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Review

Introductory overview: Evapotranspiration (ET) models for controlled environment agriculture (CEA)

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ABSTRACT

Evapotranspiration (ET) is the total amount of water lost from evaporation and transpiration via plant growing media and plant surfaces. ET models have been widely researched for outdoor plants, forests, and wetlands. However, studies on ET models for controlled environment agriculture (CEA) are limited. Reliable predictions of ET in CEA are essential for quantifying the performance of CEA systems. This review focused on evaluating the twelve existing ET models that have been used for indoor ET estimation. Also, we provided an overview of the key parameters that affect ET in existing ET models and different calibration methods for ET models. We summarized existing studies on crop coefficient and stomatal conductance and reviewed case studies that utilized ET models for different CEA applications. We identified research gaps in ET modeling and highlighted research needs for ET parameter interdependence, validation of existing models for indoor farming, and a comprehensive crop resistance model.

1. Introduction

Vertical farming as the expansion of controlled environment agriculture (CEA) advances urban food production. A key advantage to CEA is that food production can be located anywhere such as in urban or rural areas, thereby reducing food miles, carbon emissions, and improving food quality. Also, climatic variables in CEA can be controlled to optimize yield, shorten production time, or extend cultivation over a full cropping season. Compared to traditional open-field cultivation, it has the potential to significantly improve crop yield and water efficiency (Junzeng et al., 2008; Avgoustaki and Xydis, 2020).

Evapotranspiration (ET), the total amount of water lost from evaporation and transpiration via plant growing media and plant surfaces, is the major avenue for plants to lose water and exchange energy with their surroundings. ET plays a vital role in water and energy efficiency for CEA. About 99% of the water taken up by plants is lost via transpiration, with only 1% being used for metabolic activities (Rosenberg et al., 1983). Plants use this process to transport nutrients from the growing media. In hydroponic cultivation, ET estimation is crucial for water management due to the lower water holding capacity and limited volume of substrates. Furthermore, ET significantly contributes to an energy balance through mass and heat transfer in CEA, which maintains favorable environmental conditions for plant growth.

Besides ET measurements in the field using various methods such as lysimeters (Junzeng et al., 2008), substrate water balance (Cannavo et al., 2016), eddy covariance (Tanny et al., 2006), and sap flow gauge (Villarreal-Guerrero et al., 2012), ET models have been developed to predict crop ET from climatic parameters or in combination with crop physiological characteristics. ET models can be classified into reference, physical, and data-driven ET models. Reference ET is the ET rate from a reference surface (e.g. grass or alfalfa) and is represented by climatic formulas that were calibrated against lysimeter measurements from multiple locations (Wright, 1996; Allen et al., 1994). Such a reference crop is assumed to be a full, well-watered crop canopy. Reference ET models, relatively easy to use, require climatic parameters and a crop coefficient to estimate the actual ET value for a specific crop. Physical ET models are derived from energy balance equations (Allen and Hillel, 2005; Stanghellini, 1987). These models do not require crop coefficients. However, stomatal resistance, aerodynamic resistance, and/or leaf area index are commonly needed in ET estimates using physical ET models. This increases the complexity of using physical ET models. Although ET models have been widely researched for outdoor cultivated plants, forests, and wetlands, there are limited studies on ET models for CEA. The data-driven method utilizes statistical regression or machine learning methods to predict ET based on measurement data. It usually

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Nomenclature

a	Albedo [-]
A	Plant Leaf Area [cm^2]
ac	Absorption Coefficient [-]
AF	Adjustment Factor Equal to 0.19 for Coastal Zones [-]
b	Empirical Parameter [-]
c	Resistance Model/Coefficient Constants [-]
C	FAO Penman-Monteith Constants [-]
CAC	Cultivation Area Cover [-]
CAI	Canopy Area Index [-]
Cc	Canopy Resistance Coefficient [-]
Cp	Specific Heat of Air [MJ/kg °C]
Cs	Soil Surface Resistance Coefficient [-]
d	Zero-Plane Displacement Height [m]
dc	Diffusion Coefficient [-]
E	Evaporation [mm/day, mm/h, W/m^2]
ek	Extinction Coefficient [-]
ET	Evapotranspiration [mm/day, mm/h, W/m^2]
f	Jarvis Model Mathematical Functions [-]
g	Conductance [m/s]
G	Soil Heat Flux [MJ/m^2 day]
GDD	Growing Degree Day [°C/day]
Gr	Grashof Number [-]
h	Convective Heat Transfer Coefficient of Air [W/m^2 °C]
H	Crop Height [m/mm]
I	Radiation [W/m^2]
J	Total Available Energy [W/m^2]
k	Thermal Conductivity [W/m °C]
K	Empirical Parameters [-]
Kc	Crop Coefficient [-]
Kcb	Basal Crop Coefficient [-]
Ke	Soil Evaporation Coefficient [-]
Kr	Surface Soil Evaporation Attenuation Coefficient [-]
l	Characteristic Leaf Dimension [m]
L	Leaf Length [m]
LAI	Leaf Area Index [-]
Nu	Nusselt Number [-]
$PPFD$	Photosynthetic Photon Flux Density [μmol/m^2/s]
Pr	Prandtl Number [-]
r	Resistances [s/m]
Rc	Reflection Coefficient [-]
Re	Reynolds Number [-]
RH	Hourly or Daily Mean Air Relative Humidity [%]
rl	Roughness length of reference surface [m]
S	Sensible Heat Flux [W/m^2]
Sa	Salinity [g/kg]
SP	Proportion of Soil between the Soil and the Evaporation of the Soil [-]
t	Time [day]
T	Hourly or Daily Mean Air Temperature [°C]
Tc	Crop Transpiration [mm/h]
U	Hourly or Daily Mean Air Velocity [m/s]
VPD	Vapor Pressure Deficit [kPa]
W	Leaf Width [m]
WAP	Weeks After Planting
WF	Wind Function [-]
x	Reference Measurement Height [m]
z	Wind Speed Measurement Height [m]
α	Priestley Taylor Coefficient [-]
β	Bowen Ratio [-]
γ	Psychrometric Constant [kPa/°C]
Δ	The slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
λ	Latent Heat of Vaporization [MJ/kg]
λET	Latent Heat Flux [W/m^2]
ρ	Density [kg/m^3]
τ	Transmissivity [-]
χ	Vapor Concentration [g/m^3]
ΔT	Temperature Difference [°C]

Subscripts

a	Air/Aerodynamic (Crop)
abs	Effectively Absorbed
b	Boundary Layer
c	Crop Evapotranspiration
e	Aerodynamic (leaf)
eff	Effective
est	Estimated
g	Ground-Level
i	Stomatal (leaf)
ini	Initial Value
l	Leaf
max	Maximum
mid	Intermediate Value
min	Minimum
n	Net
nl	Long Wave
ns	Short Wave
o	Reference Evapotranspiration
p	Pan
R	Radiative
s	Surface (Canopy)/Stomatal (Crop)/Soil
sc	Calculated Solar Radiation
t	Unit Conversion [86400 s/day, 3600 s/h]
w	Evaporative Surface/Water
x	Extraterrestrial Solar Radiation
z	Wind Speed Measurement Height [m]

Superscripts

a	Between Mean Canopy Flow and Reference Height
c	Canopy
s	Soil

requires a large amount of data to train the ET model.

This review focused on evaluating the twelve existing ET reference and physical models that have been used for indoor ET estimation. Also, we provided an overview of the key parameters that affect ET in existing ET models and different calibration methods for ET models. We summarized existing studies on crop coefficient and stomatal conductance models and reviewed case studies that utilized ET models for different CEA applications. In the end, we identified research gaps in ET modeling research and highlighted research needs for ET parameter interdependence, validation of existing models for indoor farming, and a comprehensive crop resistance model.

2. Parameters that influence ET

Evaporation and transpiration occur simultaneously and are difficult to separate (Allen et al., 1998). At an early stage, crop ET is roughly 100% due to evaporation, while at full crop cover, ET is about 90% transpiration (Fazlil-Ilahil, 2009; Lozano et al., 2017; Sigalingging and Rahmansyah, 2018; Prenger et al., 2002). The parameters that influence ET can be categorized into three groups: climatic, plant physiological, and cultivation practices.

2.1. Climatic parameters

Climatic factors have the most influence on crop ET as well as growth. Such factors include net radiation, air temperature, relative humidity, and air velocity. Desired values for these climatic parameters were presented on common greenhouse cultivated crops (Nau, 2011; Baudoin et al., 2017; Currey et al., 2019; Meinen et al., 2018; Carney et al., 2016; Delavar et al., 2016; Drost, 2015; Duan et al., 2014; Peckenpaugh, 2004; Karlsson, 2014; Wei, 2016; Fairbanks, U.o.A. Greenhouse gardening, 2013; Europe, 2020; Struik and Wiersema, 1999; Zha and Liu et al., 2018; Incrocci et al., 2006).

Net radiation is the balance between incoming radiation to crops and outgoing radiation from the crops (Takakura et al., 2009). An increase in net radiation consequently could lead to an increase in the ET rate (Zhang et al., 2010; Jolliet and Bailey, 1992; Baille et al., 1994; Kittas et al., 1999). In considering both evaporation from the growth substrate and transpiration from plants, Villarreal-Guerrero et al. (2012) found radiation to account for about 60% of the estimated ET from the Stanghellini (Stanghellini, 1987), Penman-Monteith (Monteith, 1965), and Takakura (Takakura et al., 2005) models. While considering only transpiration from plants, Montero et al. (2001) found the radiation term to represent about 80% of the total crop transpiration during the early hours after sunrise using the Penman-Monteith model (Monteith, 1965).

Another important parameter is air temperature. Each crop has an optimal range for which temperatures must be maintained for optimal crop production. The increase of ambient temperature in CEA could increase crop ET rate (Zhang et al., 2010; Pamungkas et al., 2014; Graamans et al., 2017; Gallardo et al., 1999; Liu et al., 2008). Thermal energy transfer from warm air to crops increases evapotranspiration rates.

Vapor pressure deficit (VPD) measures the difference between saturated vapor pressure and actual vapor pressure. The relationship between ET and VPD can be more complicated than the other environmental parameters. Rather than considering VPD as an independent parameter, Monteith (1995) suggested that VPD was the outcome of the interaction between vegetation and the ambient environment. In a study by Boulard and Jemaa (1992), for hourly ET estimation, VPD significantly influenced ET (up to 43%). Prenger et al. (2002) also found both VPD and radiation to have strong correlations with ET. Liu et al. (2008) found daily banana ET to strongly depend on the mean air temperature and VPD.

Air velocity influences aerodynamic resistance and ET. Proper air circulation in CEA is required to prevent the spread of diseases by avoiding wet spots. Air velocity is less than 0.2 m/s in a closed typically CEA (Casanova et al., 2009; Fernández et al., 2010) but could be much higher for naturally ventilated CEAs (Libardi et al., 2019; Jaafar and Ahmad, 2018). The increase of air velocity decreases aerodynamic resistance and increases crop ET (Ahmed et al., 2020; Jolliet and Bailey, 1992). However, compared to other climatic parameters, the effects of air velocity on ET are small.

2.2. Plant physiological parameters

Plant physiological parameters such as leaf area index (LAI) and stomatal resistances (r_i) have been used to predict ET rates.

LAI is the ratio of the total leaf area to the cultivation surface or ground area and is an important parameter for physical ET models such as the Stanghellini model (Stanghellini, 1987). In some studies, LAI was calculated with leaf dimensions (length, width) and/or plant density (Kage et al., 2000; Demrati et al., 2007; Kittas et al., 1999; Salcedo et al., 2017) through measurements on a periodical basis (weekly or biweekly) (Cannavo et al., 2016; Villarreal-Guerrero et al., 2012; Baille et al., 1994; Pamungkas et al., 2014; Boulard and Jemaa, 1992; Toyin et al., 2015; Acquah et al., 2018; Yang et al., 1990). Image analysis software such as Image J (Gao et al., 2011; Martin et al., 2013; Ahmad et al., 2015) and Easy Leaf Area (Ahmad et al., 2015; Easlon and Bloom, 2014) can be used in estimating leaf area. LAI can be predicted by non-linear regression models as functions of crop thermal time (Salcedo et al., 2017; Carmassi et al., 2013; Rouphael and Colla, 2004) or days after sowing (DAS) (Medrano et al., 2005) as well as by crop growth models such as TOMGRO (Battista et al., 2015; Bacci et al., 2012).

Leaf stomatal resistance also affects ET, with an inverse relationship (Ali et al., 2016). At lower stomatal resistance, the stomata open and so allows the exchange of gas including water vapor, hence the increased ET rates, and vice versa. Stomatal resistance varies with the type of crop, environmental conditions, and water availability. Leaf stomatal resistance can be measured using a leaf porometer or infrared gas analyzer (IRGA). A recent study comparing leaf stomatal conductance measured using a leaf porometer and an IRGA suggested that calibration of the leaf porometer using IRGA would be necessary (Toro et al., 2019). Efforts have been made to develop stomatal resistance models which can be used for real-time estimation based on easy-to-measure parameters such as air temperature, VPD, and light levels. Stomatal resistance modeling is further discussed in depth in Section 3.2.2.2.

Also, leaf temperature is another important driver of ET. Leaf temperature represents the outcome of energy balance between plants and the ambient environment (Yang et al., 1990). Leaf temperatures were reported to be lower than air temperatures during the daytime (Montero et al., 2001; Yang et al., 1990; Rouphael and Colla, 2004) in some studies, while leaf temperatures were reported to be warmer than air temperatures in other studies of crops grown in greenhouses (Demrati et al., 2007). The relationship between leaf temperature and air temperature depends on the magnitudes of terms related to net radiation and vapor pressure deficit and the amount of evaporativing cooling (Michaletz et al., 2016).

2.3. Cultivation practices

Various cultivation practices also influence crop ET. For example, the types and composition of substrate or soil play a key role in regulating ET rates. Soils with a better water holding capacity can increase the amount of water available for ET while those with poor water-holding capacities are prone to runoffs and cannot promote increased ET. In a study by Ondrašek et al. (2007) comparing Rockwool, peat, and perlite, they found the ET rate to depend on the water holding capacity of the substrate. ET rates were lower in perlite due to its low water holding capacity. Therefore, the characteristics of the substrate should be considered in planning irrigation management strategies. These characteristics include porosity, particle sizes, permeability, thickness, and compactness (Cascone et al., 2018).

The salinity of the grow media also affects crop ET, decreasing linearly with an increase in salinity (Blanco and Folegatti, 2003). Increased salinity reduces the leaf water content, increasing stomatal resistance, and ultimately reducing the ET rate (Boulard and Jemaa, 1992).

Irrigation management techniques also influence crop ET. Depending on the level of irrigation deficit, water available for plant ET may be affected. Reference ET models however apply to well-watered conditions with no crop water stress. However, this is sometimes far from reality where water conservation requires that the right amount of water be supplied to reduce water use but also maintain a high crop yield. Irrigation level and frequency, therefore, affect crop ET. In a study by Chopda et al. (2018) investigating the effect of five manageable allowable depletion (MAD) levels: 10%, 20%, 30%, 40%, and 0% (the control in which the farmer irrigates every 7 days), the highest ET rate and crop yield were recorded at 10% MAD and the lowest at 40% MAD. Cannavo et al. (2016) also found that reducing irrigation levels to 75% of the reference, well-watered scenario, or greater had no severe effect on crop ET. As for the frequency of irrigation, they found irrigating once a day or more to be suitable for optimal crop ET.

The most controlled factor that defines a CEA is climatic. However, other factors such as irrigation practices and substrate salinity also play very important roles. In water stress conditions, even if incoming radiation, and vapor pressure deficit conditions are favorable, the ET rate would be low and could affect crop productivity. Therefore, careful attention should be paid to these factors to ensure that the plant ET rate is maintained at desired levels. In highly controlled CEA, these factors are usually continuously monitored and controlled for optimum crop yield. Existing studies have been focused on the effects of single parameters on ET rates. further research that considers the interdependent nature of these parameters on the ET rate should be further pursued. For example, an increase in temperature increases ET, however, this could be counterbalanced by an increase in resistance in the presence of increased CO_2 levels (Moriondo et al., 2015; Savabi and Stockle, 2001). The techniques of machine learning could help gain some insight into such interdependency, as well as in engineering new features as in the case of VPD, which could combine some of these parameters into a new one that better describes ET rates.

3. ET models for CEA

Although ET measurements can be conducted in the field, mathematical ET models are easy to implement, non-destructive, and suitable for real-time ET estimations. In this section, we categorize existing ET models into reference ET models, physical ET models, and data-driven ET models.

