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Review

A Review of Methods for Data-Driven Irrigation in Modern Agricultural Systems

Matthew Jenkins [1,†] and David E. Block [2,3,*]

[1] Department of Plant Sciences, University of California, Davis, CA 95616, USA; matjenkins@ucdavis.edu
[2] Department of Chemical Engineering, University of California, Davis, CA 95616, USA
[3] Department of Viticulture and Enology, University of California, Davis, CA 95616, USA
[*] Correspondence: deblock@ucdavis.edu
[†] This paper is a part of the PhD Thesis of Matthew Jenkins, presented at the University of California, Davis, CA, USA.

Abstract: More than half of global water use can be attributed to crop irrigation, and as the human population grows, so will the water requirements of agriculture. Improved irrigation will be critical to mitigating the impact of increased requirements. An ideal irrigation system is informed by measurements of water demand—a combination of water use and water status signals—and delivers water to plants based on this demand. In this review, examples of methods for monitoring water status are reviewed, along with details on stem and trunk water potential measurements. Then, methods for monitoring evapotranspiration (ET), or water use, are described. These methods are broken into coarse- and fine-scale categories, with a 10 m spatial resolution threshold between them. Fourteen crop ET technologies are presented, including examples of a successful estimation of ET in research and field settings, as well as limitations. The focus then shifts to water distribution technologies, with an emphasis on the challenges associated with the development of systems that achieve dynamic single plant resolution. Some attention is given to the process of choosing ET and water status sensing methods as well as water delivery system design given site characteristics and agronomic goals. This review concludes with a short discussion on the future directions of ET research and the importance of translating findings into useful tools for growers.

Keywords: evapotranspiration; irrigation; high-value crops; sustainability; drought; water demand

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1. Introduction

As the global population continues to grow, so do the water demands of civilization [1]. These demands are driven principally by agriculture, which over the past decade accounted for approximately 70% of freshwater withdrawals from surface and subsurface water systems worldwide; and in developing countries, this percentage may be as high as 90% [2,3]. Irrigation as defined by the Food and Agriculture Organization of the United Nations is by far the largest consumer of global water, accounting for 90% of all agricultural water use and more than 63% of overall water use [4]. Given these statistics, it is difficult to predict the impact of continually increasing irrigated agricultural land throughout the world, which has almost doubled since the 1970s and now accounts for more than 40% of the total area used for agricultural production [5]. In 2015, irrigated agricultural land was estimated to be about 3.14 million km^2 globally, but this figure is sensitive to many sources of error and has continued to rise for almost a decade since [6,7]. Irrigation's rapid acceptance over the past 70 years is the result of the proliferation of knowledge about the importance of irrigation for increasing agricultural production and reducing vulnerability of crops to failures, both critical to supporting growing populations [8]. While irrigation technology and ancillary infrastructure principally address crop survival and yield, these resources also empower farmers to grow high-value crops, which can be more sensitive to water [9].

High-value crops, like grapes or tree fruits and nut crops with structured canopies, are more water-intensive than some seasonal crops such as wheat, corn, and soy, as examples. For instance, though water footprints of all crops exhibit large spatial and temporal variation, producing 1 kg of almonds in California has been reported to require approximately 10,000 L of water [10], while producing 1 kg of wheat in Iraq, a similarly arid environment, has been reported to require approximately 1876 L of water [11]. Due to their significant water demands, nearly all commercial almond orchards in regions without ample rainfall, such as the Central Valley of California, are irrigated [12]. Adequate rainfall poses an issue for viticulturists as well. While water needs vary greatly by region, varietal, and production style, it is estimated that vineyards require about 650 mm of rainfall per year [13]. In recent years, these rainfall needs have not been met in many key viticultural areas such as California, South Australia, and parts of southern Europe. As a result, drip irrigation is increasingly used in viticulture to make up the gap between vine water demand and what is available to vines in subsurface water systems from natural rainwater. In addition, it should be noted that vine water demand will be a strong function of the desired yield, with larger fruit yield demanding larger water uptake by the plant. While drip irrigation systems are designed to sustain crops, more importantly, they sustain agricultural industries, the economic importance of which cannot be understated.

The presence of widespread, sophisticated irrigation technology, while useful, requires abundant freshwater resources in order to achieve the parallel goals of agricultural and economic sustainability. The 2012 to 2017 drought in California underscores what happens when a region depending on agriculture for the majority of its economic activity is faced with immutable natural resource limitations. Howitt et al., 2015, estimated the total drought impact on the California economy at USD 2.74 billion, with wide ranging effects on the environment, economy, and society. Those in the agricultural industry bore the brunt of the effect, contending with a severe decrease in water resources that lead directly to nearly 3% losses in crop revenue, and a 75% increase in the cost of water pumping [14]. Over time, the economic pressure created by the multi-year drought led to a 45% increase in idle land in California, over 21,000 lost jobs, and created the ideal conditions for the intense 2017 wildfires that caused unprecedented property and environmental damage [15]. This somber example is a salient reminder of the importance of natural water resources. Clearly, the management of freshwater is paramount to a successful future trajectory of our agriculture industries, if not civilization itself.

One of the ways regions like California can manage water use is to focus on optimizing agricultural water use, the majority of which is accounted for by irrigation. The importance of optimizing irrigation is not only in minimizing water use by eliminating unnecessary overwatering, but also creating optimal conditions for crop development. Generally speaking, when root zone moisture is ideal throughout a plant's life cycle, all crops will see improved yield, decreased disease pressure, and improved vigor compared to plants grown in less than ideal conditions [16]. Despite this knowledge, the most common form of irrigation used by commercial growers of high-value crops is drip systems that treat all plants in a management zone identically, even though it is known that all plants do not require the same amount of water. Water demand heterogeneity can arise from cultivar differences, complex topography, canopy orientation, soil structure, and composition, or rogueing practices for disease control, as examples [17]. When this variability is combined with complex deficit irrigation strategies, the optimization of irrigation schemes becomes quite challenging.

If high-value crop growers can meet this challenge head-on, by implementing effective irrigation strategies that can account for the complexity of plant water demand, or even approximate it, the possibility of simultaneously reducing unnecessary water use while maintaining or improving crop quality could become a reality [18]. For example, in 2017, researchers reported a two-treatment experiment using grapevines at an E&J Gallo vineyard in Galt, CA, USA. In the study, one block of "stressed" vines was irrigated with 69% of the amount of water applied to the grower standard irrigation treatment block. Not only were no significant yield differences observed between stressed and standard treatments, but the only significant qualitative difference was an increased concentration of malic acid content [19].

This review presents a comprehensive overview of the methods available to growers of high-value crops for estimating evapotranspiration (ET) and informing irrigation scheduling in commercial agriculture systems. While other reviews of methods for estimating ET exist [20–24], none are focused on applications specific to high-value perennial, woody cropping systems. To address this gap in the literature, and in order to present ET estimation options for high-value crops in an organized and digestible format, we have organized the methods into two distinct groups of coarse-scale and fine-scale estimations (Table 1). For the purpose of this manuscript, we have defined the threshold for the coarse scale as a 10 m spatial resolution or lower, a decision influenced by the 10 m resolution of images taken by the Sentinel-2A satellite [25]. We acknowledge that many of the technologies mentioned in this manuscript could be considered either the fine or coarse scale depending on the application context, but categorize them anyways for the sake of an organized discussion. In the following sections, we will first introduce the important nuance between how much water plants need, and when they need it. Then, we will discuss coarse- and fine-scale ET technologies. As each technology is introduced, related concepts are explored, and the forms of data required for calculations are discussed, as well as some examples of the successful implementation and any known weaknesses or limitations. Then, water distribution systems are considered in the context of ET estimates, with an emphasis on high-spatial-resolution distribution systems. In the conclusion section, major themes are revisited and the future directions of ET research are discussed.

Table 1. ET models are organized into coarse- and fine-scale categories, and summarizing information is given on the number of plants considered by each model, the time step of ET estimates, and the appropriate applications.

