little or no automation discussion has occurred to date. While considering a large body of literature and focusing on specific aspects, we acknowledge that the choice of factors (namely adoption rate, reported accidents, accuracy, and others) and technological considerations (type of manipulator, specialized sensor, or AI agent) for each method could further be expanded into subcategories to improve scoring. With this proposed automation score, we aimed to establish a common comparative basis among different

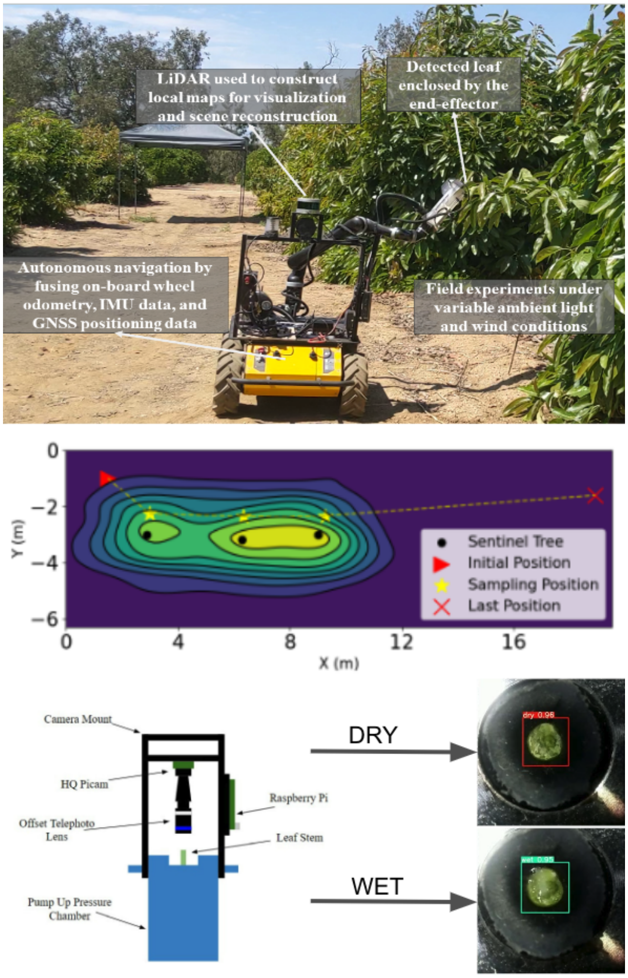

Figure 11: In Dechemi et al. (2023) a mobile robot with the leaf sampler from Campbell et al. (2022) was able to autonomously navigate to tree sampling candidates (top) with an informed path planning method considering robot energy constraints (middle), while a learning-based computer vision approach addressed the dry/wet state detection in SWP measurements (bottom). (Snapshots taken from Dechemi et al. (2023) with permission from the authors.)

methods and highlight some immediate directions for improvements in terms of integrating automation and AI toward more resource-efficient water management. The different weights provided in the proposed automation score were based on distilling information from the available literature, and on the authors' combined expertise on the topic. Still, we recognize that one might argue in favor or against any specific weighting, or suggest additional weight factors to be considered, possibly based on local and site-specific conditions. Thus, we anticipate that this work can spark further discussions within the agricultural engineering community and among researchers, consultants, and practitioners. We feel that this is an important and timely topic considering that a large body of literature on existing automation and AI efforts has focused on harvesting, weed detection, and spraying, but comparatively fewer automation and AI efforts have considered precision irrigation management leading to higher water productivity. As can be inferred from this review article, the integration of AI with automated systems for monitoring plant hydration can lead to significant labor savings and increased efficiency. This approach not only enhances water and energy conservation but also boosts crop productivity, especially as many specialty crops rely on micro-irrigation systems that pressurize water. Furthermore, the likelihood of more frequent and severe weather events such as droughts and heat waves necessitates more vigilant and accurate water management. This is crucial not only to meet the high-quality standards demanded by both local and international markets but also to implement regulated deficit irrigation strategies effectively. Such strategies aim to achieve and sustain the desired level of plant hydration (from mild to moderate stress) during critical phases of crop development. In this sense, deploying new technologies toward resource-efficient water management has multifaceted challenges and opportunities that remain to be addressed.

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