3.1. Reference ET models

Reference evapotranspiration is the evapotranspiration from a hypothetical, well-irrigated reference crop. Only climatic factors are considered in the ET estimation from reference ET models, specific crop physiological factors and soil factors are ignored. The accuracy of reference ET models depends on the type of reference used, measurement, and modeling as well as the accuracy of the crop coefficient used. The following sub-section looks at five commonly used reference ET models in CEA applications. It also discusses crop coefficients, an important parameter in computing the actual ET from reference ET.

3.1.1. Model descriptions

3.1.1.1. Priestley Taylor. This model, introduced by Priestley and Taylor (1972) ignores the aerodynamic term but uses the net radiation term in estimating ET. The aerodynamic term is instead replaced by a dimensionless multiplier α known as the Priestley-Taylor coefficient. The model equation is given in Equation (1):

$$ET_o = \alpha\frac{1}{\lambda}\frac{\Delta}{\Delta+\gamma}(I_n - G) \tag{1}$$

where:

ET_o –Daily Reference Evapotranspiration [mm/day]
α –Priestley Taylor Coefficient [-]
λ –Latent Heat of Vaporization [MJ/kg]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily or Hourly Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]

The coefficient α can be expressed as:

$$\alpha = \left(\frac{(1+\gamma/\Delta)}{1+\beta}\right) \tag{2}$$

whereβ is the Bowen ratio and takes a value of 0.6.

Transpiration can be calculated based on ET and LAI as follows (Droutsas et al., 2019):

$$Tc = ET_o\left(1 - e^{-ekLAI}\right) \tag{3}$$

where:

Tc –Crop Transpiration [mm/day]
ET_o –Daily Reference Evapotranspiration [mm/day]
ek –Extinction Coefficient [-]
LAI –Leaf Area Index [-]

The Priestley-Taylor model gives good estimates in low advection conditions which prevails in some CEAs. In a study by Sharma et al. (2017), the Priestley-Taylor model was found to underestimate the ET of chile peppers by 17.5–37%, due to the absence of the advection term in its equation. The experiment was performed in a greenhouse located in New Mexico, equipped with evaporative coolers, exhaust fans, and automatic temperature controls.

3.1.1.2. FAO-24 radiation. This model, based on solar radiation was developed by Doorenbos and Pruitt (1977). The equation of this model is given in Equation (4):

$$ET_o = \frac{b}{\lambda}\left(I_g\frac{\Delta}{\Delta+\gamma}\right) - 0.3 \tag{4}$$

where:

ET_o –Daily Reference Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_g –Ground-Level Solar Radiation [MJ/m^2 day]
b –Dimensionless Parameter [-]

The dimensionless parameter b is expressed as:

$$b = 1.066 - 0.13\times10^{-2}\cdot RH + 0.045\cdot U - 0.20\times10^{-3}\cdot RH\times U - 0.315\times10^{-4}\cdot RH^2 - 0.11\times10^{-2}\cdot U^2 \tag{5}$$

where:

RH –Daily Mean Air Relative Humidity [%]
U –Daily Mean Air Velocity [m/s]

Casanova et al. (2009) found this model to have an average value of 2.8 mm/day over 9 weeks, compared to measured lysimeter ET which was 1.5 mm/day. Thereby overestimating ET by 87% on average for ET estimation for lettuce in a chapel-type greenhouse in central Chile. In a study by Liu et al. (2008) on greenhouse banana ET estimation, the FAO Radiation model underestimated ET by roughly 40%, having a correlation coefficient of 0.52, and was outperformed by the FAO-Penman and FAO-Penman Monteith models.

3.1.1.3. Hargreaves-Samani. This model was developed by Hargreaves and Samani (1985) and is solely based on temperature and solar radiation as shown in Equation (6):

$$ET_o = \frac{1}{\lambda}(0.0023)(T_{max} - T_{min})^{0.5}(T + 17.8)I_x \tag{6}$$

where:

ET_o –Daily Reference Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
T_{max} –Daily Maximum Air Temperature [°C]

T_{min} –Daily Minimum Air Temperature [°C]
T –Daily Mean Air Temperature [°C]
I_x –Extraterrestrial Solar Radiation [MJ/m^2 day]

The extraterrestrial radiation (I_x) and solar radiation (I_s) can be related as shown in Equation (7):

$$I_s = AF \times I_x \times \Delta T^{0.5} \tag{7}$$

where:

AF –adjustment factor [-]
ΔT – mean maximum minus mean minimum temperature [°C]

Fernández et al. (2010) found the original Hargreaves-Samani equation from above to largely overestimate ET by 66% on average for a Mediterranean greenhouse without whitening. However, it improves with whitening (overestimating by 3%) and when the solar radiation term is multiplied by the greenhouse cover transmissivity τ (underestimating by 5%). Jaafar and Ahmad (2018) also tested a modified solar radiation model in a greenhouse equipped with a suction fan, in Beirut, Lebanon, based on estimates from the following expression:

$$I_{sc} = \tau \times AF \times I \times (\Delta T)^{0.5} \tag{8}$$

where:

I_{sc} – Calculated Solar Radiation [MJ/m^2 day]
τ – Transmissivity [-]
AF – adjustment factor [-]
I – Solar Radiation [MJ/m^2 day]
ΔT – mean maximum minus mean minimum temperature [°C]

3.1.1.4. FAO Penman. This model is an improvement from the original Penman (Penman, 1948) model. It includes a wind function as shown in Equation (9):

$$ET_o = \frac{1}{\lambda}\left[\left(\frac{\Delta}{\Delta+\gamma}\right)(R_n - G) + \left(\frac{\gamma}{\Delta+\gamma}\right)(6.43)(WF)(VPD)\right] \tag{9}$$

where:

ET_o –Daily Reference Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily or Hourly Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]
WF –Wind Function [-]
VPD –Vapor Pressure Deficit [kPa]

The wind function WF could be expressed as:

$$WF = 1 + 0.0536 \cdot U_z \tag{10}$$

where:

WF –Wind Function [-]
U_z –Wind Speed at Height z [m/s]

Liu et al. (2008) found the FAO Penman model to give the best correlation (0.67) for the estimation of banana ET in a greenhouse compared to four other ET models, however, it overestimated ET by roughly 27% on average. The study was performed in a greenhouse in Israel, equipped with cooling fans that operate whenever the temperatures within the greenhouse exceeded 30 °C.

3.1.1.5. FAO-56 Penman-Monteith. The FAO-56 Penman-Monteith model (Allen et al., 1998) is the standard model for estimating reference ET and has been employed in CEA ET estimation with some satisfactory results. It represents ET from an extensive surface of grass crop with a height of 0.12 m, a crop resistance of 70 s/m, and an albedo of 0.23 under non-limited soil water. The equation is given in Equation (11):

$$ET_o = \frac{0.408\Delta(I_n - G) + \gamma\frac{C_1}{T+273}\cdot U_2 \cdot VPD}{\Delta + \gamma(1 + C_2 \cdot U_2)} \tag{11}$$

where:

ET_o –Daily Reference Evapotranspiration [mm/day]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily or Hourly Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]
T –Hourly or Daily Mean Air Temperature [°C]
C_1 *and* C_2 –FAO Penman-Monteith Constants [-]
VPD –Vapor Pressure Deficit [kPa]
U_2 –Wind Speed at Height (z = 2 m) [m/s]

The values of the constants C_1 and C_2 change based on the type of reference crop. These values are presented in Pereira et al. (2015). For wind speeds at heights other than 2 m, the following adjustments can be applied (Stokes et al., 2016):

$$U_2 = U \cdot ln\left(\frac{(z_2 - rl)}{d}\right) \Big/ ln\left(\frac{(z - rl)}{d}\right) \tag{12}$$

where:

U_2 –Wind Speed at Height (z = 2 m) [m/s]
U –Wind Speed at Measurement Height z [m/s]
z_2 –Height = 2 m [m]
z –Measurement Height [m]
d –Zero plane displacement of reference surface = 0.07 m
rl –Roughness length of reference surface = 0.013 m

Generally, crop coefficients obtained using the alfalfa crop reference are usually lower compared to those obtained using clipped grass.

In a low technology greenhouse in Brazil, Libardi et al. (2019) found the FAO Penman-Monteith model to generally underestimate the ET of pre-sprouted sugarcane plantlets between 22.9 and 24.2% across three different cultivars, especially after the second week of planting. This was attributed to an increase in LAI which is not captured by the FAO Penman-Monteith model.

In many low-technology CEAs, air velocities could be approximately zero, therefore, the aerodynamic term in the above model equation could be neglected. Using both single and dual crop coefficients, Wang et al. (2018) found this model to underestimate daily eggplant ET by 1.1% and 3.3% respectively in a naturally ventilated greenhouse in China. It improves if the maximum and minimum temperatures are used alongside the mean temperature in calculating the model parameters (Naoum and Tsanis, 2003). Windspeed was assumed to be negligible, hence it was given a value of zero in the model calculation. However, Zhang et al. (2010) found such modification to give poor estimates for cucumber ET in a solar greenhouse in North-East China, with a correlation coefficient of 0.46. This was attributed to the neglect of the aerodynamic term.

The accuracy of reference ET models depends on the crop coefficients. Therefore, they are usually not preferred especially for situations where crop coefficient values are lacking, or local calibration is difficult to perform. Even for studies that compared reference ET models with physical models, the latter has been found to provide more accurate estimates. However, reference ET models are useful for situations in which some measured climatic parameters are lacking. They are also relatively easy to implement and could give quick rough ET estimates. Of the reference ET models used in CEA ET estimation, the recommended FAO Penman-Monteith model is the most widely used. It can also be used for both daily and hourly ET estimations, adjusting the constants accordingly. The next sub-section further discusses the concept of crop coefficients and how they are derived.

3.1.2. Crop coefficients

The crop coefficient concept was first introduced by Jensen (Jensen, 1968) to relate the ET of the desired crop over a chosen period to a “potential ET”. The Food and Agriculture Organization (FAO) of the United Nations recommends the single and dual crop coefficients method for the estimation of ET from reference ET models. This is because crop coefficients vary strongly with crop characteristics (Dutta et al., 2016) and to a limited extent with climate (Gallardo et al., 1999), therefore, it could be transferred to new locations and climates. For the single crop coefficient method, crop transpiration and soil evaporation effects are combined into a single value, whereas in dual crop coefficients, these two effects are treated separately. Single crop coefficient can be obtained from crop ET measurements and reference ET measurements as shown in Equation (13):

$$Kc = \frac{ET_c}{ET_o} \tag{13}$$

where:

Kc – Crop Coefficient [-]
ET_c –Daily Crop Evapotranspiration [mm/day]
ET_o –Daily Reference Evapotranspiration [mm/day]

Dual crop coefficient can be expressed as shown in Equation (14):

$$(Kcb + Ke) = \frac{ET_c}{ET_o} \tag{14}$$

where:

Kcb – Basal Crop Coefficient [-]
Ke – Soil Evaporation Coefficient [-]

In a study by Wang et al. (2018) on eggplant ET estimation, in a naturally ventilated greenhouse in China, both single and dual crop coefficients were found to give acceptable results (average mean absolute error = 0.23 mm/day and 0.22 mm/day respectively). However, the latter was closer to the measured values because the dual crop coefficient improves the accuracy of the evaporation estimate. It also predicts crop yield better, as crop yield is determined by transpiration more than by evapotranspiration.

Crop coefficients exist for many field-grown crops; however, these values cannot be used for CEA-grown crops because the microclimate is different for each case. A proper evaluation of the crop coefficient is necessary for accurate ET estimation. Crop coefficient values depend on the climatic conditions, type of calibration method and the type of ET model used (Lozano et al., 2017; Liu et al., 2008). They also depend on the irrigation management method used and apply to well-watered, optimal conditions. In situations of water stress, or conditions different from a relative humidity of 45% and wind speed of 2 m/s, adjustments are required to be able to apply FAO standard crop coefficient values (Ragab, 2002). It also depends on the type of crop, growth stage, growing season, and length, as well as the cultivation technique, employed (Pamungkas et al., 2014; Sharma et al., 2017; Perez et al., 2002). For example, for the same type of crop grown in the same conditions, the crop coefficient value can vary between a vertically supported crop and a prostrate crop (Orgaz et al., 2005). This is because the vertically supported crop is capable of intercepting more net radiation. The same applies generally between tall and short crops, with the former having greater maximum crop coefficient values. Crop coefficients can also be affected by frequent wetting of soil surface and could increase to 1 or 1.2 (Allen et al., 1998).

Furthermore, crop coefficient changes with the crop growth stage therefore a constant value cannot be used for an entire cropping season (Blanco and Folegatti, 2003). Zhang et al. (2010) found a poor correlation ($R^2 = 0.46$) between ET_o and ET_c when a constant crop coefficient value was used for the FAO Penman-Monteith model. Also, depending on the period used, the variability could be regular (Orgaz et al., 2005) or irregular (Zhang et al., 2010).

FAO provides recommended crop coefficient values for field-grown crops. In many cases values are given for the three main growth stages of a crop – initial, middle, and end. In the study by Wang et al, (2018), eggplant crop coefficients were obtained using the recommended FAO values as a basis via the following formula:

$$Kc_{est.} = Kc + [0.04(U-2) - 0.004(RH_{min} - 45)](H/3)^{0.3} \tag{15}$$

where:

$Kc_{est.}$ – Estimated Crop Coefficient [-]
Kc – FAO Recommended Crop Coefficient [-]
U – Hourly or Daily Mean Air Velocity [m/s]
RH_{min} – Minimum Hourly or Daily Mean Air Relative Humidity [%]
H – Average height of the crop during the growing period [m]

The above expression is used when the wind speed within the CEA is not 2 m/s and when the daily average minimum relative humidity is not 45%. The same equation can also be used to compute the basal crop coefficient for the dual crop coefficient, replacing the FAO recommended crop coefficient value with the FAO recommended basal crop coefficient value. While the soil evaporation coefficient can be obtained as follows:

$$Ke = Kr(Kr_{max} - Kcb) \leq SP \cdot Kc_{max} \tag{16}$$

where:

Ke – Soil Evaporation Coefficient [-]
Kr – Surface Soil Evaporation Attenuation Coefficient [-]
Kr_{max} – Maximum Surface Soil Evaporation Attenuation Coefficient [-]
Kcb – FAO Recommended Basal Crop Coefficient [-]
SP – Proportion of Soil between the Soil and the Evaporation of the Soil [-]
Kc_{max} – Maximum FAO Recommended Crop Coefficient [-]

However, the soil evaporation coefficient can be ignored if soil evaporation is prevented by mulching.

Crop coefficient values from ET experiments have been correlated with the growing degree day (GDD) for the estimation of crop coefficients. Sharma et al. (2017) developed a relationship between GDD and experimental crop coefficient values to estimate the crop coefficient values for chile peppers. Libardi et al. (2019) also established this relationship and one between the Kc and LAI values for pre-sprouted sugarcane plantlets. In this study, a strong correlation was found between crop coefficients and days after transplanting (DAT), GDD, and LAI. Therefore, a model can be created from these relationships for the estimation of crop coefficients.