	Model	Resolution		Time Step	Application
		Footprint	Number of Plants		
Coarse	Surface Energy Balance, Remotely or Proximally Sensed	10 m or greater	Multiple	Monthly, weekly, daily, hourly	Open field
	Original Penman–Monteith	10 m or greater	Multiple	Daily	Open field
	Stanghellini	10 m or greater	Multiple	Hourly	Greenhouse or indoor
	Priestly–Taylor	10 m or greater	Multiple	Daily	Open field
	Hargreaves and Samani	10 m or greater	Multiple	Daily	Open field
	Reference ET and Crop Coefficients	100 m or greater	Multiple	Hourly	Open field
	Eddy Covariance	10 m or greater	Multiple	Hourly	Open field
	Soil Moisture Sensors	10 m or greater	Multiple	Hourly	Open field, greenhouse, or indoor
	Pan Evaporation	10 m or greater	Multiple	Daily or hourly	Open field

Table 1. *Cont.*

	Model	Resolution		Time Step	Application
		Footprint	Number of Plants		
Fine	Lysimeters	Area of Lysimeter	Single or Multiple	Two minutes or less	Open field, greenhouse, or indoor
	Sap Flow Sensors	1–6 m	Single	Hourly	Open field, greenhouse, or indoor
	Gas Exchange Measurements	Less than 1 m	Single	Two minutes or less	Open field, greenhouse, or indoor
	Infrared Temperature Measurements	Less than 1 m	Single	Hourly	Open field, greenhouse, or indoor
	High-Resolution Irrigation Models and Low-Cost Sensors	1–6 m	Single or Multiple	Two minutes	Open field

1.1. How Much vs. When?

To achieve the abstract goal of watering a plant according to its needs requires two fundamental components: (1) an engineered system for targeted delivery of water to each plant, and (2) an understanding of the plant's water needs that can inform irrigation decisions. The second component, understanding a plant's water needs, requires knowing how much water to apply and when to apply it. While this may seem a trivial distinction, the questions of how much and when to water a plant have two very different answers, and arriving at those answers requires collecting and analyzing different types of data.

While estimating ET can inform how much water to give a plant, determining the best time to give this water to a plant requires understanding something about the plants' water status [26]. Water status refers to water potential, a thermodynamic concept describing the Gibbs free energy per unit volume of some phase of water relative to pure liquid water at 1 ATM. The magnitude of this value is a result of both the soil water content and evaporative demand of the atmosphere [27]. In practice, water potential can be a useful signal for growers because it can indicate whether or not a plant is experiencing debilitating water stress that prevents transpiration and reduces growth or photosynthesis [28]. Water potential is most commonly measured using a pressure chamber device, but when using this kind of device, it is important to consider the difference between stem and leaf water potential.

In woody plants, such as grapes or tree crops, leaf water potential is not a reliable indicator of the water status of the whole plant because physiological and micrometeorological differences can cause local differences in leaf water potential [28,29]. Stem water potential serves as a better indicator of whole-plant vascular performance and can be easily measured using a leaf bagging method that allows time for the leaf and petiole to equilibrate with stem water potential before measurement with a pressure chamber [26]. Although stem water potential can be a useful measurement, it is also a labor-intensive process and for this reason has only recently become more widespread in commercial agriculture [29]. Also, it is known that stem water potential fluctuates diurnally and seasonally, which makes it difficult to set absolute general water potential thresholds for irrigation management. In order to use stem water potential information to trigger an irrigation system, measurements on target plants need to be benchmarked against non-stressed plants of the same type in the same environment. Another recent study suggests developing crop- and cultivar-specific thresholds for commercial irrigation scheduling based on trunk water status measurements [30,31].

To overcome these challenges, several automated and continuous methods for measuring or inferring stem water potential have been developed, including trunk diameter fluctuation sensors, sap flow sensors, and microtensiometers. Measuring trunk diameter fluctuation on a daily basis allows the extraction of a maximum daily shrinkage factor that has been shown to be effective for estimating the water potential of trees [32–34]. Sap flow sensors, which measure the flow of water and nutrients through xylem via the compensation heat-pulse method [35], or tensiometer sensors may also be used to estimate plant water status [36,37]. In the heat-pulse method, a small wire is heated, and the rate at which this heat dissipates is correlated with the sap flow rate. Tensiometers work by measuring the tension in the xylem directly via a pressure sensor embedded in the trunk. While many measurement options exist, it is important to consider when to collect stem water potential measurements, as midday or solar noon water values for the same plant may give different results than a pre-dawn measurement, and reflect different physical concepts.

The predawn stem water potential measurement aims to understand the soil water potential based on the assumption that the roots of well-watered plants will equilibrate with the soil water potential overnight [38]. A midday or solar noon stem water potential measurement may be useful for measuring the stress experienced by the plant during the past few hours, but may not reflect whether a plant has access to water for transpiration. Despite some limitations, in commercial almond cultivation, for example, midday stem water potential is considered the best indicator of whole-plant water status because the pressure signal integrates information from the entire soil–plant–atmosphere continuum, capturing the effects of root zone and environmental conditions in one measurement [39]. While tools like pressure chambers, trunk diameter calipers, sap flow sensors, or even observation can be useful for determining when plants are transpiring or when to apply irrigation, these tools cannot directly measure how much water to apply.

1.2. Measuring Evapotranspiration

Evapotranspiration is a fundamental component of the global water cycle, connecting water, carbon, and energy systems, but it is also fundamentally difficult to measure and predict because it integrates evaporation and transpiration [24]. Evaporation is a passive process that occurs at the soil surface and other wet surfaces. Vegetation transpires principally because it allows the plant simultaneous access to carbon dioxide and a means of keeping itself cool under the heat load of the sun, but it is also essential for plant growth and drives the transport of nutrients throughout the plant [28]. Measuring the combined effect of the vaporization of liquid water from surfaces into the atmosphere and the vaporization of liquid water inside leaves, plus the transport of these water vapors away from the site of vaporization, is not straightforward. The evaporation aspect of this process is driven by incident solar energy while the water vapor transport aspect is driven by the vapor pressure difference between the water vapor near the evaporating surface and the water vapor in the atmosphere [40].

Over the years, numerous methods have been devised to measure ET but many share some common characteristics. Some can be classified as mechanistic models, and others empirical. Mechanistic models are based on physical laws, though they often include assumptions or simplifications. These models are thought to be more precise because they can account for crop-related changes, such as the Penman–Monteith model, which includes terms describing physiological responses to the environment [41]. Empirical models are based on observed correlations between multiple concepts. While these methods may be simple and often require less data, they typically lack generalizability. The Hargreaves model, for example, is well suited to closed greenhouse environments but is not validated for performance in open field settings [42]. Another limitation of many of the approaches to measuring ET is the spatial resolution of estimates, which can vary widely from several hectares to several square meters.

2. Coarse-Scale ET Estimates

In many cases, it makes more sense to measure ET at a spatial scale greater than 10 m. In fact, it is not uncommon for the scale of estimates to be orders of magnitude greater than this threshold. In some parts of the world, there is limited or no access to field measurements of meteorological data, so satellite or other remote sensing-based estimates are the best or only option for estimating ET. In other cases, there is simply not enough funding for fine-scale measurements of ET, which are relatively more expensive because of increased sensor requirements and frequency of consultations with experts for data collection and analyses. While rare, it is also possible that an environment may be nearly homogeneous in terms of soil composition, topography, and elevation. In these cases, a fine-scale estimate of ET is not necessary for adequate management of irrigation.

2.1. Original Penman–Monteith

The Penman–Monteith model is one of the first and seminal methods for estimating ET, but it is actually the culmination of two scientists' work spanning decades and institutions. Working at the Rothamsted Experimental Station, Howard Latimer Penman approached modeling the evaporation of water from an open surface and devised an equation used to this day. This model is based on only physical drivers, though, and was originally validated for open water bodies, well-watered grass, and bare soil [43]. In the 1950s and 1960s, John Lennox Monteith revisited the problem of the evaporation of water, but this time with a focus on plant transpiration. To improve estimates of evaporation over well-watered grass, Monteith measured the resistance of stomata in the field, then added this diffusion resistance to Penman's model [44]. The first example of an application of Penman–Monteith to a two-layer model, which separates energy exchange at the canopy and soil levels, marked an important shift towards next-generation modeling [45]. Many later models also focused on simplification, eliminating collinear terms and reducing data collection requirements without major impacts on accuracy of estimates [46]. Given all the options, growers must choose which of the numerous Penman–Monteith models to use. When considering which model to use, it is important that growers are well informed on which models were designed for and validated in meteorological settings closest to the field conditions in question.

The original Penman–Monteith equation [Equation (1)] is composed of two main terms, the surface resistance and aerodynamic resistance terms [40].

$$\lambda ET = \frac{\delta(R_n - G) + \rho_a C_p \frac{(e_s - e_a)}{r_a}}{\delta + \gamma\left(1 + \frac{r_s}{r_a}\right)} \quad (1)$$

The λ term is the latent heat of the vaporization of water, δ is the slope of the saturation vapor pressure curve, ρ_a is the mean air density at isobaric conditions, C_p is the specific heat of air, $e_s - e_a$ is a vapor pressure deficit term, γ is the psychrometric constant, and r_s and r_a are the surface and aerodynamic resistance terms, respectively. Surface resistance is the resistance of water vapor to movement through the leaf stomata and soil surface, while aerodynamic resistance is the resistance of vertical water vapor diffusion from the leaf to the surrounding air. Surface resistance can be further subdivided into terms for bulk stomatal resistance of a well-illuminated leaf and active leaf area index. The bulk stomatal resistance is highly dependent on the type of crop, meteorological conditions, soil moisture content, and solute concentration in water. The active leaf area index is a dimensionless measure of the upper side area of the leaf per unit area of the soil underneath it, and as a result depends on the plant type, leaf density, and life-cycle stage. Aerodynamic resistance is estimated from wind speed measurements and calculated roughness lengths. These abstract lengths represent aspects of the heat and vapor transfer process, and can be estimated as one tenth of crop height [40].