Crop coefficients can also be obtained from LAI. For partial cover horticultural crops, that is, with LAI less than 3, the Ritchie and Johnson (1990) approach can be used. First, the leaf area is estimated from the cumulative thermal time (TT) or GDD and a Gompertz function as follows:

$$A = A_{max} exp[-b \cdot exp(K \cdot GDD)] \tag{17}$$

where:

A – Plant Leaf Area [cm^2]
A_{max} – Maximum Plant Leaf Area [cm^2]
b *and* K – Empirical Coefficients [-]
GDD – Growing Degree Day [°C/day]

The crop coefficient can then be obtained as follows:

$$Kc = Kc_{ini} + \left[\frac{Kc_{mid} - Kc_{ini}}{3}\right] \times LAI \tag{18}$$

where:

Kc – Crop Coefficient [-]
Kc_{ini} – Crop Coefficient value for initial crop development stage [-]
Kc_{mid} – Crop Coefficient value for middle crop development stage [-]
LAI – Leaf Area Index [-]

However, for crops such as pepper that get pruned frequently, the above approach cannot be used. Instead, a linear relationship between the crop coefficient and cumulative thermal time using LAI must be obtained. Orgaz et al. (2005) present a regression equation for sweet pepper in a low technology greenhouse in southeast Spain, however, such expression can only be used for sweet pepper cultivated under similar management methods. It would, therefore, need calibration for other environments, the expression is given in Equation (19):

$$Kc = Kc_{ini} + 0.00176 \times (GDD - 200) \tag{19}$$

where:

Kc – Crop Coefficient [-]
Kc_{ini} – Crop Coefficient value for initial crop development stage [-]
GDD – Growing Degree Day [°C/day]

The crop coefficient also relates to the percentage of soil water content as well as weeks after planting (WAP). A regression correlation for the latter was presented by Toyin et al. (2015) as follows:

$$Kc = -0.007WAP^2 + 0.097WAP - 0.005 \tag{20}$$

where:

Kc – Crop Coefficient [-]
WAP – Weeks After Planting

Crop coefficient models have also been derived from climatic variables. Junzeng et al. (2008) derived a relation between crop coefficient and climatic factors for tomato and cowpea. The model was based on air temperature T_A, relative humidity RH, and ground surface temperature T_G as well as some parameter coefficients. The equation for tomato ($\beta = 0.317, \gamma = 0.037, \omega = -0.357, \delta = -1.513$) and cowpea ($\beta = 0.406, \gamma = -0.236, \delta = -4.141$) is shown in Equations (21) and (22) respectively:

$$Kc = \beta T_A + \gamma RH + \omega T_G + \delta \tag{21}$$

$$Kc = \beta T_A + \gamma T_G + \delta \tag{22}$$

where:

Kc – Crop Coefficient [-]
T – Air Temperature [°C]
RH – Relative Humidity [%]
T_g – Ground Surface Temperature [°C]
β, γ, δ *and* ω – Empirical Constants [-]

Crop coefficients play a key role in the simple estimation of ET from reference ET models. They make it possible to obtain accurate ET estimations while avoiding the difficulty of measuring some parameters. Crop coefficients combine several factors such as cultivar, stage of growth, plant density, season length, and canopy architecture into a single value. In many cases, such values could also be transferred from one location to another with little calibration. However, this means that for accurate estimation, local calibration must be performed which could sometimes be time-consuming. Also, only a limited number of CEA cultivated crops have published crop coefficient data, with the need for more studies to confirm the validity of such reported figures. Such studies with published data include typical greenhouse crops such as cucumber (Zhang et al., 2010; Blanco and Folegatti, 2003), tomato (Junzeng et al., 2008; Pamungkas et al., 2014; Acquah et al., 2018; Gong et al., 2019), melon (Lozano et al., 2017; Orgaz et al., 2005) and sweet pepper (Gallardo et al., 1999; Orgaz et al., 2005) as well as other crops such as banana (Liu et al., 2008), chile pepper (Sharma et al., 2017), sugarcane plantlets (Libardi et al., 2019), eggplant (Wang et al., 2018), green beans (Orgaz et al., 2005), water melon (Orgaz et al., 2005), leaf amaranth (Toyin et al., 2015), oil palm (Sigalingging and Rahmansyah, 2018) and cowpea (Junzeng et al., 2008). The validity and reliability of crop coefficient values also depends on the ET experiment design (Allen et al., 2011).

3.2. Physical ET models

Most of the physical ET models in use are based on the thermal energy balance of the canopy as shown in Equation (23). They consider the effects of net radiation I_n, soil/substrate heat flux G, sensible heat flux$S$, and latent heat fluxλET. They also require crop-specific parameters such as aerodynamic and stomatal resistance. Most models are modifications of the Penman-Monteith model (Equation (24)) to better cater to certain conditions. Most models differ in the way they treat the net radiation and resistances to vapor flux. A reason for such modifications could be to avoid the constant measurement and calibration of terms such as the stomatal and aerodynamic resistances. They consider both climatic and crop properties, in contrast, to reference ET models.

$$\lambda ET = I_n - G - S \tag{23}$$

3.2.1. Model descriptions

3.2.1.1. Penman-Monteith model. The Penman-Monteith model (Allen and Hillel, 2005; Monteith, 1965) assumes that a three-dimensional plant canopy can be modeled as a one-dimensional "big leaf". Over this surface, radiation is absorbed, heat is exchanged, and latent energy is released. The equation includes a radiation term and an aerodynamic term. The model equation can be written as in Equation (24):

$$ET_c = \frac{1}{\lambda}\frac{\Delta(I_n - G) + \frac{\rho_a \cdot Cp \cdot VPD}{r_a}}{\Delta + \gamma\left(1 + \frac{r_s}{r_a}\right)} \tag{24}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]
ρ_a –Mean Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
VPD –Vapor Pressure Deficit [kPa]
r_s –(Bulk) Surface or Canopy Resistance [s/m]
r_a –Aerodynamic Resistance [s/m]

In a study by Villarreal-Guerrero et al. (2012), the Penman-Monteith model was found to generally overestimate the evapotranspiration of greenhouse cultivated bell pepper (summer season - natural ventilation and fogging: ~ 21%, $R^2 = 0.95$, summer season - pad and fan: ~ 15%, $R^2 = 0.96$) and tomato (fall season – pad and fan: ~ 11%, $R^2 = 0.51$, spring season - pad and fan: ~ 10%, $R^2 = 0.90$, spring season - natural ventilation and fogging: ~ 13%, $R^2 = 0.94$). The authors attributed this to the fact that the model was originally developed to estimate ET for outdoor conditions. The study was performed in a medium technology greenhouse in Tucson, Arizona, using two cooling strategies (pad and fan cooling, and natural ventilation with high pressure fogging). Zhang and Lemeur (1992) also found the model to overestimate Ficus Benjamina ET by roughly 27% on average, however, it had an R^2 value (0.97) closer to unity. They concluded that this was because the model was sensitive to errors in the calculation of the aerodynamic resistance which they found to be equal to the radiation term, therefore in such cases, the accuracy of the aerodynamic resistance model is crucial.

In another study by López-Cruz et al. (2008), the model was found to generally have a similar R^2 value to the Stanghellini model (0.75) but a much larger root mean square error (17.1 to Stanghellini's 2.4) for tomato ET in a medium technology greenhouse in Mexico. The model performance also depends on the prevailing climatic conditions. In high solar radiation and VPD conditions, the model was found to have a lower R^2 value (0.62) compared to Stanghellini's (0.72).

Zolnier et al. (2004) also found the Penman-Monteith model to have a good correlation with R^2 values ranging from 0.82 to 0.93 for scenarios with LAI greater than 0.5. This was performed for three different cultivars of lettuce, in a greenhouse without environmental controls, located in Brazil. Estimated errors were less than 0.03 mm/h.

In some studies, the net radiation term is expressed as a function of the LAI and extinction coefficient k. This is because the Penman-Monteith equation considers a complete crop canopy which is not the case in practice (Qiu et al., 2013). The net radiation must, therefore, be multiplied by the radiation intercepted by the canopy given as in Equation (25):

$$(1-\tau) = 1 - exp(-ek \cdot LAI) \tag{25}$$

where:

τ –Transmissivity [-]
ek –Extinction Coefficient [-]
LAI –Leaf Area Index [-]

This helps to account for the gradual development of the canopy and improves the accuracy of the ET estimation.

3.2.1.2. Stanghellini model. This model was developed by Stanghellini (1987) specifically for ET estimation in CEA or indoor conditions. It simulates a multi-layer canopy, using tomato crop cultivated in a single glass Venlo type CEA equipped with hot-water pipe heating. It has been extensively used by researchers for CEA ET estimation. The model equation is given as in Equation (26):

$$ET_c = \frac{1}{\lambda}\frac{\frac{\Delta}{\gamma}(I_n - G) + \frac{2 \cdot LAI \cdot \rho_a \cdot Cp}{\gamma r_a}(VPD)}{1 + \frac{\Delta}{\gamma} + \frac{r_s}{r_a}} \tag{26}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]
ρ_a –Mean Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
VPD –Vapor Pressure Deficit [kPa]
LAI –Leaf Area Index [-]
r_a –Aerodynamic Resistance [s/m]
r_s –(Bulk) Surface or Canopy Resistance [s/m]
r_R –Radiative Resistance [s/m]

The inclusion of the LAI accounts for energy flux between multiple layers of leaves in a CEA canopy, while the factor of 2 includes both surfaces of the leaf. This term has been highlighted as the main reason for the improved performance under CEA conditions (López-Cruz et al., 2008). There is also the inclusion of the radiative resistance term with a more detailed calculation of the incoming radiation flux. In the Stanghellini model, for the aerodynamic term, conditions within the CEA are treated as being in mixed convection. Therefore, these modifications make it more suitable for CEA ET estimations compared to other ET models.

Net radiation for this model is obtained as the difference between the shortwave and longwave radiation as shown in the following equations (Eqs. (27)–(29)).

$$I_n = I_{ns} - I_{nl} \tag{27}$$

$$I_{ns} = 0.07 \cdot I_s \tag{28}$$

$$I_{nl} = \frac{0.16 \cdot K_t \cdot \rho_a \cdot Cp \cdot (T - T_o)}{r_R} \tag{29}$$

where:

I_n –Daily Net Radiation [MJ/m^2 day]
I_{ns} –Daily Net Short Wave Radiation [MJ/m^2 day]
I_{nl} –Daily Net Long Wave Radiation [MJ/m^2 day]
I_s –Daily Incoming Solar Radiation [MJ/m^2 day]
K_t –Unit Conversion [86400 s/day, 3600 s/h]
ρ_a –Mean Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
T –Air Temperature [°C]
T_l –Leaf Temperature [°C]
r_R –Radiative Resistance [s/m]

In that study by Villarreal-Guerrero et al. (2012), this model gave better estimates compared to Penman-Monteith and Takakura models (Takakura et al., 2005), with percentage errors between −5.5% to 7%, depending on the type of crop, season, and cooling strategy employed. Pamungkas et al. (2014) found the Stanghellini model slightly overestimated ET but had a strong correlation with the measured ET for hydroponically cultivated tomatoes in a plant factory. Acquah et al. (2018) found a high correlation ($R^2 = 0.9$) between the Stanghellini model ET and measured ET for tomatoes grown in a low technology, multi-span, Venlo-type greenhouse in Zhenjiang, China. Percentage deviation (overestimation) from measured ET was between 9.91 and 14.16% from May to July.

3.2.1.3. Fynn model. The Fynn model (Fynn et al., 1993) (Equation (30)) is derived from the Stanghellini model, using the crop canopy energy balance. However, it does not include the detailed radiation flux calculation of the Stanghellini model. The model assumes that the saturated vapor pressure at leaf temperature can be approximated as the saturated vapor pressure at air temperature as long as the temperature difference between the leaf and air temperature is less than 4 to 5 °C.

$$ET_c = \frac{\{2 \cdot LAI \cdot \rho_a \cdot Cp[VPD]/r_a\} + \Delta(I_n - G)}{\lambda\gamma\left[1 + \frac{r_s}{r_a} + \frac{\Delta}{\gamma}\right]} \tag{30}$$

where:

ET_c –Daily or Hourly Crop Evapotranspiration [mm/day]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]
ρ_a –Mean Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
VPD –Vapor Pressure Deficit [kPa]
LAI –Leaf Area Index [-]
λ –Latent Heat of Vaporization [MJ/kg]
r_a –Aerodynamic Resistance [s/m]
r_s –(Bulk) Surface or Canopy Resistance [s/m]

Prenger et al. (2002) modified the Fynn model, with the inclusion of a canopy area index (CAI) to improve the radiation flux calculation. It is defined as the ratio of the canopy area to the CEA floor area and helps to account for the radiation intercepted directly by the canopy. However, this was only tested for a scenario of four evenly spaced Red Maple trees in a greenhouse, therefore more rigorous testing is required especially for multiple plant scenarios to study its effectiveness. The modified equation is given as in Equation (31):

$$ET_c = \frac{1}{\lambda}\left[\frac{\Delta}{\Delta+\gamma\left(1+\frac{r_s}{r_a}\right)}\cdot \mathrm{CAI}\cdot(I_n - G) + \frac{\gamma}{\Delta+\gamma\left(1+\frac{r_s}{r_a}\right)}\cdot 2\cdot \mathrm{LAI}\cdot\frac{\rho_a\cdot\lambda\cdot(VPD)}{r_a}\right] \tag{31}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
Δ –Slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ –Psychrometric Constant [kPa/°C]
I_n –Daily Net Radiation [MJ/m^2 day]
G –Soil Heat Flux [MJ/m^2 day]
ρ_a –Mean Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
VPD –Vapor Pressure Deficit [kPa]
LAI –Leaf Area Index [-]
CAI –Canopy Area Index [-]
λ –Latent Heat of Vaporization [MJ/kg]
r_a –Aerodynamic Resistance [s/m]
r_s –(Bulk) Surface or Canopy Resistance [s/m]

In the study above (Prenger et al., 2002), the Fynn model was compared to the Stanghellini, Penman, and Penman-Monteith model. However, it had the poorest performance with a Nash-Sutcliffe model efficiency coefficient of −0.848, underestimating ET by roughly 45%.

3.2.1.4. Baille model. The Baille (Baille et al., 1994) model is a modified form of the Penman-Monteith model that replaces the crop parameters difficult to measure with regression constants. However, the overall model equation still considers the effects of net radiation, leaf area index, and VPD. But with a reduction in the number of required parameters, the model can be easily implemented once the model parameters K_1 and K_2 have been determined. By knowing which parameter has the strongest effect on ET, better ET control can be obtained (Carmassi et al., 2013). These model parameters are estimations of radiative and advective terms appearing in the original Penman-Monteith model. The model equation is given as in Equation (32), where K_1 and K_2 are regression coefficients:

$$ET_c = \frac{1}{\lambda}[K_1\cdot I_n\cdot(1-exp(-ek\cdot LAI)) + K_2\cdot LAI\cdot VPD] \tag{32}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
K_1 –Regression Coefficient [-]
K_2 –Regression Coefficient [-]
I_n –Daily Net Radiation [MJ/m^2 day]
ek –Extinction Coefficient [-]
VPD –Vapor Pressure Deficit [kPa]
LAI –Leaf Area Index [-]

Battista et al. (2015) used the Baille equation in the estimation of tomato ET in a glasshouse located in Italy equipped with fan-heaters, shading, and a closed-loop hydroponic system. The ET model makes use of coefficients that need to be adjusted based on the climate and crop characteristics and had an estimation error of less than 5%. A similar model was also employed by Medrano et al. (2005) for the ET estimation of cucumber cultivated in a naturally ventilated greenhouse in Almeria, Spain. The model used different day and night values for Coefficient K_2, overestimating ET by 2% and 9% for the spring and autumn cropping cycle, respectively.

3.2.1.5. Takakura model. This model was developed by Takakura et al. (2005) based on the CEA heat balance. However, it requires a crop solarimeter for accurate ET estimation. The solarimeter is used to accurately measure the net radiation and evaporative surface temperatures. The model equation is given as in Equation (33):

$$ET_c = \frac{1}{\lambda}[(I_n - G) - h(T - T_w)] \tag{33}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
λ –Latent Heat of Vaporization [MJ/kg]
G –Soil Heat Flux [MJ/m^2 day]
h –Convective Heat Transfer Coefficient of Air [W/m^2 °C]
I_n –Daily Net Radiation [MJ/m^2 day]
T –Daily Mean Air Temperature [°C]
T_w –The temperature of the Evaporative Surface [°C]

Villarreal-Guerrero et al. (2012), found this model to be fairly accurate during the early morning, but overestimates early noon ET and underestimates ET values for the remaining hours of the day. The study investigated greenhouse cultivated pepper (summer season - natural ventilation and fogging: ∼−7%, R^2 = 0.90; summer season - pad and fan: ∼−4%, R^2 = 0.89) and tomato (fall season – pad and fan: ∼−24%, R^2 = 0.66; spring season - pad and fan: ∼+7%, R^2 = 0.86; spring season – natural ventilation and fogging: ∼+2%, R^2 = 0.88). Zhang and Lemeur (1992) performed ET estimations derived from the simple energy balance equation (Equation (23)), with all fluxes being positive if entering the surface and negative if leaving. They found this model to predict Ficus Benjamina ET with an R^2 value of 0.88, overestimating by 3 to 13% on average. The model was also found to be unaffected by errors due to aerodynamic resistance.

3.2.1.6. Graamans model. Graamans et al. (2017) developed a modified form of the Penman-Monteith model for lettuce grown in a plant factory. The model iteratively solves for the leaf temperature by ensuring that the energy balance equation is satisfied. In this model, the latent heat flux was derived in terms of the difference between the canopy vapor concentration χ_s and the air vapor concentration χ_a as shown in Equation (34).

$$\lambda ET = LAI \cdot \lambda \cdot \frac{(\chi_s - \chi_a)}{r_s + r_a} \quad (34)$$

where:

λET –Latent Heat Flux [W/m^2]
LAI –Leaf Area Index [-]
λ –Latent Heat of Vaporization [J/kg]
χ_s –Vapor Concentration at the canopy level [kg/m^3]
χ_a –Vapor Concentration of the air [kg/m^3]
r_a –Aerodynamic Resistance [s/m]
r_s –(Bulk) Surface or Canopy Resistance [s/m]

It also includes a sub-model for net radiation, based on the reflection coefficient as shown in Equation (35).

$$I_n = (1 - Rc) \cdot I_{abs} \cdot CAC \quad (35)$$

where:

I_n –Net Radiation [W/m^2]
Rc –Reflection Coefficient [-]
I_{abs} –Effectively Absorbed Radiation [W/m^2]
CAC –Cultivation Area Cover [-]

The sub-models for aerodynamic and stomatal resistances are presented in Tables 2 and 3 respectively. However, a constant value was used for the aerodynamic resistance with different values to represent fan-on and fan-off scenarios.

3.2.1.7. Shuttleworth-Wallace model. This model is based on a one-dimensional energy partition which leads to a combination equation that better accounts for the transformation from a sparse to a full canopy (Shuttleworth and Wallace, 1985; Fisher et al., 2005). It also requires stomatal, aerodynamic as well as surface resistance for bare soil. The model equations are given in Equations (36)–(46):

$$\lambda ET_c = \lambda Tc + \lambda E_s \quad (36)$$

where:

λET_c –Latent heat flux [W/m^2]
λTc –Latent heat flux of transpiration from canopy surface [W/m^2]
λE_s –Latent heat flux from substrates [W/m^2]

$$\lambda Tc = Cc \frac{\Delta A + \left(\left(\rho_a CpVPD - \Delta r_a^c A_s \right) / \left(r_a^a + r_a^c \right) \right)}{\Delta + \gamma \left(1 + \left(r_s^c / \left(r_a^a + r_a^c \right) \right) \right)} \quad (37)$$

$$\lambda E_s = Cs \frac{\Delta A + \left(\left(\rho_a CpVPD - \Delta r_a^c (A - A_s) \right) / \left(r_a^a + r_a^c \right) \right)}{\Delta + \gamma \left(1 + \left(r_s^s / \left(r_a^a + r_a^s \right) \right) \right)} \quad (38)$$

$$Cc = \left[1 + \frac{c_3 c_1}{c_2 (c_3 + c_1)} \right]^{-1} \quad (39)$$

$$Cs = \left[1 + \frac{c_2 c_1}{c_3 (c_2 + c_1)} \right]^{-1} \quad (40)$$

$$c_1 = (\Delta + \gamma) r_a^a \quad (41)$$

$$c_2 = (\Delta + \gamma) r_a^s + \gamma r_s^s \quad (42)$$

$$c_3 = (\Delta + \gamma) r_a^c + \gamma r_s^c \quad (43)$$

$$J = (I_n - G) \quad (44)$$

Table 1
Aerodynamic resistance models used in different studies.

S/N	Study	Resistance Model Equation	ET Model	Remark
1.	(Villarreal-Guerrero et al., 2012)	Equation (51), Equation (55), Equation (58)	Stanghellini	The following averages were obtained for bell pepper (259 s/m) and tomato (185 s/m) Heat transfer was taken to be via mixed convection.
2.	(Villarreal-Guerrero et al., 2012)	$r_e = \frac{[ln(z-d)/z_0]^2}{K^2 \cdot u}$	Penman-Monteith	The following averages were obtained for bell pepper (59 s/m) and tomato (70 s/m) Where $K^2$is von Karman Constant (=0.41)
3.	(Acquah et al., 2018)	$r_e = 220 \cdot \frac{l^{0.2}}{U^{0.8}}$	Stanghellini	Related to the characteristic leaf dimension and average interior air velocity. The average value of 145 s/m was obtained.
4.	(Jaafar and Ahmad, 2018)	$r_e = \frac{1}{K^2 \cdot u} \cdot ln\left(\frac{x-d}{H-d}\right) \cdot ln\left(\frac{x-d}{z_0}\right)$	Penman-Monteith	Expressions for the estimation of z_0 and d were provided by the authors. Where $K^2$is von Karman Constant (=0.41)
5.	(Demrati et al., 2007)	$r_e = \frac{Cp}{1.95 \frac{\lvert T_l - T \rvert^{0.25}}{l} + 5.2 \left(\frac{U}{l}\right)^{0.5}}$	Penman-Monteith	Where U is the air velocity in the CEA and is obtained as a ratio of the ventilation flux and surface of the opening section.
6.	(Graamans, 2017)	$r_e = 350 \cdot \left(\frac{1}{U}\right)^{0.5} \cdot LAI^{-1}$	Graamans	However static values were used for forced (100 s/m) and free (200 s/m) air circulation.
7.	(Yang et al., 1990)	$r_e = \frac{1}{dc \cdot Nu}$	Modified Penman-Monteith	Where dc is the diffusion coefficient of water vapor in the air and Nu is calculated from Equation (60)
8.	(Pollet et al., 1998)	$r_e = 840 \cdot \sqrt[4]{\frac{l}{\lvert T_l - T \rvert}}$	Penman-Monteith	Modeled for conditions of free convection.
9.	(Zhang and Lemeur, 1992)	Equation (50), Equation (58), Equation (59), Equation (64).	Penman-Monteith	Mixed and forced gave stable values, while leaf temperature cooler than air gave values closer to that obtained from an energy balance.
10.	(Bailey, 1993)	Equation (51), Equation (57), Equation (58) and Equation (59)	Penman-Monteith	ET predictions made using forced and mixed convection gave better results
11.	(Baille et al., 1996)	$r_e = \frac{1174 \cdot l^{0.5}}{\left(l \cdot \lvert T_l - T \rvert + 207 \cdot U^2\right)^{0.25}}$	–	The model was based on Stanghellini's (Stanghellini, 1987) formulation.
12.	Willits, 2003; Stanghellini and de Jong, 1995)	$r_e = \frac{1174 \cdot l^{0.5}}{\left(l \cdot \lvert T_l - T \rvert + 207 \cdot U^2\right)^{0.25}}$	Penman-Monteith	The model was based on Stanghellini's (Stanghellini, 1987) formulation.
13.	(Montero, 2001; Carmassi et al., 2013; Rouphael and Colla, 2004; Qiu et al., 2013)	Equation (51), Equation (57), Equation (58) and Equation (59)	Penman-Monteith	Free, forced, and mixed heat transfer equations were used and compared.

Table 2
Stomatal resistance models used in different studies.

S/N	Study	Resistance Model Equation	ET Model	Remark
1.	(Villarreal-Guerrero et al., 2012)	$r_i = c_1 \cdot \left[\frac{(I_n/(2 \cdot LAI)) + c_2}{(I_n/(2 \cdot LAI)) + c_3}\right] \cdot (1 + c_4 \cdot VPD^2)$	Stanghellini	The model had an R^2 of 0.93 and r_s values ranged from 40 s/m during the day to 8000 s/m at night.
2.	(Villarreal-Guerrero et al., 2012)	$r_i = c_1 \cdot \left[\frac{I_n + c_2}{I_n + c_3}\right] \cdot (1 + c_4 \cdot VPD^2)$	Penman-Monteith	The model had an R^2 of 0.93 and r_s values ranged from 40 s/m during the day to 8000 s/m at night
3.	(Montero et al., 2001)	$r_i = \frac{1}{g_{min} + (g_{max} - g_{min}) \cdot (2.27 \cdot I/(I + 1888))}$	Penman-Monteith	The model was found to be a function of Incident PAR radiation only. The model had an R^2 of 0.98
4.	(Acquah et al., 2018)	$r_i = 200\left[1 + \frac{1}{exp(0.05(\tau \times I_s - 50))}\right]$	Stanghellini	Model is a function of radiation and is derived from Boulard and Wang (Boulard and Jemaa, 1992).
5.	(Kittas et al., 1999)	$r_i = r_{min}\left(\frac{b_1 + I_s}{b_2 + I_s}\right) \cdot (1 + exp[c(VPD - 2.5)])$	Baille	The model was based on the radiation and the VPD.
6.	(López-Cruz et al., 2008)	$r_i = 82 \cdot \left[\frac{(I_n/(2 \cdot LAI)) + 4.30}{(I_n/(2 \cdot LAI)) + 0.54}\right] \cdot \left(1 + 0.023 \cdot (T - 24.5)^2\right)$	Stanghellini	The model was found to be a function of radiation and air temperature.
7.	(Jaafar and Ahmad, 2018)	$r_i = \frac{1}{\frac{b_1 \cdot LAI}{r_s^c} + \frac{b_2}{r_s^s}}$	Penman-Monteith	b_1 and b_2 are empirical coefficients taken to be 1.52 and 0.05 respectively.
8.	(Demrati et al., 2007)	$r_i = r_{min}[1 + exp0.0033(I_n - 516.505)]^{-1}$	Penman-Monteith	The model uses the radiation intensity at the crop level. The fit slightly improves with the addition of the VPD or leaf temperature.
9.	(Graamans, 2017)	$r_i = 60 \cdot \frac{1500 + PPFD}{200 + PPFD}$	Graamans	The model was based on PPFD, considering other climatic parameters negligible.
10.	(Yang et al., 1990)	$r_i = 142.7 + 953.9exp(-0.0081 \cdot I)$	Modified Penman-Monteith	The model had an R^2 of 0.647. However, since r_i is a function of radiation only, it cannot account for nighttime variations.
11.	(Pollet et al., 1998)	$r_i = 164 \cdot \frac{31.029 + I_s}{6.740 + I_s} \cdot \left(1 + 0.011(VPD - 3)^2\right) \cdot \left(1 + 0.016(T - 16.4)^2\right)$	Penman-Monteith	The addition of successive parameters improved the correlation with solar radiation and VPD having the greatest effects.
12.	(Rouphael and Colla, 2004)	$r_i = 87.30 + 647.24 \times exp(-0.0022 \cdot I_{abs})$	Penman-Monteith	Fitted for CEA cultivated zucchini.
13.	(Qiu, 2013)	$r_i = \frac{1}{0.001 + 0.169(0.169 I_s/(I_s + 1169))}$	Penman-Monteith	A significant correlation ($R^2 = 0.95$) was found between solar radiation and stomatal resistance for hot pepper.
14.	(Ondrašek, 2007)	$r_i = 200\left[1 + \frac{1}{exp(0.05(\tau \times I_s - 50))}\right]$	Penman-Monteith	The model was based on the external incoming radiation and the transmissivity of the CEA cover.
15.	(Zhang and Lemeur, 1992)	$r_i = 507exp(-0.00235 \cdot I)$	Penman-Monteith	The model had an R^2 of 0.78. The model was also found to be a function of solar radiation only, with the effect of leaf temperature and VPD unclear.
16.	(Bailey, 1993)	$r_i = 46 + \frac{54500}{55 + I}$	Penman-Monteith	The model was found to be a function of Incident PAR radiation only. The model accounted for 92% of the observed variation.
17.	(Cannavo et al., 2016; Cannavo et al., 2016)	$r_i = -115 I_s - 139 RH + 139 I_s \cdot RH + 661 {I_s}^2 - 368 RH^3$ $r_i = 48.1 \frac{(316.67 + I_s)}{8.87 + I_s}\left(1 - 0.15(VPD - 2.84)^2\right)$	Penman-Monteith	The first equation represents the FFD model for pot planted New Guinea Impatiens While the second represents the Jarvis model for the same crop.
18.	(Willits, 2003; Stanghellini and de Jong, 1995)	$r_i = 82 \cdot \left[\frac{ac \cdot I_s + 4.30}{ac \cdot I_s + 0.54}\right] \cdot \left[\frac{e^{0.3 \cdot T_l} + 258}{e^{0.3 \cdot T_l} + 27}\right] \cdot \left[0.004 + e^{\frac{-0.73 \cdot \rho_a \cdot Cp_{.VPD}}{\gamma\lambda}}\right]^{-0.25}$	Penman-Monteith	The model was found to be a function of radiation, canopy temperature, and VPD. Where ac is the absorption coefficient based on the canopy transmissivity.

$$J_s = (I_{ns} - G) \tag{45}$$

$$I_{ns} = I_n exp(-ek \cdot LAI) \tag{46}$$

where:

Tc – Plant Transpiration [W/m^2]
E_g – Soil Evaporation [W/m^2]
Cc – Canopy Resistance Coefficient [-]
Cs – Soil Surface Resistance Coefficient [-]
J – Total Available Energy [W/m^2]
ρ_a – Air Density [kg/m^3]
Cp – Specific Heat of Air [J/kg °C]
VPD – Water Vapor Pressure Deficit [kPa]
r_a^c – Bulk Boundary Layer Resistance of the vegetative elements in the canopy [s/m]
J_s – Available Energy to Soil Surface [W/m^2]
r_a^a – Aerodynamic Resistance Between Mean Canopy Flow and Reference Height [s/m]
Δ – The slope of the Saturation Vapor Pressure-Temperature Curve [kPa/°C]
γ – Psychrometric Constant [kPa/°C]
r_s^c – Canopy Resistance [s/m]
r_s^s – Soil Surface Resistance [s/m]
r_a^s – Aerodynamic Resistance Between Soil Surface and Mean Canopy Flow [s/m]
G – Soil Heat Flux [W/m^2]
I_n – Net Radiation [W/m^2]
I_{ns} – Net Radiation Absorbed by Substrate [W/m^2]
ek – Extinction Coefficient [-]
LAI – Leaf Area Index [-]

Huang et al. (2020) employed this model for the estimation of cucumber ET in a Venlo-type greenhouse with an index of agreement of 0.93. On average, it overestimated ET by 8.4% in the Spring season and by 27.6% during the autumn. An advantage of this model is that crop evapotranspiration can be easily separated into crop transpiration and soil evaporation. However, in a study by Gong et al. (2019) on solar

Table 3
Models, input parameters, advantages and disadvantages of indoor ET models.

S/N	ET Model	Input Parameters	Advantages	Disadvantages	Reference
1.	Priestley-Taylor	T, I_s.	Useful in situations where complete climatic data is lacking	Based on radiation and thus is unsuitable for high advection conditions	(Liu et al., 2008; Sharma et al., 2017)
2.	FAO-24 Radiation	T, I_s.	Accurate prediction for locations with humid climates in naturally ventilated greenhouses.	Based on radiation and thus is unsuitable for high advection conditions	(Liu et al., 2008)
3.	Hargreaves-Samani	T, I_s.	Easy to use and requires few climatic parameters.	Largely overestimates ET.	(Fernández et al., 2010)
4.	FAO Penman	T, I_s, RH, U.	Takes advection term into account which improves its accuracy.	Wind function is difficult to obtain.	(Liu et al., 2008)
5.	FAO-56 Penman-Monteith	T, I_s, RH, U.	Takes advection term into account which improves its accuracy. Standard Reference ET model.	It underestimates reference evapotranspiration conditions with high evaporative demand.	(Liu et al., 2008)
6.	Penman-Monteith	T, I_s, RH, U.	It is the standard physical model and gives acceptable results in many applications.	The need for stomatal and aerodynamic resistances poses a difficulty	(Villarreal-Guerrero et al., 2012)
7.	Stanghellini Model	T, I_s, RH, U, LAI, T_l.	A suitable model for CEA applications.	The need for stomatal and aerodynamic resistances as well as the measurement of LAI poses a difficulty	(Villarreal-Guerrero et al., 2012)
8.	Takakura Model	T, I_s, U, T_w.	Easier to implement	As the crop matures, careful adjustments of the solarimeter are required	(Villarreal-Guerrero et al., 2012)
9.	Fynn Model	T, I_s, RH, U, LAI.	Easier to implement and cost-effective compared to the Stanghellini model	The assumption of equal air and leaf temperatures affects accuracy. Not well tested in multiple plant scenarios.	(Prenger et al., 2002)
10.	Baille Model	T, I_s, RH, LAI.	Easy to implement with few climatic parameters.	Cannot be applied to multiple scenarios without recalibration.	(Montero, 2001; Battista, 2015)
11.	Graamans Model	T, I_s, RH, U, LAI, T_l.	Most applicable to emerging areas of CEA e.g. plant factories, shipping container farms, etc.	The need for stomatal and aerodynamic resistances as well as the measurement of LAI poses a difficulty	(Graamans, 2017)
12.	Shuttleworth and Wallace	T, I_s, RH, U.	Separates evapotranspiration calculation into crop transpiration and soil evaporation.	The need for stomatal and aerodynamic resistances poses a difficulty	(Gong et al., 2019; Huang et al., 2020)

greenhouse tomato ET, this model was found to slightly overestimate ET at the initial growth stage, and underestimate ET at the mid-stage. It had an overall absolute relative error of 50.2%. On the other hand, for LAI values between 0.5 and 2.7, it estimated crop ET with an R^2 value of 0.91 and 0.94 in 2015 and 2016, respectively.