While Penman–Monteith is a pioneering model, it also has remarkable longevity in the field, with many examples of successful applications spanning the past 20 years. As an example, a two-layer Shuttle- and Wallace-inspired model with added sub-models for net radiation and soil heat flux was used in 2010 to estimate the ET of a Merlot vineyard in Chile [47]. The Penman–Monteith approach has also been validated on a tropical savanna and an evergreen *Eucalyptus* forest in Australia, explaining up to 74% of the variation in ET [48]. Some evidence, however, points to a shortcoming in the Penman–Monteith model, such as the lack of a term to consider the salinity of water. In the situation in which ideal meteorological conditions and soil moisture conditions exist for transpiration, high enough salinity can reduce the magnitude of the pressure gradient driving water flow through the plant without affecting model estimates [49]. One other major known drawback of the Penman–Monteith approach is its reliance on the assumption of a homogeneous local climate. This assumption may be appropriate for open field settings, but is problematic for greenhouse settings [50].

The greenhouse environment presents a particular challenge for the Penman–Monteith method. In order to calculate the aerodynamic resistance term, homogeneous local climate must be assumed, but this assumption is violated in nearly all greenhouses. Greenhouse architecture and sparse environmental control equipment typically leads to a heterogeneous environment [51]. To overcome the challenges associated with modeling ET in a greenhouse, Cecilia Stanghellini revised the Penman–Monteith approach to more accurately account for the processes associated with ET in a greenhouse, using tomatoes as a reference crop. The revised model [Equation (2)] includes modifications to the radiation flux terms in the equation, considering the effects of greenhouse components such as soil covering, surface materials, heating or cooling devices, or other electronic equipment [52].

$$\lambda ET = \frac{\delta R_n + (\frac{2 \cdot LAI \cdot \rho_a C_p}{r_e}\ \mathrm{VPD})}{\gamma(1 + \frac{\delta}{\gamma} + \frac{r_i}{r_e})} \tag{2}$$

The VPD term is the vapor pressure deficit, and the r_i and r_e terms are the canopy internal and external resistance terms, respectively. The model also includes a modified leaf area index (LAI) term, which accounts for exchange of energy from multiple layers of the canopy [53]. Notably, net radiation is described differently, giving separate weights to short- and long-wave radiation's effect on a multi-layered canopy such as those typically found in greenhouses [22]. Other differences include terms for radiation resistance, external and aerodynamic resistance that accounts for the non-logarithmic profile of wind as distance from the canopy increases, and the internal resistance of a leaf in greenhouse settings [54].

Measuring ET using the Stanghellini method requires measuring many of the same terms as other Penman–Monteith-derived methods. These include the net solar radiation, vapor pressure deficit, leaf area index, air density, leaf surface temperatures, and concentration of carbon dioxide in the air. Due to the large number of data types that need to be collected, a revised Stanghellini method was developed, including a simplified irradiance term called the Canopy Area Index (CAI) [55].

The performance of the Stanghellini method in a greenhouse has been compared to other methods including the original Penman–Monteith method. While there was not a significant difference between the performance of the two models, the Stanghellini model consistently explained more of the variation in crop ET [53]. Researchers attributed this performance gap to the Stanghellini model's inclusion of terms, which better consider the environmental factors affecting bulk stomatal resistance. In another study, the Stanghellini method was compared to the original Penman–Monteith, the pure Penman approach, and the Fynn approach, using a Red Maple Tree (Acer rubrum 'Red Sunset') grown in a greenhouse as a subject. The Stanghellini model explained nearly 88% of the variance in the maple tree ET, likely due to a relatively improved characterization of the environmental factors impacting ET, whereas the other models explained less than 50% [22].

There are situations, such as in rural areas with no access to sensors or where power is not ubiquitous, which preclude the measurement of the meteorological and climatological parameters for calculating the aerodynamic resistance terms in a Penman–Monteith ET model. To overcome these challenges, another similar approach was developed by C.H.B. Priestly and R.J. Taylor but with a simplified approach to aerodynamic resistance. This model [Equation (3)] replaces the aerodynamic resistance term in the Penman–Monteith model with a dimensionless coefficient, alpha (α) [56].

$$ET = \frac{1}{\lambda}\delta\frac{R_n - G}{\delta + \gamma}\alpha \quad (3)$$

In the original Priestley–Taylor model, researchers validated an alpha value of 1.26 for open field systems, a value used even in modern research [57]. Though 1.26 is generally accepted, researchers in 2011 showed that an alpha value of 1.26 is too low for arid and cold environments like Iran, where a value in the range of 1.82–2.14 is more appropriate [58].

When using this model, solar radiation, air temperature, and relative humidity will need to be measured. However, because the aerodynamic term is approximated with the alpha term, wind speed is not measured and roughness lengths are not approximated. Even without this term, which proponents of the original Penman–Monteith approach might argue is critical to accurately describing the environment, the Priestley–Taylor model has been shown to successfully estimate monthly canopy and soil ET [59]. Though this method can be effective on its own, several studies have demonstrated successful efforts to improve the accuracy of predictions by allowing the value of alpha to fluctuate. One method demonstrated an improved performance of the Priestley–Taylor method by introducing a term that lets the alpha value vary as a function of NDVI and leaf surface temperature [60]. In another study, researchers working with Sorghum suggested that estimates can be improved by calculating alpha based on an equation that considers the daily mean vapor pressure deficit [46].

Several more recent studies, however, have shown that the Priestley–Taylor method underestimates ET rates under advective conditions [23]. Advection is the movement of vapor, heat, and air as conveyed by the wind. When advective conditions interact with the canopy, which is not uncommon in an open field setting, the Priestley–Taylor method cannot accurately consider the dynamic effect of aerodynamic resistance in the system [61]. Many studies have highlighted this sensitivity to using an appropriate alpha term, but the alpha term has also been shown to interact with soil moisture content, solar radiation, atmospheric pressure, and other meteorological concepts [58]. For example, in one study, researchers showed that as surface resistance increases or humidity decreases, the alpha coefficient increases [62].

In remote or logistically challenging environments, such as those without access to grid power, it may be difficult to collect any meteorological data. In these situations, if air temperature alone may be measured, then it is possible to estimate the regional ET from these values [63]. The development of this ultra-simplified Penman–Monteith-inspired method for estimating ET [Equation (4)] was originally motivated by the lack of readily available meteorological data in developing countries that can limit the applicability of methods including most of the Penman–Monteith methods developed at the time.

$$ET = 0.0023(\frac{T_{max} + T_{min}}{2} + 17.8)\sqrt{T_{max} - T_{min} R_a} \quad (4)$$

In order to estimate the regional ET without any solar radiation data, or with solar radiation data of questionable accuracy, researchers devised a method using only air temperature validated for open field settings. In this method, global solar radiation at the surface (R_a) is estimated through air temperature values and empirical relationships [64].

With this approach, users measure air temperature throughout the day and night, recording daily maximum (T_{max}) and minimum (T_{min}) values. Empirical coefficients based on site location are also used, to adjust for regional differences. These coefficients are correlated with temperature, but are also typically lower for interior regions and higher for coastal regions. Air temperature may be measured or estimated using ground-based sensors or extra-terrestrial sensors mounted on orbital or aerial devices. Though they were designed to improve estimates, in one study, it was found that the empirical site adjustment coefficient may lead to the Hargreaves and Samani approach overestimating the ET rate in many situations, leading to excess irrigation [65]. While the tendency to overestimate ET poses some limitations to the applicability of the Hargreaves approach, some studies have shown that calibration parameters may be used to reduce the overestimation of ET by up to 16.3% [66].

2.2. Surface Energy Balance

Energy balance methods are based on the concept of the conservation of energy, which states that the energy in some problem domain is constant, and neither created nor destroyed. Due to its somewhat flexible footprint, this can be a cost-effective method for estimating ET on scales ranging from single plots (1–2 hectares) to entire regions [24,67]. With multispectral image data from satellite or aerial observation, surface energy is computed by combining the surface energy balance equation [Equation (5)] with land surface flux expressions and temperature sensing.

$$R_n = LE + G + H + \Delta S_{air} + \Delta S_{air} + \Delta S_{bm} + \Delta S_{ph} \quad (5)$$

The energy balance equation states that net radiation (R_n) must be in balance with the latent heat flux density (LE), ground heat flux density (G), sensible heat flux density (H), and other less significant energy sinks (ΔS terms). While remote sensing can be effective for estimating regional ET via estimates of NDVI, local effects and the effects of specific plant morphology may necessitate some proximal sensing as well. For example, the turbulent structure of air over a vineyard, which is strongly influenced by the geometry of the underlying canopy, may not be accurately modeled by remote sensing alone [68].