3.2.1.8. Other modified Penman-Monteith models. Bailey et al. (1993) developed a modified form of the Penman-Monteith model for ficus Benjamina cultivated in a naturally ventilated glasshouse and plastic-covered greenhouse in the UK and Spain respectively. The model assumes that terms with a strong temperature dependence be expressed as exponential functions of temperature while others are evaluated at a temperature of 25 °C. An extinction coefficient of 0.625 was also assumed while the net radiation was replaced with global solar radiation. The model estimates ET with an error of ± 5%, its equation is shown in Equation (47):

$$ET_c = \frac{1}{\lambda}\left[\frac{I_s \cdot exp(0.052 \cdot T)[1 - exp(-0.625 \cdot LAI)] + 49.4 \cdot LAI \cdot VPD / l^{0.5}}{2 \cdot exp(0.038 \cdot T) + 0.00274 \cdot r_s / l^{0.5}}\right] \tag{47}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
I_s –Daily Surface Radiation [MJ/m^2 day]
λ –Latent Heat of Vaporization [MJ/kg]
T –Air Temperature [°C]
VPD –Vapor Pressure Deficit [kPa]
LAI –Leaf Area Index [-]
l –Characteristic Leaf Dimension [m]
r_s –Surface Resistance [s/m]

Boulard and Jemaa (Boulard and Jemaa, 1992) developed a modified form of the Penman-Monteith model for soilless cultivated tomato, in an environment controlled plastic greenhouse, in which terms of the right and left-hand side are replaced by two constants (K_1 and K_2), leaving only the absorbed radiation and the VPD term. K_1 and K_2 can either be obtained via calculation, using measured parameters, or estimated via multiple regression:

$$ET_c = \frac{1}{\lambda}[K_1 \cdot I_s + K_2 \cdot VPD] \tag{48}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
I_s –Daily or Hourly Surface Radiation [MJ/m^2 day]
λ –Latent Heat of Vaporization [MJ/kg]
K_1 –Model Constant [-]
K_2 –Model Constant [-]
VPD –Vapor Pressure Deficit [kPa]

Airman and Houter (1990) estimated the ET of a Nutrient Film Technique (NFT) cultivated tomato in a glasshouse with a modified form of the Penman-Monteith model. Their model equation required the measurements of net radiation absorbed by the crop per unit leaf area A and the VPD as well as the estimation of two model parameters that depend on the properties of water vapor. The model equation can be seen in Equation (49):

$$ET_c = K_1(A + K_2 \cdot VPD) \tag{49}$$

where:

ET_c –Daily Crop Evapotranspiration [mm/day]
A –Leaf Area [m^2]
K_1 –Model Parameters [-]
K_2 –Model Parameters [-]
VPD –Vapor Pressure Deficit [kPa]

In addition to the properties of water vapor, these model parameters also depend on the stomatal, cuticular, and aerodynamic conductance. However, Jolliet and Bailey (Jolliet and Bailey, 1992) found this model to overestimate ET by 62% with an R^2 value of 0.59 due to its overestimation of the effect of VPD. It was concluded that the use of constant values for the stomatal conductance was the main reason for such overestimation. This study was performed for NFT cultivated tomatoes in an environment-controlled greenhouse. Massa et al. (2011) also found a modified form of the Penman-Monteith model to underestimate water uptake by between 0.4 and 6.3% on average for soilless cultivated greenhouse tomatoes.

Physical models offer a direct estimation of crop ET; however, they require a complete set of climatic data in addition to crop physiological parameters. The Penman-Monteith and Stanghellini models have been mostly used, however, accuracy varies from experiment to experiment. Simpler physical models like the Baille model offer an easier method for ET estimation, however, the constants K_1 and K_2 must be calibrated accordingly and as models include more constants for calibration, they become less physical based.

Although the Stanghellini and Graamans model has been applied to high technology CEA such as plant factories, there is the need to further validate them for different crop types and cultivation practices. A key area for modification is the net radiation term, to accurately account for the proportion of artificial light (LED Lights) absorbed by the crop canopy. Conversion factors for the calculation of net radiation from LED-based lighting are lacking, compared to other artificial light sources such as HPS and Metal Halides.

Furthermore, Environmental control through mechanical air conditioning systems helps provide optimal growth conditions. However, such systems are sometimes beset by control issues that hinder the tight control of conditions according to desired setpoints. These models also require the measurement of additional parameters such as LAI, leaf temperature, and stomatal resistance. Unlike air temperature, relative humidity, and light levels, these additional parameters are difficult to continuously measure. Therefore, spot measurements are usually taken, which in turn affects the accuracy of the model.

With advancements in software technology, there is the possibility of having an all-in-one package that includes all ET models relevant for indoor ET estimation. Guo et al. (2016) developed an R package for 17 commonly used outdoor ET models. Future studies could pursue a similar path in creating a unified package for CEA ET estimation. This would improve model consistency, implementation, comparison, and ease of selection.

3.2.2. Aerodynamic and stomatal resistance

Aerodynamic and stomatal resistance are important terms for most physical models. This sub-section discusses the different models and methods used in quantifying these terms. The stomatal resistance is the most difficult to model, however, most models are derived from two main models – the Jarvis (Jarvis, 1976) and the Ball (Ball et al., 1987; Ball, 1988) model. Some studies also try to use constant values for both resistances. While this might be acceptable for aerodynamic resistance, it could result in large errors if used for the stomatal resistance. Therefore, an accurate and dynamic model is required to obtain accurate ET estimates. For the sake of uniformity, leaf aerodynamic and stomatal resistances would be denoted by r_e and r_i. While crop or canopy aerodynamic and stomatal resistances would be denoted by r_a and r_s. In some studies, they are also treated as conductance which is simply the reciprocal of the resistance terms. Stomatal conductance is denoted by g_s while the boundary layer conductance is denoted by g_b.

3.2.2.1. Aerodynamic resistance models. It represents the resistance to the flow of water vapor and sensible heat from the surface of the leaf to the surrounding air (Graamans et al., 2017). Aerodynamic resistance depends on the type of convection and the leaf-to-air temperature difference (Zhang and Lemeur, 1992). One way to obtain the aerodynamic resistance is through the energy balance equation (Equation (23)) if the evapotranspiration is known. From here, the sensible heat can be obtained which then leads to the direct calculation of the aerodynamic resistance as shown in Equation (50).

$$S = \frac{\rho_a \cdot Cp \cdot (T - T_l)}{r_e} \tag{50}$$

where:

S –Sensible Heat Flux [W/m^2]
ρ_a –Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
T –Air Temperature [°C]
T_l – Leaf Temperature [°C]
r_e –Leaf Aerodynamic Resistance [s/m]

Alternatively, the aerodynamic resistance can also be obtained from the heat transfer coefficient h as shown in Equation (51):

$$r_e = \frac{\rho_a \cdot Cp}{h} \tag{51}$$

where:

r_e –Leaf Aerodynamic Resistance [s/m]
ρ_a –Air Density [kg/m^3]
Cp –Specific Heat of Air [MJ/kg °C]
h –Convective Heat Transfer Coefficient of Air [W/m^2 °C]

The convective heat transfer coefficient depends on the Nusselt number which in turn depends on the mode of heat transfer (free, forced, or mixed) and nature of airflow (laminar or turbulent) within the CEA. For free convection, heat transfer is mainly due to the temperature difference between the leaves and the surrounding air (McAdams, 1954). For forced convection, heat transfer is by air movement (Gröber and Erk, 1961), while for mixed, both scenarios occur simultaneously (Stanghellini, 1987). There is no consensus in the literature on whether the heat transfer in the CEA is via free, forced, or mixed convection. Also, all modes and types of flow may occur simultaneously within a crop canopy (Yang et al., 1990; Kays and London, 1984). There is also a lack of consensus as to whether the flow over the crop canopy is considered laminar or turbulent. Yan et al. (2018) summarized the equations for computing the Nusselt number for the aerodynamic resistance term based on the type of flow (laminar or turbulent) and the prevailing mode of heat transfer (free, forced, or mixed). The convective heat transfer coefficient can also be obtained from the energy balance equation if the net solar radiation, ET, leaf, and air temperatures are known (Bailey et al., 1993). Zhang and Lemeur (1992) found the aerodynamic resistance values obtained from the Nusselt number method, especially the mixed convection approach to be more stable compared to that obtained from the energy balance approach

Despite the lack of consensus over the prevalent heat transfer and airflow mode in CEA, in a few studies, a constant value has been used for the aerodynamic resistance (Prenger et al., 2002; Boulard and Jemaa, 1992; Kittas et al., 1999; Ondrašek et al., 2007; López-Cruz et al., 2008). This could be attributed to the fact that it has little impact on the accuracy of the ET model and thus the ET estimate could be said to be unsensitive to the aerodynamic resistance (Villarreal-Guerrero et al., 2012; Acquah et al., 2018). Furthermore, this makes sense in CEA with very little air movement due to its enclosure, also in combination with relatively large leaf areas (Ondrašek et al., 2007). Also, from experiments, the aerodynamic resistance is relatively stable for 24 h (Villarreal-Guerrero et al., 2012). In cases where wind speed measurements are lacking, aerodynamic resistance can be taken to be an empirical parameter (Kage et al., 2000). Table 1 summarizes several aerodynamic resistance models that have been used in CEA ET estimation studies.

3.2.2.2. Stomatal resistance models. Stomatal resistance represents the resistance to the flow of vapor through the crop to the leaf surface. Different crops have different stomatal resistances; climatic, biological, and agronomical parameters also drive changes in stomatal resistance as well as water availability. However, empirical stomatal resistance models can be derived as a function of key climatic parameters, using the popular Jarvis multiplicative model (J model) (Jarvis, 1976). A general form of this model, looking at three common climatic parameters is given in Equation (52), where r_{min}, the minimum internal resistance in s/m, is usually taken from porometer measurements and used as a constant value in the model. The mathematical functions f_1, f_2 and f_3 characterize the relationship between r_i and the chosen climatic variables:

$$r_i(I_s, T_l, VPD) = r_{min} \cdot f_1(I_s) \cdot f_2(T_l) \cdot f_3(VPD) \tag{52}$$

where:

r_i –Leaf Stomatal Resistance [s/m]
I_s –Incoming Solar Radiation [W/m^2]
VPD – Vapor Pressure Deficit [kPa]
r_{min} –Minimum Leaf Stomatal Resistance [s/m]
T_l – Leaf Temperature [°C]
$f_1, f_2 and f_3$ – Mathematical Functions [-]

Stanghellini (Stanghellini, 1987) presented a detailed model based on incoming radiation, VPD, leaf temperature, and CO_2 concentration. The leaf stomatal resistance can be measured using a porometer, after which a relationship is established between the measured values and climatic parameters such as solar radiation, VPD, and air temperature to obtain a stomatal resistance model. A brief explanation of how such measurements are performed can be found in (Demrati et al., 2007). Examples of such stomatal resistance models as developed in literature are shown in Table 3 below. Hence, the canopy resistance r_s can be obtained from the leaf stomatal resistance r_i and effective LAI as shown in Equation (53):

$$r_s = \frac{r_i}{LAI_{eff}} \tag{53}$$

where:

r_s –Canopy Stomatal Resistance [s/m]
LAI_{eff} – Effective Leaf Area7 Index [-]
r_i –Leaf Stomatal Resistance [s/m]

The actual LAI can be used in place of the effective LAI for LAI $\leq$ 2. While the effective LAI takes a value of 2 for 2 < LAI < 4 and 0.5 LAI for LAI $\geq$ 4 (Qiu et al., 2013).

Alternatively, the canopy resistance can be calculated if the transpiration rate is known (Yang et al., 1990; Baille et al., 1996). This approach is preferable to measurements by porometer as it gives more canopy resistance values for varying environmental conditions (Montero et al., 2001). Also, at low radiation levels, it is difficult to obtain stomatal resistance estimates from porometer measurements. Montero et al. (2001) found this low radiation boundary to be 25 W/m^2; and low VPD levels cause additional errors (Ewers and Oren, 2000). Porometer measurements may also affect the microclimate around the measured leaf, thereby affecting the measured transpiration (Bailey et al., 1993). It is also prone to biases and errors (Ali et al., 2016).

Other studies have also employed the Ball-Berry model by Ball, Woodrow, and Berry (Ball et al., 1987; Ball, 1988). This model is based on the net assimilation of CO_2 and environmental parameters at the canopy surface. It better describes the stomatal response to climatic and crop physiological characteristics. Compared with the Jarvis model, the Ball-Berry model gave better estimates, with the J model underestimating in low PPFD and VPD conditions, especially for young plants (Baille et al., 1996). Whereas the B model partially accounts for variation in plant age and varying climatic conditions. The use of constant values for maximum conductance or minimum resistance in the J model also affects its accuracy as well as its use of successive regression.

Several steps have been taken to improve the accuracy of the J model. One is to calibrate the model using a large data set. Another method is to apply multiple regression in place of successive regression. This way, the effect of each parameter is considered simultaneously which improves its estimation. Other approaches have improved the Jarvis model by incorporating the phenomenological feedback of VPD on stomatal resistance (Oren et al., 1999) and including plant hydraulic and photosynthetic mechanisms that lead to stomatal resistance changes with water, nutrient, and light availability (Sperry et al., 2017; Mackay et al., 2015; Mackay et al., 2020; Ewers et al., 2000). Yet again, some experiments try to use the direct method by measuring the leaf stomatal resistance rather than the indirect method of estimating it from the measured evapotranspiration. Other models also exist that could be applied for stomatal resistance modeling in water-stressed conditions. Damour et al. (2010) gave an overview of models applicable for estimating leaf stomatal conductance. It included models based on atmospheric factors such as the J and B model common to CEA applications as well as others based on water availability.

Stomatal resistance has also been modeled using the Full Factorial Design (FFD) technique (Ali et al., 2016). It is based on an optimized polynomial regression between the three key climatic parameters (radiation, relative humidity, and air temperature). Compared to the Jarvis model, it requires less data for calibration. This technique was able to estimate the stomatal resistance of pot-planted New Guinea Impatiens with an R^2 value of 0.69 and slope of 0.89, compared to the J model (R^2 = 0.65, slope of 0.45). From experiments it was found that the effect of temperature was negligible, therefore the model equation depends on only radiation and humidity measurements as shown in Table 2. A drawback of this technique however is that it is limited to the few parameters that can be replicated and controlled in a growth chamber.

Some studies make use of two climatic parameters and deem them sufficient, in fact, in a study by Demrati et al. (2007) radiation and VPD is said to account for roughly 90% of the variations of leaf stomatal resistance, therefore others such as the air temperature and CO_2 concentration can be considered negligible (Jolliet and Bailey, 1992), although any such claims should be investigated using rigorous tests of parsimony based on both uncertainty in the data and the model structure (Samanta et al., 2008). Villarreal-Guerrero et al. (2012) developed stomatal resistance models based on radiation and VPD for bell pepper and tomato. The constants for the models were obtained by taking measurements of the crop transpiration and obtaining the corresponding internal resistance values to fit the model equation. The model equation thus obtained is shown in Table 2, while the values of the constants within the equation for bell pepper and tomato are presented by the authors in their paper.

Conversely, compared to the aerodynamic resistance, using constant values for the stomatal resistance could affect the accuracy of the ET estimation. Although some studies (Willits, 2003) have supposedly gotten acceptable results (in certain conditions) with the use of constant values, generally, its use leads to errors. Villarreal-Guerrero et al. (2012) found it to produce accurate results under specific climatic conditions, but under transient radiation and humidity conditions, it gave erroneous results. Therefore, in practical CEA applications, a resistance model is required, one that considers the changing climatic and plant growth status conditions within the CEA.

The crop resistance generally fluctuates, taking up high values at night, early mornings, and late afternoons, this is because of the closure of the stomatal during this period. Whereas, during the day, the values are quite low as the presence of irradiance ensures the stomata remain opened for photosynthesis. In the case of plant factories with artificial lighting, the period for stomata opening and closure is determined by the photoperiod. Comparing the crop resistance for the Penman-Monteith and Stanghellini model from the study by Villarreal-Guerrero et al. (2012), it can be seen from the model equations that the values obtained from the latter are relatively higher due to the factor of 2LAI.

Determining what climatic parameters are to be considered in the stomatal resistance model is another area of discussion. Stomatal resistance has been found in multiple studies to depend on radiation levels (Demrati et al., 2007). Montero et al. (2001)) found the stomatal resistance of geranium leaf to decrease very slowly above a radiation value of 500 μmol/m^2 s and up to 1100 μmol/m^2 s. However, other studies have suggested the inclusion of additional parameters to increase the model accuracy.

Aerodynamic and Stomatal resistance models help improve the accuracy of ET models. However, they can be difficult to obtain, especially stomatal resistance. Air velocities in CEAs are usually low, so the effect of the aerodynamic term on ET estimation may sometimes be negligible. This has seen the use of constant aerodynamic resistance values in some studies with acceptable ET estimates. However, the same does not apply for stomatal resistance as it plays a very important role in ET estimation and varies with the type of crop and prevailing environmental conditions. Therefore, accurate modeling of stomatal resistance is important. The J and B models have been used in CEA applications, with the J model being the most popular. However, both methods have their advantages and shortcomings. There is a need for a comprehensive mechanistic crop resistance model that can better explain the interactions between the leaf characteristics, climatic variables, and fluxes. Regressive models such as the Jarvis model require local calibration on a crop by crop and sometimes season by season basis, this would not be suitable for real-time estimations due to the complexities required in generating such models. Advanced modeling techniques continue to explore the role of ABA and its effect on guard cell movements, as well as molecular level modeling of stomatal regulation. However, the goal should be the creation of a real-time, accurate, and easy-to-implement stomatal resistance model. Table 2 below summarizes the stomatal resistance models used in some studies.

The choice of the ET model also depends on the estimation time step. ET Models suitable for daily estimation include the Priestly-Taylor, Penman, FAO Penman-Monteith, and Hargreaves-Samani models. Such models are easy to utilize due to data availability and could provide quick ET estimates. ET models suitable for smaller timesteps include the Penman-Monteith, FAO Penman-Monteith, Baille, Graamans, and Stanghellini model (Acquah et al., 2018). Modified forms of the Penman-Monteith model such as the Baille (Baille et al., 1994) and Graamans (Graamans et al., 2017) have also been successfully employed for hourly ET estimation. Furthermore, hourly ET estimations can be accumulated into daily estimates. Therefore, models used for shorter timesteps such as FAO Penman-Monteith and Penman-Monteith model can also be used for daily ET estimations (Donatelli et al., 2006).

Table 3 summarizes the different ET models discussed in the subsections above. It gives information on the required input parameters, advantages, and disadvantages of each model.

3.3. Data-driven ET methods

With the advance of machine learning algorithms, data-driven models have been increasingly used for predicting real-time ET. Most of the existing studies for data-driven ET models have been used for outdoor ET estimation. Hu et al. (2021) found three machine learning techniques - deep neural network (DNN), random forest (RF), and symbolic regression (SR) to outperform surface energy balance system (SEBS), a physical-based approach for estimating field ET. Kisi et al. (2015) tested multilayer perceptron artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) with grid partition (GP), ANFIS with subtractive clustering (SC), and gene expression programming (GEP). They found these models to be successful at predicting ET even without climatic measurements, with an R^2 value greater than 0.9 in almost all cases. Zhu et al. (2020) proposed a hybrid particle swarm optimization (PSO) - extreme learning machine (ELM) model (PSO-ELM model) which outperformed the original ELM, ANN, RF, and Penman-Monteith models as well as six empirical models (Hargreaves and Samani, Priestley-Taylor, Makkink, Irmak, Dalton and Trabert models). Granata (2019) evaluated the performance of M5P Regression Tree, Bagging, RF, and Support Vector Regression (SVM) and found model performance are related to the size and structure of available data, with no single technique being the best for all problems.

In addition, several comparison studies exist for outdoor applications (Hu et al., 2021; Chen et al., 2020). Han et al. (2021) compared the back-propagation neural network with the multiple linear regression method, with the former having a higher accuracy (91.44% vs. 82.96%) and coefficient of determination (0.87 vs. 0.79). However, compared to Support Vector Regression (SVR) and Extreme Learning Machine (ELM), Yu et al. (2020) found both to be a better choice over ANN due to lower uncertainty in both cases of complete or incomplete input data. Hybrid models that combine the best attributes of individual data-driven models have been found to improve model accuracy. Maroufpoor et al. (2020) compared a hybrid artificial neural network-Gray Wolf Optimization (ANN-GWO) model with a least square support vector regression and a standalone ANN, with the hybrid model having the best Global Performance Indicator (GPI).

Only limited studies on data-driven-based ET estimation were conducted for CEAs. Artificial Neural Network (ANN) model was used for the estimation of a greenhouse cultivated sweet pepper ET (Pandorfi et al., 2016). The study was carried out in a low technology greenhouse in Sao Paulo, Brazil. The model used temperature, relative humidity, air velocity, radiation, and weighing lysimeter ET measurements collected over four months for the training and testing. Parasuraman et al. (2007) found the performance of the Genetic Algorithm (GA) to be comparable to ANN. They found both outperformed the Penman-Monteith model, thereby showing the great potential of data-driven models for ET estimation. Jolliet and Bailey created regression-based ET models for three different CEA settings for the ET estimation of NFT cultivated tomato in a greenhouse (Jolliet and Bailey, 1992). The model was based solely on incoming radiation and VPD, with other influences such as air temperature, CO_2 levels, cooling, and heating parameters considered negligible. Amiri et al. (2019) used a fuzzy regression method to estimate ET for grass reference crops based on five input parameters: maximum and minimum temperatures, average relative humidity, wind velocity, and incoming solar radiation. Compared to lysimeter measurements, the model performed well with an RMSE of 0.68 mm/day and an R^2 value of 0.98 (Amiri et al., 2019).

Data-driven models also offer a better alternative as a non-contact method for monitoring plant water status in real-time. One approach by which data-driven models predict plant water status in real-time is via model residuals between the measured transpiration and the model predicted transpiration. Adeyemi et al. (2018) used a 2nd order discrete-time transfer function based on solar radiation, VPD, and LAI to predict lettuce ET in a climate-controlled greenhouse. The model prediction closely matched the measured ET with an average coefficient of determination of 0.93 ± 0.04. Data-driven models have also been applied in the creation of virtual sensors based on transpiration which is cheaper and easier to operate and maintain compared to lysimeters. They usually make use of data from other sensors that are typically found in the greenhouse, therefore, eliminating additional installation costs. Sánchez et al. (2012) used a system identification approach to test several nonlinear dynamic virtual sensors based on solar radiation, VPD, and LAI for estimating tomato ET in a medium technology greenhouse in Spain. The final selection was a nonlinear ARX, with an average error of 5%. It was based on the first two parameters alone.

Data-driven methods of ET estimation could play a vital role in real-time ET estimation, especially for high technology CEAs. However, they require a large volume of data to train and test the model. The developed data-driven models may also be limited to specific CEAs and scenarios where data were collected and would need local calibration if applied to different conditions. Data-driven models have seen a wider application for outdoor scenarios compared to indoor and CEA applications. This creates the need for further testing and validation for CEA application. A variety of data-driven (including adaptive-learning-based) methods for ET estimations of modern CEAs should be further explored.

4. Application of ET models for CEA

Based on the level of technology employed for climate control, CEAs can be grouped into three: low, medium, and high technology CEAs. Accordingly, this also affects the type of ET models that can be accurately applied to each type. This section discusses the different types of CEAs and identifies ET models successfully employed for each type from existing literature.

4.1. Low Technology CEA

In a low technology CEA, climate control is mainly by material insulation and natural ventilation via the opening of vents. Low technology CEAs do not use mechanical cooling or heating systems. A typical example is solar greenhouses, which primarily rely on solar energy from the sun as the main source of heating (Devabhaktuni et al., 2013). In parts of Europe, Mediterranean greenhouses are a popular kind of low technology CEA (Fernández et al., 2010). They are typically unheated and made from low-cost, plastic-covered structures. Since control is limited, they heavily rely on external climate conditions. Control over pests and diseases is also low, therefore crop yield is limited.

This limited climate control affects the accuracy of different types of ET models that can be applied to this CEA type. Radiation-based ET models, for example, could lead to significant errors, especially in naturally ventilated CEAs. This is because of the mass and energy interactions between CEA and the outside environment. This generally is made up of the incoming solar radiation, heat storage changes, energy used up for evapotranspiration, and the energy exchanged with the outside environment (Liu et al., 2008). Ventilation could greatly impact the temperature and humidity within the CEA. Therefore, the effect of wind speed or advection cannot be ignored. Jaafar and Ahmad (2018) found the Hargreaves-Samani model to consistently underestimate ET for a greenhouse cultivated oregano. They, therefore, concluded that the model should not be used for CEA ET estimation, especially for ventilated CEAs without local calibration.

FAO Penman-Monteith model has been employed for ET estimation in low technology CEAs. Zhang et al. (2010) performed experiments for the estimation of cucumber ET in a low technology greenhouse in China using the pan evaporation ($R^2 = 0.865$) and FAO Penman-Monteith model ($R^2 = 0.46$). Wang et al. (2018) also carried out experiments for the ET estimation of eggplant in a low technology greenhouse with cold-proof quilting for insulation and roof and side vents using the FAO Penman-Monteith model. Lozano et al. (2017) successfully used a low technology greenhouse covered with polyethylene film and white shade screens for the ET estimation of melon using the FAO Penman-Monteith equation. Orgaz et al. et al. (2005) used a class A evaporation pan for ET estimation in a passively ventilated Mediterranean greenhouse for four common horticultural crops (melon, green beans, sweet pepper, and watermelon) with $R^2 = 0.93$ and a percentage error of −5.9 to 34.1%. In a study by Fernández et al. (2010) the FAO Penman-Monteith model also underestimated ET in a Mediterranean greenhouse by 17%. The greenhouse was in Almeria, Spain with no heating system and passive ventilation via side panels and roof vents for cooling. Moazed et al. (2014) compared thirteen reference ET models to find out which models gave the best estimates in low technology greenhouse and outdoor conditions. Of these thirteen models, from existing literature, four have been used for ET estimation in CEA conditions with favorable results. They include the FAO Penman-Monteith, Hargreaves-Samani, Priestley-Taylor, and the FAO Radiation models. In this study, the FAO Penman-Monteith model was found to give the best ET estimate ($R^2 = 0.911$), followed by the FAO Radiation ($R^2 = 0.874$), Priestley-Taylor model ($R^2 = 0.836$), and the Hargreaves-Samani ($R^2 = 0.561$). However, the FAO Penman-Monteith model still underestimated the crop ET by 12%.

4.2. Medium Technology CEA

Medium technology CEAs employ the use of some level of environmental control technology such as fans, heaters, shades, etc. but also use vents for natural ventilation. They also have better envelope properties compared to low-technology systems. They lie in between, similar to low technology in terms of construction method but closer to high technology systems in climate control.

In a study on ET estimation of bananas using pan evaporation and five reference ET models, Liu et al. (2008) used a greenhouse equipped with fans but they were programmed to only operate when the greenhouse air temperature exceeded 30 °C. While temperatures were below this, side vents were operated for natural ventilation. Amongst the ET models used, the FAO Penman gave the best estimates ($R^2 = 0.67$). However, it overestimated ET by approximately 27% on average. In the study by Villarreal-Guerrero et al. (2012), on ET estimation for greenhouse bell pepper and tomato, for three different growing seasons under natural ventilation and fan and pad cooling strategies, the Stanghellini model performed best compared to the Penman-Monteith and Takakura model. However, in considering both cooling strategies and growing seasons, not much difference was found statistically and so any of these models could be employed in real-time CEA cooling strategy. The only limitation may come down to the ease of implementation of these models. Compared to the Penman-Monteith model, the Stanghellini model also provided better estimates ($R^2 = 0.72$, root mean square error $= 2.4$, compared to $R^2 = 0.62$, root mean square error $= 17.1$ for PM model) for tomato ET estimation in a greenhouse equipped with automatically operated side and roof vents (López-Cruz et al., 2008). Battista et al. (2015), used a modified Penman-Monteith model, the Baille equation, for the ET estimation of tomatoes in a greenhouse equipped with fan heaters, and external shading, with $R^2 = 0.8$ with a percentage error of −4.3 to 1.2%. Ondrašek et al. (2007) also successfully studied tomato ET using the Penman-Monteith model in a greenhouse equipped with automatic heating, ventilation, and fertigation systems. Different types of growing media were tested. For experiments performed in 2002, the Penman-Monteith underestimated ET by roughly 5% for Rockwool and overestimated ET by 0.06% and 17% for peat and perlite respectively.

Solar transmissivity comes into play as regards the effectiveness of ET models for this type of CEA. Prenger et al. (2002) found all ET models tested in their study using a double-polyethylene covered greenhouse with an evaporative pad and fan ventilation system to overestimate ET, however, the Stanghellini model was the closest to the measured ET values while the Fynn largely overestimated ET and had a poor Nash-Sutcliffe model efficiency coefficient of −0.848. For low solar radiation conditions, the Fynn model was much closer to estimates from the Stanghellini model. This is because their VPD terms are the same, the only difference lies in the solar radiation term. Therefore, one of the reasons for Stanghellini's superior performance could be traced to its treatment of solar irradiance which is more suited to such an environment. While for the Fynn model, the reasons for its poor performance were the treatment of the solar irradiance as well as the assumption that the leaf and air temperatures were the same. Comparing the Penman-Monteith and Stanghellini model, for the same value of internal and external resistances, their ET estimates were found to differ by 25%, which was due to the inclusion of the LAI term and the modified solar irradiance calculation in the Stanghellini model.

For this type of CEA, the physical ET models seem to give better estimates, however, some reference models such as the Penman model can also be used. The indoor growth environment for medium technology CEA is better controlled compared to the low technology CEA, therefore models such as the Stanghellini model which gives better estimates at low advection conditions can be successfully employed. For low irradiance conditions that occur when estimating nighttime ET or if shades have been used to block out excess solar radiation to control inside temperatures, physical models that include the LAI term perform better than others. The importance of the LAI term can be highlighted from the Prenger et al. (2002) study above. During periods of low irradiance, the Penman and Penman-Monteith models (without the LAI) underestimated ET. However, because of the inclusion of the LAI, the Stanghellini and Fynn models gave better estimates.

4.3. High Technology CEA

High-technology CEAs employ more sophisticated climate control equipment compared to medium technology CEAs. They also have more advanced construction methods often using envelope properties that help insulate the structure. Internal temperature, humidity, lighting, and airflow are closely controlled in such systems. It is quite capital intensive with high equipment costs; however, this could be offset by a reduction in labor costs due to automation. They also employ soilless cultivation which helps manage water and nutrient resources as well as provide better control of crop yield and production.

One such CEA was used in a study by Sharma et al. (2017) for the ET estimation of chile peppers. The greenhouse was clad in double-layer polycarbonate polymer, equipped with shading, automatic climate control, heaters, exhausts, and evaporative coolers. Both the FAO Penman-Monteith (1.6–27.3% underestimation) and Priestley Taylor (17.5–37% underestimation) models were tested, with the former providing better ET estimates. Boulard and Jemaa (1992) also studied tomato ET using a modified Penman-Monteith model in a computer-controlled greenhouse with heating, fog, and air circulation systems.

This category of CEA also includes closed cultivation systems such as plant factories, vertical farms, and shipping container farms. For such closed cultivation systems, energy exchange with the exterior environment is limited. Therefore, energy flux is primarily driven by forced air conditioning and circulation. Because of this, they also rely heavily on artificial lighting, therefore the formulation of the net radiation term is a bit different compared to conventional greenhouses that utilize solar energy. Plants are also subjected to a highly stable interior climate (Graamans et al., 2017). They mostly make use of soilless cultivation systems that improve water use efficiency, although in some cases the same amount of water is used compared to conventional systems, however, it is efficiently delivered to minimize losses due to percolation (Benis et al., 2017).

Plant factories are closed CEAs that solely make use of mechanical heating and cooling systems and uses artificial lighting to provide the required irradiation for crop photosynthesis. Pamungkas et al. (2014) successfully studied the ET of tomatoes in a plant factory in Japan using the Stanghellini model. Graamans et al. (2017) also studied the ET of lettuce in a plant factory with a modified Penman-Monteith model. However, due to the need for artificial lighting and properly controlled climatization, an accurate estimate of all energy fluxes is vital in managing energy use and costs. Therefore, ET estimation in such facilities is crucial, however, very few studies exist on ET estimation in closed CEAs. Vertical farms are simply multi-story plant factories, and like plant factories, rely on mechanical air conditioning systems as well as artificial lighting.

It can be concluded that based on the type of CEA used, ET models should be carefully chosen to provide the best estimates for the prevailing conditions within the CEA. Several studies have performed ET experiments on low and medium technology CEAs, but few studies exist for high technology CEAs. Especially for those that rely heavily on artificial lighting and mechanical air conditioning, modified forms of existing ET models to cater to its unique characteristics are required. Existing modifications must be thoroughly tested by multiple studies to validate their effectiveness. With the high level of climate control in these advanced systems, proper ET estimation has become more important than ever to properly quantify energy use and monitor the efficient use of resources as well as crop yield. Table 4 below gives a summary of CEA types and the ET models that have been applied in each type from several studies.