In the context of the plant–soil–atmosphere system, energy balance theory states that net radiation must be in balance with the latent heat flux density, ground heat flux density, sensible heat flux density, and other less significant energy sinks. Ground heat flux density is the rate of heat storage into the soil and vegetation due to conduction, and is either measured directly or computed using information from Normalized Difference Vegetation Index (NDVI) measurements [69]. Sensible heat flux density is the energy lost to the air from the plant, soil, and cover crops via convection and conduction. Multiple methods have been developed to estimate sensible heat flux including eddy covariance, the Bowen ratio method, and surface renewal [70]. The energy stored in the air layer and in the biomass and chemical energy stored in the carbohydrate bonds of plant sugars, formed using ATP and NADPH from the light reactions of photosynthesis, are usually considered negligible compared to other terms and are therefore ignored [71]. The latent heat flux density is the heat lost from the system due to the evaporation of water, and is calculated as a residual, once all other parameters in the model are determined. Dividing the latent heat flux by the latent heat of the vaporization of water will give ET.

Generally, surface energy balance methods can be categorized as either one- or two-layer models, though there are recent examples of three-layer models as well [72]. Single-layer models do not distinguish between soil and vegetation components of ET, but recognize contributions to ET from both [73]. Sensitivity to local calibration and relatively extensive local reference data requirements restrict the use of single-source methods to several-hectare or smaller-scale applications [24]. The Surface Energy Balance for Land (SEBAL) overcomes these limitations by empirically estimating the essential meteorological parameters and can therefore be applied over much larger areas, but it may lack regional specificity [74]. Two-source surface energy balance methods account for the individual contribution of soil and vegetation to total heat flux but require more data inputs [73,75]. The three-source model applies to cropping systems such as vineyards, where the row and inter-row represent two distinct zones of vegetation. The row is the perennial vine crop but the inter-row is typically composed of seasonally rotated cover crops. In three-source models, the contributions to ET are partitioned into the soil layer, the cover crop layer, and the crop layer. Independent of the number of layers, energy balance models require frequent and spatially contiguous measurements using ground-based sensors and potentially also orbiting satellites or airplanes mounted with multispectral cameras for detecting parameters affecting ET [76]. If overhead sensing is being performed, leaf area index (LAI) data may also be remotely collected in parallel and these data can be used to improve Penman–Monteith directly, or other energy-balance-based ET estimates via empirical relationships between LAI and NDVI [48,77–79].

In one of the earliest studies quantifying large-scale ET trends, researchers reported a successful implementation of a satellite-sensed NDVI-based model called the Process-based Land Surface Evapotranspiration/Heat Fluxes algorithm (P-LSH) that separately computes the contributions of the canopy, soil, and open water bodies to ET [80,81]. Then, in 2021, researchers successfully used data-driven models to estimate the ET rate, using physical energy balance models coupled with machine learning, regression, and neural networks [82]. Three-source models have also been shown to perform well in vineyards, except under extreme advective conditions [72]. However, methods requiring aerial and orbital data collection methods may be sensitive to cloud cover and dust, which can impact estimates of parameters important for calculating ET [83]. Also, sensible heat flux is sensitive to factors impacting the distribution of energy sources in the canopy including wind speed and surface roughness, and is therefore affected by canopy size, structure, trellising, plant phenological stage, and even ground surface heterogeneity [70].

2.3. Reference ET and Crop Coefficients

In other regions of the world, reference ET systems and crop coefficients are one of the options for estimating local ET. In California, USA, for example, this is an important method for estimating ET, which allows growers throughout the state to schedule irrigation based on proxy measurements along with correction factors known as crop coefficients, specific for the type of plant being grown nearby and management factors [40,84]. These proxy ET values, known as reference ET, are calculated at 1 of over 200 California Irrigation Management Information System (CIMIS) weather stations distributed throughout the state [85]. Some other states in the USA have similar systems including Florida [86], Colorado [87], Arizona [88], and Washington [89], as well as other countries including Australia [90], India [91], and the United Kingdom [92]; but the specific data types available from these systems may differ from CIMIS. At each CIMIS station, meteorological data are collected at a weather station 2 m above well-watered clipped grass, and then fed into a modified version of the original Penman–Monteith known as FAO56 Penman–Monteith because it was introduced in Irrigation and Drainage Paper 56 from the United Nations Food and Agriculture Organization. While FAO56 Penman–Monteith is generally used for CIMIS reference ET estimates, it is also possible to use the CIMIS–Penman model, which is a modified version of the Pruitt/Doorenbus Penman–Monteith equation that includes wind speed and cloud cover parameters [93].

Once reference ET (ET_o) is known, it can be used to calculate true ET of crops grown nearby by multiplying by a scaling factor known as the crop coefficient [Equation (6)].

$$ET = ET_o \cdot\ K_c \tag{6}$$

The crop coefficient (K_c) is an experimentally derived value, specific to the cultivar, seasonal canopy development, and vine spacing, and sometimes adjusted for other management factors [94]. The work of Williams showed that the crop coefficient may be a function of the shaded area under a grapevine, but this relationship has not been quantified [95]. Other studies have explored a two-part definition for the crop coefficient, splitting the coefficient into separate terms for the basal crop coefficient representing a factor for crop transpiration, and the soil evaporation coefficient representing a factor for evaporation from the soil surface.

Compared to the other approaches for ET estimation, this method has the distinct advantage of being virtually free for California growers and other growers in areas with similar programs. However, this approach is limited by its reliance on the assumptions of generalizable regional reference ET values and crop coefficients. As a result, this method can be quite effective at estimating regional reference ET but it can lack local specificity, not adequately accounting for or ignoring complex factors influencing slight differences in plant water demand such as management practices, phenological stage, topography, soil characteristics, and many others [85]. One study found that the difference between crop coefficients recommended by FAO56 Penman–Monteith methods and locally observed data can be greater than 40% [20]. Researchers in this study attributed the results to crop coefficients, which attempt to integrate several physical and biological concepts into one signal, leaving significant potential for error if they are estimated incorrectly. Due to its Penman–Monteith origins, the reference ET approach is inherently sensitive to local climatic conditions at the reference ET measurement site, which may differ from local conditions at the prediction site. When climatic variation exists between the reference and prediction site, it may be possible to use direct measurements of stomatal and boundary layer resistance to calibrate estimates [25,54]. Additionally, these methods do not perform well under deficit irrigation, when they cannot completely account for the response of plants to water stress, a common feature in high-value viticulture operations [96].

2.4. Eddy Covariance

Eddy covariance methods are considered one of the only ways to directly measure ET, via estimates of the sensible heat flux density (H) term in the energy balance equation [see Equation (5)]. In this method, a flux tower is used to measure changes in vertical air velocity while simultaneously measuring the concentrations of water vapor in the air, in order to calculate the vertical flux of water vapor, giving an estimate of ET [97]. This method is validated for open field crops, vineyards, open water bodies, and grasslands [97,98]. Like other fundamental energy balance concepts, the eddy covariance method is most suited to open, flat, and homogeneous vegetation canopies, an uncommon motif in agricultural settings. The fluxes observed by sensors mounted on flux towers represent ET from a dynamic area that depends on wind and air stability. This area is called the "footprint" or "fetch" [99,100]. The uncertainty of the exact dimensions of this area propagates through calculations, contributing to the error observed in estimates of sensible heat flux and other parameters, which often only account for 70–80% of total incident energy [101,102]. In the 2022 Grape Remote Sensing Atmospheric Profile and Evapotranspiration eXperiment (GRAPEX) project, for example, researchers employed the eddy covariance method and observed a mean energy closure of 75% across multiple sites and years in the North Coast and Central Valley of California, USA [17].

In the eddy covariance method, data are recorded at a high frequency, usually about 20 hertz. Data include wind speed and direction and are typically recorded using a sonic anemometer. Relative humidity and air temperature are also recorded with research-grade sensors. Gas concentrations in the air are measured using an infrared gas analyzer. Recording all of these data at high frequency quickly leads to large files, which are difficult to store locally. Recent progress in computation and automated sensing capabilities was critical to bringing eddy covariance methods into practice [17]. Also, efforts have been made to improve data collection protocols in eddy covariance systems by separating monitoring systems for tall vegetation such as orchard trees and soil surfaces [103,104]. In these approaches, independent estimates of soil evaporation and crop transpiration are calculated, but the footprint of ground sensors is typically much smaller than above-canopy measurements [105].