5. ET calibration

5.1. Calibration methods

Actual ET measurement plays a key role in evaluating and calibrating ET models. This section seeks to discuss different calibration methods as well as discuss their common sources of error, advantages, and disadvantages. These methods are based on the measurement of climatic factors, soil water content, and characteristics of the evaporative surface. Therefore, they can be classified into three: hydrological, micrometeorological, and plant physiological methods (Ding et al., 2010).

Hydrological methods measure ET via the water balance of the growing media and plant. They include the use of lysimeters and soil or substrate water balance. Lysimeter methods are quite popular amongst researchers as a direct method for determining crop water requirements due to their accuracy and ease of use (Allen et al., 2011). Three types of lysimeters are commonly used, they include non-weighing or constant table lysimeters, drainage lysimeters, and weighing lysimeters. Soil water balance provides an indirect method for ET estimation as the residual of soil water balance (Rana and Katerji, 2000). Soil water balance can be difficult to perform because water movement in the soil is multidirectional, although, it provides a cheaper alternative to the use of lysimeters. However, the accuracy of this method depends on the quality of the sensor used, common types include capacitance-based, neutron thermalization, and time-domain reflectometry-based (TDR) sensors (Allen et al., 2011). Soilless cultivation is popular in controlled environment agriculture, therefore, calibration through substrate water balance is another common method. This is usually done by monitoring the amount of nutrient solution added to the system using an appropriate flow meter (Ondrašek et al., 2007).

Micrometeorological methods depend on the canopy energy balance and can measure ET from the latent heat flux. Such methods include Bowen Ratio Energy Balance, Eddy Covariance, and the use of Scintillometers. Bowen ratio energy balance is an indirect approach that measures ET by solving the energy balance equation through measured gradients of air temperature and vapor pressure above the evaporating surface. A drawback of this approach is difficulty in the accurate measurement of net radiation and soil heat flux. However, it presents a non-destructive, automated method for ET measurement. Eddy Covariance method is not common in CEA applications as it requires a representative and adequate fetch. However, it can measure multiple fluxes and is based on the statistical correlation between fluxes of vapor or sensible heat within vertical turbulent eddies (Allen et al., 2011). A scintillometer measures small fluctuations in the refractive index of air due to changes in temperature, humidity, and pressure. They are easy to operate and require low maintenance. However, the cost of equipment is relatively high, they also depend on the accurate measurement of net radiation and soil heat flux, and may require post-processing corrections (Allen et al., 2011).

Plant physiological methods measure transpiration directly from plants. Sap flow gauges have been used for the measurement of actual ET in CEA crops. In this method, low-grade heat is used to measure the flow of water through the stem via the velocity of heat pulse (heat pulse technique) or the dissipation of heat due to convection (heat balance technique) (Rana and Katerji, 2000).

In summary, care must be taken in direct ET measurement using the techniques discussed above to avoid errors. Allen et al. (2011) gave a detailed enumeration of common types of errors that could be encountered in ET measurement. Furthermore, only a handful of methods can be successfully applied to modern CEA applications like vertical soilless cultivation. For such systems, it could be possible to monitor supply and return flow rates or continuously weigh supply reservoir tanks. However, more studies are required to validate this and other potential calibration methods for such systems. Table 5 also shows the different types of calibration methods that have been used in ET estimation in CEA studies. The selection of the type of ET calibration technique to use

Table 4
Summary of relevant indoor ET model studies.

S/N	Study	Type of CEA	ET Model	Experiment Period	Remark
1.	(Liu et al., 2008)	Medium Technology	Priestley Taylor, FAO Radiation, Hargreaves, FAO Penman, FAO Penman-Monteith, Pan Evaporation	35 Days	FAO-Penman gave the best estimation followed by the FAO Penman-Monteith, FAO Radiation, Hargreaves, and lastly the Priestley-Taylor model.
2.‘	(Sharma et al., 2017)	High Technology	Penman-Monteith, Priestley Taylor	Three Growing Seasons (2011 – 140 Days, 2013 – 168 Days, 2014 – 153 Days)	Both models underestimated ET. The authors attributed this to the partial canopy cover and variations of humidity in the CEA.
3.	(Libardi et al., 2019)	Medium Technology	FAO Penman-Monteith	46 Days	Compared to the crop coefficient value for three cultivars of sugarcane.
4.	(Villarreal-Guerrero et al., 2012)	Medium Technology	Stanghellini, Penman-Monteith, Takakura	Three Growing Seasons (Spring, Summer, Fall) 3 Months – Bell Pepper, 7 Months – Tomato. Test Period – 4 to 10 Days.	The Stanghellini model performed best, however, no significant difference was found between the three models.
5.	(Wang et al., 2018)	Low Technology	FAO Penman-Monteith	9 Months	Compared single and dual crop coefficients in the estimation of ET using the FAO Penman-Monteith model
6.	(Zhang, 2010)	Low Technology	FAO Penman-Monteith, Pan Evaporation	31 Days	Pan Evaporation gave better estimates. However, the aerodynamic term of the FAO Penman-Monteith was neglected which may explain poor performance.
7.	(Pamungkas et al., 2014)	High Technology (Plant Factory)	Stanghellini	13 Days	The Stanghellini model was used to estimate ET for plant factory cultivated tomatoes.
8.	(Lozano et al., 2017)	Low Technology	FAO Penman-Monteith	100 Days	Crop coefficients obtained were higher than those recommended by FAO which highlights the importance of conducting situation-specific crop coefficients experiments.
9.	(Orgaz et al., 2005)	Low Technology	Class A Evaporation Pan	Melon – 119, 135, 90 Days. Green Beans – 114 Days. Sweet Pepper – 258, 248 Days; Watermelon – 90 Days.	Crop coefficients were correlated with cumulative thermal time (TT) and LAI for initial and mid-crop growth stages.
10.	(Montero, 2001)	Low Technology	Penman-Monteith	42 Days	Stomatal resistance was found to depend strongly on solar radiation. The Penman-Monteith model also gave good estimates for geranium ET.
11.	(López-Cruz et al., 2008)	Medium Technology	Penman-Monteith, Stanghellini	Several Days in 3rd week of June 2008	The Stanghellini model gave better estimates compared to the Penman-Monteith model especially in high solar radiation and high VPD conditions.
12.	(Moazed et al., 2014)	Low Technology	FAO Penman-Monteith, Hargreaves-Samani, FAO-24 Radiation, Priestley-Taylor, Pan Evaporation	110 Days	FAO Penman-Monteith, FAO Radiation, and Priestley-Taylor were the best performers for CEA ET estimation
13.	(Battista, 2015)	Medium Technology	Modified Penman-Monteith	4 Months	A modified form of the Penman-Monteith model called the Baille equation was used for tomato ET estimation, with LAI estimates obtained from a TOMGRO crop growth model.
14.	(Medrano et al., 2005)	Low Technology	Modified Penman-Monteith	Autumn (Low Radiation Conditions) Cycle – 117 Days; Spring (High Radiation Conditions) Cycle – 111 Days.	Including VPD and LAI terms in the estimation of ET using a modified Penman-Monteith model gave better estimates than using one with Solar Radiation alone.
15.	(Bailey, 1993)	Low Technology	Penman-Monteith, Modified Penman-Monteith	2 Days	The Penman-Monteith model gave acceptable results with an estimation error of less than 3%
16.	(Ondrašek, 2007)	Medium Technology	Penman-Monteith	2 Years (230 Days – 2001; 246 Days – 2002)	Found ET rates to also depend on the type of substrate used and tested the effect of three types (rock wool, peat, and perlite) on ET rate
17.	(Yang et al., 1990)	Medium Technology	*Stanghellini	73 Days	The focus was on the effect of leaf temperature on ET rate and estimation of stomatal resistance. With the latter being a function of solar radiation only.
18.	(Boulard and Jemaa, 1992)	High Technology	Modified Penman-Monteith	6 Months; Experiment for 12 Days.	A modified form of the Penman-Monteith model was proposed. Two methods were also proposed for deriving the needed constant. The first, being from measured parameters gave more accurate estimates than the second which was based on multiple regression.
19.	(Zhang and Lemeur, 1992)	Low Technology	Penman-Monteith, Energy Balance	59 Days	Models for aerodynamic resistance were tested for conditions in which the canopy temperature was less than the air temperature, as well as vice versa for mixed and forced convection.
20.	(Prenger et al., 2002)	Medium Technology	Penman, Penman-Monteith, Stanghellini, Fynn.	14 Days	The Stanghellini model gave the best estimate, this was attributed to its modified solar irradiance model and LAI.
21.	(Jaafar and Ahmad, 2018)	Medium Technology	Penman-Monteith, Hargreaves-Samani, Atmometer	306 Days -With Ventilation 163 Days – Without Ventilation	The performance of the Atmometer was compared to the Penman-Monteith and Hargreaves-Samani models. A calibrated model for atmometer ET was developed

(continued on next page)

Table 4 (*continued*)

S/N	Study	Type of CEA	ET Model	Experiment Period	Remark
					from the Penman-Monteith model using mean temperature and relative humidity values.
22.	(Toyin et al., 2015)	Low Technology	FAO Penman-Monteith	10 Weeks	The relationship was found between the crop coefficient and weeks after planting, as well as crop coefficient and percentage of soil moisture content.
23.	(Acquah et al., 2018)	Low Technology	Stanghellini	ET Measurement – 62 Days Calibration – 24 Days Validation – 24 Days	The Stanghellini model estimates had a strong correlation to the measure ET.
24.	(Willits, 2003)	Medium Technology	Penman-Monteith	3 Years	Using constant values for stomatal resistance gave better estimates than resistance models derived from Stanghellini (1987).
25.	(Gallardo et al., 1999)	Low Technology	Class A Evaporation Pan	258 Days	ET rate was found to vary with the season due to the evaporative demand. Taller crops were also found to intercept more net radiation compared to shorter ones.
26.	(Demrati et al., 2007)	Low Technology	Penman-Monteith	Spring and Autumn – 6 Days Summer – 21 Days	Leaf temperature, as well as the humidity, was found to vary along with the height of the crop.
27.	(Blanco and Folegatti, 2003)	Low Technology	Reduced Evaporation Pan	115 Days	ET was found to vary with substrate salinity, reducing linearly with an increase in salinity.
28.	(Jolliet and Bailey, 1992)	Medium Technology	Penman, Stanghellini, Jolliet, Chalabi, and Aikman	11 Days	ET models with constant values for stomatal resistance performed poorly compared to those which account for its variability.
29.	(Junzeng et al., 2008)	Low Technology	20 cm Evaporation Pan	Tomato – 123 Days Cowpea – 70 Days	ET increases with crop development and is highest when the plant growth is most active.
30.	(Graamans, 2017)	Plant Factory	Modified Penman-Monteith	Lettuce – 3 Days, 28 Days, 8 Days.	Found latent heat flux to exceed input energy especially at lower PPFD values.
31.	(Cannavo et al., 2016)	Medium Technology	Penman-Monteith	1 week	Used the FFD technique for the stomatal resistance model. Tested effect of deficit irrigation and irrigation frequency on crop ET, concluding a deficit of 75% or greater and a frequency of once per day or more has no severe effect on ET.
32.	(Nikolaou, 2017)	Medium Technology	Baille Model	4 Months (Spring) 3 Months (Autumn-Winter)	Baille Model was used with a modified form developed to replace the VPD with Leaf temperature.
33.	(Carmassi et al., 2013)	Medium Technology	Penman-Monteith	Autumn (110 Days) Spring (83 Days) Winter (42 Days)	The effect of salinity on ET was studied, with ET decreasing with increasing salinity.

should depend on the type of experiment, level of expertise, costs, sensor specifications, as well as allowable errors.

5.2. Calibration equipment

An important part of ET experiments or model validation is the proper selection of equipment and sensors. However, this can only be possible through prior knowledge of the range of applicable equipment and sensors. Therefore, Table 6 presents a summary of this information, for different sensors and equipment that monitor key parameters in a CEA ET experiment. References are also provided from existing studies to serve as a preliminary guide for equipment selection.

6. Current challenges

Although existing studies have been conducted on ET estimation in CEAs, a pressing issue that has been frequently highlighted is the difficulty in modeling crop stomatal resistance. This is a concern on the measurement/calibration as well as the modeling front. On the measurement front, obtaining reliable real-time direct measurements using porometers could still be challenging (Villarreal-Guerrero et al., 2012; Montero et al., 2001). Such issues include altering leaf functioning due to contact with leaf surface (Irmak and Mutiibwa, 2009; Craparo et al., 2017), and the inability to capture spatial and temporal variations at canopy level (Craparo et al., 2017). Therefore, direct, non-contact methods using thermal imaging provide a remote, rapid, continuous, and effective method for crop resistance measurement (Craparo et al., 2017; Blonquist et al., 2009). However, this technique requires further testing and validation for CEA.

From the modeling point of view, the major challenge for modeling crop resistance is that the physiological mechanisms controlling the stomatal response to environmental conditions are complex and not fully understood yet (Liu et al., 2008; Li et al., 2012; Misson et al., 2004; Tuzet et al., 2003). Two popular models have been widely used in modeling crop resistance – the Jarvis model and the Ball model (Li et al., 2012). There appears to be no clear outperformer, with both models having their limitations. The Jarvis model requires a lot of parameterization, tuning, and re-calibration for different environmental conditions (Damour et al., 2010; Li et al., 2012). While the Ball model is inadequate in modeling for plants with some degree of water stress without modifications (Misson et al., 2004; Tuzet et al., 2003). Furthermore, since it is a photosynthesis-based model, errors associated with calculating photosynthesis can become associated with estimating crop resistance (Li et al., 2012; Misson et al., 2004).

Therefore, a few modifications to these models as well as new approaches to modeling crop resistance has been pursued. Modified forms of the Jarvis model include the NOE and Giersch model (NOE and Giersch, 2004) and the GM-model (Green and McNaughton, 1997) which uses fewer parameters, the Mission model (Misson et al., 2004) which has a water stress response component, and the NMJ model (Irmak and Mutiibwa, 2009) which accounts for the effect of LAI on crop resistance. For the Ball model, modified forms include the BWB-Leuning model (Leuning, 1995) which used a hyperbolic function of VPD in place of a linear function of relative humidity and the BWB-Leuning-Yin model (Yin and Struik, 2009) which includes the mitochondrial respiration rate in the light to avoid negative values when PAR drops below the light compensation point.

In terms of new approaches, estimation of crop resistance using statistical modeling methods is increasingly gaining more attention (Liu et al., 2008). An example has been the use of Full Factorial Design (FFD). This method has the advantage of requiring less amount of calibration data and model parameters, however, it requires further validation and

Table 5
Calibration methods and ET ranges from literature for different crops.

S/N	Study	Calibration Method	Crop	ET Range	CEA Type
1.	(Liu et al., 2008)	Weighing Lysimeter	Banana	0.22 to 1.89 kg/day	Medium Technology (Greenhouse)
2.	(Sharma et al., 2017)	Soil Water Balance	Chile Pepper	Year 2011: − 55.85 to 59.73 cm. Year 2013: − 66.5 to 72.58 cm. Year 2014: − 50.31 to 73.92 cm	High Technology (Greenhouse)
3.	(Libardi et al., 2019)	Weighing Lysimeter	Pre-sprouted sugarcane plantlets	3.6 to 6.6 mm/day	Medium Technology (Greenhouse)
4.	(Villarreal-Guerrero et al., 2012)	Sap Flow Gauges, Lysimeter	Bell Pepper, Tomato.	Bell Pepper Natural Ventilation – 0 to 310 W/m^2 Pad and Fan – 0 to 260 W/m^2 Tomato Natural Ventilation – 0 to 480 W/m^2 Pad and Fan – 0 to 300 W/m^2	Medium Technology (Greenhouse)
5.	(Wang et al., 2018)	Micro Lysimeter, Soil Water Balance	Eggplant	2 to 4 mm/day	Low Technology (Greenhouse)
6.	(Zhang, 2010)	Weighing Lysimeter	Cucumber	0.81 to 4.46 mm/day	Low Technology (Greenhouse)
7.	(Pamungkas et al., 2014)	Weighing Lysimeter, Substrate Water Balance	Tomato	ET_{max} = 0.24 mm/h	High Technology (Plant Factory)
8.	(Lozano et al., 2017)	Constant Water Table Lysimeter	Melon	ET_{max} = 5.16 mm/day	Low Technology (Greenhouse)
9.	(Orgaz et al., 2005)	Drainage Lysimeter, Soil Water Balance	Melon; Green Beans; Sweet Pepper; Watermelon	Melon – ET_{avg} = 4.5 mm/day Green Beans – ET_{avg} = 1.53 mm/day Sweet Pepper– ET_{avg} = 0.3 mm/day Watermelon – ET_{avg} = 1.89 mm/day	Low Technology (Greenhouse)
10.	(Moazed et al., 2014)	Microlysimeter	Grass (Luliom Cultivar)	ET_{avg} = 6.63 mm/day	Low Technology (Greenhouse)
11.	(Battista, 2015)	Water Balance	Tomato	ET = 300.2 to 382 L/m^2	Medium Technology (Greenhouse)
12.	(Medrano et al., 2005)	Weighing Lysimeter	Cucumber	ET = 128 to 4332 g/ m^2 day	Low Technology (Greenhouse)
13.	(Yang et al., 1990)	Weighing Lysimeter	Cucumber	ET = 0.99 to 1.69 L/day	Medium Technology (Greenhouse)
14.	(Fernández et al., 2010)	Free Drainage Lysimeter, Soil Water Balance	Perennial Grass	ET = 1 to 4 mm/day	Low Technology (Greenhouse)
15.	(Toyin et al., 2015)	Weighing Lysimeter	Leafy Amaranth	ET = 0.6 to 2.0 mm/day	Low Technology (Greenhouse)
16.	(Acquah et al., 2018)	Sap Flow	Tomato	Initial Stage ET = 0.165 mm/h Development Stage ET = 0.148 mm/h Mid Stage ET = 0.192 mm/h Late Stage ET = 0.154 mm/h	Low Technology (Greenhouse)
17.	(Chopda et al., 2018)	Soil Water Balance	Green Chilli	Initial Stage ET_{avg} (10% MAD) = 1.52 mm/day Mid Stage ET_{avg} (10% MAD) = 2.98 mm/day Late Stage ET_{avg} (10% MAD) = 4.01 mm/day	Low Technology (Greenhouse)
18.	(Sigalingging and Rahmansyah, 2018)	Volumetric Soil Moisture Content	Oil Palm	ET = 1.85 to 2.00 mm/day	Low Technology (Greenhouse)
19.	(Jolliet and Bailey, 1992)	Weighing Lysimeter	Tomato	ET = 3.19 to 3.5 mm/day	Medium Technology (Greenhouse)
20.	(Junzeng et al., 2008)	Weighing Lysimeter	Tomato, Cowpea	Tomato – ET_{avg} = 1.00 mm/day Cowpea - ET_{avg} = 2.41 mm/day	Low Technology (Greenhouse)
21.	(Graamans, 2017)	Weighing Lysimeter	Lettuce	ET_{avg} = 115 g/m^2 h	High Technology (Plant Factory)
22.	(Salcedo et al., 2017)	Water Balance	Cucumber	ET_{avg} = 1.63 mm/day	Low Technology (Greenhouse)

*Conversion between different units can be found in Cascone et al. (2018).

testing (Ali et al., 2016). Other methods such as Partial Least Square (PLS) and Neural Net Analysis (NNA), and Radial Basis Function Network (RBF) have been used to successfully predict crop resistance (Liu et al., 2008; Vitale et al., 2007).

These modified models and new approaches have been found to give better estimates of crop resistance. However, they require further investigations and validation in other climatic settings. Future studies should also further explore modern statistical modeling and machine learning methods.

Furthermore, few studies focus on high technology CEA that utilizes artificial lighting, mechanical cooling/heating, hydroponic cultivation, and continuous irrigation. Two main research gaps exist for these high technology CEAs. The first is with model implementation and validation. Only a couple of models (Stanghellini and Graamans's models) have

Table 6
Key equipment used in ET parameter measurements.

S/N	Measured Parameter	Equipment	Reference
1.	Plant Weight	Load Cells, Electronic Balance	(Junzeng et al., 2008; Cannavo et al., 2016; Prenger et al., 2002; Zhang, 2010; Montero, 2001; Pamungkas et al., 2014; Liu et al., 2008; Libardi et al., 2019; Yang et al., 1990; Rouphael and Colla, 2004; Medrano et al., 2005; Wang et al., 2018; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Bailey, 1993; Willits, 2003; Nikolaou, 2017)
2.	Soil Water Content	Soil Moisture Sensors	(Gallardo et al., 1999; Fernández et al., 2010; Chopda et al., 2018; Sharma et al., 2017; Wang et al., 2018; Orgaz et al., 2005; Qiu, 2013)
3.	Substrate Water Content	Water Content Sensor	(Cannavo et al., 2016; Pamungkas et al., 2014)
4.	Crop Transpiration	Sap Flow Gauges	(Villarreal-Guerrero et al., 2012; Acquah, 2018; Qiu, 2013)
5.	Pan Evaporation	20 cm Diameter Evaporation Pan, Class A Evaporation Pan	(Zhang, 2010; Liu et al., 2008; Fernández et al., 2010; Orgaz et al., 2005)
6.	Air Temperature	Temperature Sensors, Thermocouple	(Cannavo et al., 2016; Villarreal-Guerrero et al., 2012; Prenger et al., 2002; Zhang, 2010; Montero, 2001; Pamungkas et al., 2014; Liu et al., 2008; Fernández et al., 2010; Libardi et al., 2019; Jolliet and Bailey, 1992; Demrati et al., 2007; Acquah et al., 2018; Yang et al., 1990; Medrano et al., 2005; Ali, 2016; Sharma et al., 2017; Wang et al., 2018; Bailey, 1993; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Zolnier et al., 2004)
7.	Leaf Temperature	Thermocouple, Infrared Thermometer	(Prenger et al., 2002; Montero, 2001; Jolliet and Bailey, 1992; Demrati et al., 2007; Yang et al., 1990; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Qiu, 2013; Bailey, 1993; Willits, 2003; Nikolaou, 2017)
8.	Relative Humidity	Relative Humidity Sensors	(Cannavo et al., 2016; Villarreal-Guerrero et al., 2012; Pamungkas et al., 2014; Liu et al., 2008; Fernández et al., 2010; Libardi et al., 2019; Demrati et al., 2007; Acquah et al., 2018; Ali, 2016; Sharma et al., 2017; Wang et al., 2018; Willits, 2003; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Zolnier et al., 2004; Qiu, 2013)
9.	Solar Radiation	Pyranometers, Solarimeter	(Villarreal-Guerrero et al., 2012; Prenger et al., 2002; Zhang, 2010; Montero, 2001; Liu et al., 2008; Fernández et al., 2010; Jaafar and Ahmad, 2018; Demrati et al., 2007; Acquah et al., 2018; Yang et al., 1990; Rouphael and Colla, 2004; Medrano et al., 2005; Bailey, 1993; Willits, 2003; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Zolnier et al., 2004)
10.	Net Radiation	Net Radiometer, Crop Solarimeter (Takakura model), Ceptometer,	(Villarreal-Guerrero et al., 2012; Zhang, 2010; Montero, 2001; Libardi et al., 2019; Demrati et al., 2007; Acquah et al., 2018; Rouphael and Colla, 2004; Medrano et al., 2005; Sharma et al., 2017; Wang et al., 2018; Zhang and Lemeur, 1992; Qiu, 2013; Bailey, 1993)
11.	Photosynthetically Active Radiation (PAR)	Quantum Sensor	(Pamungkas et al., 2014; Gallardo et al., 1999; Rouphael and Colla, 2004; Medrano et al., 2005)
12.	Air Velocity	Air Velocity Sensor, Ultrasonic Anemometer	(Villarreal-Guerrero et al., 2012; Pamungkas et al., 2014; Fernández et al., 2010; Libardi et al., 2019; Demrati et al., 2007; Yang et al., 1990; Rouphael and Colla, 2004; Bailey, 1993; Willits, 2003; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Zolnier et al., 2004; Qiu, 2013)
13.	Leaf Stomatal Resistance	Porometer	(Cannavo et al., 2016; Montero, 2001; Demrati et al., 2007; Rouphael and Colla, 2004; Ali, 2016; Zhang and Lemeur, 1992; Qiu, 2013)
14.	Leaf Area	Digital Leaf Area Meter, Electronic Planimeter, Plant Canopy Analyzer	(Villarreal-Guerrero et al., 2012; Kage et al., 2000; Rouphael and Colla, 2004; Medrano et al., 2005; Orgaz et al., 2005; Zhang and Lemeur, 1992; López-Cruz et al., 2008; Qiu, 2013; Willits, 2003; Nikolaou, 2017)
15.	Canopy Surface Temperature	Crop Solarimeter, Infrared Pyrometer	(Villarreal-Guerrero et al., 2012; Qiu, 2013)
16.	Soil Heat Flux	Heat Flux Plates	(Demrati et al., 2007; Wang et al., 2018; Zhang and Lemeur, 1992)
17.	Soil Temperature	Thermistors	(Demrati et al., 2007)
18.	Data Sampling and Storage	Data Logger	(Cannavo et al., 2016; Villarreal-Guerrero et al., 2012; Prenger et al., 2002; Montero, 2001; Liu et al., 2008; Fernández et al., 2010; Libardi et al., 2019; Demrati et al., 2007; Acquah et al., 2018; Yang et al., 1990; Rouphael and Colla, 2004; Ali, 2016; Wang et al., 2018; López-Cruz et al., 2008; Qiu, 2013; Bailey, 1993)

been successfully used for ET estimation in such systems. Therefore, validation of these models from a wide range of studies and possible model enhancement is important to ensure the reliability and our confidence in these ET models. Furthermore, for key elements of ET models such as net radiation, experiments need to be conducted to estimate the net radiation of crops for indoor farming facilities relying on grow lights. Ideally, the methods for calculation or estimation of net radiation should be generalized based on different configurations and grow light capacity.

As can be seen in many of the studies summarized, existing ET studies in CEA, center on a few common crops such as lettuce, tomato, cucumber, and melon. On the other hand, current CEA crops such as microgreens and strawberries have been scarcely dealt with. This same deficiency occurs in the publication of crop coefficients for reference ET models. The majority of the recommended FAO-published crop coefficients are for field-grown crops. This highlights the need for more studies in this area. Several existing studies also limit ET estimation to short periods, which does not capture the variations of ET over a full cropping season. Therefore, studies spanning a longer period should be encouraged as such a complete picture would be important for proper irrigation management over a full season. It would also provide important data for energy use and conservation studies as well as life cycle assessment studies.

Finally, research that considers the interdependent nature of important parameters on the ET rate should be further pursued. Such interdependence makes it difficult to isolate the effect of each parameter on ET. This has created a lack of consensus when highlighting such effects since several studies consider the effect of each parameter independently. Whereas a more robust approach that considers them simultaneously may help paint a better picture. The area of machine learning could help in this case. With the combination of domain knowledge, new features that combine existing parameters could give a better insight to improve ET estimations.

7. Conclusion

Advances in agriculture have seen the emergence of vertical farms and plant factories. These high technology farms are energy-intensive and rely on artificial lighting and closed environmental controls. However, they shorten production time and improve crop production per unit hectare. Current and future research seek to quantify and evaluate the energy efficiency of such systems. To do this, comprehensive knowledge of the energy exchange between key elements such as the plant canopy, surrounding air, CEA envelope, and external boundary conditions is important. A key component of such an energy exchange in CEA is crop ET. However, only a handful of studies exist on crop ET for such systems.

ET models exist to estimate ET based on easily measurable parameters. Such models have seen extensive use in open field cultivation and to a lesser extent, greenhouse crop production. It, therefore, serves as a natural starting point. Existing ET models were reviewed, of these, twelve models most suitable for indoor ET estimation were selected. The accuracy of these models based on the type of ET model, type of CEA, and implementation timestep was investigated.

Penman-Monteith model appears to be the most popular model used in both its original and modified forms. It has been successfully used for the ET estimation of a variety of greenhouse cultivated crops such as lettuce (Zolnier et al., 2004) (R^2 = 0.73–0.93 depending on cultivar type), bell-pepper (Villarreal-Guerrero et al., 2012) (R^2 = 0.95–0.96 depending on greenhouse cooling strategy), geraniums (Montero et al., 2001) (R^2 = 0.96), tomato (López-Cruz et al., 2008) (R^2 = 0.75), cucumber (Medrano et al., 2005) (R^2 = 0.97), Ficus benjamina (Zhang and Lemeur, 1992) (R^2 = 0.97–0.98 depending on the prevalent type of surface geometry and convection), banana (Demrati et al., 2007) (R^2 = 0.91) and gerbera (Carmassi et al., 2013) (R^2 = 0.90–0.95 depending on season). However, it has been found to be outperformed by the Stanghellini (Villarreal-Guerrero et al., 2012; Prenger et al., 2002; López-Cruz et al., 2008) and data-driven models (Parasuraman et al., 2007).

A few studies have reported that the Stanghellini model (Villarreal-Guerrero et al., 2012; Prenger et al., 2002; López-Cruz et al., 2008) outperformed the Penman-Monteith model in several greenhouse applications. López-Cruz et al. (2008) compared Stanghellini model to Penman-Monteith model for greenhouse tomato crop (R^2 = 0.72 vs. R^2 = 0.62). Guerrero et al. (2010) found that the Stanghellini model outperformed the Penman-Monteith model and Takakura model for greenhouse bell pepper and tomato crops. Prenger et al. (2002) found Stanghellini model outperformed the Penman, Penman-Monteith, and Fynn model for greenhouse red maple tree (Nash-Sutcliffe Correlation Coefficient = 0.872 vs. 0.214, 0.481, −0.848 respectively). It outperformed the Penman, Chalabi, and Aikman models (R^2 = 0.77 vs. R^2 = 0.59, 0.57, 0.73) in a study by Jolliet and Bailey (1992) for greenhouse tomato crop. In the same study, although the Jolliet model had a better R^2 value of 0.81, it underestimated ET by 8% on average compared to the Stanghellini model which overestimated ET by 3% on average. This could be attributed to the fact that the Stanghellini model was purposely created for the greenhouse environment (Pamungkas et al., 2014; Acquah et al., 2018). Furthermore, in the Stanghellini model, the LAI term accounts for energy flux between multiple leaf layers, and the radiative resistance term improves the modeling of the incoming radiation flux, as well as treating the airflow as mixed convection (Villarreal-Guerrero et al., 2012; López-Cruz et al., 2008). However, there are very limited number of case studies and comparison studies for high technology CEAs using the Stanghellini model and most studies have either been low technology CEAs or CEAs with limited indoor environment controls. Also, only limited crop types have been focused on in existing ET studies. Would the model perform consistently well for other types of CEA crops such as microgreens? Furthermore, not all the twelve models are evenly studied and compared. Some of the models such as the Graamans model are relatively new and have not been compared with other models yet. Comparison studies are essential for the selection of ET models in different CEA applications, especially high technology CEAs (Iddio et al., 2020).

Amongst the mass transfer-based models, only the Penman model has seen extensive use in CEA applications. In larger studies on mass transfer-based models (mostly outdoor applications), the Penman model and several other mass transfer-based models such as Trabert, Jensen-Haise, and Mahringer models have been found to give acceptable results (Djaman et al., 2017; Valipour, 2014; Islam and Alam, 2021). Although we can assume that these models could be successfully validated for CEA, these models would require further testing and calibration to demonstrate their ability in successfully predicting ET in modern CEA facilities.

A major challenge in ET modeling is the difficulty in the modeling of crop stomatal resistance. This creates the need for improved sensor technology on the measurement side and a comprehensive mechanistic approach on the modeling side. A second challenge is the limited number of studies on emerging types of high technology CEAs such as vertical farms and plant factories. An increase in the volume of studies would help with widespread model implementation and validation, and appropriate ET calibration methods. Also, it would ensure heterogeneous studies that cover a variety of indoor cultivated crops instead of the narrow range of crops currently studied. An added benefit would be the provision of reliable data to create a crop coefficient database relevant to indoor crop production.

Future ET modeling efforts would profit from advancements in computer technology and machine learning techniques that can potentially be integrated with the first principles of mass and energy budgets so that ET predictions can be extended beyond training data. Especially for high technology CEAs for which data collection is crucial, such data could be used to create high fidelity ET models. Plant water use would be better managed by regulating irrigation based on predicted plant ET in real-time. This would have major implications on water use efficiency, crop growth, and overall energy efficiency for such systems.

Besides centralized vertical farming facilities, indoor crop growth can be integrated with building systems (façade, interior, and mechanical systems) as part of urban food production. In this case, crops, people, and building systems will interact with each other. On one hand, ET from indoor crops affects human comfort and potentially reduces building cooling demands. On the other hand, human behaviors and building system operations influence crop performance. Therefore, the enhancement of our knowledge of ET rates for indoor growing crops is essential for quantifying the performance of indoor crops and contributes to our understanding of the interaction between indoor crops and the built environment.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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