In one of the more innovative applications of the eddy covariance approach, researchers used the Keeling Plot technique to partition ET data measured at the ecosystem level into soil and vegetation sources [106]. This work was accomplished using spatially distributed flux towers, which in addition to measuring parameters for estimates of ET, were able to detect the portion of heavy isotopes (^{2}H, ^{18}O) in the evaporating water inside their respective footprint. It is known that water evaporated from soil is depleted in heavy isotopes relative to other liquid water at the Earth's surface [107]. Some of the other literature reports the eddy covariance method as logistically challenging due to the necessity of high-frequency meteorological measurements and complex data processing procedures, which usually require experts [21].

The eddy covariance method, while favored by researchers for its ability to directly estimate ET, is very challenging to validate. The large scale and high variability of the flux footprint, as well as the open boundary layer of the volume studied, both affected by the degree of advection, create issues for those seeking to make direct comparisons of other ET estimates to the estimates generated by eddy covariance methods [98,108]. The issue of the flexible footprint, which results in energy imbalance between the total available energy and turbulent fluxes calculated by the eddy covariance technique, can lead to overuse of water in agricultural settings. Different approaches for computationally distributing this imbalance to create pseudo-balance can lead to uncertainty in daily ET estimates up to 50% [17]. The Bambach et al., 2022, team of researchers went on to show that over the growing season this uncertainty can amount to up to a third of the total annual applied irrigation.

2.5. Soil Moisture Sensors

Unlike indirect energy balance methods, soil moisture sensors directly measure the moisture content of the soil environment. Many different techniques have been developed, but two of the most commonly used categories in high-value crop agriculture are volumetric and tensiometric sensors. Volumetric moisture sensors, such as neutron probes, capacitance sensors, and time-domain-reflectometry sensors, measure the way a signal behaves in the soil, then estimate the percent of water in the soil by volume using known correlations [109]. Tensiometric sensors, on the other hand, directly measure capillary tension, the physical force holding the water in the soil [110].

Soil moisture sensors have the benefit of automation and continuous data collection, but these advantages are outweighed by myriad practical disadvantages, including a fundamental sensitivity to the heterogeneous distribution of moisture in the soil environment. Soil moisture sensors are also immobile once placed, and therefore what a sensor measures is often not what is perceived by the deep, diffuse roots of vines and trees, which can explore soil space over time. Most importantly though, there is no simple or direct way to estimate plant water status or ET using soil moisture content [111].

Despite no direct method for calculating ET, soil moisture sensors may be used for irrigation management provided there is some knowledge about the water balance properties of the growing medium. Water balance is a concept referring to the range between the maximum water holding capacity of a growing medium, or field capacity, and the level at which the plant can no longer transpire, also known as the wilting point [112]. The field capacity and wilting point of a growing site may be determined via laboratory tests, sensor-based estimates, or using the Rosetta model, which exploits pedotransfer equations to estimate the terms indirectly [113]. It is not uncommon for researchers to simply assume a field capacity soil matric potential of −33 kPa, though some studies suggest that an assumption of −10 kPa may be more generalizable [114]. The wilting point may also be assumed, and the generally accepted value is −1500 kPa, though this value is a function of soil texture, crop type, and other local factors, which may impact the true wilting point [115].

2.6. Pan Evaporation Method

With the pan evaporation method, it is possible to use nothing more than a standardized pan of open water, a scale, and a watch to estimate local crop ET. While the most basic of pan evaporation approaches can achieve the aforementioned elegance of nearly optimal operational efficiency, modern examples of this method typically require the collection of supplemental meteorological data for model building purposes. Other approaches involve calculating a pan coefficient (K_p) that when multiplied by pan evaporation (E_p) yields an estimate of reference and then crop ET [Equation (7)].

$$ET = K_p \cdot E_p \tag{7}$$

The most widely used method for determining a pan coefficient value is a table from the United Nations Food and Agriculture Organization, which categorizes different values based on the composition of the ground surrounding the pan, the local climate type, and the size and type of vegetation near the pan [116].

The pan evaporation method is effective because it takes advantage of the correlation between pan evaporation and reference ET, which in turn has a known correlation with crop ET. To reduce error caused by differences between pans, there is a standard pan called the "class A evaporation pan" issued by the United States National Weather Service, which allows for more accurate comparisons between sites. While the relationship between pan evaporation and reference ET is valid under many conditions, there can be conditions causing differences in energy fluxes and heat storage in an open water pan relative to vegetation. This effect is pronounced at night when energy stored in the pan during the day increases the overnight evaporation rate of water in the pan, while canopy resistance to transpiration will cause little to no nighttime ET [117].

Nevertheless, properly used, the pan evaporation method can produce useful estimates of crop ET. In one study, researchers developed a method wherein pan coefficient values can be estimated, eliminating the need for wind speed and relative humidity data. With a scale, the pan evaporation can be measured and this alone was shown to be a strong predictor of the pan coefficient value [117]. In another recent study, researchers in the central Himalayas trained machine learning models using multiple types of data including pan evaporation, air temperature, relative humidity, wind speed, and illuminated hours. Of the five artificial intelligence models trained, the neural network and the inference models were the best performing in terms of estimating crop ET, further demonstrating the relevance of the pan evaporation technique [118].

3. Fine-Scale ET Estimates

For many years, the methods for fine-scale ET estimation have been relegated to research applications, but recently several options designed for commercial use have come to fruition, opening the door to widespread acceptance [31,119]. The development of these tools was driven by the need for technology that allows for irrigation management at smaller spatial scales, specifically addressing the spatially heterogeneous water demand of high-value crops grown in topographically complex and heterogeneous environments. Intra-vineyard spatial variability, for example, poses a particularly difficult challenge and has been well characterized as a nearly ubiquitous feature, which has been linked to vine performance [120–123]. When irrigated with a conventional drip system controlled by coarse-scale ET estimates, the consequence of this spatially heterogeneous water distribution is a non-uniform ripening of berries. Ultimately, non-uniform ripening results in an increased fraction of the resulting must being composed of immature and over-ripe berries compared to a more uniformly ripened harvest from the same vineyard [124].

In grapes and other high-value crops, water balance contributes directly to overall fruit quality, not just yield and ripening, layering additional complexity into its management. For example, in perennial woody crops, well-timed water stress can help control vegetative vigor and may increase fruit quality at harvest [125,126]. Conversely, moderate-to-severe water stress caused by extreme deficit irrigation can damage cellular components for light harvesting, limiting photosynthesis. If this water stress is prolonged, delays in ripening, sudden plant collapse, and reduced fruitfulness can negatively impact yield and quality [127]. These constraints can create a problem, however, because the irrigation manager's goal is finding this narrow range of applied water by considering the plant's needs, but these needs usually vary in a complex way through space and time. Fine-scale ET estimates seek to reveal this complex patchwork of variable plant water needs.

3.1. Lysimeters

Lysimeters directly measure ET by sensing changes in the mass of soil and vegetation inside of a container mounted on a scale. These complex devices were designed by researchers to study the process of ET, develop ET models, and measure precipitation and dew and water flow in the unsaturated zone of the soil profile [119,128,129]. A properly designed lysimeter replicates the natural environmental conditions of the target environment and vegetation combination. Generally, this means that the overall size, pruning habit, and other management factors applied to the lysimeter plant are comparable to the management strategies applied to the vegetation of the same type in the local area [21]. Some lysimeters are buried underground to protect sensory equipment and ensure that vegetation is maintained at a plausible height, and soil is maintained at a plausible temperature, but examples of above-ground lysimeters demonstrate that this is not a necessity for achieving good results [119]. Lysimeters may also be equipped with an adjustable ground water level watering system maintaining soil hydration at levels equal to the surrounding soil [130]. Typically, all soil plant and meteorological sensors are mounted on the potted plant infrastructure and then all of this is mounted on a three- or four-point load cell with a sensitivity of at least 0.01 kg. The surface area of the lysimeter soil may be used to translate mass units of water into spatial units of millimeters per area.

If the lysimeter is a closed system, in other words, if it has no drain, then ET is calculated by taking the integral of the derivative of load cell mass with respect to time, ignoring irrigation and precipitation events [Equation (8)].

$$ET = \int_0^t \frac{d}{dt} mass \tag{8}$$

If, however, the lysimeter has a drain to allow for excess water to flow out the bottom of the potted soil enclosure, mimicking groundwater recharge, then in order to calculate the ET, this overflow must be measured in addition to the mass of the load cell. ET can then be calculated by taking the integral of the derivative with respect to time of the load cell data, adjusted for groundwater recharge. Though calculating ET may be slightly more complicated, the advantage of lysimeters with drains is that they can provide information about soil water retention and the percolation of excess irrigation water that no other methods can provide [108].

The high cost of installation and maintenance of lysimeters limit their applicability to research applications and some particularly high-value crops [21]. Typically, lysimeters are used to validate other forms of ET estimates that are less difficult to move to new areas. For example, in 2017, lysimeters were used by researchers in Switzerland to validate eddy covariance for ET estimates using well-watered grass as a research subject [129]. Measurements were taken hourly from 2009 to 2015, and using lysimeter data as a reference, researchers were able to show eddy covariance performs well to estimate ET, especially on the annual time scale. In this study, direct comparison to lysimeter ground truth ET allowed researchers to demonstrate that eddy covariance underperforms during and immediately after precipitation events. This finding highlights the limitations of eddy covariance sensors under rainfall conditions, contributes to researchers' understanding of why eddy covariance methods underestimate ET and how this impacts the energy balance gap, and demonstrates the value of lysimeters for model validation.

3.2. Sap Flow Sensors and Microtensiometers

Sap flow sensors are another promising technology, with several advantages over other fine-scale methods. These sensors directly measure the movement of fluid inside the xylem from the roots to stems and to leaves, where water is transpired through stomata—a process called sap flow. Sap flow is essential for the maintenance of the hydraulic continuum from the soil to plant to atmosphere; thus, monitoring this process can yield important information about the hydraulic function or dysfunction of the plant [131]. Various methods for estimating the sap flow rate have been developed, including thermal dissipation probes and the steam heat balance method [132–134]. Both are based on the concept of measuring the difference between a heated element and a non-heated reference element; as the sap flow rate increases, the temperature difference between the two elements decreases. A variation of this method is also used for standard flow meters in pipes. When applying this theory to plants, with variable xylem size and flow resistances, a calibration coefficient must be determined, and this coefficient is sensitive to stress-induced cavitation [131].

Microtensiometer sensors are based on the same principles as soil tensiometers but have been designed to suit the purpose of measuring plant water status. Sensors such as the flagship model from *FloraPulse* in Davis, California, are based on a microelectromechanical design that allows measurement of plant stem water potential continuously with a high degree of precision [31,135]. They are also small, consume very little power, allow for wireless data transmission, and like sap flow sensors are fully automated once installed. These sensors, mounted on the plant using a custom drill bit and mounting kit, have been tested extensively, and in one recent study, they were used in *Vitis vinifera* L. cv. Shiraz and Cabernet Sauvignon and compared to pressure chamber measurements. Trunk water potential measurements from the microtensiometers generally agreed with seasonal and diurnal patterns of stem water potential measured by a pressure chamber [30,136].

While the sap flow and microtensiometer methods will fundamentally achieve single-plant resolution, individual sensors are expensive and require skilled labor for installation and routine maintenance. As a result, sensors are typically mounted on only one to three plants per management zone. Plants are chosen to represent the range of variability, a problematic assumption that can ignore many sources of heterogeneity.

3.3. Gas Exchange Measurement Systems

Portable gas exchange systems give direct measurements of parameters at the leaf level, and thereby give estimates of leaf-level gas exchange including carbon dioxide and water vapor. In these systems, at least one leaf of the target plant is isolated from the environment, usually by sealing it inside of a clear chamber with several micrometeorological sensors and a regulated carbon dioxide gas supply [137]. Gases including carbon dioxide and water vapor concentrations are measured at the inlet and outlet of the sealed chamber using an infrared gas analyzer that can determine the concentration of gases in air based on the characteristic absorption of infrared radiation by different gases [138].

When portable gas exchange measurement systems were first introduced in the 1970s, their adoption was limited to research applications largely due to the size and complexity of the necessary equipment. These early devices measured the concentrations of carbon-14 dioxide in the air within plexiglass domes to determine the photosynthesis rate of grasses [139]. In the 2000s, portable gas exchange systems became much smaller and easier to use, engendering an era of non-research applications. Despite vast improvements in the size and portability of these technologies with innovations from companies such as LI-COR Biosciences (Lincoln, NE, USA), their substantial price, which was USD 50,000 in 2018, prohibits many growers from being able to use these systems [140]. Furthermore, this technology provides leaf-level estimates of gas exchange and photosynthesis rates, and extrapolating these rates to whole plants or groups of plants may not be straightforward.

In one recent study, researchers used portable gas exchange measurements to measure leaf-level photosynthesis and gas exchange rates, then successfully upscaled these estimates to calculate whole-plant fluxes. Though the efforts to understand canopy level fluxes were successful, researchers noted that upscaling was sensitive to the accuracy of the leaf area index and photosynthetic light curve data used in calculations [141]. Many of the applications of this technology aim to improve ET estimates with other technologies that are more easily generalized over areas relevant to commercial agriculture. For example, an infrared gas analysis was used to estimate the effect of increasing carbon dioxide concentration on the stomatal resistance of plants. Researchers found that elevated carbon dioxide concentrations reduce transpiration per unit of leaf area, and also water use efficiency may be improved but only because the photosynthesis rate is increased, not because transpiration is reduced [40]. These findings are vital for understanding and anticipating the effects of increasing atmospheric carbon dioxide on Earth.

3.4. Infrared Temperature Measurement Systems

It is also possible to increase the resolution of coarse-scale ET estimates using infrared temperature sensors, though this technology alone will not provide enough data to calculate estimates of ET [142]. These sensors take advantage of the cooling effect that happens when leaves are transpiring water through their stomata, in which the temperature difference between ambient air and the surface of the leaf reflects the transpiration rate [28]. If the temperature of the leaf is lower than the ambient temperature, then the leaf is transpiring, but if the temperature of the leaf is equal to or higher than the ambient temperature, then the leaf is not transpiring and is experiencing acute stress [143]. With leaf surface temperature data, it is possible to add another term to other ET estimation models, such as one of the surface energy balance models. This new term accounts for when leaves are actually transpiring instead of assuming this is a constant process during sunlight hours.

Though it is a straightforward concept, the measurement of leaf temperature is non-trivial. Leaves are not static in space, because of wind, growth over time, and other factors, and are subject to the meteorological uncertainty associated with an outdoor environment. The thermocouple approach to measuring leaf temperature involves the direct contact of a thermocouple to the leaf surface, a design that presents many challenges to the user. Physical contact with the leaf may be interrupted at any time for numerous unpredictable reasons, and even when perfect contact is maintained throughout the duration of measurement windows, the thermocouple may absorb solar radiation, causing error [144]. Despite these challenges, thermocouples are quite a popular method for measuring leaf temperature because of their low cost, simple operation, and relatively fast measurement time [145]. Recently, infrared sensors have gained popularity for measuring leaf surface temperature because of their fast measurement time, accuracy, and reliability over longer measurement windows such as full seasons. However, infrared leaf temperature sensors are sensitive to changes in the quality of air that affect the way light travels, and as a result, dust, mist, or smoke may impact the quality of measurements with these sensors [145].

3.5. High-Resolution Irrigation Models

The high-resolution irrigation (HRI) models were developed as algorithms along with low-cost sensors designed to provide growers with up to single-plant ET resolution in vineyard and orchard cropping systems [119]. These methods utilize non-destructive, largely automated proximal sensing and a computation pipeline, feeding data from biometeorological sensors to the models. In this process, wind speed, air temperature, and relative humidity are measured in or near the plant canopy. There are three HRI models that can be used to calculate the estimated ET rate per area, or mass flux ($\dot{m}_e$ in Equation (9)).

The convective mass transfer (CMT) model is one of two HRI models inspired by first principles. CMT relates transpiration to theory describing the convective mass transfer from a flat surface of water into moving air. This theory is based on an application of the Reynolds analogy, which suggests a simple relationship between different transport phenomena [146]. Using convective heat transfer from a flat solid plate into a fluid with laminar flow over its surface as an analogy, transpiration is defined as convective mass transfer from a flat surface of liquid or a gas saturated with water vapor into a gas with laminar flow over its surface [146]. From this theory, the estimated mass transfer flux depends on the mass transfer coefficient and the difference between the partial pressure of water in the air at the saturated surface and in the air in the greater atmosphere.

The CMT model maintains three assumptions. First, all transpiring leaf surfaces are saturated with water vapor, perfectly flat and having a uniform temperature equal to the temperature of the air in the canopy. Second, it is assumed that the boundary layer is maintained at a constant level of saturation, and finally, it is assumed that a laminar flow of air exists at the leaf surface, which carries water vapor away from the boundary layer.

While most agricultural systems violate some or all of these assumptions, the CMT model has been shown to perform well in *Vitis vinifera* L. cv. Zinfandel vines, explaining up to 86% of the variation in the lysimeter ET rate over three seasons [119].

The second first-principles-inspired HRI model, the Mass Balance (MB) model, is based on the concept of the conservation of mass, which states that in any closed system, mass is constant. In the case of a plant canopy, this means that the mass flow rate of water out of the canopy is equal to the mass flow rate of water into the canopy plus the mass flow rate from the plant. However, in order for this theory to be used for estimating the ET rate, it is assumed that the cross-sectional area of the canopy is constant, as is the velocity of wind through the plant. With these assumptions, the ET rate can be calculated as a product of the bulk velocity of air, the cross-sectional area of the canopy, and the difference between the absolute humidity outside and inside the canopy. To capture the characteristics of air flowing out of the canopy and air flowing into the canopy, meteorological sensors are mounted both inside and outside of the canopy but the ideal location of these sensors, specifically the sensor outside the canopy, is not obvious. Typically, the outside of canopy sensors is mounted downwind of the canopy, given the prevailing wind direction. This is a problematic assumption though, which does not consider the seasonal and diurnal variability of wind speed and direction [119]. Researchers suspect the sensitivity to sensor placement to be the reason the MB model was observed to be the most variable over three seasons, explaining between 7% and 91% the variability in the lysimeter ET rate [119].

The third HRI model is called the empirical model (EM) because it was selected by researchers using only statistical methods from a set of more than 25 candidate models, exploring mass flux as a function of various combinations of biometeorological parameters. The goals of EM model development were generalizability and dimensional reduction. In addition to computational efficiency, dimensional reduction has the added benefit of reducing the number of sensors that would need to be included in the low-cost sensors being developed in tandem with the HRI project. The final EM model was selected because in addition to achieving reduced dimensionality, it also performed well in terms of ET predictions when compared to other candidate models [119].

Unlike the other HRI models, the EM model only includes bulk wind speed and air temperature parameters as well as the interaction of these parameters. This approach assumes that humidity measurements and related parameters are not strong enough predictors of the ET rate to be included in a model designed to explain variation in mass flux and inform irrigation decisions. Despite having no physical meaning, researchers observed the EM model to perform well in a viticulture setting, explaining between 57% and 92% of the variation in lysimeter ET over a three-year period [119].

Once mass flux has been calculated using one of the three HRI models, it is possible to calculate ET. Each HRI model generates an estimated instantaneous mass flux for every two-minute interval. This mass flux ($\dot{m}_e$) is integrated over time and multiplied by a plant scaling coefficient (A_s), giving estimated ET [Equation (9)].

$$ET = A_s \cdot \int_0^t \dot{m}_e dt \tag{9}$$

In Jenkins et al.'s work, 2023 [119], the researchers calculated model-estimated ET over the span of a single hour, surrounding solar noon and a full day, then compared this to lysimeter measurements. Together, the models explained nearly 63% of the variability in hourly lysimeter ET and 82% of the variability in daily lysimeter ET. Compared to eddy covariance and crop coefficient methods, the HRI method explains a similar amount of the variation in reference ET.

While the observed correlations with ET persisted over multiple plants and multiple seasons, results indicated that an accurate prediction of ET depends on an accurate calculation of the plant scaling term, which varies with the plant and over time. The area terms for two of the models, CMT and MB, have an actual physical meaning (leaf area for CMT and canopy cross-sectional area for MB), but the area term in the EM does not. In order to expand the generalizability of HRI estimates and encourage industry adoption, it will be essential for researchers to develop methods for the direct calculation of area terms from physical data such as ground-based imagery collected during normal tractor passes. A downstream image analysis could be automated using a deep learning approach, similar to the approach used in [147], to extract physical parameters of the vine that are well correlated with model area terms.

4. Distribution Systems

Fine-scale ET estimates and automated water status sensing may shed light on the previously undetectable heterogeneity of water demand at small spatial scales, even individual plants [37,119], but this knowledge is not very useful without an irrigation system that can accomplish differential water delivery based on this information. Recent research has shown that remotely sensed data including LAI and NDVI may be used to identify areas of relative homogeneity within an overall heterogeneous growing area [148]. These sub-areas of homogeneous conditions are considered management zones, and may be identified from LAI and NDVI data using time-series clustering if fine-scale ET estimates and high-density automated water status are not available. However, not all agricultural areas are appropriate for a broad subdivision of growing areas into several or even tens of management zones. In some growing areas, the landscape is too uneven and heterogeneous to identify any areas larger than 10 square meters with consistent conditions. In others, management practices such as rogueing for disease control, or the spatial dynamics of water demand over time, may necessitate higher-resolution irrigation control to achieve optimal plant health.

Once information about the spatial distribution of water demand is available, through fine-scale ET estimates and automated water status sensing or via remotely sensed approximations, it is important to choose an appropriate water delivery system. If time-series clustering results indicate that the growing area in question is characterized by a temporally stable patchwork of a small number of homogenous areas, it may be optimal to use an irrigation zoning technology such as the one from Verdi that allows growers to monitor the health of each zone and adjust settings remotely (Verdi, Vancouver, BC, Canada). If, however, time-series clustering results indicate that the growing area in question consists of a small number of homogenous areas but these areas are not stable through time, a more dynamic approach may be needed. If there are several distinct seasonal stable states of stable homogeneous zones, then perhaps a Verdi Ag-style system could be developed for all seasons and adapted from season to season. However, if the dynamism of the location of homogenous areas is not predictable, then a system that allows for irrigation delivery at the single plant level may be most appropriate. It is also possible in some extremely heterogeneous environments or in particularly high-value cropping systems such as some vineyards or indoor cannabis or cut flower farms that fine-scale individual plant control will be the most appropriate choice for achieving highly valuable yield and quality outcomes.

Any system designed to deliver water to plants based on their individual needs, or the needs of small groups of plants, would consist of a high density of water delivery equipment such as valves and flow sensors. In order to be useful, this armada of water delivery hardware must have access to power, a system for harmonious and reliable communication, and sufficient computational power.

To be functional at scale, high-precision water delivery equipment would need to be low-powered, but still operate 24 h a day in harsh conditions and often in remote locations without access to grid power. In these situations, researchers have had success using portable solar energy harvesting panels as well as large-capacity lead-acid batteries to power field equipment [98,119]. Miniaturized versions of this technology could be used to power groups of valves, though choosing the location of solar panels would be important to ensure sufficient sun coverage while also not interfering with plant management practices. Also, batteries will need to be resistant to outdoor environmental conditions including many extreme temperature cycles as well as having high energy density. Thanks to recent advances in lithium iron phosphate battery technology including an improved thermal stability, long lifespan, and low risk of combustion, this may be possible [149]. However, changing thousands of batteries may require too many natural resources and labor to be sustainable, especially if the batteries cannot be easily recycled. In situations where grid power is available at growing sites, it could also be possible to use irrigation lines with incorporated low-voltage power lines, providing a constant supply of power to valves and other devices mounted along the lines.

Even if power is available to all the irrigation equipment, in order for this equipment to function properly and deliver water only when conditions warrant it, it is essential that spatially distributed devices can rapidly and reliably communicate with each other. In the case of powering irrigation valves with wires embedded in tubing, it would be possible to also include communication wiring in this tubing. This method would ensure that devices communicate with each other and any central nodes, and data could be sent from any central nodes to control each device or many simultaneously. However, in the absence of irrigation tubing with embedded wires or a similar wired solution, low-power wide-area networks may provide the best option. Low-power wide-area networks are an ideal option for low-power IoT devices in agricultural settings.

Several low-power wide-area networks have been investigated for their applicability to large-scale deployment of networks of devices in rural settings. The Long-Range Wide-Area Network (LoRaWAN) is a low-data-rate communication protocol specifically designed for minimum energy budget applications and the longest range coverage for communication [150]. Another popular low-power wide-area network technology, called Narrowband IoT (NB-IoT), was developed for efficient connectivity in cellular IoT networks and to optimize for minimal power consumption [150]. A third option, Sigfox, was designed for IoT applications operating with only small infrequent data packets. This technology transmits in the sub-gigahertz range, allowing for extremely low-power consumption, and because sensor networks are managed by Sigfox, infrastructure management is relatively simple compared to other options (Sigfox, Labège, France) [151].

Overall, while each of these technologies show great potential to support development in different areas of IoT innovation, research has shown that the NB-IoT option may be the most promising for agriculture applications. With NB-IoT, there is the distinct advantage of being able to connect massive numbers of devices, more than fifty thousand, to a single node, whereas LoRaWAN and Sigfox are limited to thousands of connections per node [152]. Furthermore, because it supports larger numbers of devices with a low packet error rate, NB-IoT is thought to have better scalability properties than LoRaWAN [153]. In terms of coverage, NB-IoT seems to be the frontrunner. In one study, it was found that LoRaWAN could not provide sufficient indoor coverage, while NB-IoT achieved connectivity with less than a 5% error rate [154]. Another study demonstrated that NB-IoT has the best coverage probability, even though link loss with devices was slightly higher when compared to LoRaWAN [155]. Perhaps the most compelling evidence for NB-IoT's promise was a comparative study in rural and urban areas in 2020, which showed in a real-life scenario that NB-IoT outperformed LoRaWAN. Researchers attributed the relatively better performance of NB-IoT to directional antennas that allowed for better coverage to devices [156].

Beyond the energy and communication needs of the irrigation distribution system are the computational needs. Though irrigation control and status monitoring would likely require very little onboard computation, if any, it is possible that the data communication and analysis centers used for irrigation control could also be used for meteorological data storage and processing, as described in [119]. Whether or not this is the case, onboard computation hardware would include a low-power consumption design, low-power communication protocol compatibility, and the ability to control low power and valves. However, ideally, onboard computation hardware would also include the ability to receive and store data from flow, meteorological sensors and water status sensors, and sufficient computation power to perform some onboard analyses. Especially if fine-scale ET sensors such as those in the HRI approach are used in combination with a single plant or a high spatial density of irrigation control, then it will be important to strike a balance between onboard computation and the transmission of raw data in order to achieve optimal energy efficiency.

5. Discussion

Capitalizing on the potential for ET sensing technologies to improve irrigation management will be crucial to sustaining agricultural industries amidst rising global competition for water resources. Especially in high-value cropping systems such as grapes or tree fruits and nuts, ET sensing will be important to reducing water use without preventing growers from continuing to hit economically important yield and quality targets [18], that is, higher water use efficiency. Beyond higher efficiency, in some high-value crops like grapes, proper timing of deficit irrigation can improve quality at harvest. Given this knowledge, in order to fully realize the water use reduction and quality outcomes associated with a well-designed irrigation management system, growers need to be able to understand and measure water demand. In this case, water demand represents the integration of two concepts, how much water plants are using and when plants need this water to be replaced. Combining water use and water status signals, growers can understand the water demand of crops but the resolution of this understanding is fundamentally defined by the resolution of ET and water status measurements (Table 1).

Many of the ET estimation options available to growers were designed for performance at spatial resolutions greater than 10 m. These technologies were originally developed for situations in which a host of field-level research-grade sensors are available, as is the case with the original Penman–Monteith approach [43], or alternatively for situations where there is little or no access to field-level meteorological data, as is the case with some remotely sensed methods [24,67]. While most of the methods for estimating coarse-scale ET are adaptations of the original Penman–Monteith model, others rely on direct measurements of the environment and empirical correlations for estimating parameters and then ET. Independent of their origin, each of the coarse-scale approaches relies on some assumptions that limit their generalizability.

For example, in order to calculate estimates of ET using the SEBAL approach, researchers must assume that the conditions impacting measurements are not significantly affecting the accuracy of measurements and therefore ET estimates. In practice, this assumption is often violated, as orbiting satellites with spectral cameras routinely encounter obstructions such as clouds, dust, or other airborne particles [83]. In the Penman–Monteith approach, many of the factors influencing ET are taken into account, but some soil characteristics are not included, such as salt stress. The assumption that salt stress can be ignored negatively affects this model's accuracy in situations where salt stress is limiting root uptake of otherwise available water [49]. The foundation of the Priestley–Taylor model is rooted in an assumption that the aerodynamic resistance term in the original Penman–Monteith model can be well represented by a dimensionless constant. While the use of this constant expands the utility of the Priestley–Taylor approach beyond the scope of other Penman–Monteith-style approaches, it also restricts the model to situations without advective conditions [61]. The reference ET and crop coefficient approach is similarly dependent on the acceptance of at least one assumption. In this case, it is assumed that crop coefficients are generalizable despite reports of up to a 40% difference between crop-coefficient-adjusted FAO56 Penman–Monteith-based reference ET estimates and local estimates [20]. Despite the fundamental concept of energy balance in a closed system, in the eddy covariance approach for estimating ET, the average observed energy closure is reported to be about 75% in vineyards. Furthermore, when growers apply methods to redistribute the residual energy to other terms in the energy balance model, this can lead to uncertainty in daily estimates of ET up to 50% [17].

Other methods for estimating ET were developed for performance at fine spatial scales of less than 10 m. These methods are especially useful in high-value cropping systems where heterogeneity of terrain is a common feature of growing areas. Landscape heterogeneity such as soil differences, slope angle, shade, and edge effects, as examples, as well as genetic and phenotypic heterogeneity, can all lead to differences in water demand. Even more, in some high-value cropping systems such as vineyards and orchards, it is common to observe rogueing or replacement as disease control and recovery management strategies. In situations such as these, fine-scale ET methods along with water status sensing will empower growers with knowledge of the spatially heterogeneous water demand in their growing areas. However, like the methods for coarse-scale ET estimates, fine-scale methods also rely on assumptions that limit their applicability.

For example, informing irrigation decisions with sap flow and microtensiometer data requires accepting the assumption of generalizable-crop- and -cultivar-based trunk water status thresholds [30]. When using leaf-level gas exchange measurement systems to estimate whole-plant ET, it is assumed that upscaling methods are accurate, even though these methods include empirical relationships between plant morphology and measurements of LAI and light response, which have not been extensively validated [141]. Even simple methods such as using infrared sensors to measure leaf surface temperature rely on the assumption of adequate conditions for measurement; otherwise, measurement error caused by particles in the air like dust or smoke may be ignored [145]. The HRI models also rely on assumptions of environmental conditions in order to calculate estimates of ET. The CMT model assumes saturated boundary layer conditions of all leaves and laminar flow of air over these surfaces, while the MB model assumes a constant cross-sectional area of the whole plant.

Each of these approaches to ET estimation show great potential for improving irrigation management in different sectors of agriculture, but determining the most appropriate method for a particular setting can be challenging. Choosing how to measure ET requires striking a balance between achieving yield and quality goals while also minimizing overhead and operational costs. Though some landscapes are highly heterogeneous, planted with very-high-value crops, and represent ideal use cases for high-resolution irrigation systems along with fine-scale ET sensing technologies, economic limitations or knowledge access may prohibit the use of these technologies, especially as they are still being developed. Also, the correlation between increasing spatial resolution of ET estimates and increasing costs associated with installing and operating them leads many growers towards compromising on spatial resolution and accuracy in order to achieve low costs. According to a recent survey conducted by the Almond Board of California, 89% of farmers in California still use the hand feel method for scheduling irrigation, though a notable fraction reported using science-based methods, too [29]. Crop ET estimates were used by 75% of respondents, soil moisture sensors were used by 61%, and 23% reported using water district estimates. Another 43% of respondents reported measuring water status with microtensiometers and 31% reported monitoring water status with pressure chambers.

Ultimately, the choice of ET and water status sensing method must be compatible with irrigation system design. If the growing area in question is mostly homogeneous in terms of landscape and will be planted with an isogenic or a morphologically stable crop, then a low-cost-per-area coarse-scale estimate of ET would likely be sufficient. For areas such as these that do not require a high spatial resolution of control over water delivery, the current industry standard approach of block-based irrigation would likely be sufficient to achieve agronomic goals. However, if the environment necessitates sub-block-level control, growers may benefit from choosing a fine-scale estimate of ET along with a plant-level or sub-block-level irrigation system design.

The future of ET research looks promising. The potential for operational applications of several new and innovative technologies is substantial and will address the growing need for higher-resolution, lower-cost, and more reliable ET sensing and water delivery systems. Single-plant ET methods have recently undergone advancements, with important findings that will improve how growers determine water status or when to apply water [31] and water use or how much water to replace [119]. There is also research being performed to improve high-resolution water delivery systems. Even with recent advances in variable rate drip irrigation [157], systems will need to be developed that can simultaneously measure dispensed water and modulate water flow, to achieve the ideal of truly single-plant resolution delivery. Coarse-scale ET technologies are improving as well, with recent advances in eddy-covariance-based estimates and remote sensing technologies. For example, a two-source energy balance approach including the eddy covariance technique was recently successfully applied in an environment with significant advective conditions [158]. Also, remote sensing was recently shown to be an effective means of estimating daily ET, and identifying distinct irrigation management zones within a larger block of crops [76,148].

Unfortunately, though, honing the spatial resolution of ET technologies and improving the accuracy of estimates will not be sufficient for achieving widespread acceptance in commercial agriculture. Technologies simply delivering utility may earn acceptance among the scientific community, but the alleged target audience of our work in the irrigation space, the grower, has historically been more challenging to engage. To bridge the gap between the scholars and the growers, the future workforce in this space will need to seriously consider how to make water use and water status information available to growers in a practical, digestible format. Eliminating friction at all steps—from the acquisition, installation, and operation of hardware to dealing with routine maintenance or troubleshooting, as well as in user interfaces where carefully curated results may be absorbed or just as easily ignored—will be essential to driving the acceptance of ET technologies beyond the borders of the ivory tower.

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